Johannes Gutenberg University Mainz

CoV-2 (and Covid-19) Economics

2020/2021 winter term

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7 CoV-2 infections and business cycles

- Why talk about CoV-2 infections and Covid-19 in a macroeconomics lecture?
  - Big field of health economics
  - Business cycle effects of infection risk and public health measures
  - Methodologically identical basis of epidemiology models and modern labour market theory: continuous-time Markov chains
- Lectures on Covid-19 research from public health perspective
- This type of research is typical for epidemiologists and for health economists
- Some background (in German) is e.g. on Corona-Blog Prof Wälde

- The structure of this chapter and this lecture
  - We first talk about facts on CoV-2 and Covid-19
  - Then we offer introduction to conceptual frameworks – theory of epidemics
  - Applied public health research
  - Economic aspects of the epidemic
  - Summary – where do we stand?

7.1 Some facts on CoV-2 and Covid-19

7.1.1 The infection, the disease and what we would like to know

- The five steps of Covid-19
  - Infection with SARS-CoV-2 (Severe acute respiratory syndrome - Coronavirus 2)
  - With corresponding symptoms, individual has developed Covid-19 (Coronavirus disease 2019) and might visit a general practitioner (GP)
  - In more severe cases, patient enters hospital
  - Patient might end up on intensive care
  - Worst case: patient deceases
- Society would like to be fully informed, at least from a statistical perspective, about these 5 steps
  - This is of central importance for
    - private decision making
    - for public health measures
  - Do we have *informative* (representative) statistics?

7.1.2 The number of *reported* CoV-2 infections over time

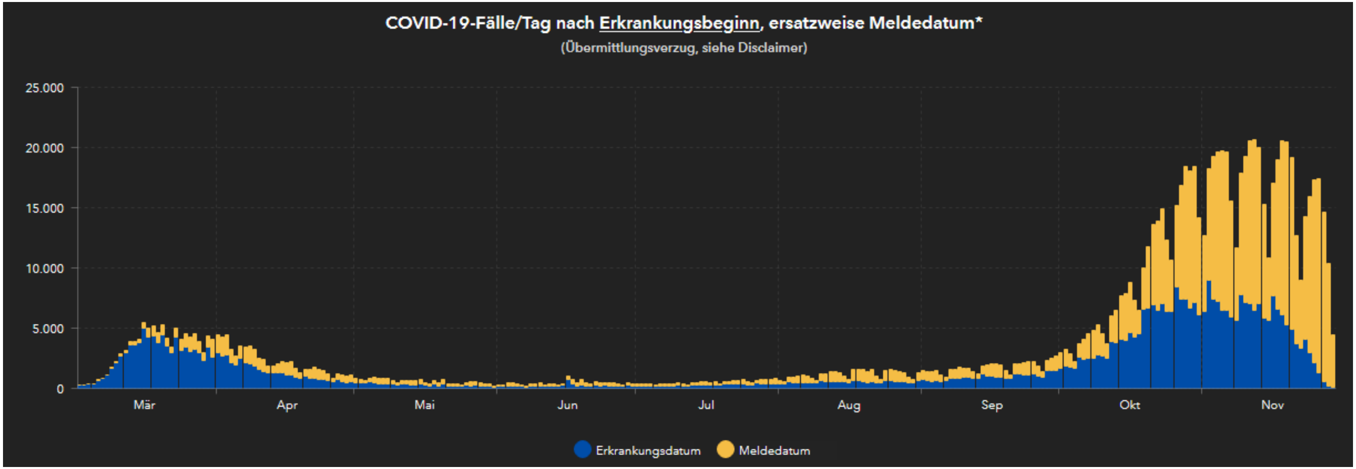


Figure 1 *Number of CoV-2 infections according to RKI Covid Dashboard for Germany (note the title 'Covid-19 cases' even though these are CoV-2 infections)*

- Figure shows (and data reports) *reported* CoV-2 infections
  - It is far from obvious that *reported* numbers are a good measure of *true* epidemiological state
  - In statistical terms: Do we have an unbiased estimator of true parameter?
  - Probably we do not (see Wälde 2020a for a summary, 2020b for the argument in short in German, 2020c for the full model analysis in English and ch. 7.2.2 below)
- see JHU Covid Dashboard (Global) for world wide data (probably also not representative)
- Despite this issue of looking at a
  - biased estimator of the epidemic, it is still
  - the best estimator we have (at this point, Nov 2020)

7.1.3 The number of *reported* tests in Germany

- Data sources are described by Staat et al. (2020)
  - University medical centers (Universitätskliniken)
  - Research Institutes
  - Laboratories, independent and in clinics
- Four reporting channels
  - internetbased survey by RKI via Voxco (RKI-Testlaborabfrage)
  - Netzwerk für respiratorische Viren (RespVir)
  - Antibiotika-Resistenz-Surveillance (ARS) des RKI
  - Survey of a "labormedizinischen Berufsverbandes"
- Capacity limits for tests are also recorded by survey
- Quality of data
  - Unclear whether data is representative
  - There is no list of laboratories undertaking tests in Germany (Nov 2020)

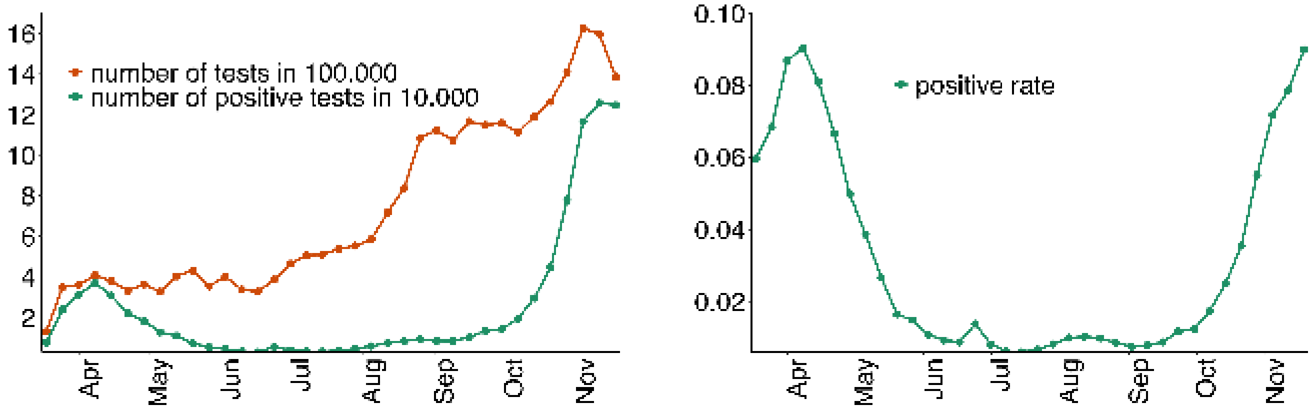


Figure 2 *The number of reported tests (probably non-representative), the number of (non-representative) positive cases (left panel) and the positive rate (right panel)*

7.1.4 The number of Covid-19 cases over time (Germany)

As of step 2 above (visiting a GP), we talk about Covid-19

- no information on step 2 (Covid-19 cases in Germany)
- no (public) information on Covid-19 patients in hospital
- Public information on Covid-19 cases (not patients) in intensive care (https://www.intensivregister.de, Karagiannidis et al. 2020)
- Public information on Covid-19 related fatalities (RKI Dashboard and via API)

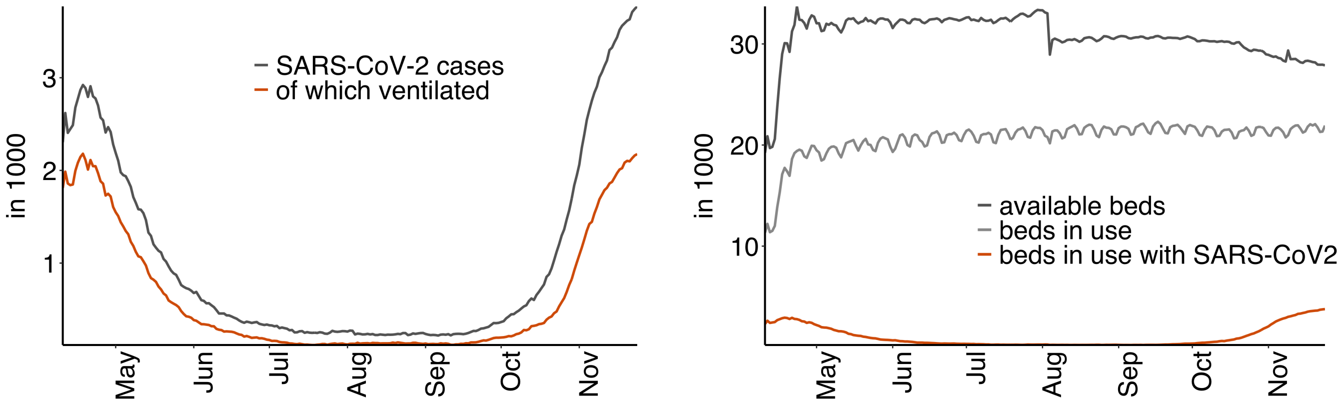
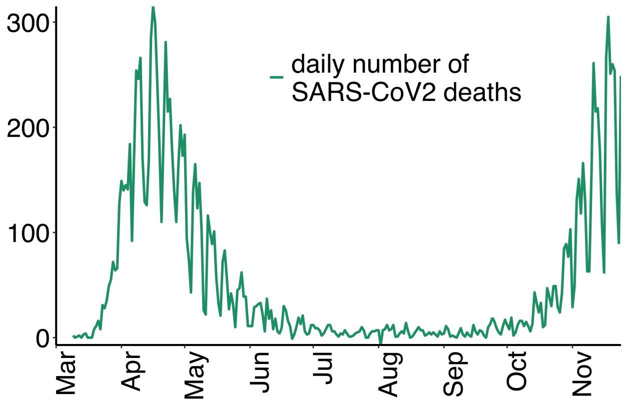


Figure 3 *SARS-CoV-2 cases in intensive care in Germany (left) and total number of intensive care beds (right)*



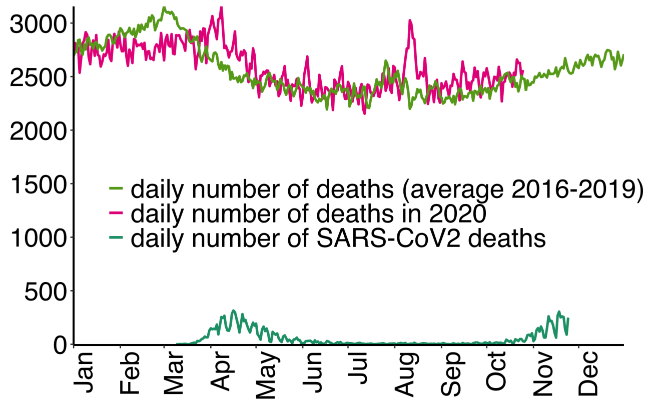


Figure 4 *Daily number of fatalities associated with Covid-19 (left) and total number of fatalities (showing excess fatalities in 2020) (right)*

7.2 Conceptual frameworks to understand epidemics

7.2.1 The SIR model of an epidemic

- Let us look at some concepts on epidemics
- Why do we need theory?
  - to understand existing and non-existing time series
  - to study the effect of public health measures (PHM)
  - to be able to recommend PHM

- The classic SIR model (Kermack und McKendrick, 1927, Hethcote, 2000)
  - Three types of individuals: susceptible $\tilde{S}(t)$, infectious $\tilde{I}(t)$, removed $\tilde{R}(t)$ (recovered or deceased)
  - Arrival rates (as in search & matching models) determine transitions

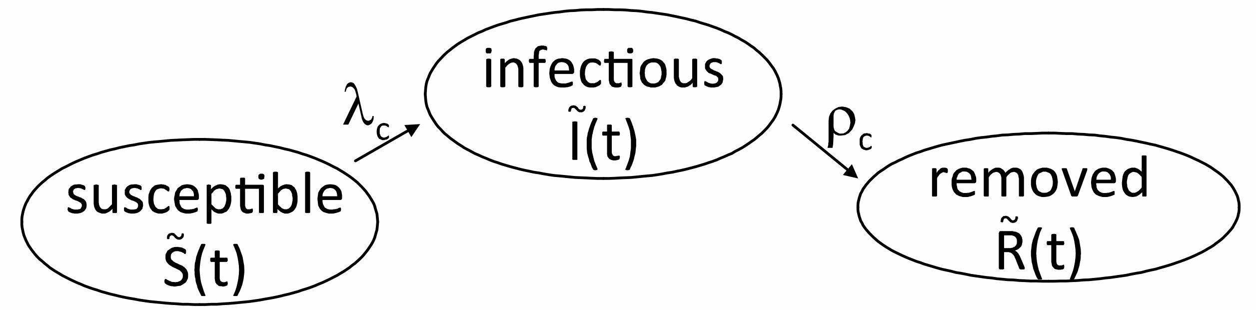


Figure 5 *Transition between states in the classic SIR model*

- The algebra

  - The number of susceptible individuals falls according to

$$\frac{d}{dt}\tilde{S}(t) = -\lambda_c(t)\,\tilde{S}(t),$$

    where r is a constant and

$$\lambda_c(t) \equiv r\tilde{I}(t)$$

    called the individual infection rate

  - Infection rate captures idea that risk of becoming infected is the greater, the higher the number $\tilde{I}(t)$ of infectious individuals
  - Merging individual recovery rate and death into one constant ρ_c, the number of infectious individuals changes according to

$$\frac{d}{dt}\tilde{I}(t) = \lambda_c(t)\,\tilde{S}(t) - \rho_c\tilde{I}(t)$$

  - As a residual, the number of removed individuals rises over time according to

$$d\tilde{R}(t)/dt = \rho_c\tilde{I}(t)$$

- Numerical solution of SIR model

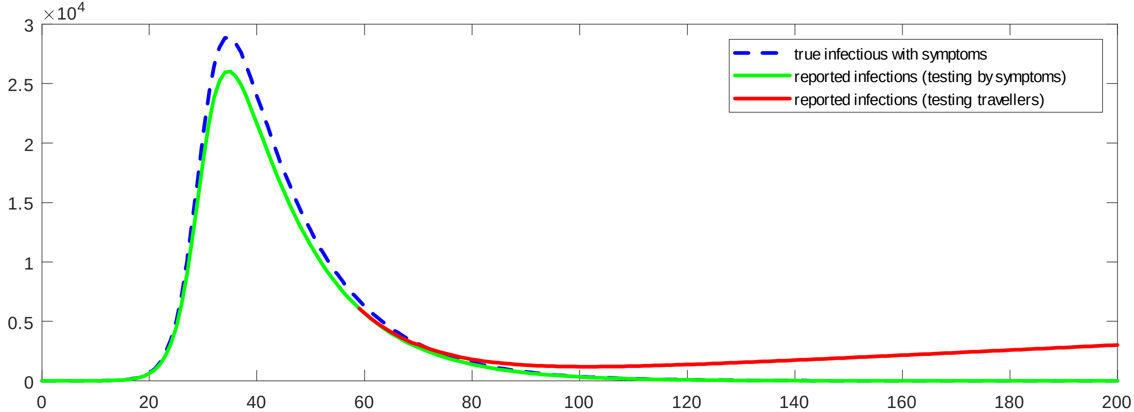


Figure 6 *True epidemiological dynamics (blue), correct reporting (green) [and an example of a bias (red) of the reported number of infections – see ch. 7.2.2 or Wälde, 2020c]*

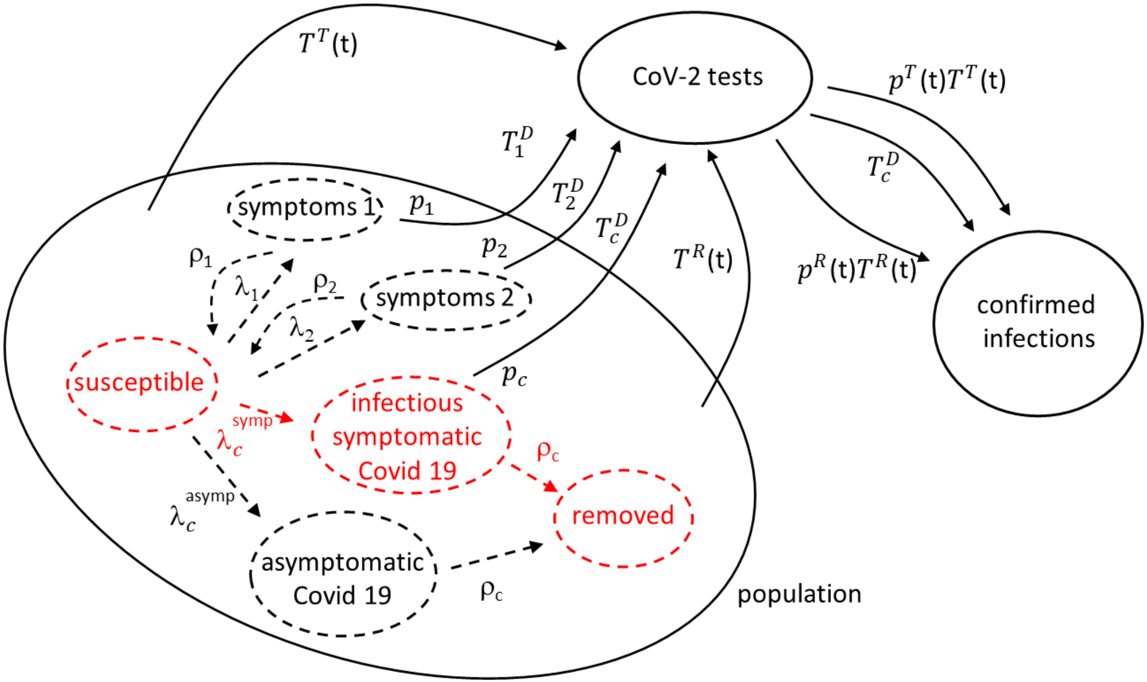
- Extensions of the classic SIR model
  - Allowing for non-symptomatic cases
  - Allowing for testing and unobserved true state
  - Allowing for distinction between infected and infectious
  - Allowing for empirically realistic durations (approx. log-normal) in states
  - For references see e.g. Donsimoni et al. (2020a, b), Dehning et al. (2020) or Mitze et al. (2020)
- Applications of (extended) SIR model(s)
  - Predictions of the epidemic (first wave, second wave)
  - Understanding the effects
    - of public health interventions
    - of vaccines

7.2.2 A model of CoV-2, Covid-19 and testing in Germany

[not in this lecture]

- Reported numbers of CoV-2 infections are probably not comparable over time.
  - When public health authorities report x new cases on some day in October 2020, these x new cases do not have the same meaning as x new cases in April, May or June 2020.
  - Bias results from different testing rules applied simultaneously. Private and public decision making should not be based on time series data as they do not provide information about the true epidemic dynamics in a country.
  - If the reason for testing was known, an unbiased measure of the severity of an epidemic could be computed easily

- Therefore we ask
  - What do these numbers mean?
  - What does it mean that we talk about a “second wave”?
  - Intuitive interpretations of “the curve” suggest that the higher the number of new infections, the more severe the epidemic. Is this interpretation correct?
  - When the number of infections increases, decision makers start to discuss additional or tougher public health measures. Is this policy approach appropriate?



- **Figure 7** *The SIR model with testing (for more details see Wälde, 2020 (testing bias slides))*

7.3 Public health research on Covid-19 – Preliminary steps

7.3.1 The effect of public health measures

- How do we identify the effect of public health measures (PHM)?
  - Imagine the government passes regulations imposing pubic health measures
  - Imagine the measures enter in force on some specific date
  - How can we test that they were effective, i.e. that they reduce numbers of (reported) CoV-2 infections?
- First make sure to understand when PHM are implemented where (next section 7.3.2)
- Take incubation and reporting delays into account (section 7.3.3)
- Apply (more or less) sophisticated statistical methods (section 7.4)

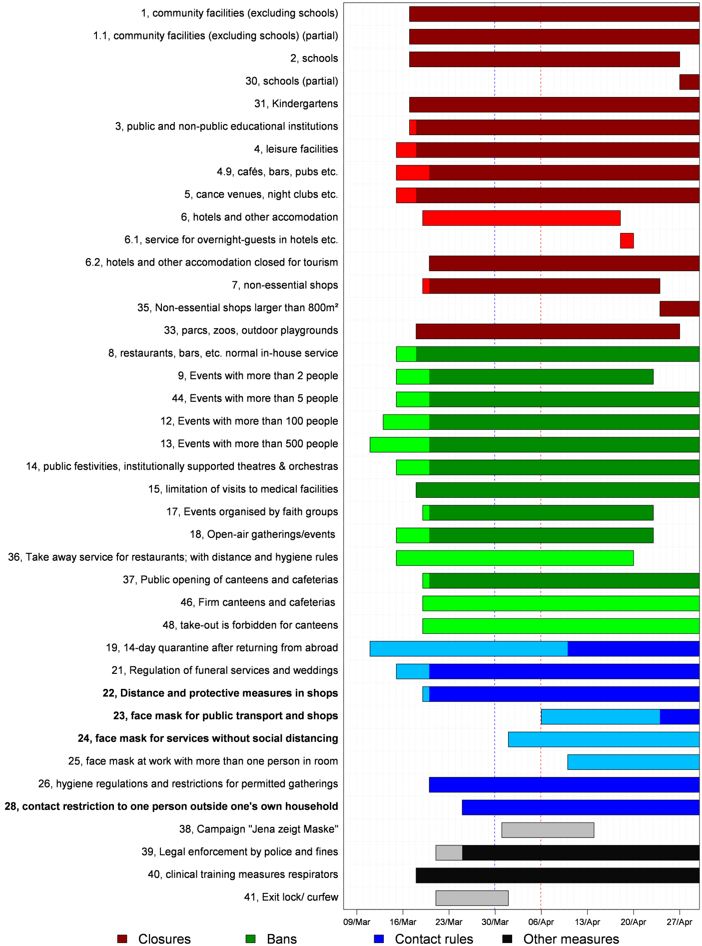
7.3.2 Monitoring public health measures

- Not enough to focus on one measure
  - overview of the timing of other public health measures (PHM) needed
  - individual effects must be disentangled
- Let us take example of Jena, Thuringia and face masks
  - (taken from Mitze et al., 2020, app. A.2)
  - Figure 8 shows timing of measures in Jena and Thuringia
  - (all measures for Thuringia are also binding for Jena)
- Jena introduced three regulations concerning face masks
  - April 1: face masks for services where a distance of 1.5 meters cannot be kept
  - April 6: masks for public transports, shops, food deliveries, stores and offices of craftsmen and service providers,
  - April 10: masks at work and in public buildings where a distance of 1.5 m cannot be kept
- Measures of April 1 and 6 were also employed by federal states later, while measure of April 10 was only in Jena (at least in this wording)

Figure 8 *Time line of public health measures in Jena. Light bars indicate measures in force only in Jena, dark bars indicate measures in force in Thuringia (and thereby also in Jena)*

Figure for the lecture (turn right)

7.22



- This type of work is extremely time consuming
  - See http://waelde.com/Verordnungen/ for a collection of regulations
  - Regulations need to be coded
  - See https://www.bsg.ox.ac.uk/research/research-projects/ coronavirus-government-response-tracker for an international measure
- This type of work is basis of all subsequent statistical methods
  - The less clear government measures are, the harder it is to identify effects
  - Gold standard: Randomization
  - More cooperation by the public represented by politicians needed
  - At least it would help to better understand infection channels (and much more)

7.3.3 Incubation and reporting delays

- Imagine a PHM is implemented on a certain day and that it is effective. When should we see the effects in the data?

- Delay between PHM and statistical visibility depends on

  - incubation period and
  - reporting delay

- Incubation period is well-studied and has a median of 5.2 days, approx. log-normally distributed (Linton et al., 2020; Lauer et al., 2020).

- Reporting delay is not as well-studied. It consists of a delay due to diagnosis, testing, and reporting of the test

  - Person with symptoms needs to go to GP
  - A test is undertaken
  - Results needs to be reported to authorities

- Why is this question important?
  - Some argue that there is no CoV-2
  - Some argue that public health measures do not have any effect
  - If we understand when PHM *should* have an effect, we can test *whether* they have an effect
  - We can "prove", i.e. provide evidence that PHM do help
  - Of major importance for our common understanding in society how to react to Covid-19

- Formal structure – [not in this lecture] nicht relevant bis einschließlich Seite 7.33
  - [taken from Mitze et al., 2020, app. A.3]
  - D_I random variable for incubation period
  - D_R RV for delay between perceptible symptoms and reporting to authorities
  - Overall delay D obviously
$$D = D_I + D_R$$
  - One can take median of D as measure for how long it takes before effects of PHM are visible in the data

- Findings for incubation
  - Linton et al. (2020), Lauer et al. (2020) and others describe the delay between infection and symptoms, i.e. the incubation period, by a log-normal distribution
  - Log-normal distribution of a random variable X has the density

$$f(x) = \frac{1}{\sqrt{2\pi\sigma x}} e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}},$$

    for $x > 0$, where σ is the dispersion parameter and μ the scale parameter
  - Mean, median and variance are given by

$$E[X] = e^{\mu+\frac{\sigma^2}{2}}, \; m = e^{\mu}, \; Var[X] = \left[e^{\sigma^2} - 1\right] e^{2\mu+\sigma^2}$$

  - Lauer et al. (2020) report
    * $m = 5.1$ and that
    * 95% of all cases lie between 2.2 and 11.5 days
    * The latter means, given our density assumption,

$$\int_{2.2}^{11.5} f(x)\, dx = 0.95$$

    * Numerically computing the parameter σ from this equation yields $\sigma = 0.4149$
    * The scale parameter is given by $\mu = \ln(5.1) = 1.63$

- Findings for reporting
  - RKI (2020) provides information on date of reporting and on day of first symptoms (for ∼80% of all reported cases)
  - Difference between these two dates gives a vector of realizations of the RV D_R
  - There are 119,917 observations with information on day of infection (until reporting day May 6, 2020). We focus on 118,618 with $D_R \geq 0$

Mean	**Median**	**Variance**	**Standard deviation**
6.80	6	30.92	5.56

Tabelle 1 *Descriptive statistics for the reporting delay D_R*

- Next slide shows histogram

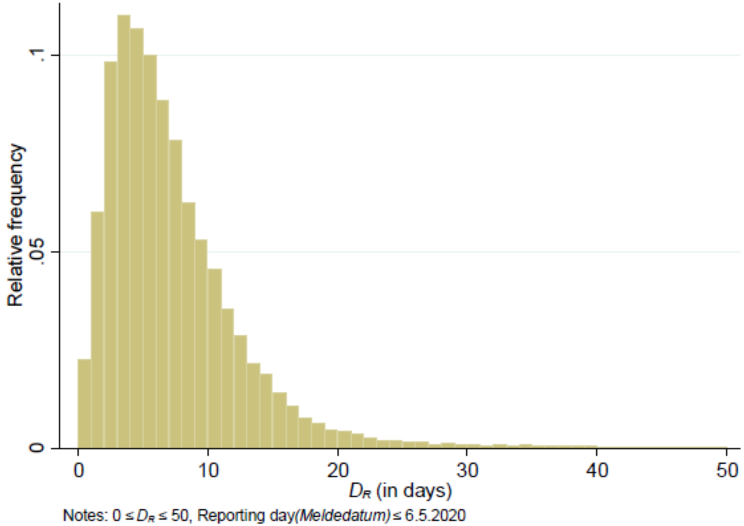


Figure 9 *Histogram of delay between first symptoms and reporting*

- Merging incubation and reporting delay
  - Let us return to total delay $D = D_I + D_R$ (defined above)
    * Mean is $E[D] = E[D_I] + E[D_R]$
    * Variance reads $Var[D] = Var[D_I] + Var[D_R]$
      · ... assuming independence between the two RVs
      · Are diagnosis or reporting lags influenced by the length of the incubation period
      · no $\rightarrow$ weak assumption

- The corresponding distribution of D
  - We study the distribution of a sum of two random variables
  - Denote distribution by $F_D(\delta) =$Prob$(D \leq \delta)$, describing the probability that $D < \delta$, where δ is some constant
  - The densities for incubation and reporting are $f(\delta_I)$ and $g(\delta_R)$, respectively
  - Distribution $F_D(\delta)$ is given by

$$Prob\left(D_I + D_R \leq \delta\right) = \int_0^{\delta} \left[\int_0^{\delta-\delta_I} f\left(\delta_I\right) g\left(\delta_R\right) d\delta_R\right] d\delta_I$$

  - Idea of double integral
    * we are interested in values below or equal to δ
    * we let δ_I run from 0 to δ and δ_R from 0 to $\delta - \delta_I$ such that the sum of the two is always smaller than or equal to δ
  - Integrating over the joint density (which is a product given independence) gives the desired probability

- Density for D
  - If we needed the density $f_D(\delta)$, we could compute the derivative of the probability with respect to δ giving us convolution expression

$$
\begin{aligned}
f_D(\delta) = \frac{dF_D(\delta)}{d\delta} &= \frac{d}{d\delta}\int_0^{\delta}\left[\int_0^{\delta-\delta_I} f(\delta_I)\, g(\delta_R)\, d\delta_R\right] d\delta_I \\
&= \int_0^{\delta-\delta} f(\delta)\, g(\delta_R)\, d\delta_R + \int_0^{\delta} \frac{d}{d\delta}\left[\int_0^{\delta-\delta_I} f(\delta_I)\, g(\delta_R)\, d\delta_R\right] d\delta_I \\
&= \int_0^{\delta} f(\delta_I)\, g(\delta-\delta_I)\, d\delta_I .
\end{aligned}
$$

  - We work with the assumption that $f(\delta_I)$ is the density of the exponential distribution and that $g(\delta_R)$ is the density corresponding to the histogram in Figure 9
  - We can easily compute the density numerically (see Figure 10)

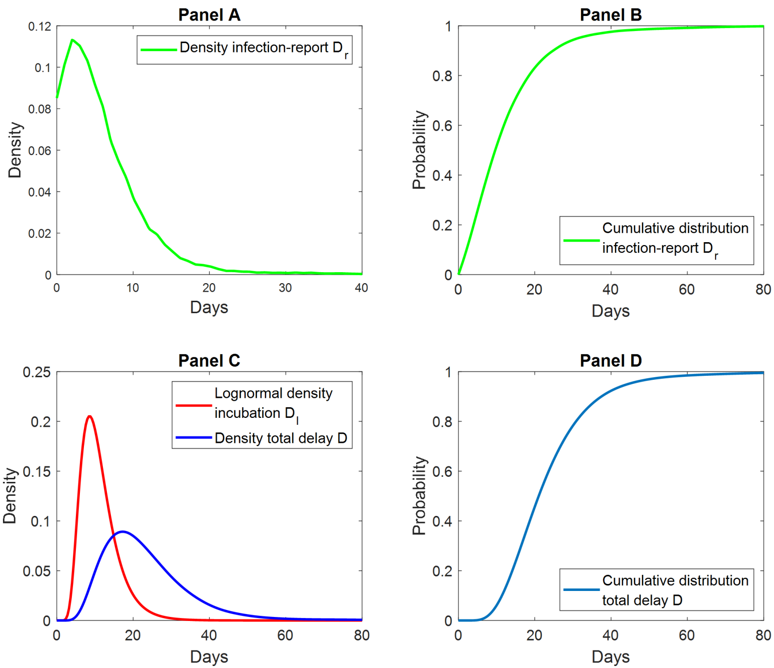


Figure 10 *Density of the total delay D*

- What do we get out of this analysis?
  - Figure with distribution and density (see earlier slide)
  - Information on the share of individuals that are reported as being infected after a delay of D days since infection

1	**2.5**	**5**	**10**	**25**	**50**	**75**	**80**	**90**	**95**	**97.5**	**99**
3.42	4.09	4.78	5.70	7.65	10.52	14.30	15.41	18.74	22.22	26.29	34.23

Tabelle 2 *Percentiles of total delay D*

- How to read this table
  - 1% of all individuals that are infected on day 0 are reported to be infected at the latest after 3.42 days
  - 10% of all individuals are reported at the latest after 5.7 days
  - ... and so on ...
  - For 5% of all individuals that are infected on day 0, it takes more than 22.22 days to be reported to be infected

* overall message: PHM should be visible after 10.5 days in the data

7.4 Public health research on Covid-19 – Analyses

- Objectives of studies
  - Do public health measures mitigate the spread of CoV-2 infections?
  - How long will the epidemic last?
    - ... in the absence of any public health measures
    - ... in their presence
    - ... when there are vaccines
  - What are the effects of individual public health measures (like e.g. face masks)?
  - ... and other questions

7.4.1 The effect of public health measures

- First simple approaches
  - Observe time series of CoV-2 infections
  - Record point in time of public health measures
  - Take incubation (plus reporting?) delay into account (see section 7.3.3)
  - Ask whether breaks in daily growth rates of confirmed cases can be observed

- Reminder of events: initial three (regulatory) phases
  - Unrestricted spread before 13 March 2020
  - Social restrictions and restrictions on firms as of 16/17 March
    - 16 March onwards: no schooling, no major sports events
    - 22 March onwards: no restaurants, theaters, public sports facilities
  - Partial exit as of 20 April (relatively heterogeneous across Federal States)

- Regression testing
  - Linear (log-linear) regression of confirmed CoV-2 cases
  - Specification with two trend breaks captures the dynamics of confirmed cases well
  - See e.g. in Hartl et al. (2020)

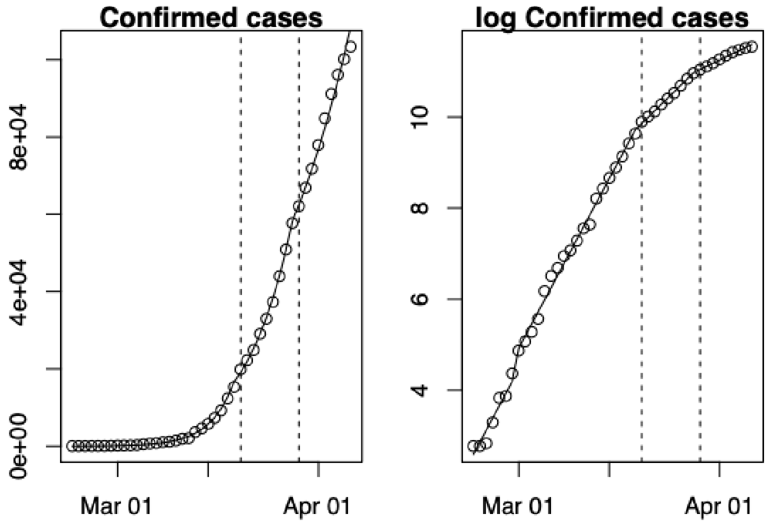


Figure 11 *Fitted values for a log-linear trend model with trend breaks on 20 March and 30 March. Left panel shows levels, right panel shows log of confirmed cases*

- Interpretation
  - Log-linear model shows breaks on 20 and 30 March
  - Breaks show that increase in number of confirmed cases slowed down
  - Drop in growth rates is significant (from 27% to 14% daily growth rate on 20 March)
  - Breaks are statistically significant at 1% level
  - PHM of 13 and 22 March helped to reduce infections
- We would expect similar results for lockdown of
  - Monday 2 November (see rules)
  - Wednesday 25 November (see rules)
- Huge literature with more detailed analyses exists (see e.g. Dehning et al., 2020, Mitze et al., 2020 or Kosfeld et al., 2020 for short surveys)

11. DS

7.4.2 First projections from beginning of pandemic

- One valid question concerning an epidemic asks: When will it be over?
  - A lot of factors influence infection dynamics and not all of them are well understood
  - Yet, one can combine current knowledge, observe evolution of epidemic up to some point and then predict future infection numbers
  - This is what quantified SIR models do
- We are presenting one such model and prediction (taken from Donsimoni et al., 2020, see also Dehning et al., 2020)
  - We first present idea of model structure
  - How to link model with data (calibration) is illustrated
  - Predictions of the model

- Idea of model structure

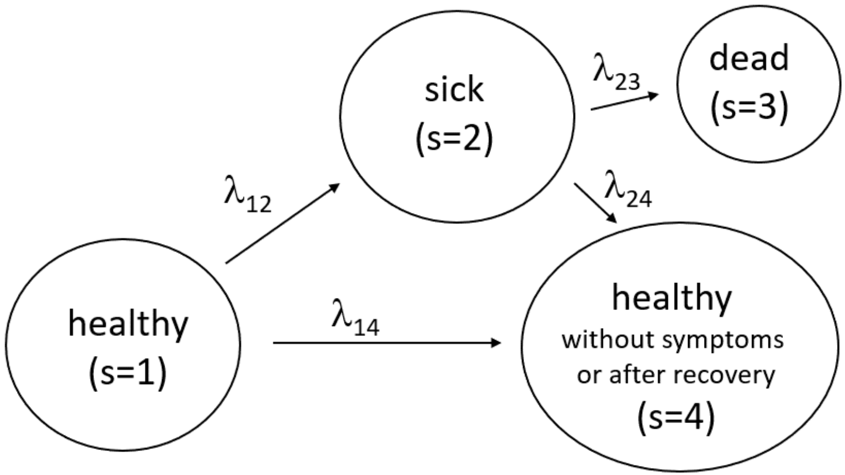


Figure 12 *Transitions between the state of health (initial state), sickness, death and health despite infection or after recovery*

- Model structure [not in this lecture] nicht relevant bis einschließlich 7.44
  - Transition rates are key to dynamics of epidemic
  - From healthy to sick

$$\lambda_{12}(t) = aN_1(t)^{-\alpha}(N_2(t) + \eta N_4(t))^{\beta}[\bar{\rho} - \rho(t)]^{\gamma}, \tag{7.1}$$

    where $0 < \alpha, \beta, \gamma < 1$ allows for some non-linearity in the process, $a > 0$, a share ρ of society is sick (state 2) or healthy after infection (state 4), while long-run infection rate is denoted by $\bar{\rho}$.
  - From healthy to healthy without symptoms or recovered:

$$\lambda_{14} = \frac{1-r}{r}\lambda_{12}, \tag{7.2}$$

    where the share r of individuals that show symptoms after infection gives the flow into sickness.
  - From sick to healthy without symptoms or recovered:

$$\lambda_{24} = 1/n_{\text{rec}}, \tag{7.3}$$

    where n_{rec} is the average number of days until recovery once sick.
  - From sick to dead: constant death rate λ_{23}

- Calibration
  - We have data on the one hand (see e.g. figure 11 above)
  - We have numerical solutions of a SIR model on the other hand (see e.g. figure 6 above)
  - How do we reconcile the two?
    * We want to make sure that quantified theoretical model explains observed empirical data well
    * This is a prerequisite for trusting the prediction which results from this model
    * We choose (numerically) appropriate parameter values such that this holds
    * This works via calibration or (structural) estimation
    * (Both approaches minimize some measure of distance between model values and data. Estimation approach also delivers distributional properties of estimators)

- Main output of a SIR-type model
  - The number of new individuals who become sick ($N_2^{\text{new}}(t)$) as well as
  - The number of individuals who were ever sick ($N_2^{\text{ever}}(t)$)
  - Outcome of calibration approach is illustrated in figures on slides to come
  - Central question: how does the epidemic end?
    * Will the number $lim_{t \to \infty} N_2^{ever}(t)$ change as a function of infection dynamics?
    * Will the limit be independent of the epidemic? (Yes in this model)

- Calibration under the magnifier

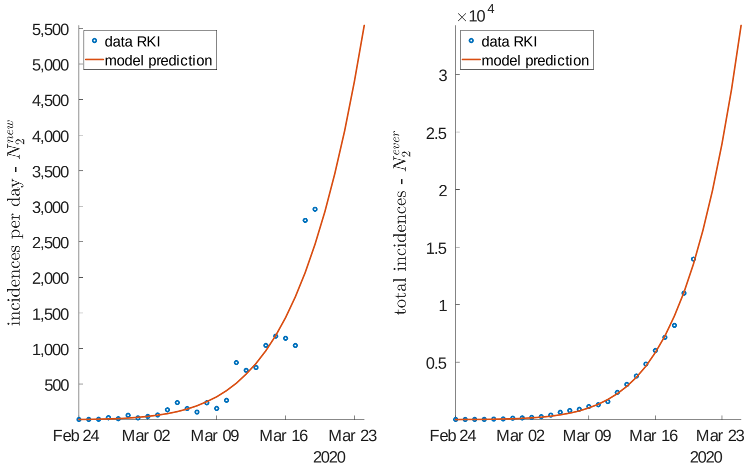


Figure 13 *New incidences (reported) in the model (curve) and in the data (dots) (left) and the number of sick individuals (ever) in the model and data (right)*

• Calibration outcome with implied prediction

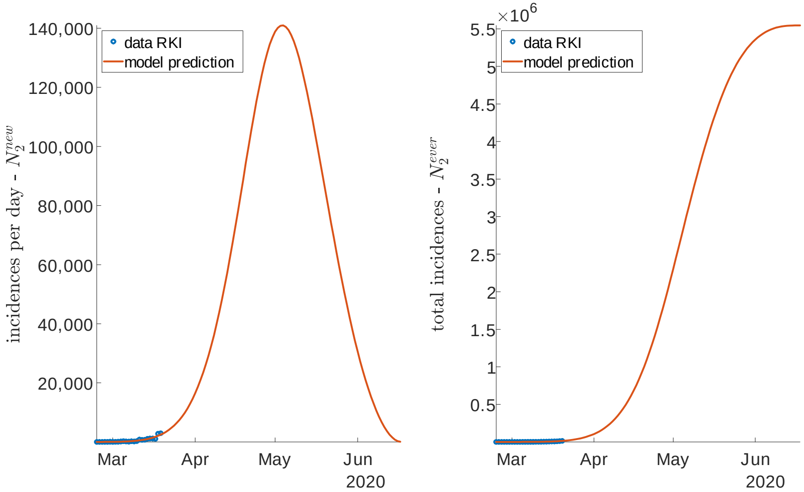


Figure 14 *New incidences (reported) in the model (curve) and in the data (dots) (left) and the number of sick individuals (ever) in the model and data (right) for the epidemic without public health measures (data as of 21 March 2020)*

- Predicting the effects of shutdowns

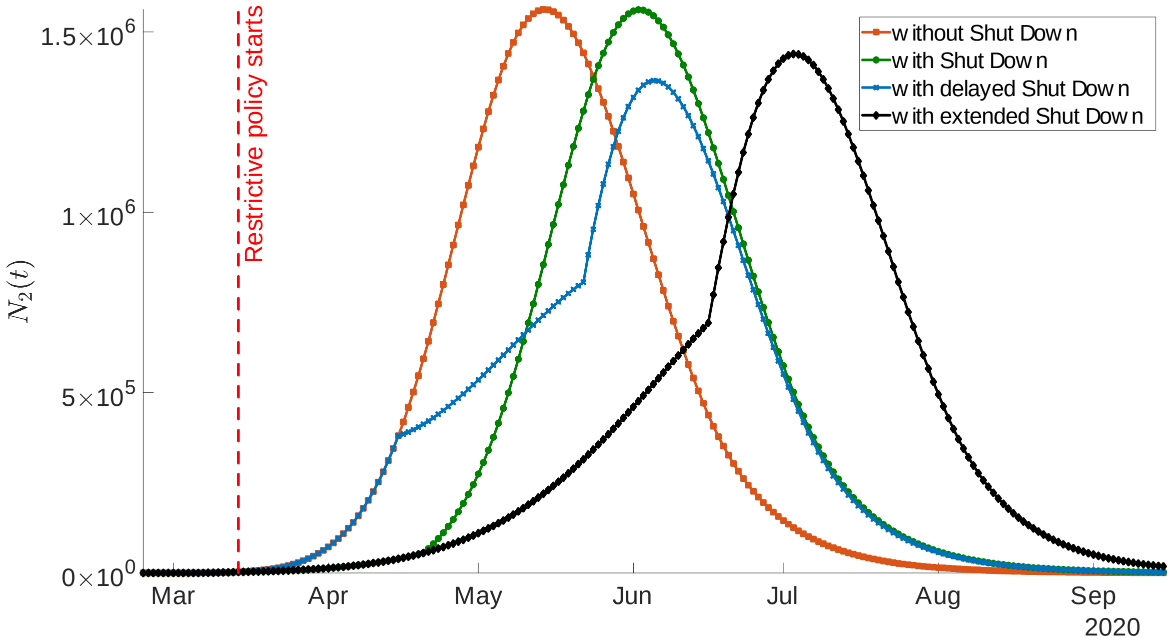


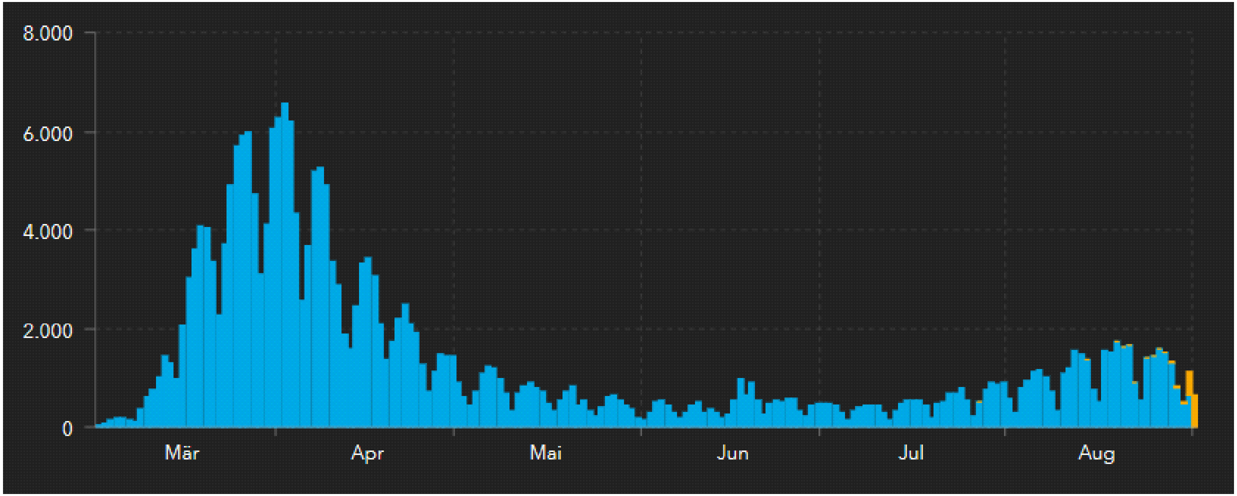
Figure 15 *The effect of a shut down under various scenarios*

- Model predictions
  - No shut-down (red curve) leads to a fast increase of the number of infections
    - Absolute number of simultaneously sick individuals $N_2(t)$ would reach a peak at a level that depends on various crucial parameter assumptions
    - Independently of these assumptions (see Donsimoni et al., 2020, for detailed discussion), health system (intensive care in hospitals) would have soon been overloaded
    - Epidemic would have ended with herd-immunity (and probably a breakdown of public order)
    - no optimal option

- A (temporary) shut-down (green curve)
  * The number of infected rises less quickly
  * Once the shut-down is over, increase is almost at the same speed as before
  * The peak is hardly lower
- A delayed shut-down (blue curve)
  * Theoretically a good idea
  * Reduces peak as more individuals are infected initially
- A temporary shut-down only delays infections
  * Due to properties of this (relatively standard) SIR model
  * Herd immunity implies that $lim_{t\rightarrow\infty}N_2^{ever}(t)$ is independent of time path of infections

7.4.3 Updating the projection (gesamter Abschnitt 7.4.3 nicht relevant)

- Once the first wave was over and PHM were being relaxed, various questions arose
  - How will the epidemic continue?
  - Should we relax PHM faster or should authorities be more careful?
  - Updating of projection took place mid April



- Purely statistical approach
  - Almost entirely observation-based forecast for Covid-19 in Germany
  - Assumption that PHM do not change
  - Fitting a Gompertz-curve model (i.e. double exponential model)
  - See Donsimoni et al. (2020b) for the paper and Gompertz curves (in German)

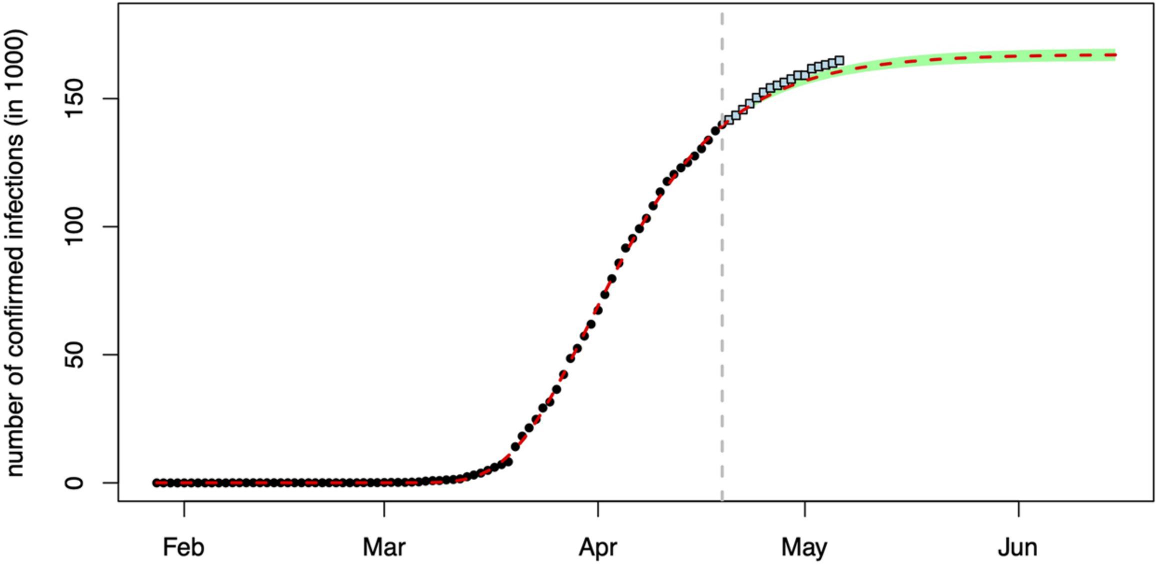


Figure 16 *Predicting the number of reported infections under the regime in place before 20 April (Donsimoni, Glawion, Plachter, Wälde, and Weiser, 2020)*

- Estimates were fed into SIR model from above (data up to 20 April 2020)

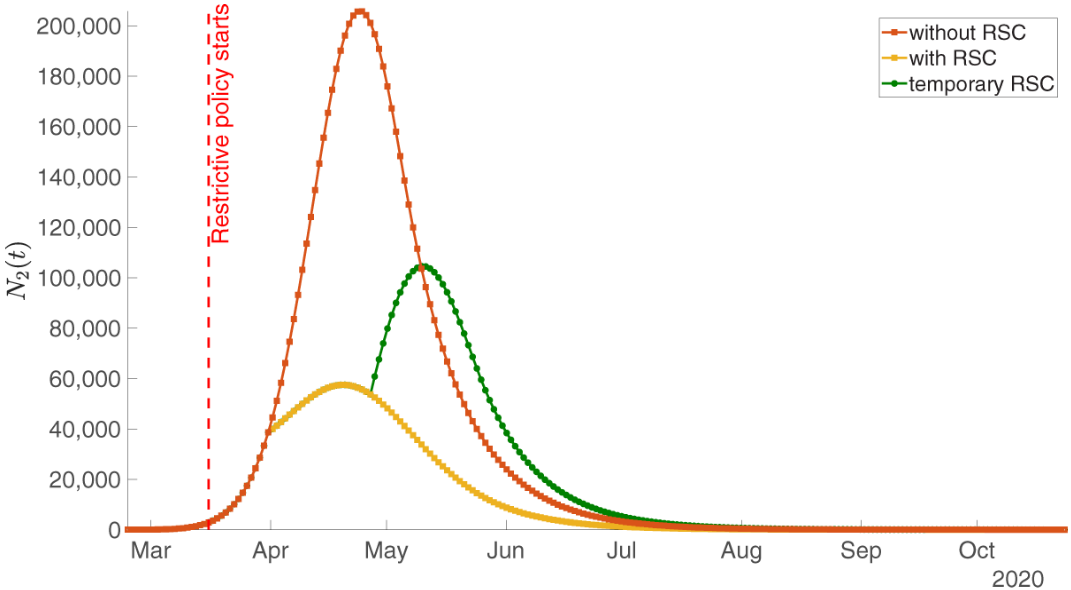


Figure 17 *The epidemic without restrictions of social contacts (RSC, red curve), the effect of permanent RSC (yellow) and the effect of a temporary RSC (green) as measured by prevalence* $N_2(t)$

- The red curve in the left panel illustrates, in a situation without RSC, the number of incidences would continue to increase and so would the risk to get infected
- The yellow curve shows that incidences are now falling and so does the risk to get infected
  - If measures had been upheld permanently, the peak of Covid-19-prevalence $N_2(t)$ would have been reached end of April
- Due to the delay between infection and reporting, we assume that the effects of a lift are visible as of 27 April. We therefore plot a green curve that starts on 27 April when RSCs are lifted on 20 April

7.4.4 The mask study

- The role of face masks and their effects on the spread of Covid-19 has been a central issue for debate in many countries

- One way to test for their effectiveness is to model their effects on the number of infectious individuals

- For a brief overview (in German), see Ökonomenstimme.org, for the paper and article,(PNAS), see Mitze et al. (2020a,b)

- What we would expect from face masks
  - SIR model: face masks reduce infection rate (think of a lower a in (7.1))
  - Effects are visible due to the incubation and reporting delay (see section 7.3.3)

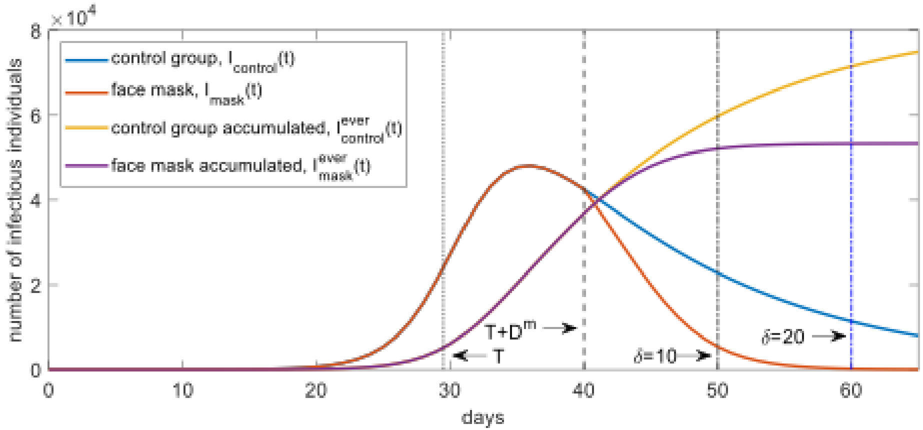


Figure 18 *Theoretical effects of face masks on the number of infectious individuals $I(t)$ and on the accumulated number of infectious individuals $I^{ever}(t)$*

- Empirical strategy
  - Synthetic control method (SCM)
  - SCM can help quantify the effectiveness of public health measures when these are implemented exogenously (without input from the public) to multiple regions
  - The identification approach exploits regional variation in the point in time when measures enter into force
  - Data from multiple regions is then used to estimate the effect of this particular policy intervention on the development of registered infections with Covid-19
  - Compare the Covid-19 development in various regions to their synthetic counterparts, constructed as weighted average of control regions that are structurally similar to treated regions
    - Structural dimensions considered include prior Covid-19 cases, the demographic composition and the local health care system.

- Application to face masks
  - In Jena masks were made mandatory on 6 April but effects became visible within 3-4 days (faster than expected)
  - Announcement effect may have played a role
  - Robustness checks in other regions

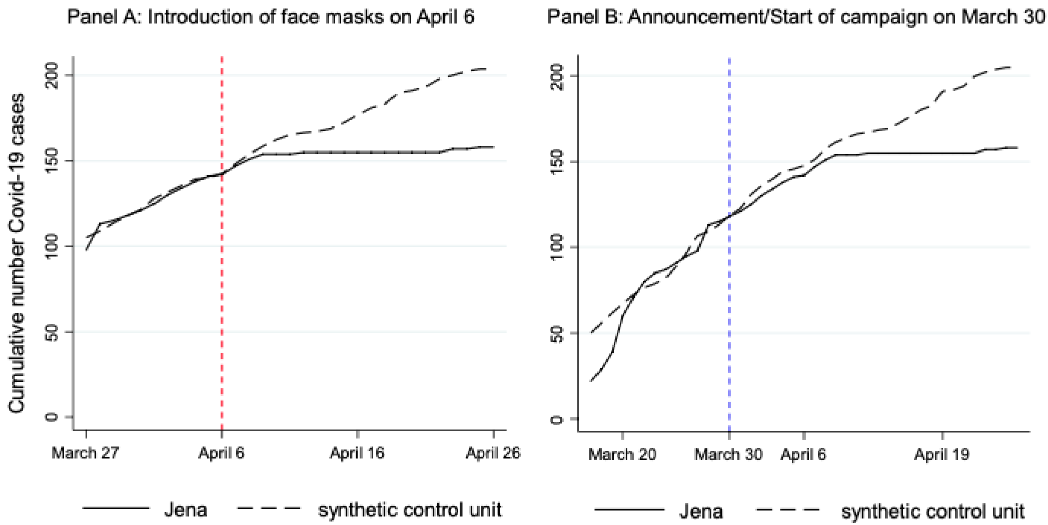


Figure 19 *Treatment effects of face masks in Jena over time*

- Summary of findings (in words)
  - Depending on the region, face masks reduced the number of newly registered SARS-CoV-2 infections between 15% and 75% over a period of 20 days after their mandatory introduction
  - Assessing the credibility of the various estimates
    - face masks reduce the daily growth rate of reported infections by around 47%
    - 20 days after becoming mandatory, face masks have reduced the number of new infections by around 45%
  - As economic costs are close to zero compared to other public health measures, masks seem to be a cost-effective means to combat Covid-19

- Summary of findings (in percentages, see section D.2 of Mitze et al., 2020)

Difference between treated region(s) and synthetic control group(s)	Jena	multiple treatment s (all)	multiple treatments (cities)
Absolute change in cumulative number of Covid-19 cases over 20 days	-46,9	-7,0	-28,4
Percentage change in cumulative number of Covid-19 cases over 20 days	-22,9%	-2,6%	-8,9%
Percentage change in newly registered Covid-19 cases over 20 days	-75,6%	-15,7%	-51,2%
Difference in daily growth rates of Covid-19 cases in percentage points	-1,28%	-0,13%	-0,46%
Reduction in daily growth rates of Covid-19 cases (in percent)	70,6%	14,0%	47,3%

7.5 Covid-19 and the economy

7.5.1 Macroeconomic literature

- Covid-19 offers rare example of shock to both demand and supply
  - Demand for goods has decreased (e.g. restaurants and concerts, as individuals try to avoid large gatherings)
  - Supply has also decreased as supply chains got disrupted around the world
- Shock also impacted labour market

  (better: short-time work)
  - Sudden increase in unemployment as firms laid off workers
  - Reduction in vacancy openings as firms are unsure of future demand

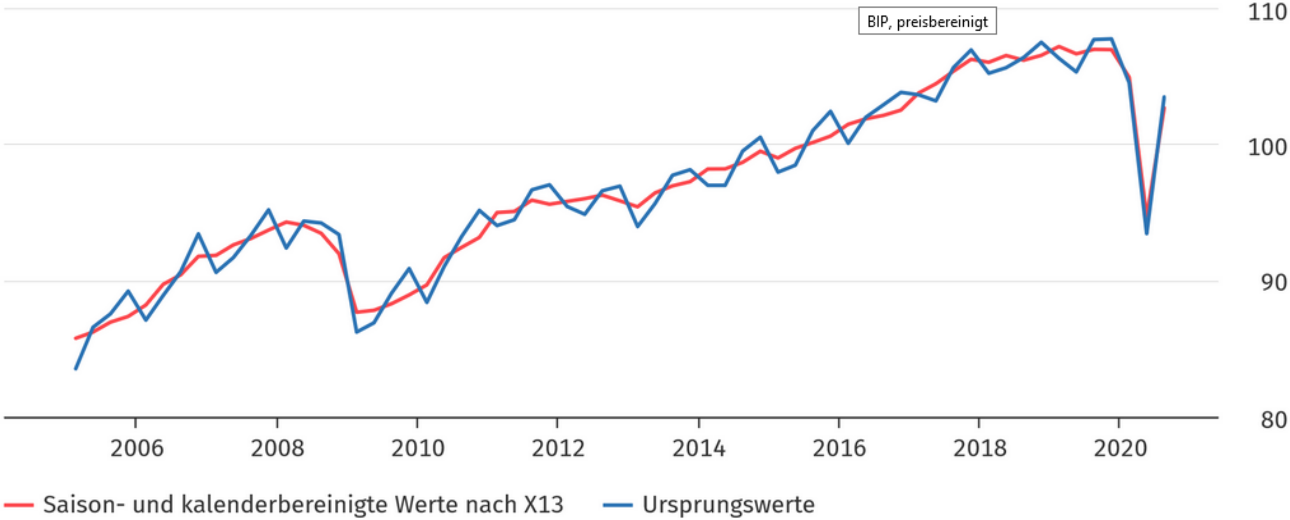


Figure 20 *Index of GDP in Germany, quarterly data from Statistisches Bundesamt*

- Focus on business cycles
  - What is the impact of PHM ~~testing~~ on the economy?
  - What are the channels through which Covid-19 affects consumption and labour supply?
  - Can policies mitigate looming economic depression?
- Various macroeconomic papers looked at Covid-19 effects on economy
- Following slide provide a first overview on
  - macroeconomics of the pandemic
  - effects of policy on disease spread and business cycle

- Brotherhood et al. (2020) Seiten 7.65 bis 7.6.8 nur informativ
  - partial equilibrium with consumption-leisure choices + augmented SIR model
  - individuals can consume, work, work at home, enjoy leisure outside, or leisure at home
  - spending time outside (for work or leisure) increases infection risk and transmission rate
  - consumers can be either healthy, symptomatic (common cold or CoV-2), infected with CoV-2 (revealed upon testing), recovered, or dead
  - testing reveals whether it is CoV-2, leading to (targeted) quarantine
  - age differences matter for targeting and create heterogeneity in risk-taking
    * the young take more risk as they are more resistant
    * creating more risks for the old but also speeding up time to herd immunity
  - aggregate output: summing total labour income across health states and individuals

- Acemoglu et al. (2020)
  - multi-group age-based SIR model
  - focuses on targeted lockdown measures
  - quantifies effects on GDP, (excess) mortality rate in the absence of vaccine/cure, and infection across groups
  - economic loss is measured from each group: susceptible, infected, recovered, and dead
- Eichenbaum, Rebelo, and Trabandt (2020a)
  - general equilibrium with consumption-leisure choice + classical SIR framework
  - individuals optimally choose consumption and hours worked
  - and can be either susceptible, infected, recovered, or dead
  - infected individuals have lower labour productivity than susceptible and recovered individuals
  - consuming and working less reduce infection risk
  - government taxes consumption and redistributes via lump-sum transfers

- Eichenbaum, Rebelo, and Trabandt (2020b)
  - general equilibrium with consumption-leisure choice + classical SIR framework + testing
  - testing leads to lower infection rates, lower death rates, and a reduction in the size of output drop
  - infected individuals do not work and finance consumption via transfers from the government levied from taxing non-infected
- Eichenbaum, Rebelo, and Trabandt (2020c)
  - general equilibrium with New Keynesian framework + classical SIR framework
  - due to sticky prices, recession is larger than in Neoclassical framework
  - inflation rate is reduced compared to the steady-state in an epidemic

  → as consumption drops in an epidemic, firms face lower demand
  - optimal choice of prices is then lowered as firms maximise profits in the face of low demand

- Fernández-Villaverde and Jones (2020)
  - SIR(D) framework with social distancing
  - individuals can be susceptible, infected/infectious, resolving (i.e. infected but no longer infectious), dead, or recovered
  - social distancing captures how infectious a contact with a susceptible individual is (for the latter)
  - simulating the model, the authors forecast disease spread and time to herd immunity
- Krueger, Uhlig, and Xie (2020):
  - follow Eichenbaum, Rebelo, Trabandt (2020a)
  - introduce different likelihoods of contagion across consumption sectors in addition to general infection via social interactions
  - with heterogeneity in infection across sectors, consumption shifts to the low infection sector (e.g. shopping in a supermarket vs. online)
  - effect mitigates drop in aggregate consumption

- General framework can be constructed to encompass major results
  - individuals maximise lifetime utility in consumption, hours worked (in office or at home), and leisure (outside or at home)
  - consumers can be in one of four states: susceptible, infected (whether infectious or not), recovered, or dead
  - testing works as a revealing mechanism to determine who is infected and refine targeting of containment policies
  - discovery of a vaccine/cure eliminates (or at least severely reduces) future infection rates (assuming widespread availability and adoption)
  - epidemic has multiple effects on the economy:
    * being infected can reduce productivity, thus reducing output the higher the share of the population with the disease
    * working from home or isolating can reduce transmission and infection rates but also lower utility and labour income
    * consumption can shift to low-risk sectors reducing negative impact on aggregate consumption and output
    * inflation can slow down as firms choose lower prices in a low-demand environment

7.5.2 How to think about economic impacts

- Why does GDP fall?
  - The effect of individual decisions
  - The effect of public health measures

- The effect of individual decisions
  - productivity falls when infected (Eichenbaum et al., 2020a and Acemoglu et al., 2020)
  - isolation for infected or susceptible groups and slow return to work for the recovered (Acemoglu et al., 2020 and Eichenbaum et al., 2020b)
  - working from home is less productive (Brotherhood et al., 2020, Acemoglu et al., 2020)
  - aggregate demand falls as individuals seek to reduce risk of exposure to virus, reducing output in general equilibrium (Krueger et al., 2020)
  - lower total labour from deaths (none of those models consider births as they do not matter over period of 5 years)
  - Eichenbaum et al. (2020b) consider extensive margin of labour supply
    * infected individuals are removed from the labour force
    * finance consumption via lump sum transfers from the government
    * Government obtains income from consumption tax

- The effect of public health measures
  - general lockdowns (for everyone): Eichenbaum et al. (2020a), Krueger et al. (2020)
  - targeted lockdowns/quarantines (when infected): Acemoglu et al. (2020), Brotherhood et al. (2020), Eichenbaum et al. (2020a, 2020b),
  - testing: Acemoglu et al. (2020), Eichenbaum et al. (2020b), Brotherhood et al. (2020)
  - work from home: Brotherhood et al. (2020), Acemoglu et al. (2020)
  - social distancing: Brotherhood et al. (2020), Fernández-Villaverde and Jones (2020)
  - vaccine/cure: Brotherhood et al. (2020), Eichenbaum et al. (2020a), Acemoglu et al. (2020)

* Overall message
    * individual channels well understood from a theoretical perspective
    * lot of work left to quantify individual channels

7.6 Summary: where do we stand?

- We understand how to predict evolution of pandemic over time
  - Pandemic would have been over after few months without intervention
  - Public health system would have collapsed
- We understand the effects of some public health measures
  - Face mask effects well understood
  - Other PHM also studied
  - Statistical challenges remain

- The role of the political system
  - politics could help much more (randomization of PHM)
  - unaware of regional and national scientific advisory board that
    - coordinate scientific discussion
    - employ scientific insights for policy discussions
- Where are we heading to?
  - Hoping for vaccines
  - How long will is last until sufficiently large share of population is vaccinated?
  - PHM forever?
- The effects on the economy
  - conceptional issues are only being started to be understood
  - obvious huge (temporary?) effects
    - 14 percentage points from 4th quarter 2019 to 2nd quarter 2020
    - 5 percentages points from 4th quarter 2019 to 3rd quarter 2020

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