Princeton Webinar

markus'academy

Hosted from **PRINCETON**
Available for **EVERYONE, WORLDWIDE**

Seasonality of COVID-19

Bengt Holmström
MIT

Markus Brunnermeier
Princeton

Coming momentarily
At 12:30 p.m.

Poll Results

academy

1. How much does *your fear* of Covid-19 affect *your* daily life?
   a. A lot
   b. Moderately
   c. Not at all

2. When do you believe the US will get Covid-19 under control?
   a. By the end of spring 2021
   b. By the end of 2021
   c. Later than 2021

3. Will major universities (like Princeton) mostly return to traditional forms of teaching post-Covid or do you expect the teaching to change fundamentally?
   a. Return
   b. Change

Markus' **Introductory Remarks**

m academy

1. Health crisis
   - Behavioral response (social distancing) matters
     - Fear/anxiety or externality
2. Economic crisis
   - Record unemployment, GDP drop, …
   - K-recession (winner and losers)
3. Financial crisis
   - Record stock market levels, IPO issuance of stocks (SPACs) and bonds, …
   - Financial market disconnect?

Special purpose acquisition companies

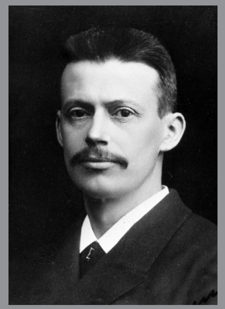
- The illusory health-wealth tradeoff and long-run congruence
  - Lockdown vs. shutdown
  - Social distancing -> lower GDP now, but higher GDP in the long-run

Health focus

- Health crisis is the driver!
  - Aerosols, UV light
- Weather, seasonal patterns

- Questions:
  - Should the stringency of COVID measures depend on sunshine/humidity/temperature (on that day)?
  - Should we equip our AC units with UV lights?

  - X



Niels Finsen
(Nobel Prize in
medicine, 1903)

Thank you!

markus@princeton.edu

Seasonality of Covid-19 - why it matters

Marcus’ Academy, Princeton

October 22, 2020

Bengt Holmström (MIT), Martti Hetemäki (Helsinki GSE),
Juhana Hukkinen (Bank of Finland)

Two hypotheses

1. Covid-19 is seasonal
   Strong wave in the fall, weak (or no) wave in the spring
   Historical and current evidence

2. Seasonality is driven by UV
   Physical and empirical case for UV
   UV strong relative to other factors

Outline

Historical vs current patterns

The case for UV

Mobility and stringency

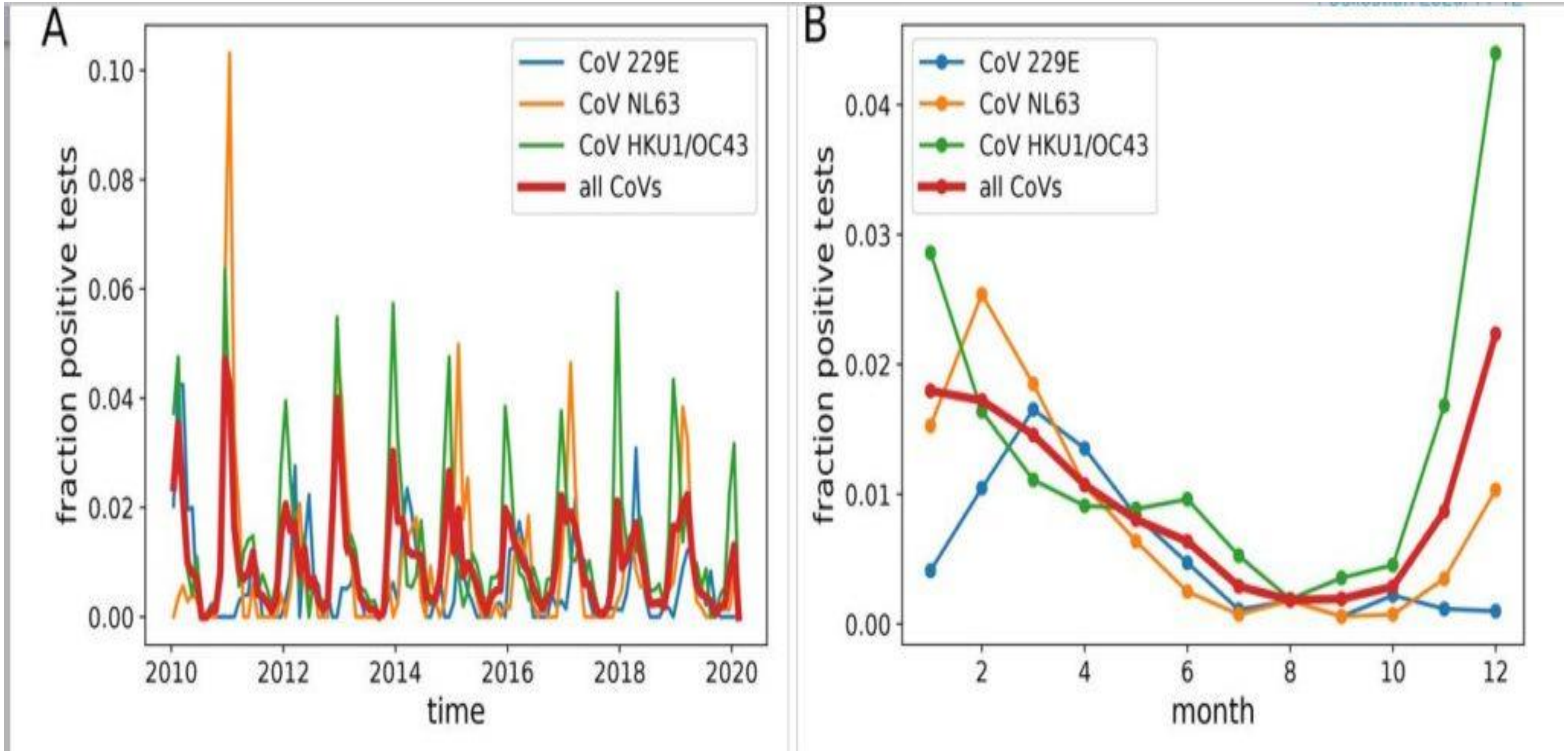
Regression results

Qualifications

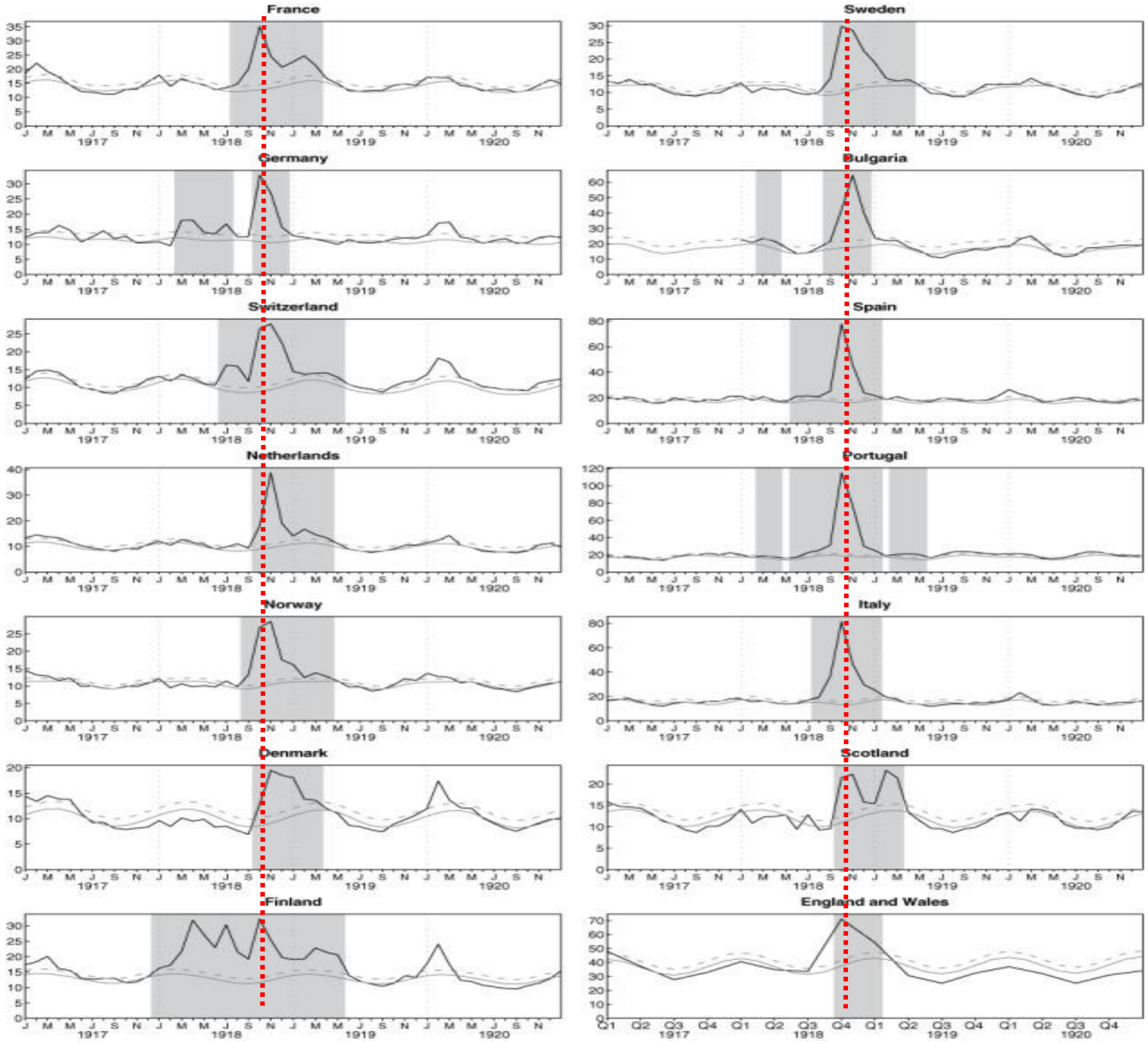
Conclusion

Historical vs current patterns

Data from all corona tests in seven hospitals in Stockholm area in 2010-2019



Source: Neher at al (2020) https://smw.ch/article/doi/smw.2020.20224



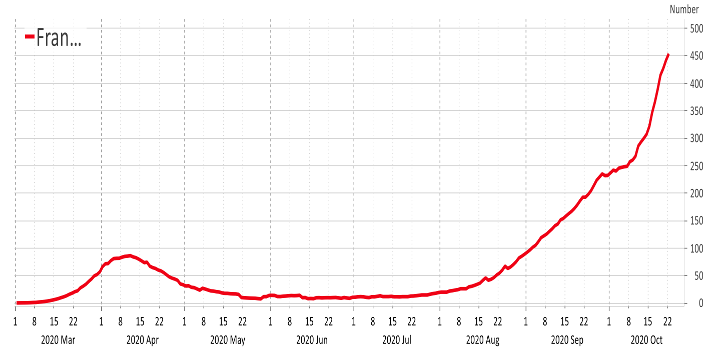
Mortality rate (per 10 000) in 14 European countries from 1917 to 1921.

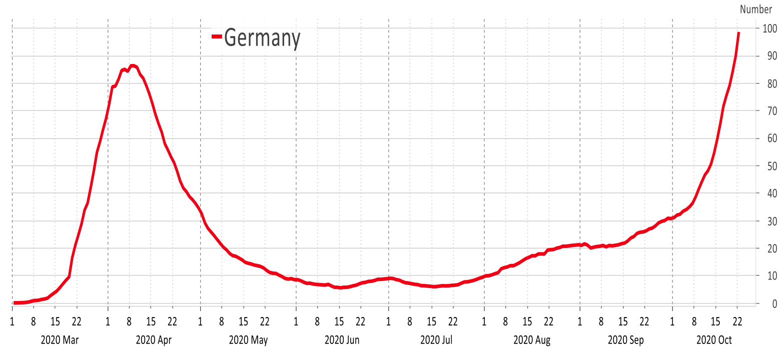
”Excess-death curves showed high synchrony in 1918– 1919 with peak mortality occurring in all countries during a 2-month window (Oct–Nov 1918).”

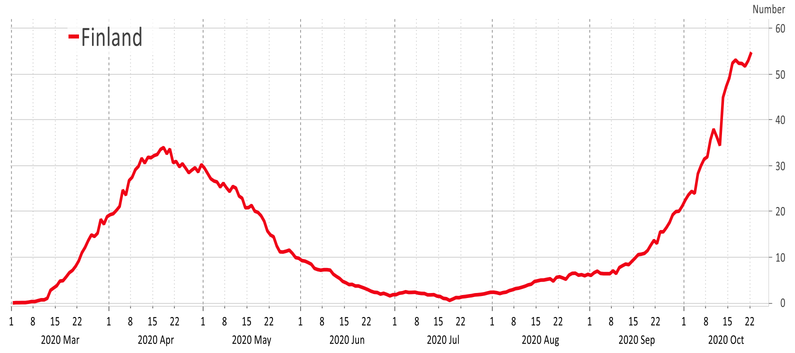
Source: Ansart et al (2009), Mortality burden of the 1918–1919 influenza pandemic in Europe. *Influenza and Other Respiratory Viruses, 3, 99–106.*

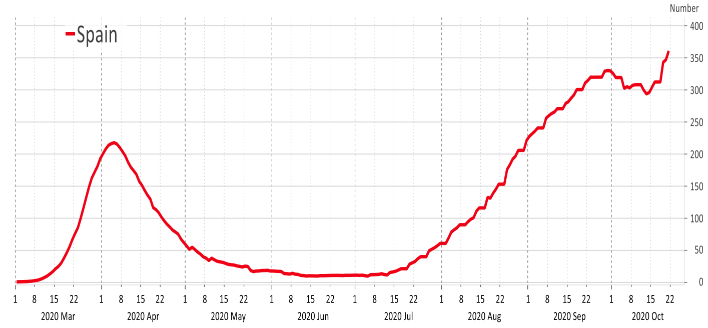
https://europepmc.org/backend/ptpmcrender.fcgi?accid=PMC4634693&blobtype=pdf

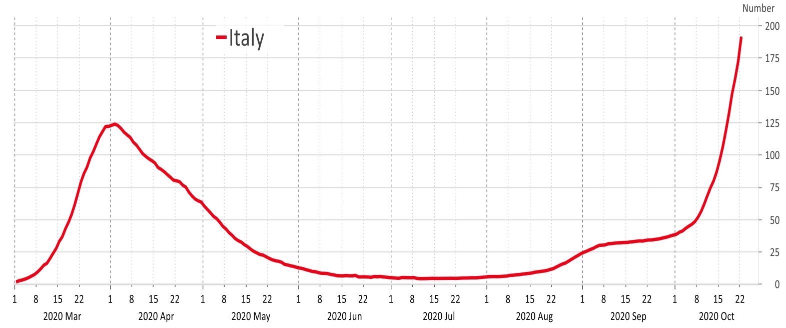
New Covid-19 cases, 14 day sum of new Covid-19 cases per 100 000 persons March 1 – 20, October 2020

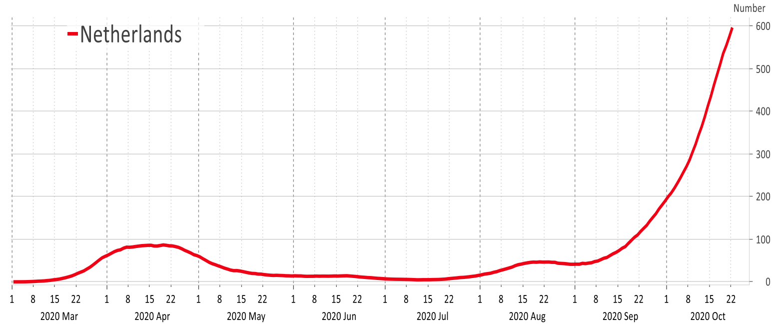


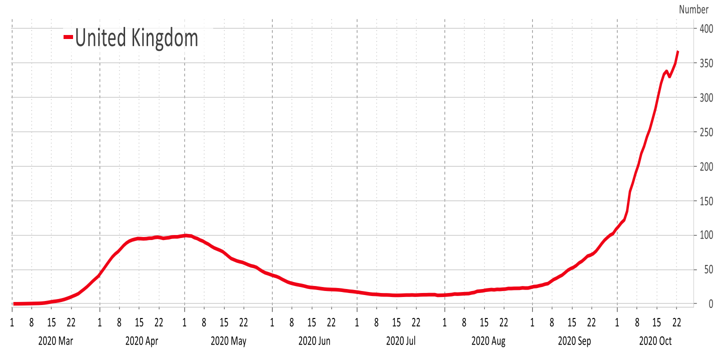


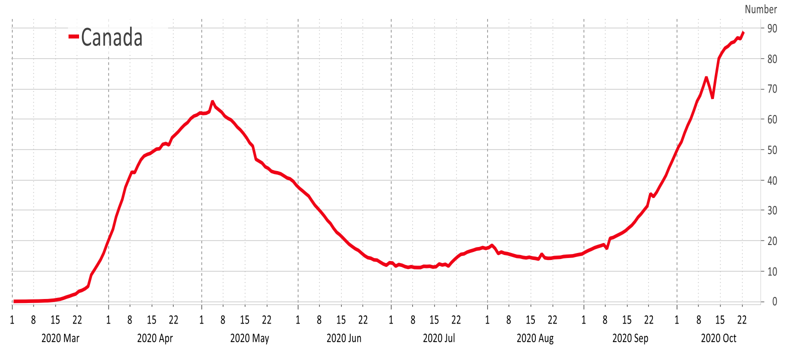


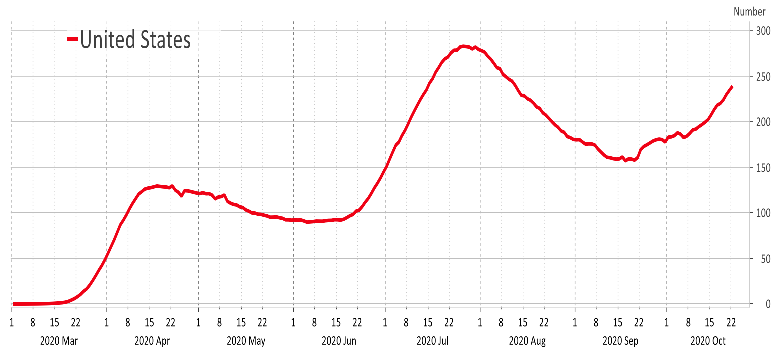


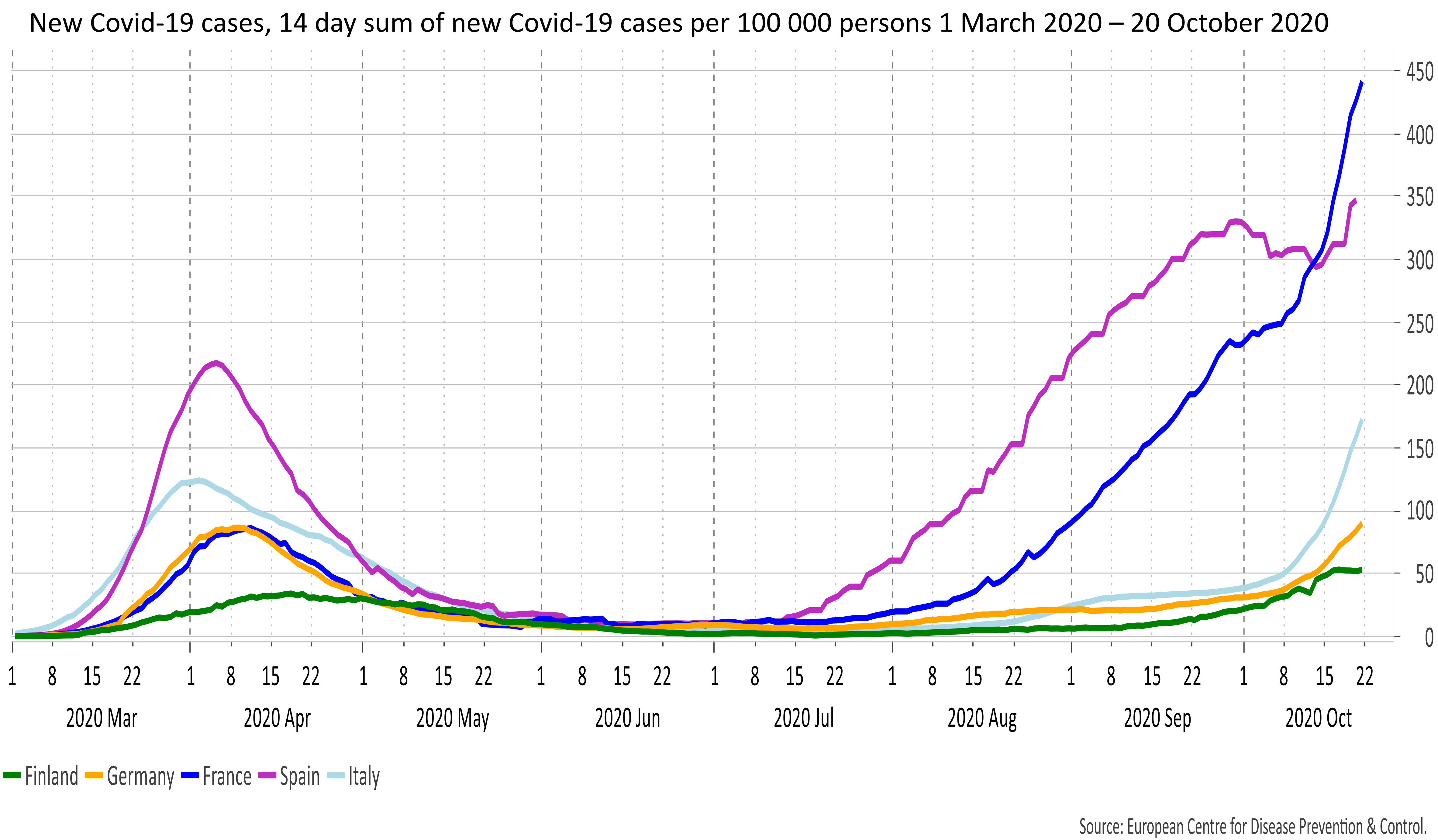








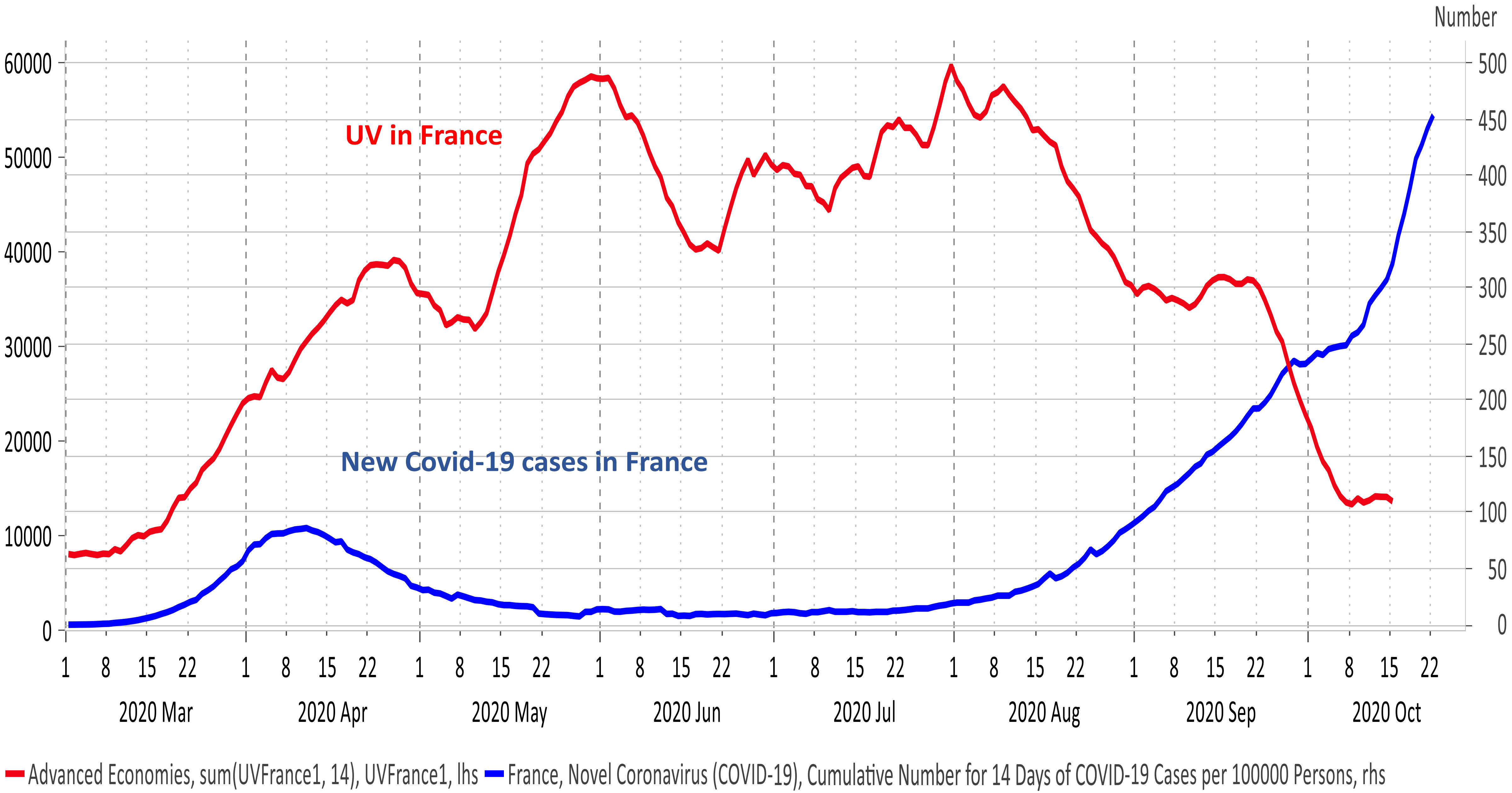




New Covid-19 cases, 14 day sum of new Covid-19 cases per 100 000 persons 1 March 2020 – 20 October 2020
450
400
350
300
250
200
150
100
50
0
1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22
2020 Mar
2020 Apr
2020 May
2020 Jun
2020 Jul
2020 Aug
2020 Sep
2020 Oct
Finland
Germany
France
Spain
Italy
Source: European Centre for Disease Prevention & Control.

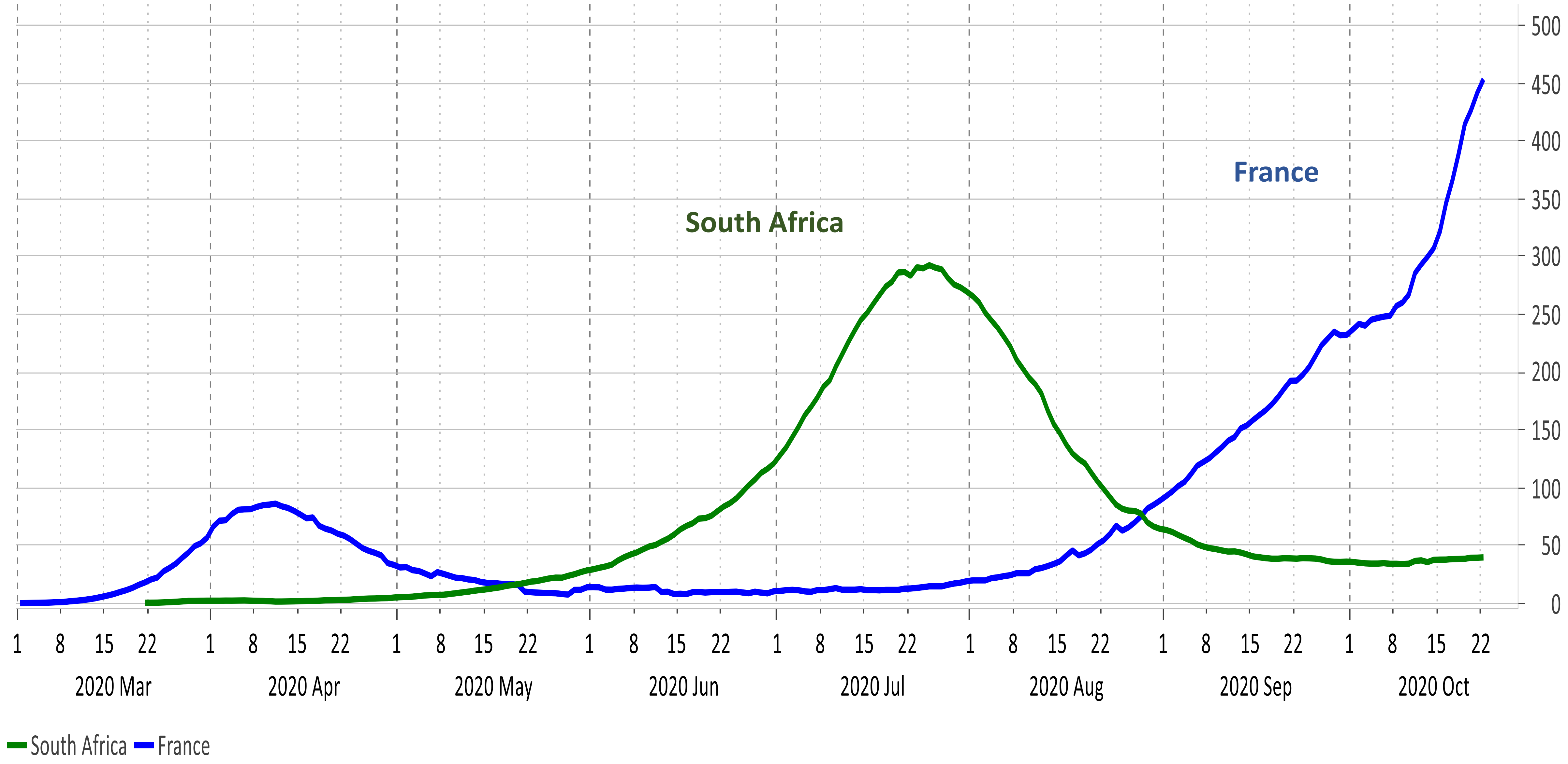
The case for UV

UV load (left scale) and new Covid-19 cases (right scale) in France, March 1 – 17 October 2020



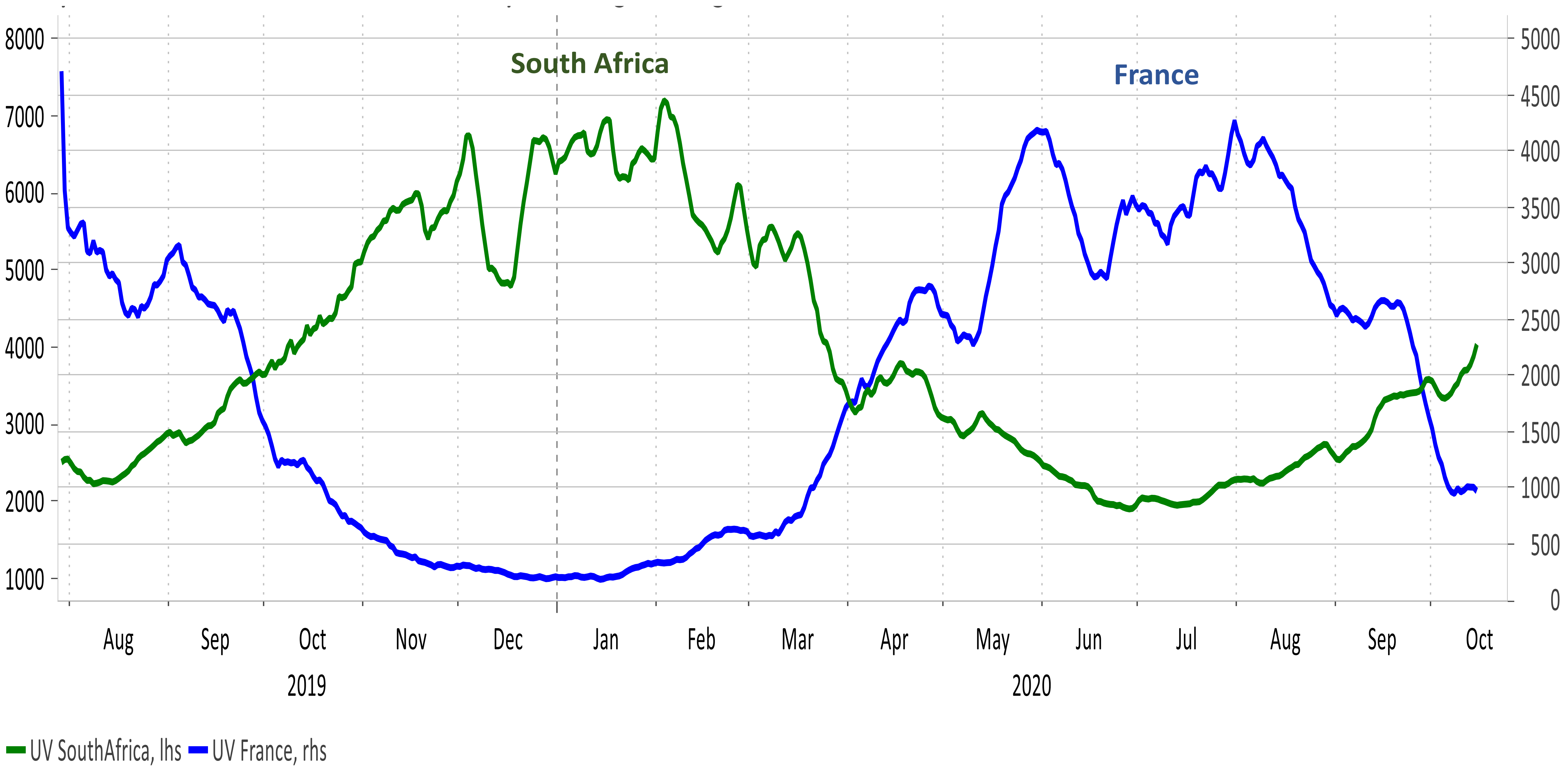
Source: European Centre for Disease Prevention & Control, French National Institute of Statistics & Economic Studies (INSEE), Google & NASA, Goddard Space Flight Center.

New Covid-19 cases in France and South Africa March 1 – 20, October 2020



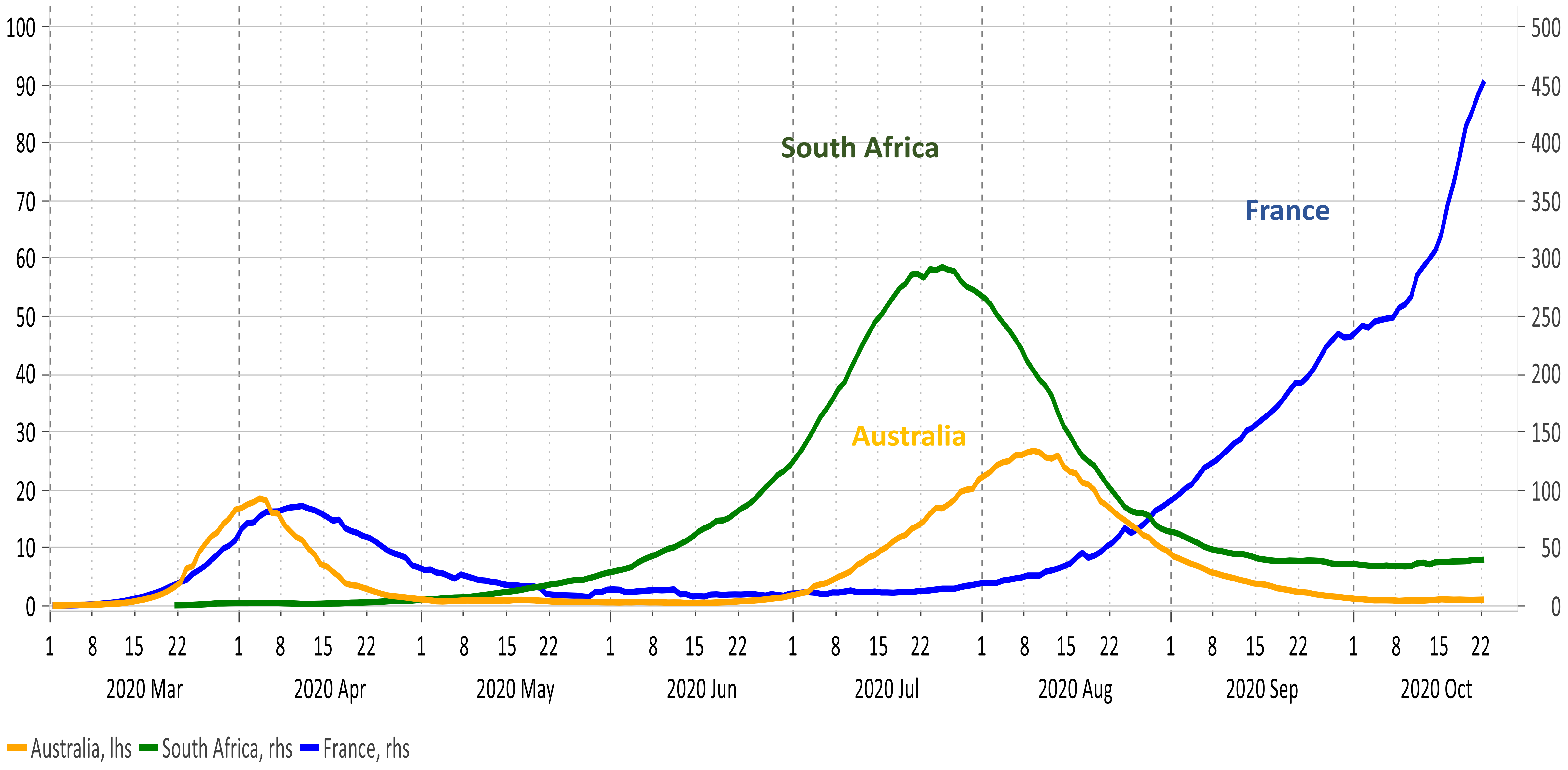
Source: European Centre for Disease Prevention & Control.

UV load in South Africa and France August 2019 – October 2020



Source: NASA, Goddard Space Flight Center.

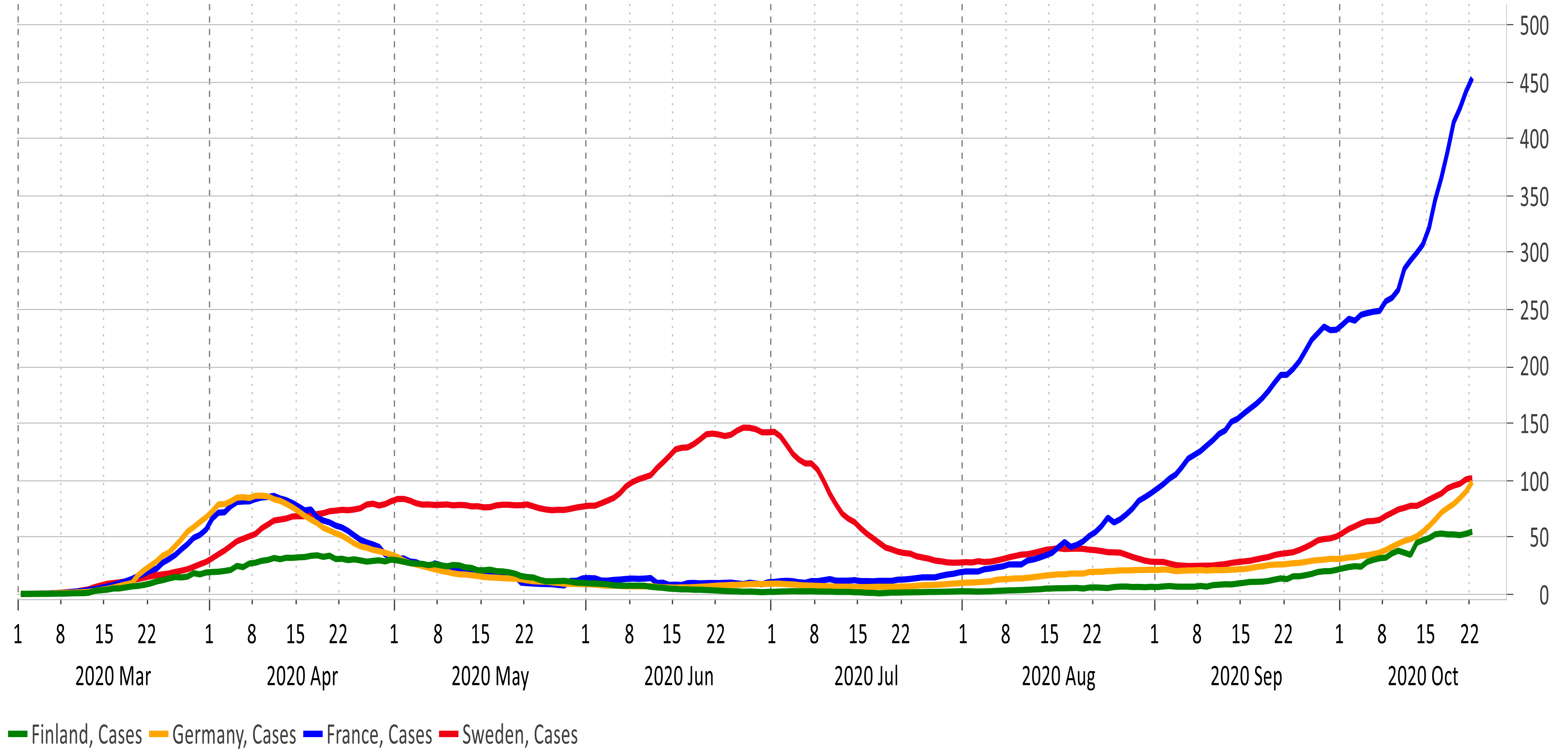
New Covid-19 cases in France, South Africa and Australia March 1 – 20 October, 2020



Source: European Centre for Disease Prevention & Control.

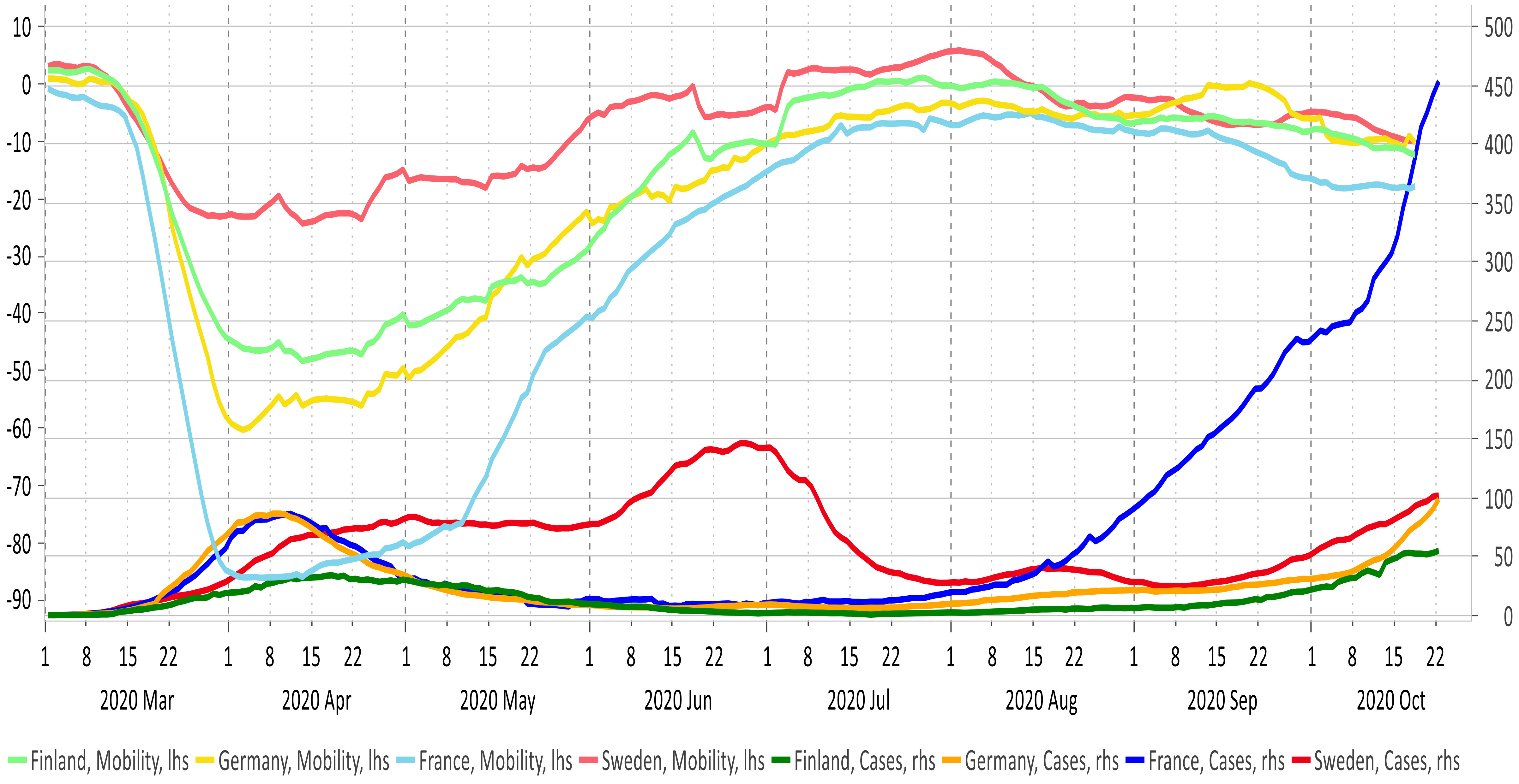
Mobility and Stringency

New Covid-19 cases in Finland, Germany, France and Sweden March 1 – October 20, 2020



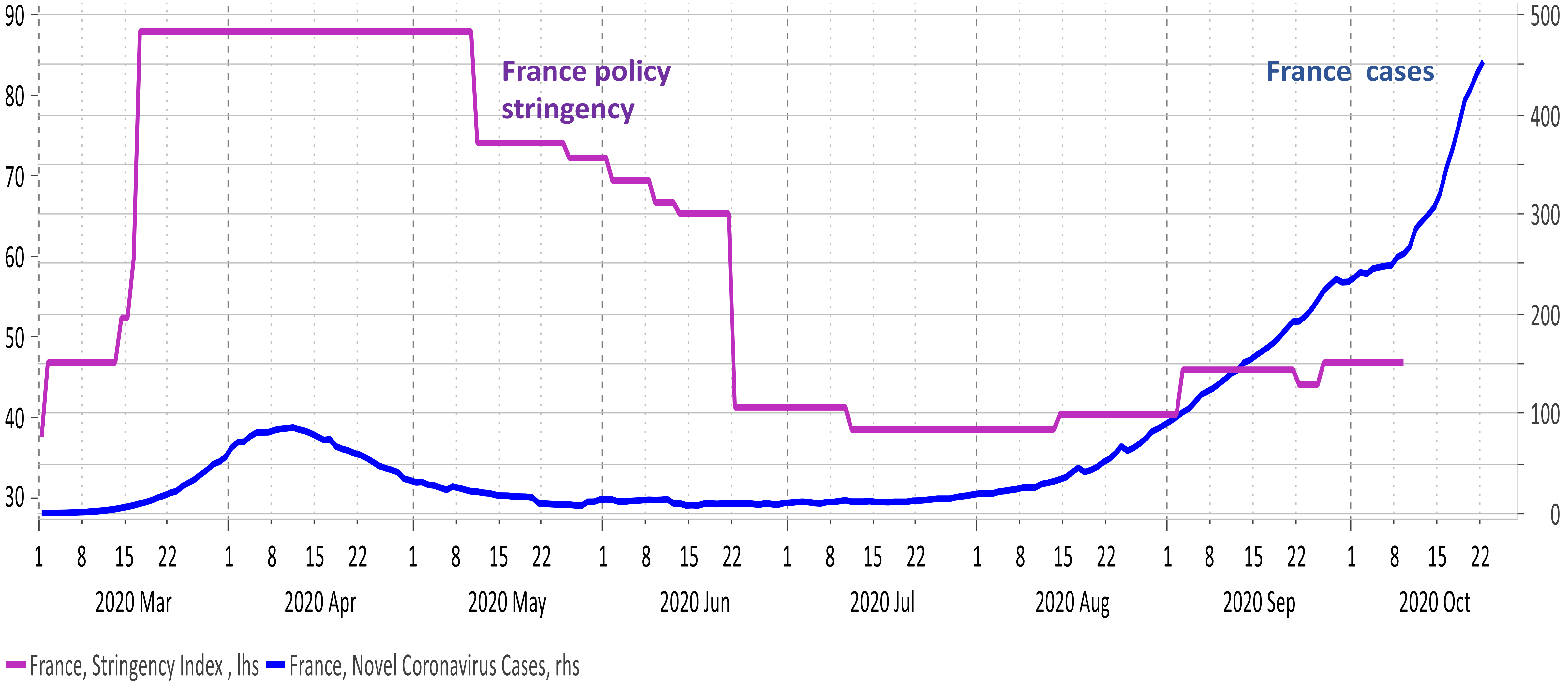
Source: European Centre for Disease Prevention & Control, Google.

Mobility (Retail & Recreation, left scale) and new Covid-19 cases (right scale) 1 March 2020 – 20 October 2020



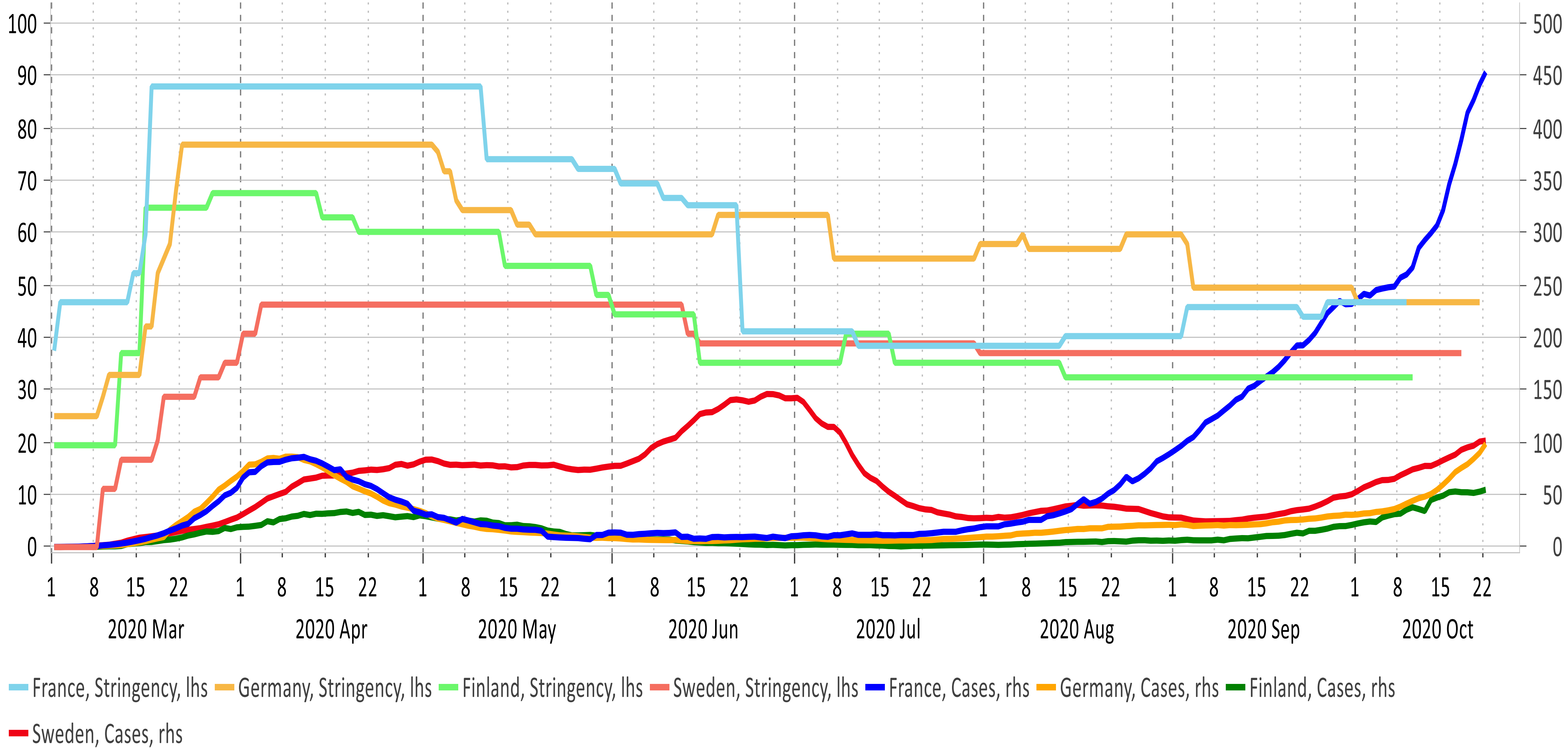
Source: European Centre for Disease Prevention & Control, Google.

Policy stringency (left scale) and new Covid-19 cases 1 March 2020 – 20 October 2020 (right scale) in France



Source: European Centre for Disease Prevention & Control, University of Oxford, Google.

Policy stringency (left scale) and new Covid-19 cases 1 March 2020 – 20 October 2020 (right scale)



Source: European Centre for Disease Prevention & Control, University of Oxford.

Regression

Model for new Covid-19 cases

Low immunity → exponential case growth

UV drives seasonality

Policy to control Covid-19

Mobility

$$logC = \eta + \mu t + \vartheta logUV + \omega logP + \varphi logM$$

C=14 day sum of new Covid-19 cases/100 000 persons (ECDC data)
t=time trend
UV=14 day sum of UV radiation load (country satellite data)
P=Policy stringency index, relative to pre-Covid time (Oxford University data)
F=Mobility, % deviation from pre-Covid-19 time at the start of 2020 (Google and Apple data)

New Covid-19 cases equation with a lag structure and alternative additional explanatory variables

France

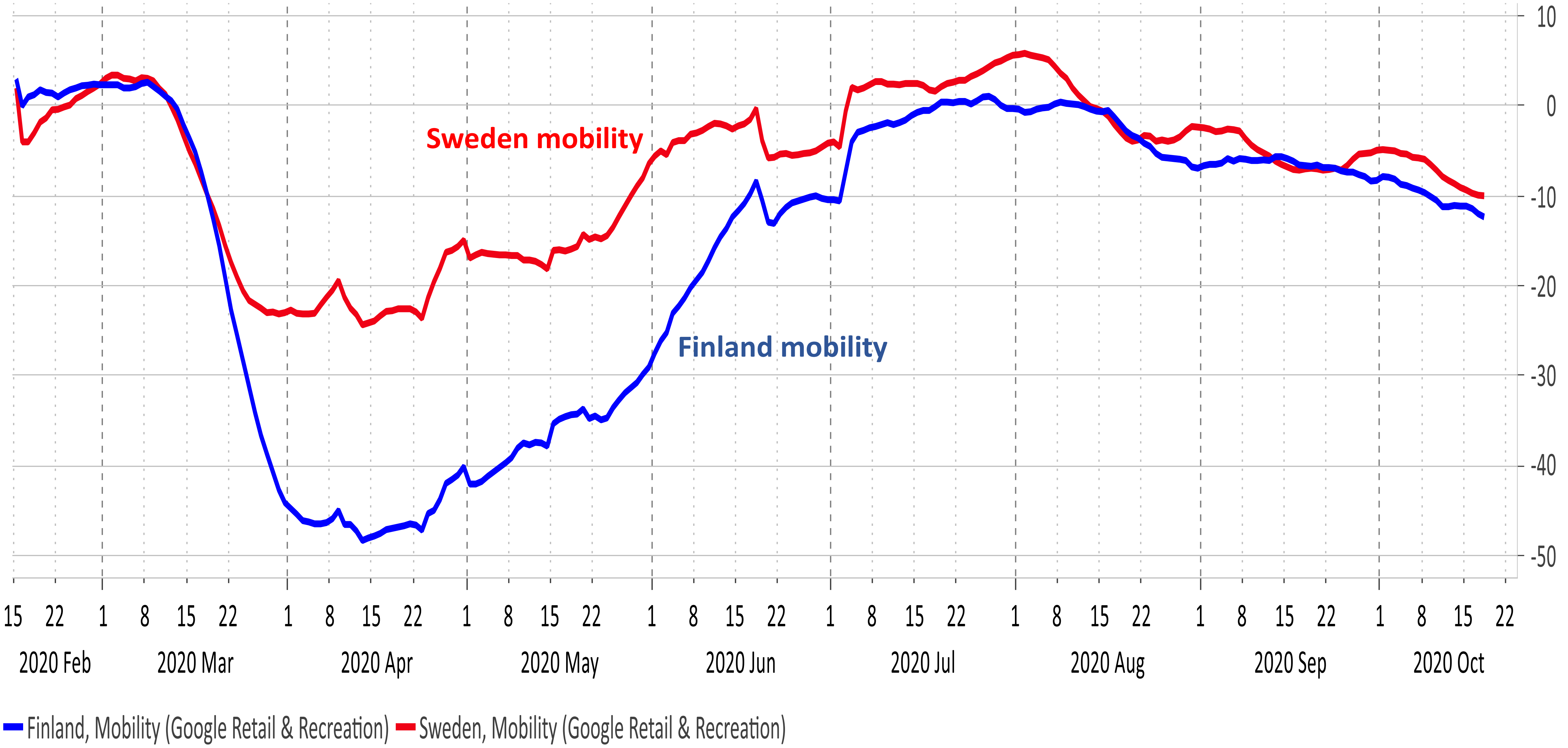
Dependent Variable:	ΔlogC							
Model	1		2		3		4	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,73290	13,16731	0,73488	13,36776	0,55801	6,72658	0,58905	5,34432
Trend	0,00060	7,42048	0,00053	6,29270	0,00029	2,46754	0,00037	2,70039
logC 1 day lag	-0,04520	-8,48418	-0,04710	-8,86134	-0,02976	-3,68060	-0,04080	-6,07018
logUV 3 week lag	-0,16623	-12,38027	-0,16160	-12,07227	-0,09581	-3,56828	-0,13354	-5,87462
logUV difference 3 week	-0,03428	-1,62681	-0,06423	-2,67979	-0,01857	-0,64872	-0,05720	-2,35071
logUV deviation of long run level			-0,17247	-2,51886	-0,06775	-0,88015	-0,11616	-1,49679
logStringency 3 week lag					-0,06619	-2,81220		
logTransit mobility 3 week lag							0,01883	1,52490
R-squared	0,48612		0,50119		0,51937		0,50668	
F-statistic	49,89979		42,19993		37,64158		35,77611	
Durbin-Watson stat	1,90173		1,96275		2,06519		1,99389	
LM(2) #	3,78586		1,99549		1,34634		1,81105	
LM / Prob. Chi-Square(2) #	0,15060		0,36870		0,51010		0,40430	
# Breusch-Godfrey Serial Correlation LM Test.								
Sample:	3/04/2020 10/05/2020							
Included observations:	216							
Long-run elsticity of new Covid-19 cases;								
Underlying growth rate, % / day	1,32		1,12		0,97		0,89	
Elasticity w.r.t. UV	-3,68		-3,43		-3,22		-3,27	
Median lag from UV	35,98		35,37		43,94		37,64	

Long-run elasticity of new Covid-19 cases w.r.t. UV

New Covid-19 cases equation with alternative additional explanatory variables

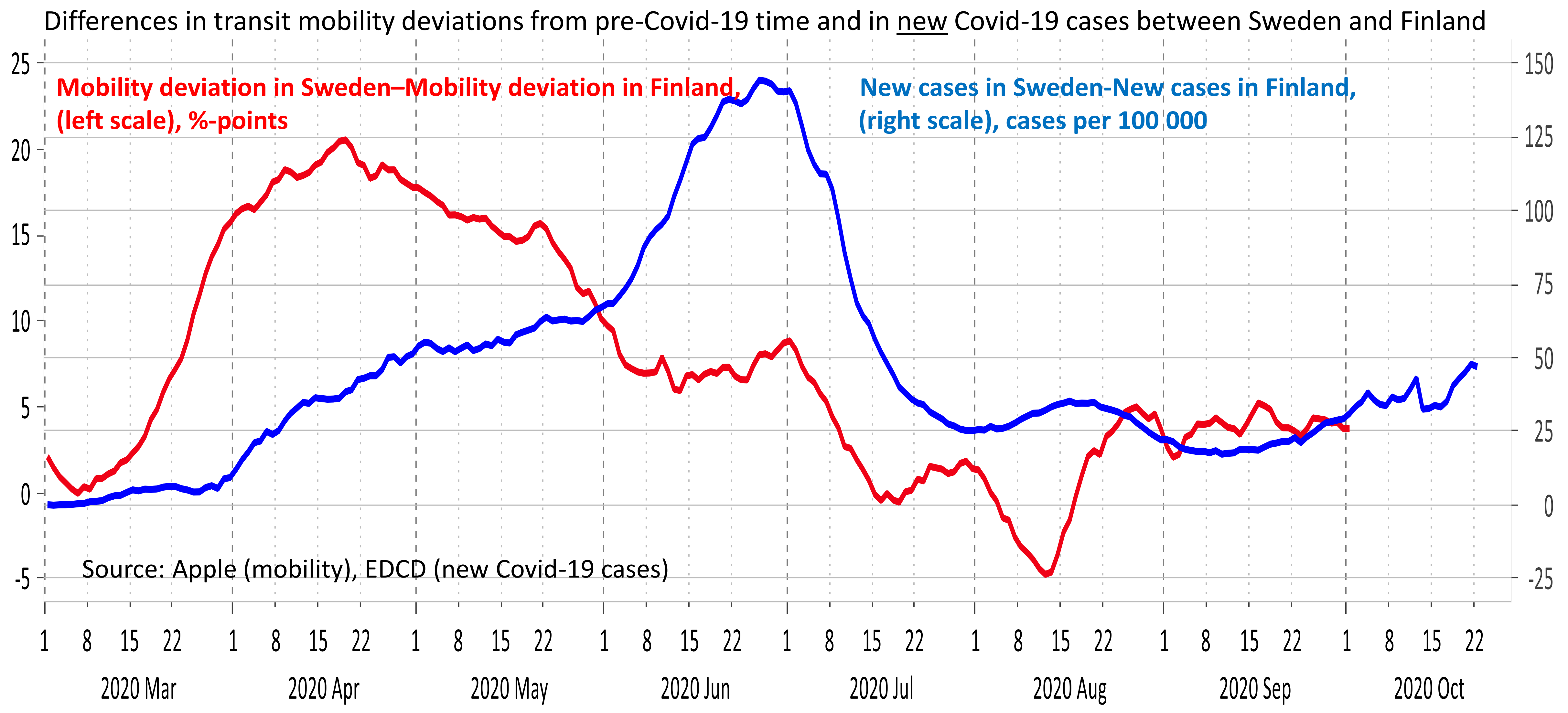
	Model 1	Model 2 = Model 1 + policy	Model 3 = Model 1 + mobility
France	-3,43	-3,22	-3,27
Germany	-3,13	-2,60	-2,84
Finland	-2,99	-2,74	-3,77

Mobility data (Retail and recreation) in Sweden and Finland



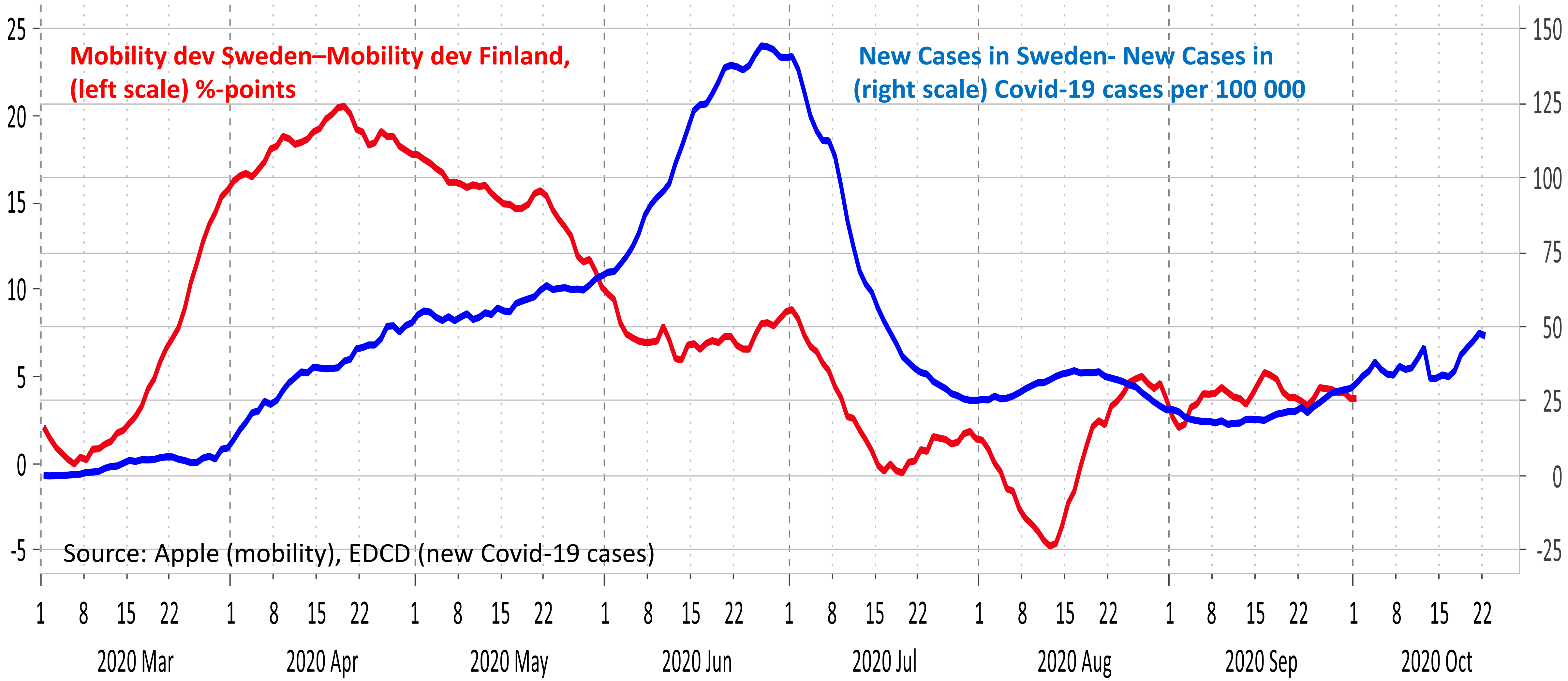
Source: European Centre for Disease Prevention & Control, Google.

”Natural experiment” - Sweden versus Finland



$$\Delta(\log C^S - \log C^F) = \underset{(1.6)}{0.015} - \underset{(-3.4)}{0.028}(\log C^S - \log C^F)(-1) + \underset{(5.0)}{0.277}(\log M^S - \log M^F)(-42) - \underset{(-2.7)}{0.203}(\log UV^S - \log UV^F)(-21)$$

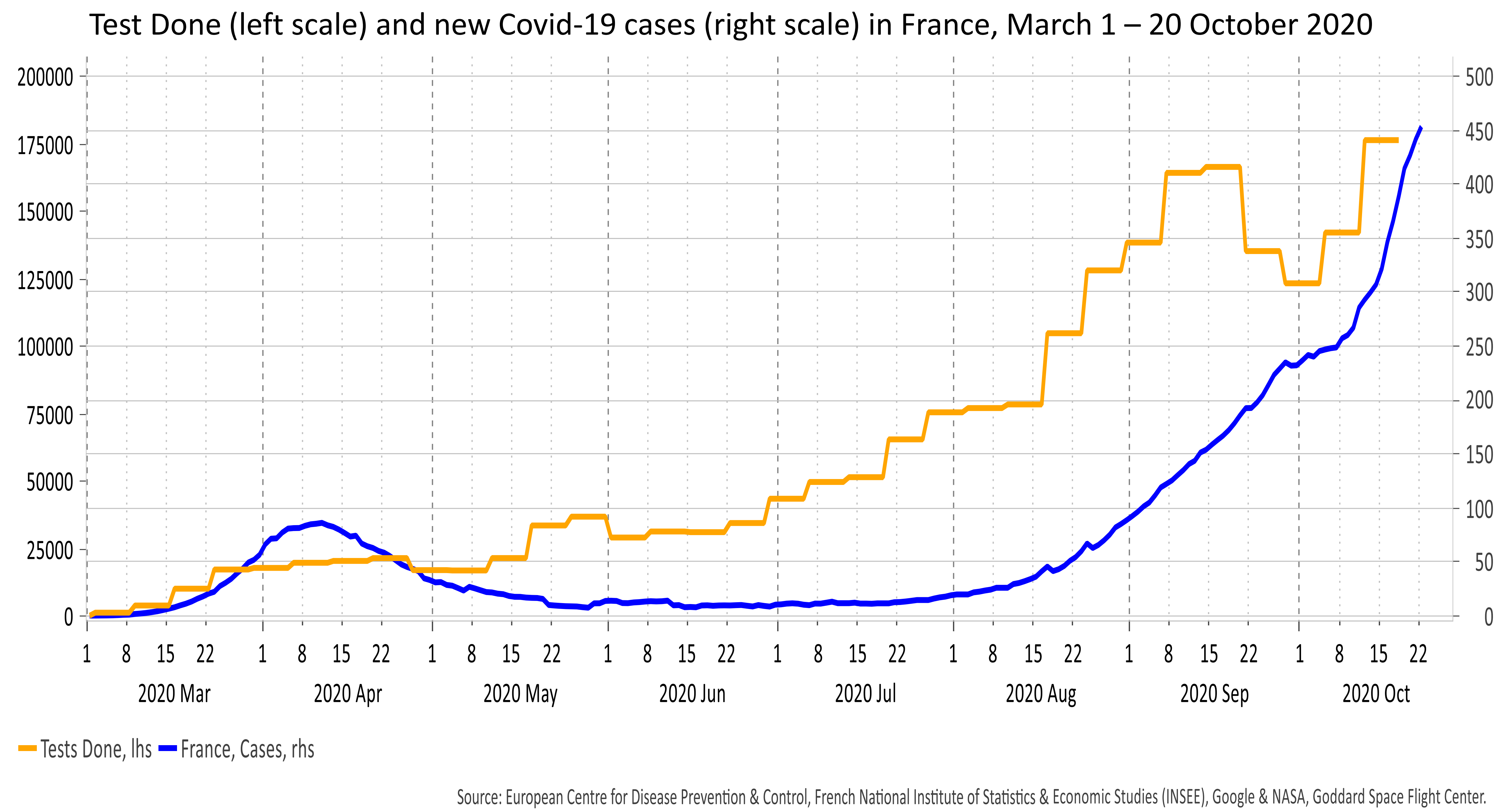
Differences in transit mobility deviations from pre-Covid-19 time and in new Covid-19 cases between Sweden and Finland



Qualifications

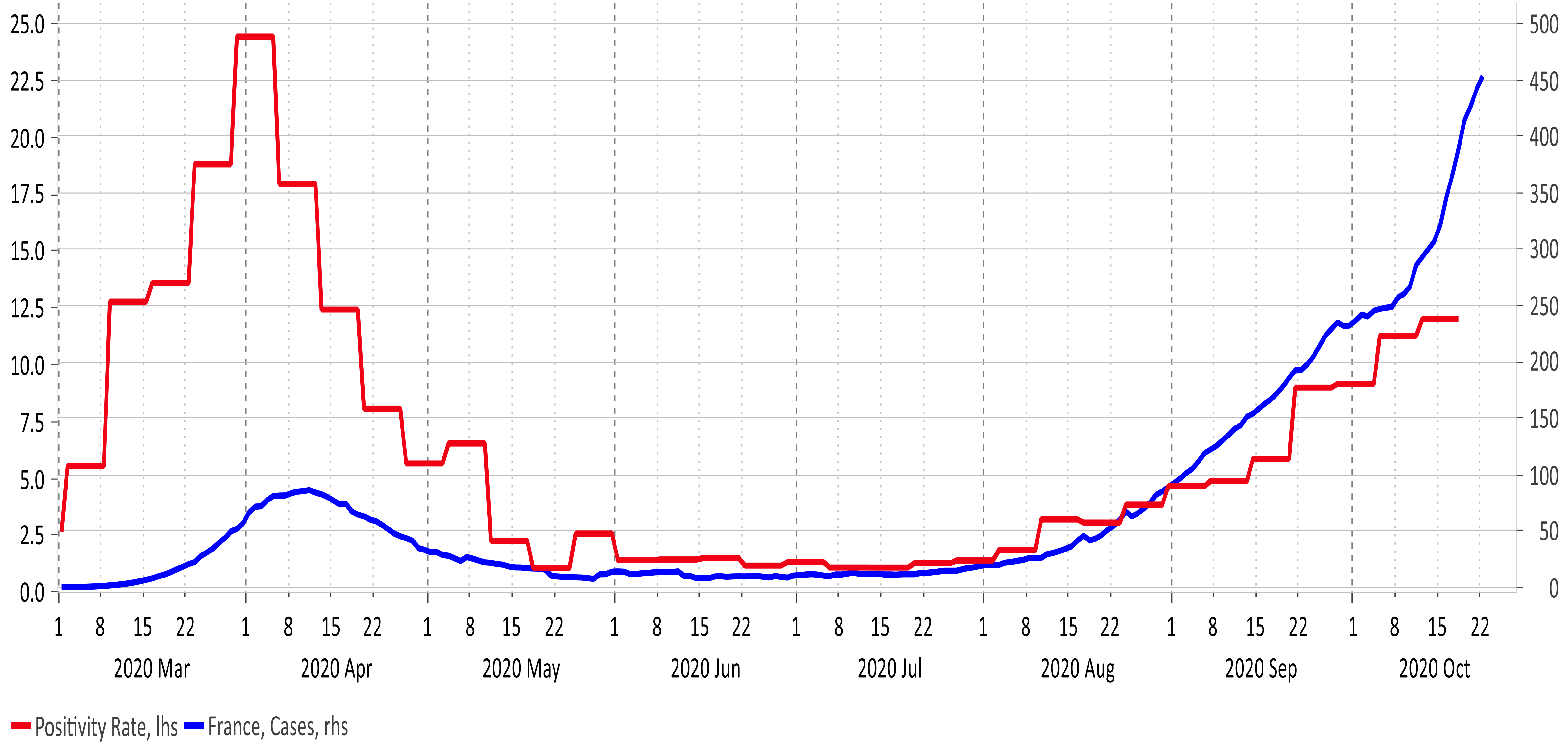
Conclusions still tentative - but risks are high

- UV effects may come through other factors (behavioral patterns)
- Endogeneity and collinearity problems (possible instrument: UV affected by altitude – but also infections)
- We haven’t seen full cycle yet (US may still fall in line)
- Increase in testing affects case count and positivity rate



Test Done (left scale) and new Covid-19 cases (right scale) in France, March 1 – 20 October 2020
200000
175000
150000
125000
100000
75000
50000
25000
0
500
450
400
350
300
250
200
150
100
50
0
1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22 1 8 15 22
2020 Mar
2020 Apr
2020 May
2020 Jun
2020 Jul
2020 Aug
2020 Sep
2020 Oct
Tests Done, lhs
France, Cases, rhs
Source: European Centre for Disease Prevention & Control, French National Institute of Statistics & Economic Studies (INSEE), Google & NASA, Goddard Space Flight Center.

Positivity Rate (left scale) and new Covid-19 cases (right scale) in France, March 1 – 20 October 2020



Source: European Centre for Disease Prevention & Control, French National Institute of Statistics & Economic Studies (INSEE), Google.

Conclusions

Main takeaways

- Asymmetric waves:
  - Virus has tail-winds in the fall – the next months may be very severe
  - Virus has head-winds in the spring – we'll get a rest over the summer
- Seasonality important for:
  - Proactive policy
  - Correct modeling

THANKS!

APPENDICES

Annexes

Annex A: A simple model of Covid-19
Annex B: Data
Annex C: Possible reasons for large effects of mobility and UV on spread of Covid-19
Annex D: Challenges in modelling Covid-19
Annex E: Estimation results with robustness analysis

Annex A: A simple model of Covid-19

Assumption 1: New Covid-19 cases per capita (or per 100 000), C, depend positively on the initial exponential growth rate of the epidemic, μ, and negatively on UV radiation load, UV, policy, P, and behavioral (fear), F, variables and population Covid-19 immunity rate, I.

$$(1) \quad c=f(\overset{+}{\mu}, \overset{-}{uv}, \overset{-}{p}, \overset{-}{f}, \overset{-}{I})$$

where c=logC, uv=logUV, p=logP, f=log*F.*

Annex C reports evidence that population Covid-19 immunity rate has stayed so low (e.g. 0.3 % in Finland) that *I=0* is a reasonable approximation*.*

Assumption 2: Covid-19 deaths per capita depend positively on C and negatively on UV, P and F.

$$(2) \quad d=g(\overset{+}{c}, \overset{-}{uv}, \overset{-}{p}, \overset{-}{f}), \text{ where } d=\log D.$$

Assumption 3: Control and behavioral variables do not have statistically significant additional explanatory power in equations (1) and (2).

Assumption 3 was not made a priori, but empirical results provided partial support for it. This does not mean that, say, mobility does not affect spread of Covid-19. Rather, it indicates that it difficult to infer the effect of mobility on Covid-19 from equations (1) and (2). An apparent interpretation to this finding is that μ and UV explain, via their effects on Covid-19 cases and deaths, also the policy and behavioral reactions. This leads to the following empirically testable assumption.

Assumption 4: The responses of control and behavioral variables, M, to Covid-19 cases and deaths are determined by μ and UV so that one can write

$$(3) \quad p=p(\overset{-}{\mu}, \overset{+}{uv}), \qquad f=h(\overset{-}{\mu}, \overset{+}{uv}).$$

Substituting first (3) into (1), and taking into account that $I=0$ in (1), and substituting c from this into (2), onr can write

(4) $d=j(\overset{+}{\mu}, \overset{-}{uv})$.

The model leads into a testable hypothesis that the deviation of the economy from its pre Covid-19 path is determined, other things being equal, by μ and UV, which are exogeneous and reliably forecastable variables where μ is, in fact, a constant as long as $I=0$.

Relaxing assumption 4 that responses of control and behavioral variables to cases and deaths are determined by μ and UV, one can write

(5) $c=k(\mu, uv, p, f)$.

(6) $d=l(\mu, uv, p, f)$.

Assuming that P and F can be measured jointly with mobility M, and denoting m=logM, one can write

(7) $c=k(\mu, uv, m)$.

(8) $d=l(\mu, uv, m)$.

(7) and (8) are used to estimate the empirical country difference equation in the presentation. Note that assuming the same underlying growth rates μ in two countries, A and B, conditional on UV and its causes in terms of policy and behavior reactions, μ cancels out in the difference Equations. One can then write the equations for Covid-19 cases and deaths as (9) and (10), which are used to estimate Sweden-Finland equations.

(9)) $(c^A - c^B)=m\{(m^A-m^B),(uv^A-uv^B)\}$

(10) $(d^A - d^B)=n\{(m^A-m^B),(uv^A-uv^B)\}$.

Annex B: Data

This annex lists the data sources and it provides graphs of the variables used in estimation. From the graphs on Covid-19 deaths, it is apparent that there are irregularities in that data in the case of Spain. Assuming that these irregularities are to due to reporting lags and corrections made afterwards but that the total cumulative number of deaths is measured correctly, a mechanical smoothing was applied by, in case of a negative death observation that negative obsevation was evenly distributed to 30 previous days and similar smoothing was applied for a very large positive observations. For Italy's Covid-19 cases equation, 14 days moving averages, instead of 14 days cumulative numbers, wew used.

Data source: Covid-19 cases and deaths
All the data on Covid-19 cases and deaths used in the empirical analysis are from European Centre for Disease Prevention and Control (ECDC).
https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide

Data sources: UV load
The UV load is measured as Erythemal Daily Dose (J/m^2) or EDDose
The UV data used in the estimation was obtained from following national data sources:
Finland: https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_helsinki.kumpula.txt
Sweden https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_norrkoeping.txt
https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_vindeln.txt
Germany https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_offenbach.txt
France https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_palaiseau.txt
Italy https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_ispra.txt
Spain https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/aura_omi_l2ovp_omuvb_v03_el.arenosillo.txt
The authors thank experts at the Finnish Meteorological Institute for advise and help with sattellite data.

Data source: Mask wearing (This data was not used to estimate the equations of Annex B. Next slide shows the limited variability in that data.)
COVID-19 resources. Institute for Health Metrics and Evaluation. University of Washington, USA. http://www.healthdata.org/covid

Variables used in Covid-19 cases and deaths equations

Definitions of variables used in estimating the regression equations:
logC= log(14 days cumulative number of Covid-19 cases/100 000 persons)
logD= log(14 days cumulative number of Covid-19 deaths/100 000 persons)
logUV14=log(14 days cumulative sum of UV radiation load).
logUV28S and logUV35S are the corresponding 28 and 35 days sums, respectively.
logWork mobility=log(14 days moving average of Google work-related mobility variable).
This and other publicly available Google mobility variables are perecentage differences from the beginnig of year reference period. Hence, if, e.g., mobility was 75 % below the reference period level, the variable would have a value of -75. In this case, the corresponding variable would be reported as 25, i.e. the per cent level from reference period.
In the empirical application, the Google variables were used in a similar way as the Apple variables are reported.
This obtained by adding 100 to reported Google mobility variables.
logRec. mobility Google=log(14 days moving average of Google recreation-related mobility variable).
logTransit mobility Apple= log(14 days moving average of Apple transit mobility variable).
logStringency=log(policy stringency index, relative to pre-Covid time) (Oxford University data)
T=Time trend.

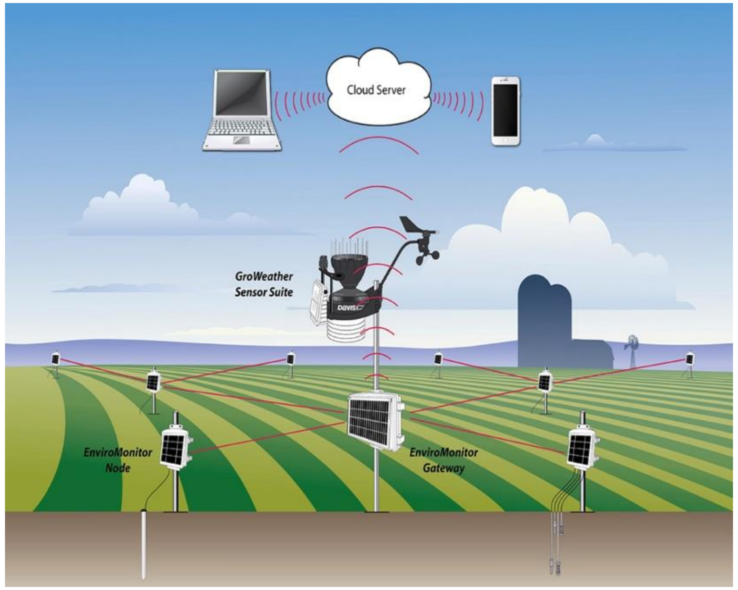
UV radiation estimated by satellites

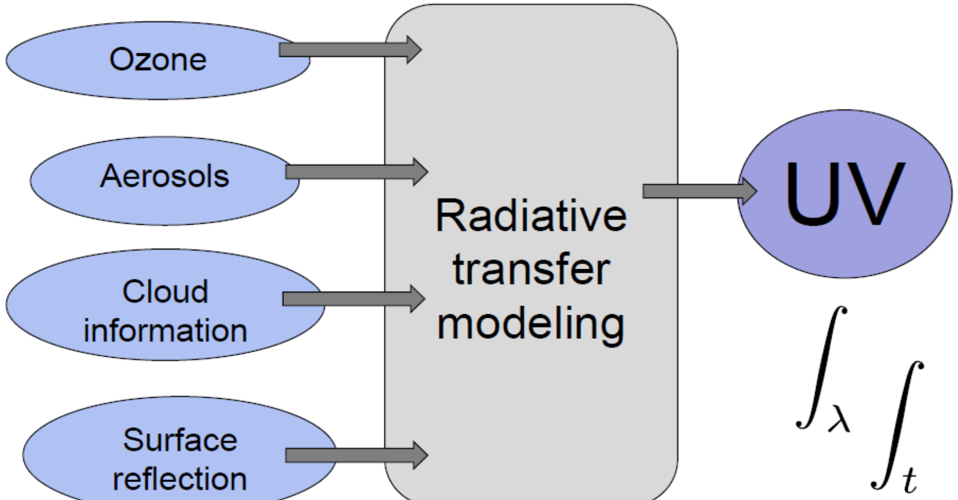
Background

- Local private Davis Enviromonitor weather station in Palojoki Finland https://www.davisinstruments.com/enviromonitor/
- Dutch-Finnish built Ozone Monitoring Instrument (OMI) on-board Nasa's EOS-Aura satellite was launched in 2004. It provides global and nearly daily UV radiation estimates. UV radiation products are developed by the Finnish Meteorological Institute.

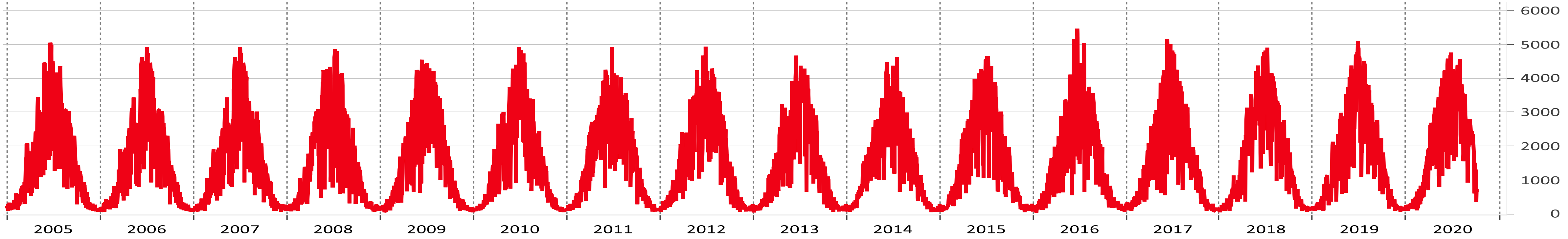
Satellite UV algorithm

- The UV radiation that reaches the Earth surface depends on atmospheric ozone, aerosols, clouds and surface reflection. Satellite measures ozone and clouds in the atmosphere. The UV radiation is estimated using radiative transfer modeling and climatology for aerosols and surface reflection.
- Global data are available via https://avdc.gsfc.nasa.gov/pub/data/satellite/Aura/OMI/V03/L2OVP/OMUVB/

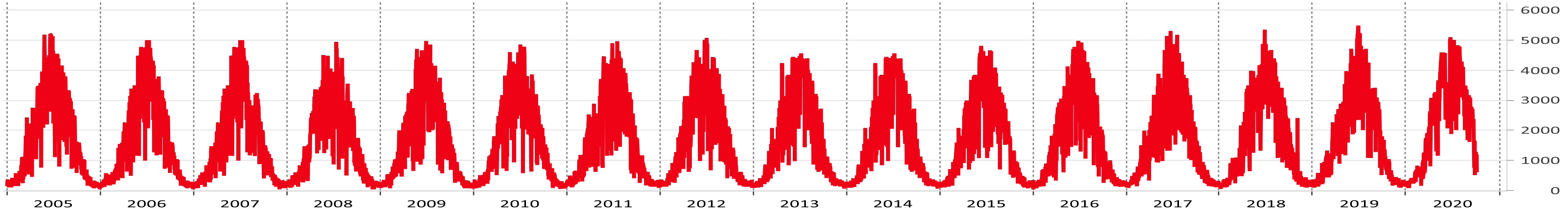




Germany, UVGerLong

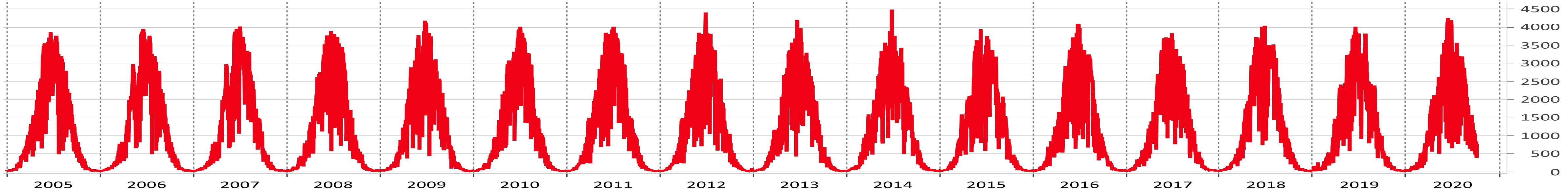


France, UVFraLong



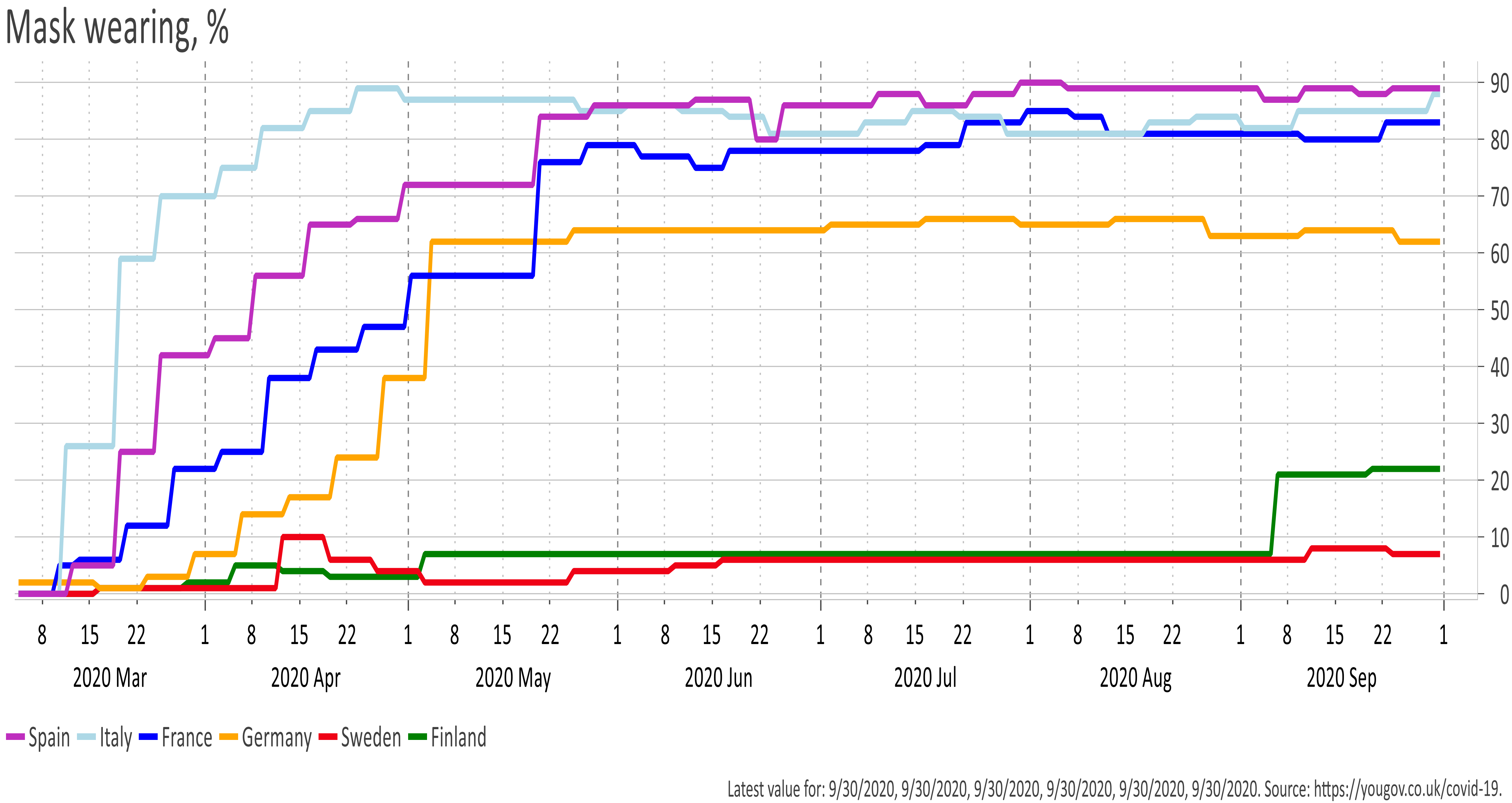
Advanced Economies, UVFraLong

Finland, UVFinLong



Advanced Economies, UVFinLong

Latest value for: 10/5/2020. Source: NASA, Goddard Space Flight Center.



Mask wearing, %
90
80
70
60
50
40
30
20
10
0
8
15
22
1
8
15
22
1
8
15
22
1
8
15
22
1
8
15
22
1
8
15
22
1
8
15
22
1
2020 Mar
2020 Apr
2020 May
2020 Jun
2020 Jul
2020 Aug
2020 Sep
Spain
Italy
France
Germany
Sweden
Finland
Latest value for: 9/30/2020, 9/30/2020, 9/30/2020, 9/30/2020, 9/30/2020, 9/30/2020. Source: https://yougov.co.uk/covid-19.

Annex C: Possible reasons for large effects of mobility and UV on the spread of Covid-19

This annex provides short explanations of possible reasons why mobility and UV may have large effects on spread of Covid-19.

Why leisure & work mobility may have large effects on spread of Covid?

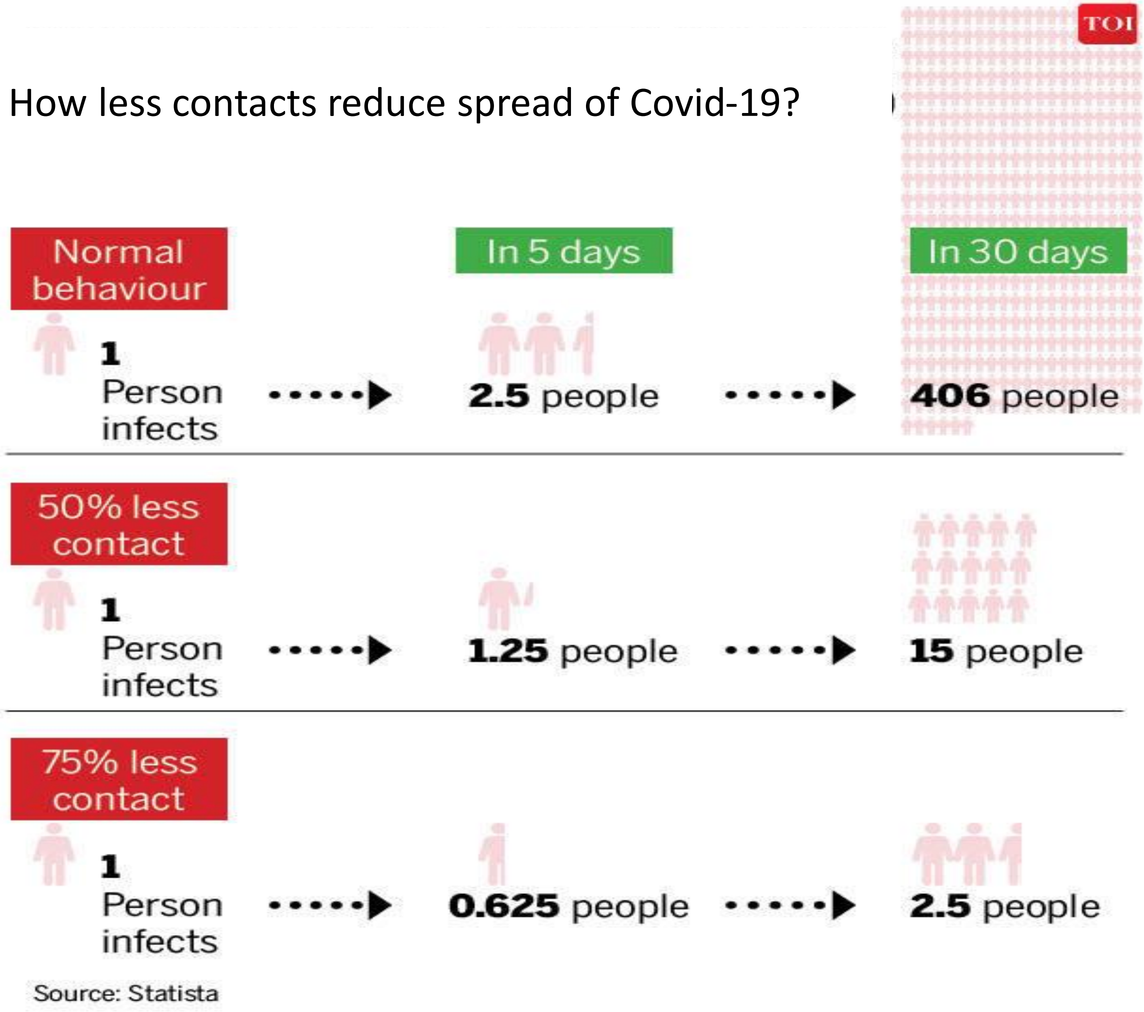
The basic reproduction number R0=βγ, where β=average infection-producing contacts per unit time and γ=mean infectios period. Assume:
- Leisure- and work-related mobility involve contacts with other people.
- Under normal conditions R0=2.5, i.e. one infected infects 2.5 others.
- An infected person infects for 5 days while she is asymptomatic.
- After 5 days she gets symptoms, quarantines and stops infecting others.
- Reduce R0 by 50% (R0=1.25) or by 75% (R0=0.625).

Consider one infected person. The total number of people that would become infected in 30 days = $1 + R0^1 + R0^2 + R0^3 + R0^4 + R0^5 + R0^6$, i.e.

$$Infected\ people\ at\ 30\ days = \sum_{n=0}^{6} R0^n$$

One caveat is that when R0<1, the number of cases will actually decline over time and eventually go to zero. This is because an infected person cannot infect 0.625 people, it is either zero, one or more. When it is zero, transmission chain ends. Exact calculation of the 75% reduction thus requires more complex probability calculations.

How less contacts reduce spread of Covid-19?



The text and graph are based on *"Coronavirus Calculations & Infographic"* by Robert A.J. Signer, Ph.D., Assistant Professor of Medicine, University of California San Diego. https://robertsigner.wordpress.com/coronavirus/

Why UV radiation may have large effects on spread of Covid-19?

- In, e.g., Europe and the US, annual corona virus and influenza cycles are closely aligned with the strong UV cycle (following four slides).

Ultraviolet light is usually divided into three groups by radiation wavelengths:

1. Ultraviolet A or UVA that has wavelength of 320-400 nanometers (nm). UVA from sun reaches earth's surface.
2. Ultraviolet B or UVB that has wavelength of 280–320 nm
3. Ultraviolet C or UVC that has wavelength of 200–280 nm. UVC from sun does not reach, or reaches to a limited extent, earth's surface.

UVC's germicidal effectiveness peak wavelength is 260–265 nm, which is equivalent to the peak of ultraviolet radiation absorption of nucleic acids. Since UVA radiation is insufficiently absorbed by viral nucleic acid, UVA is not considered germicidal. However, in a recent article, Rezaie et al (2020)* report results that UVA effectively reduces bacteria and viruses including coronavirus. Rezaie et al (2020) note that:

- *"Our study has several limitations. While multiple daily short-term UVA treatments did not harm human cells and appeared safe in vivo, longer term use may require further study. We assessed UVA against several microbes, but more studies are needed to address additional pathogens, including multi-drug resistant organisms, mycobacteria, and archaea. We did not evaluate UVA against SARS-CoV-2 specifically. However, given the efficacy of UVA against coxsackievirus and CoV-229 (both positive sense, single-stranded RNA viruses), SARS-CoV-2 is likely also UVA-sensitive."*

In a recent article, Ratnesar-Shumate et al (2020)** find that simulated sunlight rapidly inactivates SARS-CoV-2 on surfaces. They note that:

- *"Simulated sunlight rapidly inactivated SARS-CoV-2 suspended in either simulated saliva or culture media and driedon stainless steel coupons. Ninety percent of infectious virus was inactivated every 6.8 minutes in simulated saliva and every 14.3 minutes in culture media when exposed to simulated sunlight representative of the summer solstice at 40°N latitude at sea level on a clear day. Significant inactivation also occurred, albeit at a slower rate, under lower simulated sunlight levels. The present study provides the first evidence that sunlight may rapidly inactivate SARS-CoV-2 on surfaces, suggesting that persistence, and subsequently exposure risk, may vary significantly between indoor and outdoor environments."*

Merrow and Urban (2020)*** note also the possible immune resistance enhacing effect of UV:

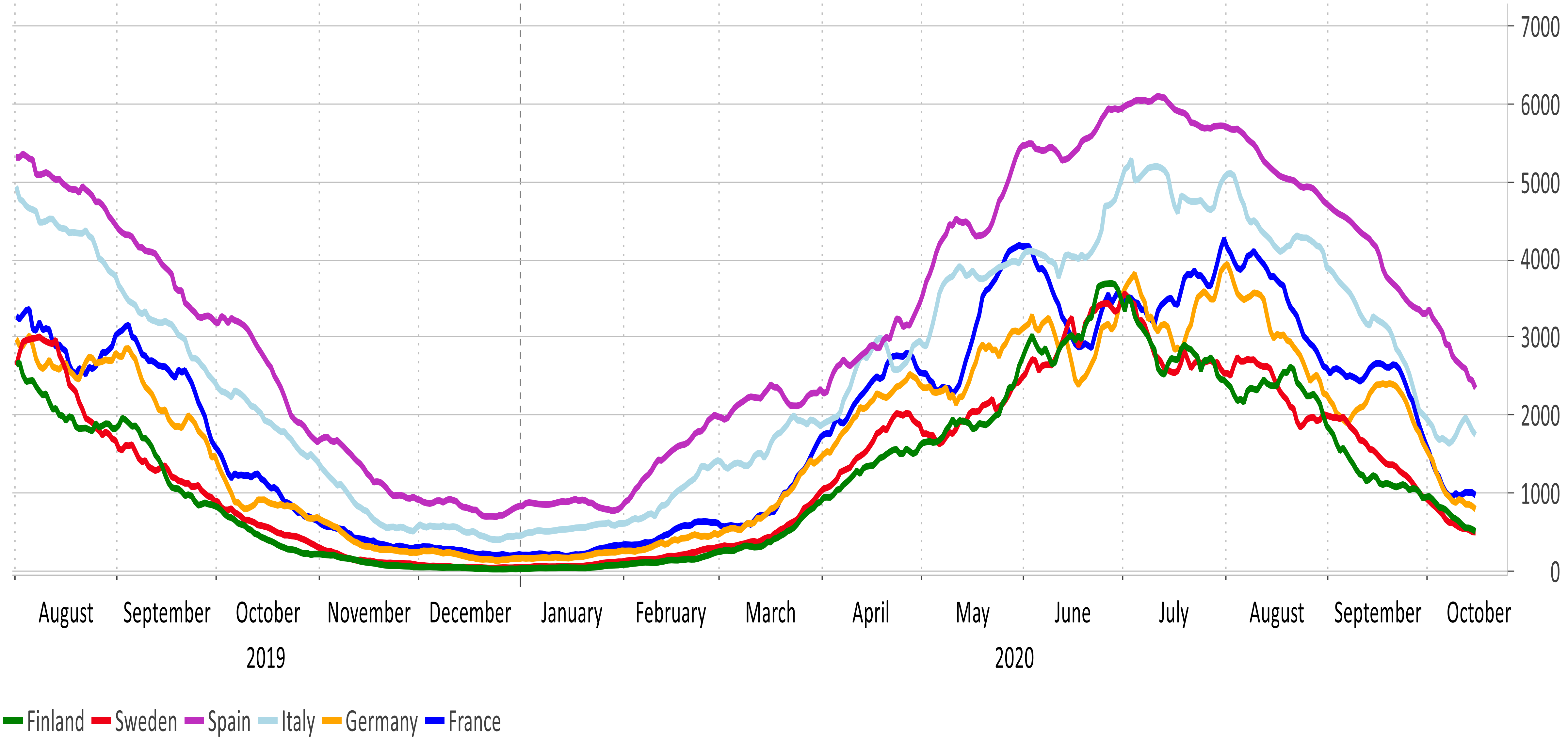
- *"Ultraviolet (UV) light effectively inactivates many viruses (19), especially larger coronaviruses (24) like SARS-CoV-1 (25). Sunny days might decrease outdoor transmission or promote immune resistance via vitamin D production (26)."*

*Rezaie A, Leite GGS, Melmed GY, Mathur R, Villanueva-Millan MJ, Parodi G, et al. (2020) Ultraviolet A light effectively reduces bacteria and viruses including coronavirus. PLoS ONE 15(7): e0236199. https://doi.org/10.1371/journal.pone.0236199 https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0236199

**Ratnesar-Shumate et al (18 other authors) (2020), Simulated sunlight rapidly inactivates SARS-CoV-2 on surfaces. *The Journal of Infectious Diseases*, Volume 222, Issue 2, 15 July 2020, Pages 214–222, https://doi.org/10.1093/infdis/jiaa274 *https://academic.oup.com/jid/article/222/2/214/5841129*

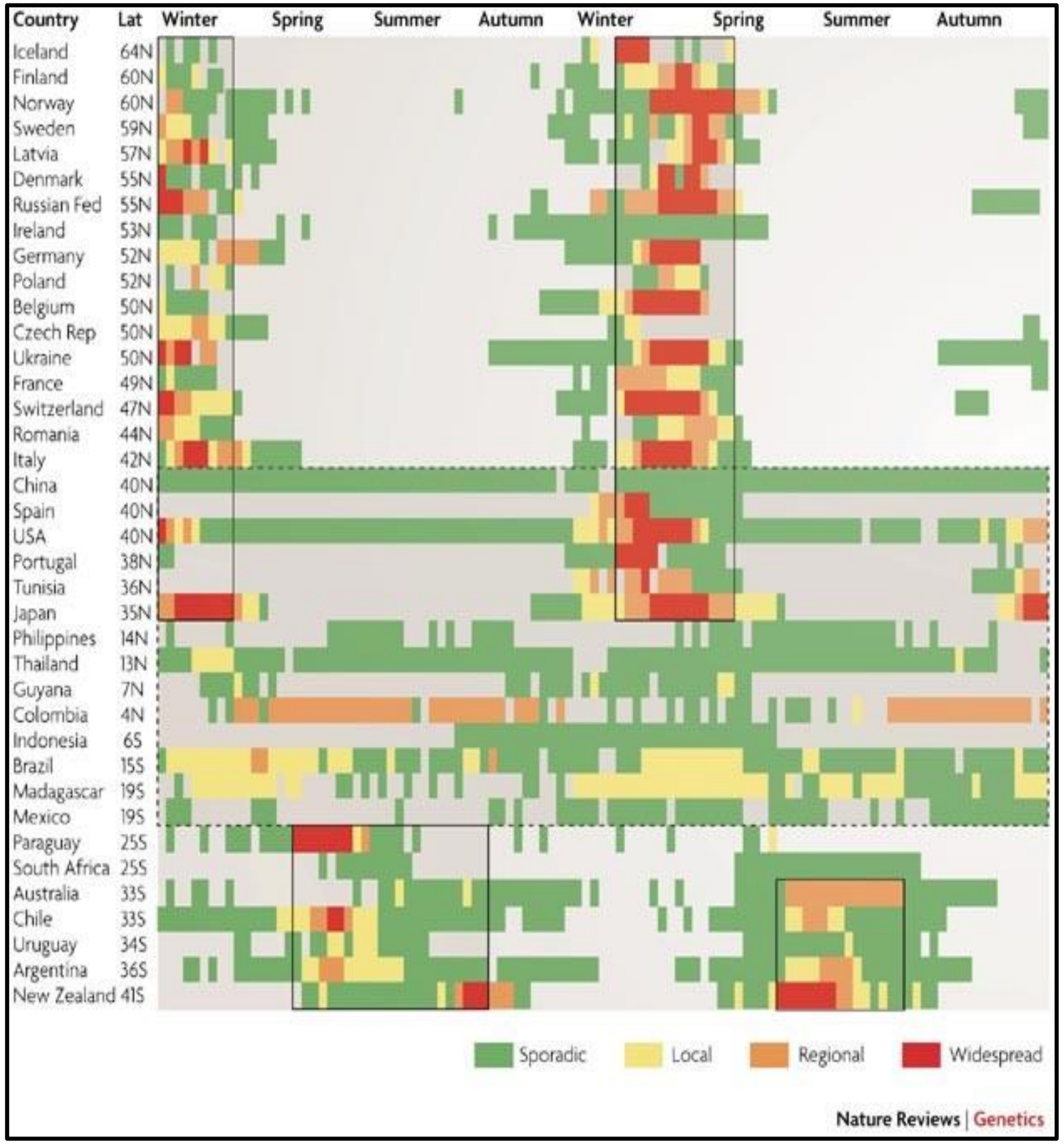
***Merow Cory and Mark C. Urban (2020), Seasonality and uncertainty in global COVID-19 growth rates. PNAS, 2020 October,1-9. https://doi.org/10.1073/pnas.2008590117 https://www.pnas.org/content/early/2020/10/14/2008590117

Daily sattellite data of UV load, 14 day moving average



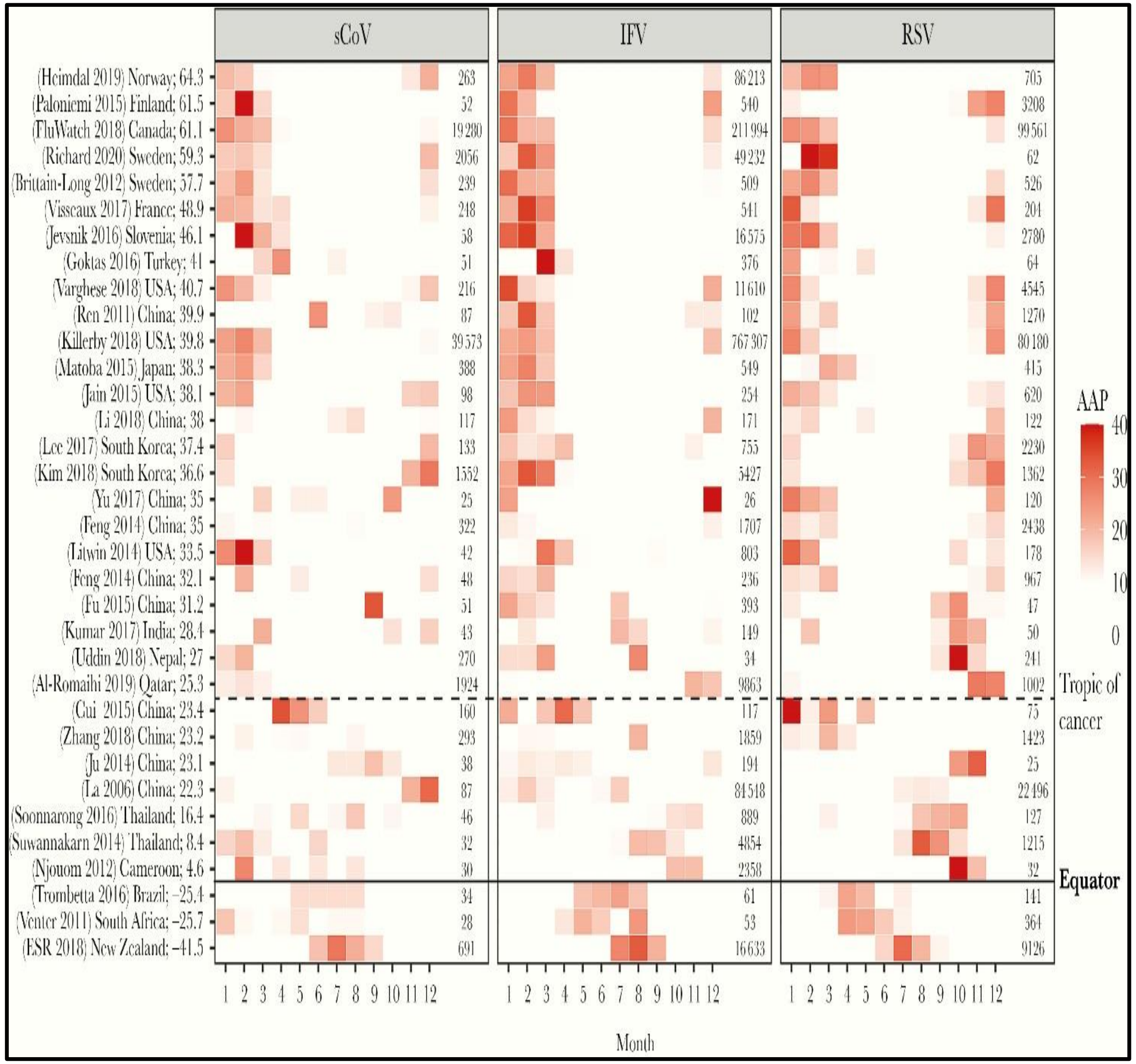
Latest value for: 10/15/2020, 10/15/2020, 10/15/2020, 10/15/2020, 10/15/2020, 10/15/2020. Source: NASA, Goddard Space Flight Center.

Influenza-like illness (ILI) by WHO Influenza virus activity peaks at similar times at similar latitude, e.g. during winter and early spring in the northern hemisphere.



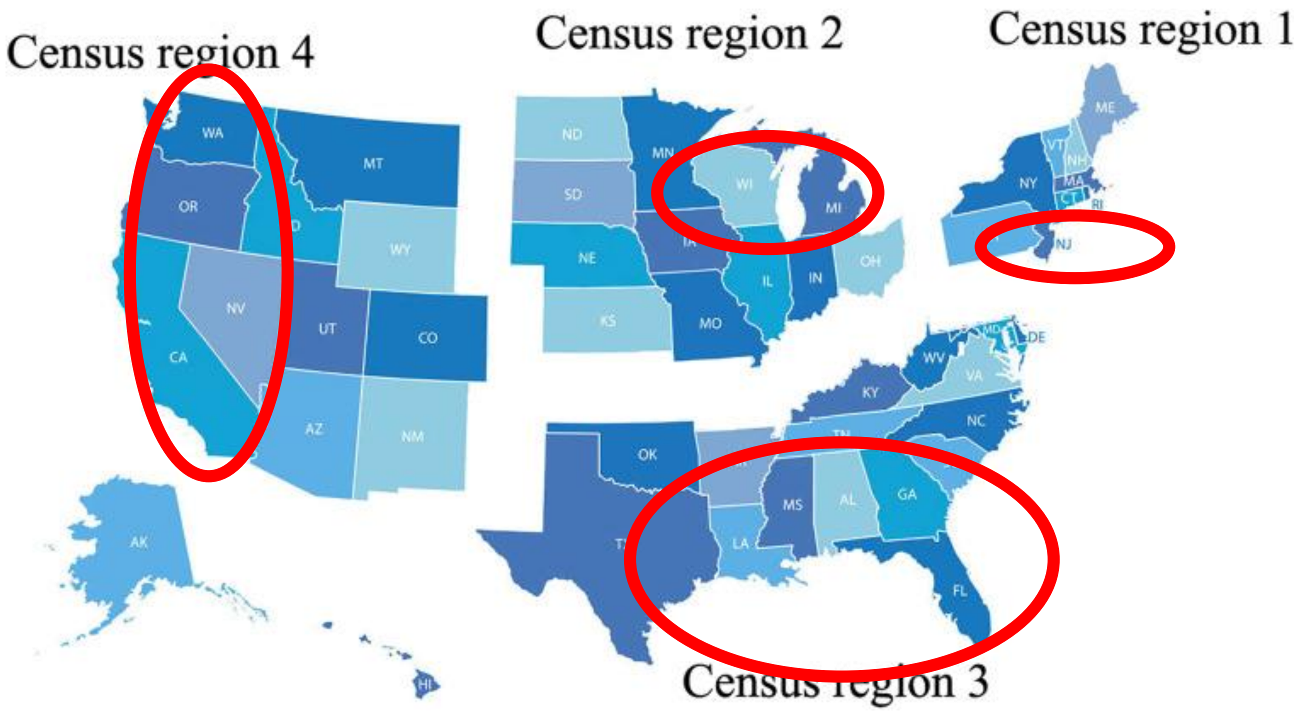
Nelson, M., Holmes, E. The evolution of epidemic influenza. *Nature Review Genetics* **8,** 196–205 (2007). https://doi.org/10.1038/nrg2053 https://www.nature.com/articles/nrg2053#Fig5

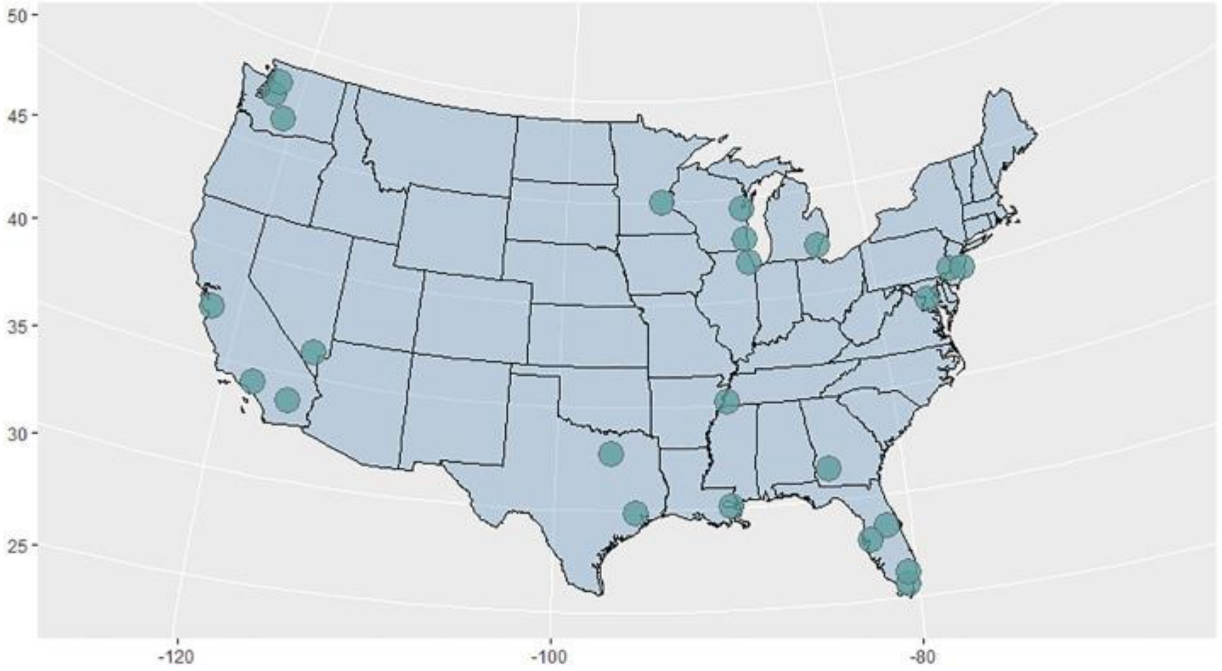
Heat maps of global monthly activity of seasonal coronaviruses (sCoVs), influenza virus (IFV), and respiratory syncytial virus (RSV). Each square indicates share of virus cases are observed in a month. AAP=annual average % as the strength of virus.



Li et al (2020), Journal of Infectious Diseases. https://academic.oup.com/jid/article/222/7/1090/5874220

Next slide shows the seasonality of positive corona test results in the four census regions

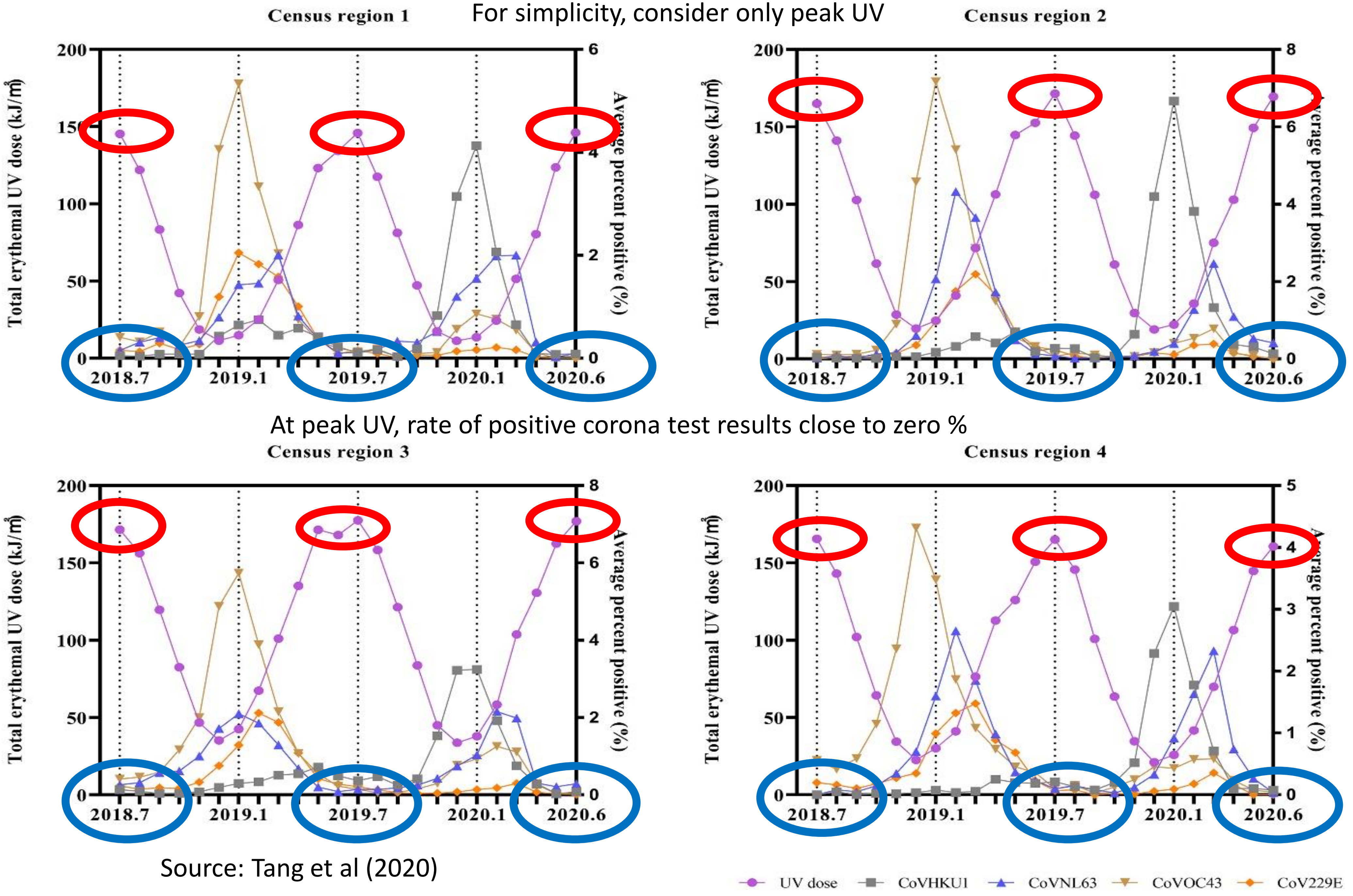




Source: Tang et al (2020)

https://www.sciencedirect.com/science/article/pii/S0048969720353456

For simplicity, consider only peak UV



At peak UV, rate of positive corona test results close to zero %

Source: Tang et al (2020)

Annex D: Challenges in modelling Covid-19

Empirical modelling of Covid-19 includes following challenges:

- The epidemic is still at a relatively early stage. In Europe, the epidemic started more generally in March 2020.
- There seems to be already a strong seasonal component because the epidemic slowed abruptly in Spring.
- That slowdown, in spite of simultaneous easing of control measures and low immunity rate, supports strong seasonality.
- In practice, all control and behavioral variables, to explain Covid-19 cases or deaths, are endogenous to those variables.
- Moreover, instrumental variable estimation is hard when potential instruments seem to be endogenous to cases or deaths.

In earlier research, following solutions have been applied due to lack of data and other difficulties:

- Neher et al (2020) and Kissler et al (2020) have applied seasonal forcing. https://smw.ch/article/doi/smw.2020.20224
- https://science.sciencemag.org/content/early/2020/04/14/science.abb5793.full
- Many studies use time varying and multiple parameter functional forms to fit models to Covid-19 data.

The drawbacks of these approaches include the following:

- Covid-19 seasonality remains a black box.
- When the drivers of seasonality are unknown, it is difficult to infer the true parameters of other drivers of Covid-19 epidemic.
- With time varying and increasing number of parameters, the models become less informative.
- These models may still be of use in forecasting, but they may not help one to understand the epidemic.

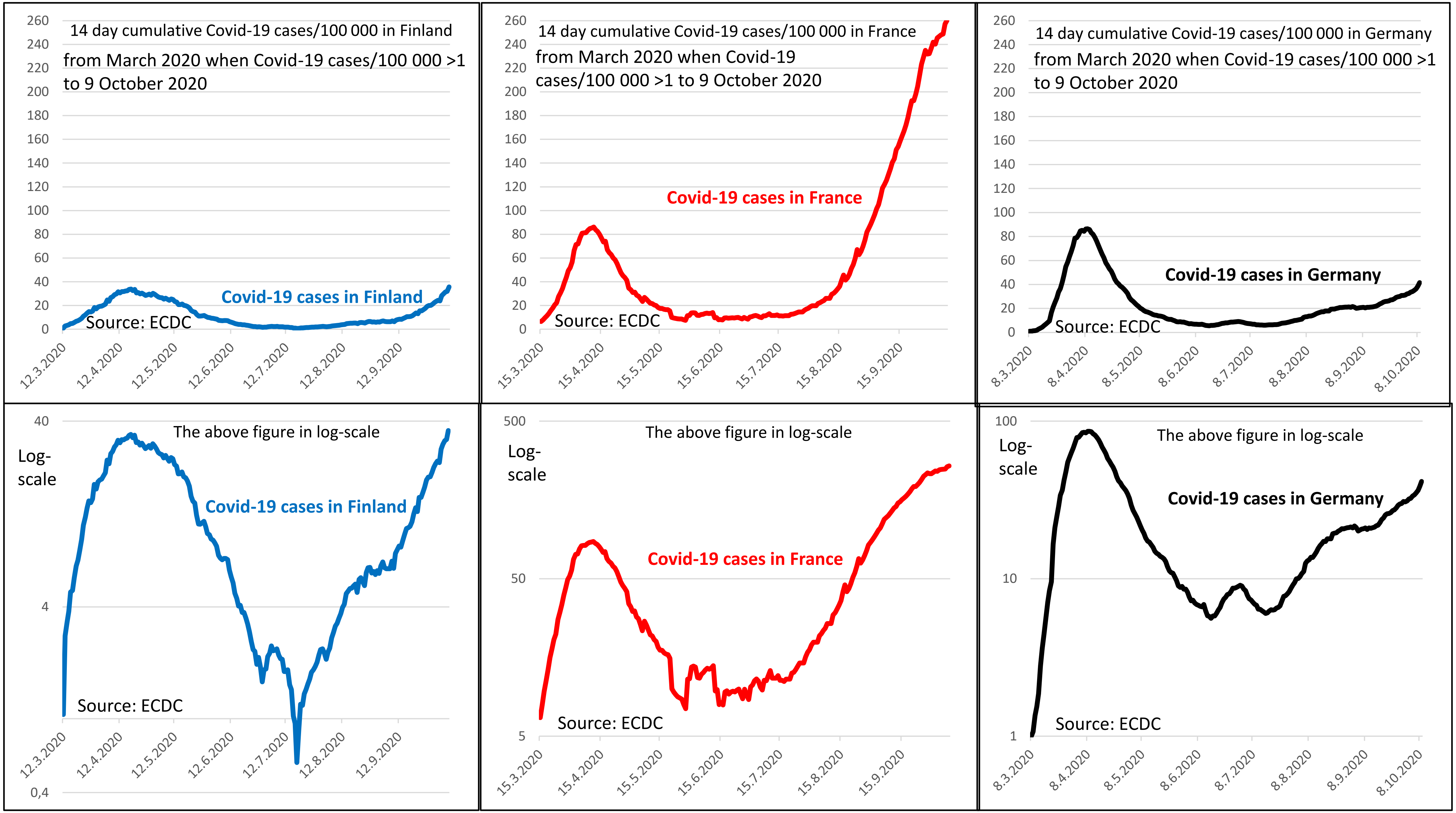
To overcome these drawbacks, this presentation:

- Uses previous research on corona and influenza seasonality to model seasonality explicitly.
- Takes into account that the Covid-19 epidemic does not seem to follow, say, a SIR-model given the very low immunity rate.
- Aims, based on previous research, at a as simple and parsimonious model as possible.
- Puts forward an empirically easily refutable hypothesis about the drivers of Covid-19.

Epidemiologist Marc Lipsitch*: *"…at least three things that are affecting the growth rate or decline rate of the epidemic."*

1. *"The first is control measures…". "…control measures are not just what the government says to do, but what people actually do…"*
2. *"The second is seasonal variation in terms of the suitability of environmental conditions for transmission.*
3. *"… the third is population level immunity."*

https://www.hsph.harvard.edu/news/features/coronavirus-covid-19-press-conference-with-marc-lipsitch-08-13-20/


14 day cumulative Covid-19 cases/100 000 in Finland
from March 2020 when Covid-19 cases/100 000 >1
to 9 October 2020
Covid-19 cases in Finland
Source: ECDC
260
240
220
200
180
160
140
120
100
80
60
40
20
0
12.3.2020
12.4.2020
12.5.2020
12.6.2020
12.7.2020
12.8.2020
12.9.2020
14 day cumulative Covid-19 cases/100 000 in France
from March 2020 when Covid-19
cases/100 000 >1 to 9 October 2020
Covid-19 cases in France
Source: ECDC
15.3.2020
15.4.2020
15.5.2020
15.6.2020
15.7.2020
15.8.2020
15.9.2020
14 day cumulative Covid-19 cases/100 000 in Germany
from March 2020 when Covid-19 cases/100 000 >1
to 9 October 2020
Covid-19 cases in Germany
Source: ECDC
8.3.2020
8.4.2020
8.5.2020
8.6.2020
8.7.2020
8.8.2020
8.9.2020
8.10.2020
The above figure in log-scale
Log-
scale
Covid-19 cases in Finland
Source: ECDC
40
4
0,4
12.3.2020
12.4.2020
12.5.2020
12.6.2020
12.7.2020
12.8.2020
12.9.2020
The above figure in log-scale
Log-
scale
Covid-19 cases in France
Source: ECDC
500
50
5
15.3.2020
15.4.2020
15.5.2020
15.6.2020
15.7.2020
15.8.2020
15.9.2020
The above figure in log-scale
Log-
scale
Covid-19 cases in Germany
Source: ECDC
100
10
1
8.3.2020
8.4.2020
8.5.2020
8.6.2020
8.7.2020
8.8.2020
8.9.2020
8.10.2020

Weekly report of serological population study of Covid-19 in Finland based on random samples

Sample week	Tested samples	Positive tests	Share with positive tests	Samples which belong to an MNT test set	MNT-tested samples	MNT-positive samples	Share of MNT positiive samples
2020-W16	362	9	2.49% (1.31–4.66)	362	9	1	0.28% (0.05–1.55)
2020-W17	674	17	2.52% (1.58–4)	674	17	2	0.3% (0.08–1.08)
2020-W18	426	12	2.82% (1.62–4.86)	426	12	2	0.47% (0.13–1.7)
2020-W19	514	8	1.56% (0.79–3.04)	514	8	0	0% (0–0.74)
2020-W20	401	4	1% (0.39–2.54)	401	4	1	0.25% (0.04–1.4)
2020-W21	210	9	4.29% (2.27–7.94)	210	9	1	0.48% (0.08–2.65)
2020-W22	178	5	2.81% (1.21–6.41)	178	5	0	0% (0–2.11)
2020-W23	214	8	3.74% (1.91–7.2)	214	8	1	0.47% (0.08–2.6)
2020-W24	174	5	2.87% (1.23–6.55)	174	5	0	0% (0–2.16)
2020-W25	78	0	0% (0–4.69)	78	0	0	0% (0–4.69)
2020-W26	32	0	0% (0–10.72)	32	0	0	0% (0–10.72)
2020-W27	85	5	5.88% (2.54–13.04)	85	5	0	0% (0–4.32)
2020-W28	51	0	0% (0–7)	51	0	0	0% (0–7)
2020-W29	7	0	0% (0–35.43)	7	0	0	0% (0–35.43)
2020-W30	9	1	11.11% (1.99–43.5)	9	1	1	11.11% (1.99–43.5)
2020-W31	75	2	2.67% (0.73–9.21)	75	2	1	1.33% (0.24–7.17)
2020-W32	49	2	4.08% (1.13–13.71)	49	2	1	2.04% (0.36–10.69)
2020-W33	64	1	1.56% (0.28–8.33)	64	2	0	0% (0–5.66)
2020-W34	63	5	7.94% (3.44–17.27)	63	5	0	0% (0–5.75)
2020-W35	48	2	4.17% (1.15–13.98)	48	2	1	2.08% (0.37–10.9)
2020-W36	60	1	1.67% (0.29–8.86)	60	1	0	0% (0–6.02)
2020-W37	17	0	0% (0–18.43)	17	0	0	0% (0–18.43)
All weeks	3791	96		3791	97	12	
Share of positives		2.5 %				0.3 %	

Tested samples: Number of samples which have arrived at THL and for which an antibody test has been performed until the reporting day. **Samples with positive antibodies**: Number of tested samples with positive antibodies **Samples which belong to an MNT test set**: Number of samples which have been possible to consider in a microneutralisation test (MNT). The number of MNT positives should be compared to this number. **MNT tested samples**: Number of samples with positive antibody results for which a microneutralisation test was performed until the reporting date. **MNT positive samples**: Number of microneutralisation tested samples with a positive result.

Source: THL https://www.thl.fi/roko/cov-vaestoserologia/sero_report_weekly_en.html

The Finnish Institute for Health and Welfare (THL) publishes regular results on a serological population study on its website. The main purpose of the study is to obtain up-to-date information on how large a proportion of the population among different age groups and regions have developed antibodies to coronavirus (seroprevalence).

The study is based on random sampling. The presence of antibodies is studied using two different tests developed at THL. First, a sensitive test is used to measure whether the sample contains antibodies identifying coronavirus SARS-CoV-2. Positive results are then verified with a microneutralisation test that measures the ability of antibodies to neutralise the virus, which provides a very reliable indication whether the sample contains antibodies that have formed specifically for the new coronavirus. Neutralizing antibodies can be considered the most reliable method to detect coronavirus infection, but only a few microneutralization (MNT) positive results have been observed.

Results reported by several countries on the proportion of antibody-positive samples (seroprevalence) vary greatly and are mostly based on the results of individual antibody tests where neutralizing antibodies have not been measured. There are differences between study samples and the performance of the tests used. Even with an accurate antibody test, the risk of false positives is significant when the actual number of infections in the population is low.

So far, samples have only been collected from people aged 18 to 69. Approximately 750 subjects are invited to participate in the study each week, but participation is spread across several calendar weeks. So far, around 60% of those invited have participated in the study.

Low population Covid-19 immunity

Epidemiological models assume typically that infections result in permanent or long lasting immunity. To take into account the decreasing effect of the increasing population immunity, typically a logistic model is fitted to explain the evolution of the epidemic. However, serological studies on Covid-19 suggest that seroprevalence has stayed low. For example, Stringhini et al (2020)* note (see also next slide):
"At what appears to be the tail end of the first wave of the pandemic in Switzerland, about one in ten people have developed detectable antibodies against SARS-CoV-2, despite the fact that it was one of the more heavily affected areas in Europe. Thus, assuming that the presence of the IgG antibodies measured in this study is, at least in the short term, associated with protection, these results highlight that the vast majority of the population is still immunologically naive to this new virus."

The seroprevalence figures for France, Germany, Italy, Spain and Finland are even lower than in Switzerland. On July 13, the German authorities reported on a study that showed that only 1.3 % had antibodies in blood sample of 12 000 persons. https://www.reuters.com/article/us-health-coronavirus-germany-immunity-idUSKCN24E0X7 Also in the other four countries, low levels of antibodies have been detected. The results from a weekly random sample in Finland are presented in the previous slide. The possible explanations for the very low Covid-19 immunity rate in populations include that a) not all infected persons create antibodies and b) antibodies decrease relatively rapidly. According to recent study by Edridge et al (2020)**:
"Caution should be taken when relying on policies that require long-term immunity, such as vaccination or natural infection to reach herd immunity. Other studies have shown that neutralizing SARS-CoV-2 antibody levels decrease within the first 2 months after infection, especially after mild COVID-19[7,8], and we observed a similar decrease in anti-nucleocapsid antibodies of seasonal coronaviruses…" An exponential model is warranted as long as seroprevalence for Covid-19 continues to be very low.

*Stringhini, S. et al (2020), Seroprevalence of anti-SARS-CoV-2 IgG antibodies in Geneva, Switzerland (SEROCoV-POP): a population-based study. *The Lancet* Volume 396 Issue 10247 Pages 313-319 (August 2020). DOI: 10.1016/S0140-6736(20)31304-0
https://www.thelancet.com/journals/lancet/article/PIIS0140-67362031304-0/fulltext

**Edridge, A.W.D., Kaczorowska, J., Hoste, A.C.R. *et al.* (2020), Seasonal coronavirus protective immunity is short-lasting. *Nature Medicine* (2020). https://doi.org/10.1038/s41591-020-1083-1 https://www.nature.com/articles/s41591-020-1083-1#citeas

Empirical finding: higher altitude reduces Covid-19 growth rate (two recent studies)

Arias-Reyes et al (2020a)

- *”... we analyze the epidemiologic data of COVID-19 of Tibet and high-altitude regions of Bolivia and Ecuador, and compare to lowland data, to test the hypothesis that high-altitude inhabitants (+2500 m above sea-level) are less susceptible to develop severe adverse effect in acute SARS-CoV-2 virus infection. ...Our epidemiological analysis of the Covid-19 pandemic clearly indicates a decrease of prevalence and impact of SARS-CoV-2 infection in populations living at altitude of above 3,000 masl. ... Although the data of the present study suggest a strongly decreased pathogenicity of SARS-CoV-2 in high-altitude, there is yet no evidence of an underlying physiological mechanisms that could affect to severity of infection.”*

https://www.researchgate.net/publication/340793665_Does_the_pathogenesis_of_SARS-CoV-2_virus_decrease_at_high-altitude

Arias-Reyes et al (2020b):

- *“We have suggested previously that the infection rate of this virus might be lower in people living at high altitude (over 2,500 m) compared to that in the lowlands. Based on data from official sources, we performed a new epidemiological analysis of the development of the pandemic in 23 countries on the American continent as of May 23, 2020. Our results confirm our previous finding, further showing that the incidence of COVID-19 on the American continent decreases significantly starting at 1,000 m above sea level (masl).”*
- *“Finally, evaluating the differences in the recovery percentage of patients, the death-to-case ratio, and the theoretical fraction of undiagnosed cases, we found that the severity of COVID-19 is also decreased above 1,000 m. We conclude that the impact of the COVID-19 decreases significantly with altitude.”* https://www.medrxiv.org/content/10.1101/2020.07.22.20160168v2

An apparent explanation for the finding is the effect of altitude on UV radiation load. According to the WHO:

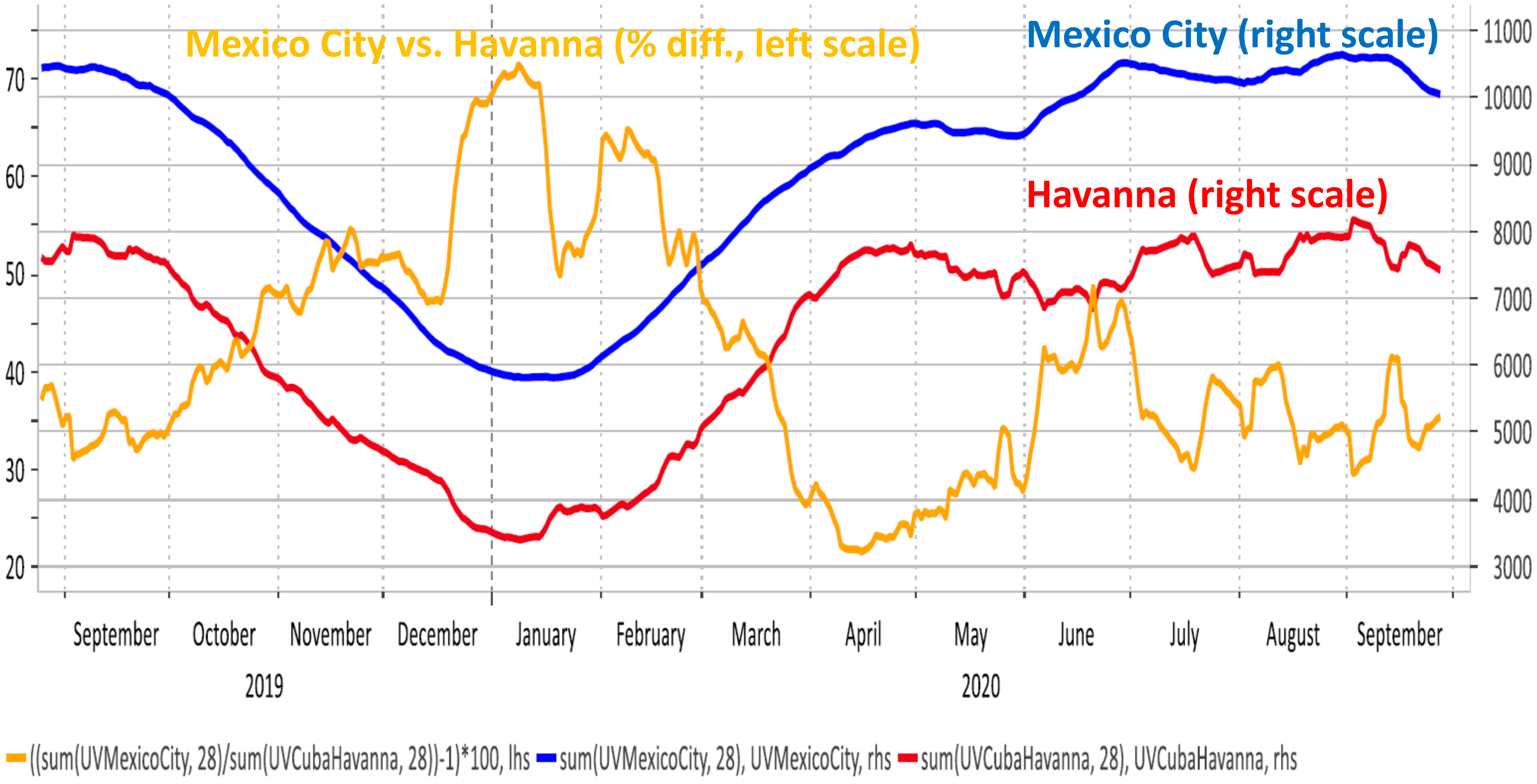
- *“… at higher altitudes, a thinner atmosphere filters less UV radiation. With every 1000 metres increase in altitude, UV levels increase by 10% to 12%.”*

https://www.who.int/uv/uv_and_health/en/

Consider Mexico Cityn ja Havanna in Cuba. These cities are roughly in the same latitude. Havanna is 50 meters and Mexico City is 2268 meters above sea level. During last 12 months, sum of daily UV radiation load has been 39 % higher in Mexico City compared to Havanna (see next slide).

Evidence on 23 countries in the American continent: higher altitude reduces Covid-19 cases and the death-to-case ratio (annex C). Apparent reason, WHO: *"… at higher altitudes, a thinner atmosphere filters less UV radiation. With every 1000 metres increase in altitude, UV levels increase by 10% to 12%."*

UVLoad Mexico City vs. Cuba Havanna (approximately same geographical latitude)



Latest value for: 9/27/2020, 9/27/2020, 9/27/2020. Source: .

Annex E: Estimation results with robustness analysis

1. Robustness of Covid-19 model for France, Germany and Finland with respect to adding alternatively the policy stringency index variable or one of the Apple or Google mobility variables

a) Using cases as dependent variable
b) Using deaths as dependent variable

2. Robustness od Sweden-Finland difference model with respect to adding alternatively the policy stringency index variable or one of the Apple or Google mobility variables

a) Using cases as dependent variable
b) Using deaths as dependent variable

Estimation equation

Covid-19 cases are assumed to depend on an exponential growth rate and UV radiation load. A log-linear functional form is assumed. The long run equation for Covid-19 cases is written as

(1) $\log C=\eta+\mu t+\theta \log UV+\omega \log P+\xi \log M$,

where C=14 day sum of new Covid-19 cases per 100 000 persons, t=time trend, UV=load of UV radiation, P=policy stringency index, M=mobility variable (either a work- or recreation-related mobility variable based on data provided publicly by Google or Apple).

In estimating the relation, a geometric lag distribution is assumed. Moreover, also initial lags from UV and M are allowed. If coefficients of P and M are not statistically significant at 5 % level, they are left out and the estimation equation reduces to

(2) $\Delta \log C_t=\alpha+(\lambda-1)\log C_{t-1}+\delta t+\beta \log UV_{t-n}+u_t$, where u_t is an error term and $\Delta \log C_t=\log C_t-\log C_{t-1}$.

The parameters of (1) are obtained as $\mu=\delta/(1-\lambda)$, $\theta=\beta/(1-\lambda)$ and $\omega=\varphi(1-\lambda)$.n and p are the number of days due to, e.g., reporting lags. The median lag from UV to C is obtained as $m1=n+(\log 0.5/\log\lambda)$.

The long run relation of (1) exits only if $\lambda<1$, i.e. only if the coefficient of $\log C_{t-1}$ is significantly negative. Breusch-Godfrey test is used to test that residuals do not deviate from white noise.

In estimating (2), differences in logUV where included as explanatory variables to reduce autocorrelation in the error term. In addition, UV deviation from its 2005-2019 average was included to reduce autocorrelation. This variable may capture effects of an omitted variable. An omitted variable can be the amount of UVC radiation. As the second slide in annex C notes, UVC's germicidal effectiveness (virus destroying effectiveness) peak wavelength is 260–265 nm. Normally UVC from sun does not reach, or reaches to a limited extent, earth's surface. When daily UV deviates from its long-term average, possible causes for that include weather conditions (e.g. clouds) and thickness of the ozone layer. The thinner the ozone leyer is, the more UVC reaches earth's surface and vice versa. If, e.g., the ozone layer is unusually thin, or if it has a hole, UV's germicidial effect is likely be unusually large.

	France									
Dependent Variable:	ΔlogC		ΔlogC		ΔlogC		ΔlogC		ΔlogC	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,73290	13,16731	0,73488	13,36776	0,55801	6,72658	0,58905	5,34432	0,48741	2,65452
Trend	0,00060	7,42048	0,00053	6,29270	0,00029	2,46754	0,00037	2,70039	0,00037	2,49571
logC(-1)	-0,04520	-8,48418	-0,04710	-8,86134	-0,02976	-3,68060	-0,04080	-6,07018	-0,03519	-3,01989
logUV(-21)	-0,16623	-12,38027	-0,16160	-12,07227	-0,09581	-3,56828	-0,13354	-5,87462	-0,11507	-3,17656
Δ(21)logUV	-0,03428	-1,62681	-0,06423	-2,67979	-0,01857	-0,64872	-0,05720	-2,35071	-0,03496	-1,04891
logUVdev.LRAv.(-22)^			-0,17247	-2,51886	-0,06775	-0,88015	-0,11616	-1,49679	-0,11164	-1,36001
logStringency(-21)					-0,06619	-2,81220				
logTransit mobility(-21) Apple							0,01883	1,52490		
logRecretion mob.(-21) Google									0,02315	1,47872
R-squared	0,48612		0,50119		0,51937		0,50668		0,25040	
F-statistic	49,89979		42,19993		37,64158		35,77611		10,74507	
Durbin-Watson stat	1,90173		1,96275		2,06519		1,99389		1,99653	
LM(2)^^	3,78586		1,99549		1,34634		1,81105		1,82666	
LM / Prob. Chi-Square(2)^^	0,15060		0,36870		0,51010		0,40430		0,40120	
Sample (adjusted):	3/04/2020 10/05/2020		3/04/2020 10/05/2020		3/04/2020 10/05/2020		3/04/2020 10/05/2020		3/20/2020 10/05/2020	
Included observation:	216		216		216		216		200	

^logUVdev.LRAVv. = log(42 day moving sum of UV) - log(42 day moving sum of the daily average of UV in 2005-2019).

^^Breusch-Godfrey Serial Correlation LM Test.

Long-run elsticity of new Covid-19 cases					
Underlying growth rate, % / day	1,32	1,12	0,97	0,89	1,04
Elasticity w.r.t. to UV	-3,68	-3,43	-3,22	-3,27	-3,27
Median lag from UV	35,98	35,37	43,94	37,64	40,35

	Germany									
Dependent Variable:	ΔlogC		ΔlogC		ΔlogC		ΔlogC		ΔlogC	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,62183	15,97510	0,57627	14,62604	0,43224	6,36318	0,317849	3,222976	0,47310	4,73278
Trend	0,00032	6,18957	0,00025	4,90722	0,00015	2,31522	5,03E-05	0,574677	0,00015	2,41100
logC(-1)	-0,03964	-11,01701	-0,03987	-11,44458	-0,02462	-3,60634	-0,035984	-9,75206	-0,04460	-7,01758
logUV(-28)	-0,13863	-14,14570	-0,12475	-12,33416	-0,06401	-2,50821	-0,090367	-5,777362	-0,12652	-8,13236
Δ(14)logUV(-14)	-0,08132	-3,26431	-0,08376	-3,47194	-0,04537	-1,61686	-0,052087	-1,987193	-0,09253	-5,39608
logUVdev.LRAv.(-15)^			-0,20186	-3,95898	-0,13966	-2,50345	-0,032901	-0,423616	-0,05502	-0,96446
logStringency(-21)					-0,07519	-2,58640				
logTransit mobility(-21) Apple							0,066621	2,849898		
logRecretion mob.(-21) Google									0,06936	2,83030
R-squared	0,68076		0,70217		0,71108		0,712916		0,60234	
F-statistic	116,74980		0,70217		89,01098		89,8126		49,73249	
Durbin-Watson stat	1,69209		1,82226		1,90096		1,882433		0,81324	
LM(2)^^	5,37017		1,29952		0,95157		0,733275		39,70008	
LM / Prob. Chi-Square(2) ^^	0,06820		0,52220		0,62140		0,6931		0,00000	
Sample (adjusted):	2/29/2020 10/09/2020		2/29/2020 10/09/2020		2/29/2020 10/09/2020		2/29/2020 10/09/2020		3/20/2020 10/09/2020	
Included observation:	224		224		224		224		204	

^logUVdev.LRAVv. = log(42 day moving sum of UV) - log(42 day moving sum of the daily average of UV in 2005-2019).

^^ Breusch-Godfrey Serial Correlation LM Test.

Long-run elsticity of new Covid-19 cases										
Underlying growth rate, % / day	0,79		0,63		0,61		0,14		0,34	
Elasticity w.r.t. to UV	-3,50		-3,13		-2,60		-2,51		-2,84	
Median lag from UV	45,14		45,04		55,81		46,91		43,19	

	Finland												
Dependent Variable:	ΔlogC			ΔlogC			ΔlogC			ΔlogC			ΔlogC	
	Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic
Constant	0,46958	9,90543		0,45984	9,69923		0,51685	9,19025		0,74438	4,50785		0,31312	1,08078
Trend	0,00034	5,06696		0,00034	4,98628		0,00051	4,41131		0,00057	3,89262		0,00029	1,91478
logC(-1)	-0,03888	-5,64519		-0,03683	-5,31296		-0,05713	-4,42333		-0,05373	-4,60892		-0,02281	-1,23027
logUV(-21)	-0,11218	-9,31406		-0,11010	-9,15667		-0,15661	-5,64646		-0,14725	-6,16802		-0,08587	-2,41044
ΔlogUVdev.LRAv.(-14)^				-0,06663	-1,87673		-0,07888	-2,19669		-0,05617	-1,56923		-0,05781	-1,89455
logStringency(-21)							0,08281	1,85835						
logTransit mobility(-21) Apple										-0,07897	-1,79801			
logRecretion mob.(-21) Google													0,01933	0,24736
R-squared	0,31563			0,32697			0,33796			0,33727			0,20475	
F-statistic	32,28324			25,38375			21,23607			21,17052			10,19545	
Durbin-Watson stat	1,94795			1,99171			1,99802			1,98925			2,01510	
LM(2)^^	0,18718			0,26800			0,42601			0,42047			3,08229	
LM / Prob. Chi-Square(2)^^	0,91070			0,87460			0,80820			0,81040			0,21410	
Sample (adjusted):	3/10/2020	10/09/2020		3/10/2020	10/09/2020		3/10/2020	10/09/2020		3/10/2020	10/09/2020		3/20/2020	10/09/2020
Included observation:	214			214			214			214			204	

^ΔlogUVdev.LRAVv. = log(14 day moving sum of UV) - log(14 day moving sum of the daily average of UV in 2005-2019)-log(14 day moving sum of UV(-14)) - log(14 day moving sum of the daily average of UV in 2005-2019(-14)).

^^Breusch-Godfrey Serial Correlation LM Test.

Long-run elsticity of new Covid-19 cases					
Underlying growth rate, % / day	0,88	0,91	0,90	1,06	1,25
Elasticity w.r.t. to UV	-2,89	-2,99	-2,74	-2,74	-3,77
Median lag from UV	38,48	39,47	32,78	33,55	51,04

	France										
Dependent Variable:	ΔlogD			ΔlogD			ΔlogD			ΔlogD	
	Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic
Constant	0,88074	12,42599		0,51947	3,66475		0,98201	7,15759		0,52589	1,46907
Trend	0,00029	3,78791		0,00005	0,43386		0,00038	2,93210		0,00034	2,47258
logD(-1)	-0,03379	-5,93820		-0,01914	-2,55150		-0,03619	-5,70884		-0,01766	-1,16743
logUV(-42)	-0,18336	-11,84462		-0,07609	-1,91698		-0,20387	-7,18148		-0,11782	-1,74895
Δ(21)logUV(-21)	-0,13294	-6,41240		-0,06933	-2,32804		-0,13577	-6,46427		-0,07639	-1,83519
logStringency(-42)				-0,07304	-2,92529						
logTransit mobility(-42) Apple							-0,01007	-0,86227			
logRecretion mob.(-42) Google										-0,00147	-0,07967
R-squared	0,45949			0,48188			0,46151			0,18620	
F-statistic	42,29229			36,83018			33,93893			8,09954	
Durbin-Watson stat	1,96930			2,09027			1,97142			2,04825	
LM(2)^^	2,09858			1,29558			2,06341			1,87850	
LM / Prob. Chi-Square(2) ^^	0,35020			0,52320			0,35640			0,39090	
Sample (adjusted):	3/20/2020 10/09/2020			3/20/2020 10/09/2020			3/20/2020 10/09/2020			4/10/2020 10/09/2020	
Included observation:	204			204			204			183	
^^Breusch-Godfrey Serial Correlation LM Test.											
Long-run elsticity of Covid-19 deaths											
Underlying growth rate, % / day	0,86			0,25			1,05			1,95	
Elasticity w.r.t. to UV	-5,43			-3,98			-5,63			-6,67	
Median lag from UV	62,17			77,87			60,80			80,91	

	Germany							
Dependent Variable:	ΔlogD		ΔlogD		ΔlogD		ΔlogD	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,87671	15,75324	1,02303	7,89567	1,18866	8,04214	0,65935	3,24678
Trend	0,00013	1,35034	0,00016	1,66446	0,00045	2,65045	0,00035	3,64426
logD(-1)	-0,05648	-9,45709	-0,06733	-6,39431	-0,06113	-9,77376	-0,02717	-2,56737
logUV(-44)	-0,17153	-11,76544	-0,21627	-5,59808	-0,22650	-8,04678	-0,13798	-4,36275
Δ(7)logUV(-23)	-0,10320	-2,20143	-0,10058	-2,14633	-0,07190	-1,48576	-0,07047	-2,18239
logStringency(-42)			0,04171	1,25015				
logTransit mobility(-42) Apple					-0,05938	-2,27440		
logRecretion mob.(-42) Google							-0,02367	-0,78111
R-squared	0,59547		0,59864		0,60577		0,29757	
F-statistic	73,23298		59,06467		60,84949		14,99639	
Durbin-Watson stat	1,72775		1,71443		1,76045		1,63353	
LM(2)^^	1,45088		1,15653		1,52273		7,94453	
LM / Prob. Chi-Square(2) ^^	0,48410		0,56090		0,46700		0,01880	
Sample (adjusted):	3/20/2020 10/09/2020		3/20/2020 10/09/2020		3/20/2020 10/09/2020		4/10/2020 10/09/2020	
Included observation:	204		204		204		183	
^^Breusch-Godfrey Serial Correlation LM Test.								
Long-run elsticity of Covid-19 deaths								
Underlying growth rate, % / day	0,22		0,24		0,73		1,30	
Elasticity w.r.t. to UV	-3,04		-3,21		-3,70		-5,08	
Median lag from UV	55,92		53,94		54,99		69,16	

	Finland													
Dependent Variable:	ΔlogD			ΔlogD			ΔlogD			ΔlogD			ΔlogD	
	Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic		Coefficient	t-Statistic
Constant	0,48201	4,35335		0,55041	4,90274		0,31880	2,09888		-0,18583	-0,66436		0,21083	0,47987
Trend	-0,00005	-0,25717		-0,00002	-0,12482		-0,00026	-1,23490		-0,00059	-2,18903		-0,00047	-2,03388
logD(-1)	-0,03888	-3,13067		-0,04276	-3,46903		-0,02155	-1,39452		-0,03306	-2,63373		-0,06112	-2,57719
logUV(-28)	-0,10105	-3,43397		-0,11672	-3,94045		0,00132	0,02189		-0,00906	-0,19068		-0,11089	-1,56399
ΔlogUVdev.LRAv.(-12)^				-0,20377	-2,56759		-0,20559	-2,61874		-0,25158	-3,16050		-0,32500	-3,19849
logStringency(-42)							-0,16211	-2,23488						
logTransit mobility(-42) Apple										0,19220	2,86328			
logRecretion mob.(-42) Google													0,21744	2,35042
R-squared	0,12054			0,15145			0,17436			0,18841			0,11998	
F-statistic	8,31493			8,07596			7,60229			8,35739			4,41744	
Durbin-Watson stat	2,03303			2,07388			2,16206			2,17841			2,16851	
LM(2)^^	0,81932			0,57958			1,30798			1,65882			1,25497	
LM / Prob. Chi-Square(2)^^	0,66390			0,74840			0,52000			0,43630			0,53390	
Sample (adjusted):	3/23/2020	10/09/2020		3/23/2020	10/09/2020		3/23/2020	10/09/2020		3/23/2020	10/09/2020		3/23/2020	10/09/2020
Included observation:	186			186			186			186			186	

^ΔlogUVdev.LRAVv. = log(14 day moving sum of UV) - log(14 day moving sum of the daily average of UV in 2005-2019)-log(14 day moving sum of UV(-14)) - log(14 day moving sum of the daily average of UV in 2005-2019(-14)).

^^Breusch-Godfrey Serial Correlation LM Test.

Long-run elsticity of Covid-19 deaths					
Underlying growth rate, % / day	-0,12	-0,05	-1,22	-1,78	-0,78
Elasticity w.r.t. to UV	-2,60	-2,73	0,06	-0,27	-1,81
Median lag from UV	45,48	43,86	59,82	48,62	38,99

Including Covid-19 policy stringency indicator (Oxford) or other mobility variables in the Sweden-Finland new Covid-19 cases equation

	Sweden minus Finland							
Dependent Variable:	ΔlogC		ΔlogC		ΔlogC		ΔlogC	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,01459	1,62911	0,00791	0,86840	0,00674	0,76601	0,00333	0,35219
logC(-1)	-0,02848	-3,44715	-0,02562	-2,68632	-0,02277	-2,85239	-0,01889	-2,24882
logUV(-21)	-0,20344	-2,72864	-0,10138	-1,14393	-0,08940	-1,00803	-0,11835	-1,27858
logTransit mobility(-42) Apple	0,27727	4,99986	0,14342	0,81423	0,19562	2,15306	0,23946	4,35009
logRecreation mob.(-42) Google			0,14326	0,72263				
logWork mob.(-42) Google					0,11846	0,91002		
logStringency(-42)							-0,03335	-1,22096
R-squared	0,12353		0,15234		0,15380		0,16030	
F-statistic	9,91279		7,95269		8,04266		7,97027	
Durbin-Watson stat	1,98515		1,87043		1,87485		1,88734	
LM(2)^	0,06154		3,65373		3,67055		2,36416	
LM / Prob. Chi-Square(2)^	0,96970		0,16090		0,15960		0,30660	
Sample (adjusted):	3/08/2020 10/08/2020		4/10/2020 10/08/2020		4/10/2020 10/08/2020		4/20/2020 10/08/2020	
Included observation:	215		182		182		172	

^Breusch-Godfrey Serial Correlation LM Test.

Long-run elasticity of new Covid-19 cases				
Transit Mobility (Apple)	9,7	5,6	8,6	12,7
Recreation Mobility (Google)		5,6		
Work Mobility (Google)			5,2	
Stringency				-1,8
Median lag, days	66	69	72	78

Including Covid-19 policy stringency indicator (Oxford) or other mobility variables in the Sweden-Finland new Covid-19 deaths equation

	Sweden minus Finland							
Dependent Variable:	ΔlogD		ΔlogD		ΔlogD		ΔlogD	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	0,04184	1,49421	0,03810	1,21132	0,04916	1,55706	0,04468	1,35900
logD(-1)	-0,08404	-3,40532	-0,06023	-1,90776	-0,08988	-3,16322	-0,08521	-2,92709
logUV(-21)	0,53280	2,89641	0,33580	1,39404	0,51351	2,42600	0,45672	1,92650
logTransit mobility(-63) Apple	0,83789	4,43932	1,40873	3,48733	0,65835	2,36080	0,81220	3,55855
logRecretion mob.(-63) Google			-0,84490	-1,68532				
logWork mob.(-63) Google					0,34518	0,95206		
logStringency(-63)							-0,03332	-0,50390
R-squared	0,12543		0,14739		0,13375		0,12926	
F-statistic	7,31450		5,18613		4,63219		4,08236	
Durbin-Watson stat	2,26096		2,42841		2,31867		2,33812	
LM(2)^	0,68614		3,25278		0,77689		0,72242	
LM / Prob. Chi-Square(2)^	0,70960		0,19660		0,67810		0,69680	
Sample (adjusted):	3/29/2020 10/05/2020		5/01/2020 10/05/2020		5/01/2020 10/05/2020		5/11/2020 10/05/2020	
Included observation:	157		125		125		115	
Long-run elasticity of new Covid-19 deaths								
Transit Mobility (Apple)	10,0		23,4		7,3		9,5	
Recreation Mobility (Google)			-14,0					
Work Mobility (Google)					3,8			
Stringency							-0,4	
Median lag, days	71		74		70		71	

^Breusch-Godfrey Serial Correlation LM Test.

THANKS!