Measuring the impact of the German public shutdown on the spread of Covid-19

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We investigate the impact of the German public shutdown from 13 March 2020 on the spread of Covid-19. In a simple model, we search for a trend break in cumulated confirmed Covid-19 cases as reported by the Johns Hopkins University (2020). We identify a trend break on 20 March that is in line with the expected lagged impact of the German policies and which reduces the growth rate by 48.2%. While the growth rate has almost halved, the number of cases is still doubling every 5.35 days.

1. Introduction

There is no need to stress the importance of the coronavirus disease (Covid-19) for public health, economic consequences and the wellbeing of individuals. Yet, there is a need for more careful analysis of what we actually know. Knowledge is probably needed most urgently from an epidemiological perspective, but just as important is the need to know what the effects of public health measures are on the spread of Covid-19.

This paper aims to understand the effects of the decision of German authorities on 13 March 2020 to shut down schools and stop major sports events, which was closely followed by further decisions regarding restaurants, shops and others. Given a median incubation of 5.2 days (Lauer et al., 2020; Linton et al., 2020)

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and a certain delay between feeling symptoms, contacting a doctor, and the case being reported (say, 2-3 days), we would expect the consequences of these decisions and the resulting measures to be visible as of 20 or 21 March 2020. If the policy measures impact the spread of Covid- 19, as we expect, the growth rate of the number of reported sick individuals should display a drop around 20 or 21 March. In fact, this is what we investigate.

We employ data from the Johns Hopkins University (2020). While official data for Germany that evolve similarly can also be obtained from the Robert Koch Institute (2020), we prefer the former source as it links data from the Robert Koch Institute, the World Health Organization, and the European Centre for Disease Prevention and Control. Furthermore, official statistics from the Robert Koch Institute are downward biased on weekends, as some local administrations only report their case numbers on workdays. The data then enter the official statistics on Monday and Tuesday, yielding an upward bias of the statistics on new infections. We find that the data from the Johns Hopkins University (2020) are more robust to these biases.

In a simple model, we search for a trend break in the cumulated confirmed Covid-19 cases by means of maximum likelihood. We find that a trend break around 20 March fits the data best and is highly significant. Our main finding is that confirmed Covid-19 cases in Germany grew at a daily rate of 26.7% until 19 March. From March 20 onwards, the growth rate drops by half to 13.8%, which is in line with the lagged impact of the policies implemented by the German administration on 13 March and implies a doubling of confirmed cases every 5.35 days. Before 20 March, cases doubled every 2.93 days.

The structure of the paper is as follows. In Section 2 we describe the data on confirmed cases of Covid-19 in Germany obtained from the Johns Hopkins University (2020). Next, a model is set up to estimate average growth of log confirmed cases and test for a trend break in Section 3. We present estimation results and show that the implemented polices are likely to have affected the spread of Covid-19. Section 4 concludes.

2. The data

To address these questions, we study the development of the number of confirmed cases of Covid-19 in Germany. Due to the high testing capacities of Germany compared to other industrialised countries – while acknowledging the natural uncertainty regarding unperceived cases – we consider German data on the number of confirmed cases of the novel coronavirus as a more reliable source of the actual number of people infected. For several other industrialised countries – such as Italy, where the measured mortality rate is clearly higher – the number of people who are unaware they are infected can be expected to be substantial, and the reported number of confirmed cases thus a less reliable source for the overall spread of Covid-19 compared to the German data.

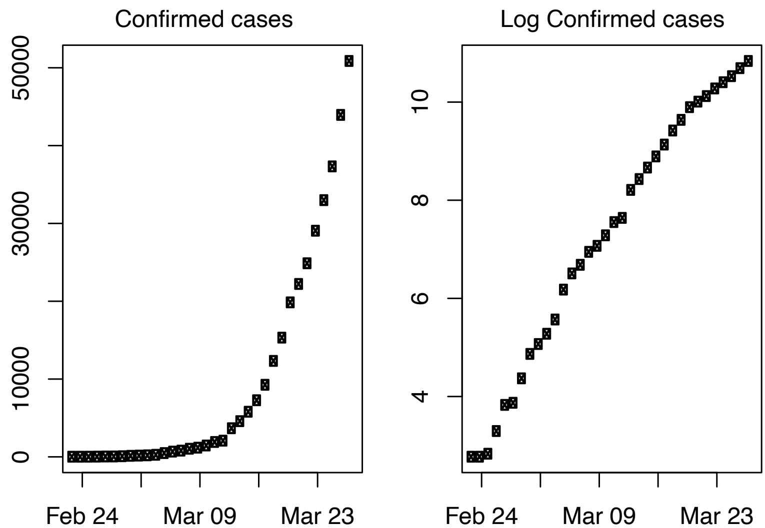

Figure 1 Number of confirmed cases with the new corona virus.

Notes: The left plot shows the data in levels, the right plot takes logs.

Source: Data obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 1 plots the dynamics of the spread of Covid-19 in Germany in levels and logs from 23 February to 27 March. As the figure shows, the number of confirmed cases grew exponentially, such that taking logs yields a time series with a linear trend. The figure suggests that a linear time trend may capture the dynamics of log confirmed cases well, although there are small outliers at the beginning of the sample (where variation was relatively small and case numbers are low) and around 10 March (when an outbreak of Covid-19 among ski tourists from Austria increased the case numbers).

In light of the rapid growth of confirmed cases, the German administration implemented several measures to contain the spread of Covid-19, including closing schools, cancelling mass events, and the shuting down universities from 14 March onwards. Several additional measures have since been implemented to reduce public contact, including the closure of public spaces, churches, mosques and synagogues, restaurants, shops, hairdressers, theatres and libraries. In addition, public awareness of Covid-19 was likely affected by the increased media coverage.

These policies cannot be expected to immediately slow down the spread of Covid-19, since there is a time lag between infection with the virus and the case entering the statistics of approximately seven to eight days. The incubation period of the coronavirus is estimated to be five days (Lauer et al.; 2020; Linton et al.; 2020), and it may take another 1-2 days to get tested. Finally, 1-2 days are required until the case is reported. Thus, we can expect to see any impact of the implemented policies and of changed individual behaviour in the case numbers from 20 March onwards.

In fact, visual inspection of log confirmed cases in Figure 1 shows a slowdown of the spread of Covid-19 from 20 March onwards. However, distinguishing between unsystematic random impacts and a systematic reduction of the growth rate requires a proper statistical analysis of the Covid-19 data.

3. Testing for a trend break

In order to investigate the impact of the aforementioned policies, we search for a trend break in the spread of Covid-19. For this purpose, we specify a simple linear trend model for log confirmed cases that is given by

$$y_t = \mu_0 + \mu_1 \mathbb{1}(t \geq t^*) + \gamma_0 t + \gamma_1 \mathbb{1}(t \geq t^{**})(t - t^{**} + 1) + u_t, \qquad t = 1, ..., n, \tag{1}$$

where μ_0 is a constant, μ_1 allows for a level shift, γ_0 measures the linear growth rate, γ_1 allows for a trend break and $\mathbb{1}(t \geq s)$ is an indicator function that becomes one for $t \geq s$, else zero. The residuals u_t are assumed to be normally distributed white noise $u_t \sim \text{NID}(0,\sigma_u^2)$. Since log confirmed cases increase quite linearly in t, as Figure 1 shows, we expect specification (1) to capture the dynamics well. More sophisticated models may be required for a proper understanding of the drivers of log confirmed cases, such as weather and seasonal effects. But since such effects are currently unlikely to correlate with a linear trend, we expect the estimates of (1) to hardly be affected. Furthermore, the time series on confirmed cases is relatively short, hindering a more sophisticated modelling of the data. Lags of the endogenous variable turned out to be irrelevant.

As a first approach to measuring the growth of log confirmed cases, we fit a linear trend to the data via ordinary least squares, thereby setting $\gamma_1 = 0$. Since visual inspection of Figure 1 shows a level shift on 29 February, we include a shift dummy by allowing for $\mu_1 \neq 0$ from that date onwards. For the simple model without trend break, we estimate the intercepts $\hat{\mu}_0 = 2.387$ (0.100), $\hat{\mu}_1 = 0.761$ (0.143), together with a trend parameter $\hat{\gamma}_0 = 0.240$ (0.006), where standard errors are denoted in parentheses and all parameters are significant at a 1%

level. The residual standard error is estimated to be $\hat{\sigma}_u = 0.239$. Our results show a mean growth rate of 24.0%, implying a doubling of confirmed cases every 3.22 days on average.

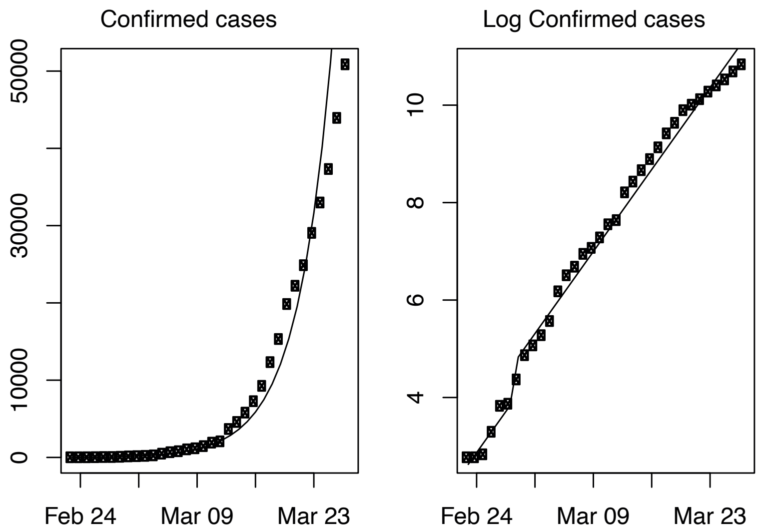

Figure 2 Fitted values for model (1) without trend break

Notes: The dots show the number of (log) confirmed cases; the solid line shows estimated confirmed cases. The data was obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 2 plots the fitted values from (1) with $\mu_1 = 0$. As the figure shows, a specification without trend break catches the dynamics of confirmed cases well at the beginning and the middle of the sample. On the right of the time series, the linear trend overestimates the spread of Covid-19, which may indicate a trend break.

Hence, our estimation results together with the Covid-19 data suggest that growth has slowed down at the end of March. To take this into account, we include a trend break – i.e., we set $\gamma_1 \neq 0$. Since the date of the trend break is unknown, we search for a t^{**} thatmaximises the likelihood of (1), which is identical to a minimisation of the residual sum of squares (Bai, 1997; Bai and Perron, 1998). Hence, we estimate (1) for $t^{**} = 2, 3, ..., n$ sequentially and choose the specification t^{**} that maximises the likelihood.

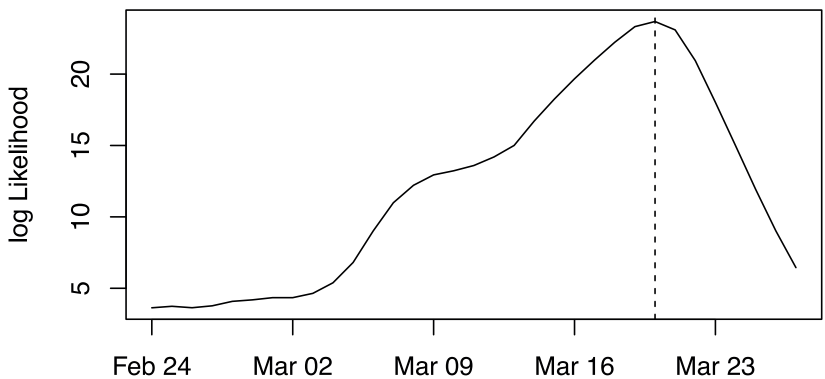

Figure 3 Sequential trend break search

Note: The figure plots the likelihood values corresponding to a trend break at t^{**}.

Figure 3 plots the estimated likelihood against t^{**}. As the figure shows, a trend break on 20 March yields the highest likelihood and therefore minimises the residual sum of squares. The likelihood is steep around 19–21 March, suggesting only a little uncertainty about the actual period where the trend break occurred. While breaks on 19–21 March yield a similar fit, all other possible trend break points perform substantially worse. Uncertainty regarding the exact break point within the small window between 19 March and 21 March remains, which is likely to reflect the gradually increasing impact of the different policy measures that start to kick in at this period of time. We add a trend break on 20 March to our model, but choosing 19 or 21 March would not lead to any relevant differences.

Estimation results with $\gamma_1 \neq 0$ and a trend break on 20 March 20 as follows. For the intercepts, we estimate $\hat{\mu}_0 = 2.325$ (0.052) and $\hat{\mu}_1 = 0.460$ (0.086). The slope estimates are $\hat{\gamma}_0 = 0.267$ (0.005) and $\hat{\gamma}_1 = -0.128$ (0.016). All parameters are significant at a 1% level,[4] and $\hat{\sigma} = 0.128$. We do not find evidence for a violation of the normality assumption of the residuals from the Jarque-Bera test, which yields a p-value of 0.994. The slope estimates can be interpreted as follows. From 23 February to 19 March we estimate a daily growth of 26.7%, indicating a doubling of confirmed cases every 2.93 days. From 20 March onwards, the daily growth reduces to 13.8%, which implies a doubling of confirmed cases each 5.35 days. Hence, we find that the growth of confirmed cases slowed considerably (by 48.2%) from 20 March onwards.

4 Note that the trend break search induces additional uncertainty to our model, since test statistics are calculated under the hypothesis that the model is correctly specified, while in reality the true date of the trend break is uncertain. But since the t-statistic for $\hat{\gamma}_1$ is 8.219, simulation-based critical values that account for the model selection uncertainty would not change our test results.

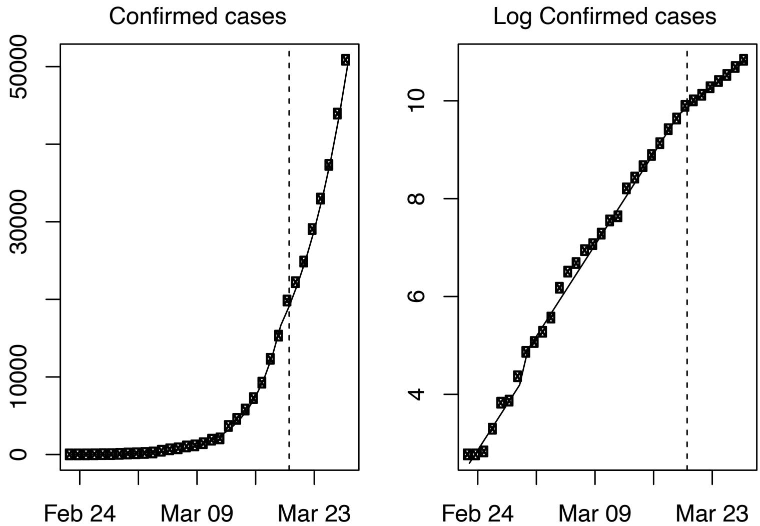

Figure 4 Fitted values for model (1) with trend break on 20 March

Notes: The dots show the number of (log) confirmed cases, while the solid line sketches estimated confirmed cases. The dashed line indicates the trend break.

Source: Data obtained from the Johns Hopkins Coronavirus Resource Center.

Figure 4 plots the fitted values of (1) with $\mu_1 \neq 0$ allowed and a trend break on 20 March. It shows that a specification with trend break captures the development of confirmed cases well, in particular at the end of the time series. A trend break on 20 March is clearly visible and captures the slowdown in the growth of confirmed cases.

4. Conclusion

Our analysis confirms a pronounced slowdown in the growth of confirmed Covid-19 infections in Germany around 20 March. While the growth rate has almost halved, the number of cases is still doubling every 5.35 days. Due to substantial delays between new infections and their measurement in statistics, we could see further effects from the German lockdown measures in the next few days. We will follow the development of growth rates closely, as they are central to both public health and to the economy. Our findings will also be employed by Donsimoni et al. (2020) for future projections of the Covid-19 epidemic in Germany.

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