NBS Working paper
2/2022

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This publication is available on the NBS website
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ISSN 2585-9269 (online)

COVID-19 epidemic in Slovakia through the lens of a parsimonious behavioral SIR model*

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August 8, 2022

Abstract

This paper presents a parsimonious behavioral SIR model with compartments for hospitalized and vaccinated shares of population, contagion among vaccinated and loss of immunity. A model variant with vaccination, the transmission rate endogenously responding to the share of hospitalized patients, seasonal variation and pandemic fatigue matches the epidemic evolution from July 2020 to February 2022 in Slovakia remarkably well. We find that vaccination, despite being among the slowest in the EU, reduced the death toll in Slovakia by up to 18,500 deaths. Assuming the pace of EU countries with the highest vaccination rates lowers the cumulative deaths by another 8,000.

Keywords: COVID-19; epidemiological model; forecasting; SIR model

JEL-Codes: C0, I0

*I would like to thank Branislav Albert, Martin Feješ, Miroslav Gavura, Milan Gylánik, Michal Horváth, Martin Šuster, seminar participants at the National Bank of Slovakia (NBS) as well as the referees, Martin Smatana and Srečko Zimic, for many valuable comments and suggestions. All mistakes and errors remain my own. The views presented here are my own and do not represent the opinions of the National Bank of Slovakia.

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1. INTRODUCTION

A quantitative exploration of pandemic evolution, be it for purposes of forecasting or policy analysis, has been an important undertaking during the COVID-19 pandemic. To this end, economists widely adopted the SIR class of epidemiological models (Avery, Bossert, Clark, Ellison, and Ellison (2020); SIR for susceptible-infectious-recovered) and argued for incorporating the endogenous response of agents to pandemic dynamics (e.g. Cochrane (2020) and Eichenbaum, Rebelo, and Trabandt (2021)).

In this vein, Atkeson (2021) provides a reduced-form behavior SIR model which, when calibrated to the UK and US, can reproduce the epidemic evolution reasonably well. The crucial model features are the behavioral aspect of the endogenous transmission responding to the daily death rate, the exogenous seasonality in the transmission rate and the pandemic fatigue shock modelled as a one-time reduction in the semi-elasticity of the transmission rate to the daily death rate.

To provide a quantitative assessment of the epidemic evolution in Slovakia we expand Atkeson (2021) by introducing vaccination and contagion among the vaccinated. For the sake of forecasting, loss of immunity is introduced as well. We provide evidence in favor of the argument in Atkeson (2021) that seasonality and pandemic fatigue are important aspects for matching empirical evolution of the COVID-19 pandemic by calibrating the model to Slovakia. However, we show that only a model variant which involves an important role for vaccination is able to explain the past epidemic evolution.

The case of Slovakia might be informative for other countries for several reasons. First, Slovakia was one of the first countries to apply the policy of testing the whole population, accompanied by a strict lockdown to contain the outbreak. We show that in the case of Slovakia, this measure proved to be highly effective, even though only temporarily, as it was followed by easing containment measures and conducted only as a one-time policy. Second, the vaccination rate in Slovakia, as of March 2022, was the third lowest in the EU and the model results confirm the clear benefits of a higher share of the vaccinated. Third, as documented by survey data in Slovakia, non-compliance with containment measures negatively impacted the pandemic evolution which provides empirical evidence in favor of pandemic fatigue.

The Slovak COVID-19 pandemic experience from the outbreak till February 2022 can be briefly summarized as follows. The first wave in spring 2020, given a strict countrywide lockdown, essentially did not materialize and Slovakia belonged to the EU countries least impacted by the pandemic in terms of cases and deaths. This changed, however, during the second wave from October 2020 to April 2021, during which the Slovak death rate due to COVID-19 belonged among the highest in the world. The third wave, driven by the emergence of the delta variant, hit Slovakia hard and in December 2021 Slovakia was worldwide one of the countries with the highest number of positive PCR cases relative to population. The outbreak of the omicron variant affected Slovakia later than in other European countries, with omicron becoming the dominant variant by the end of January 2022. The rise in cases in February 2022 outpaced all the previous variants, confirming the high contagion of omicron in other countries.

The motivation for providing a quantitative pandemic model for Slovakia is threefold. First, to contribute to the identification of triggers and drivers of the Slovak pandemic evolution from July 2020 to February 2022. Second, to conduct counter-factual analysis of different containment measures. And third, to use the model for forecasting purposes.[1]

We show that a model variant with vaccination, the transmission rate endogenously responding to the share of hospitalized patients, seasonal variation and pandemic fatigue, modelled as a reduction in the sensitivity of the transmission rate to the number of hospitalizations, matches the epidemic evolution from July 2020 to February 2022 in Slovakia remarkably well.

The model features the emergence of the alpha variant which amplified the second wave in winter 2020/2021, the delta variant which caused the third wave in autumn 2021 and the omicron variant causing the last wave in winter 2021/2022. However, our results suggest that it is the combination of new virus variants and pandemic fatigue which explains and matches the empirical pandemic evolution in Slovakia well. Atkeson (2021) argues that without pandemic fatigue his model cannot replicate the epidemic evolution in the US and UK. However, he does not find strong empirical support for the timing of the shock as the window of time in which pandemic fatigue should kick in does not coincide with empirical evidence of higher mobility measured by cell phone activity.

In Slovakia, there is empirical evidence for pandemic fatigue. The pandemic fatigue shock affects the degree to which the transmission rate changes with the epidemic evolution, i.e. the number of deaths or hospitalizations. Notably, this parsimonious way of modelling the behavioral dimension captures both the voluntary and the forced activity reduction. Forced reduction can be interpreted as the introduction of mandatory containment measures by gov-

[1]A simple sketch of the model and its usage for forecasting the short-term private consumption of households was provided in the Autumn 2021 forecast of the National Bank of Slovakia (NBS). An update of the forecast was presented in the Winter 2021 forecast of the NBS. Source: https://www.nbs.sk/en/publications-issued-by-the-nbs/economic-and-monetary-developments/2021.

ernment whereas voluntary reduction refers to individual social distancing. We show that Slovakia lifting the mandatory pandemic measures in December 2020, as measured by the stringency index, paved the way for the alpha variant to spread and thus amplified the magnitude of the second wave. Furthermore, survey data suggests that it was the disobedience of measures by people at the onset of the delta wave which significantly contributed to the worsening of the third pandemic wave.

The model results confirm the benefits of vaccination, which has proved to be very effective in saving lives (Barro, 2022). Despite being among the slowest in the EU, vaccination reduced the death toll in Slovakia by up to 18.500 deaths. Yet model simulations suggest that a hypothetical pace of vaccination given by the average of the five EU countries with the highest vaccination rates could have lowered the cumulative number of deaths by another 8.000.

Another important outcome of the quantitative exploration of the Slovak epidemic is the evidence in favor of a combination of mass testing and lockdown being an effective containment policy reducing epidemic outbreaks (Johanna, Citrawijaya, and Wangge, 2020). However, its timing and frequency is crucial.

The remainder is structured as follows. Section 2 introduces the model and its calibration. Section 3 presents the main results. Section 4 discusses the results of the counter-factual analysis of different vaccination rates, the impact of mass testing and the contribution of pandemic fatigue during the delta wave. Section 6 concludes.

2. Model description

Time is discrete. The population is in each period t divided into six groups: (1) the susceptible people of mass S_t who when exposed to the virus may contract the disease but are not infected at the moment, (2) the infected people of mass I_t, (3) the hospitalized people of mass H_t, (4) the recovered people of mass R_t, (5) the vaccinated of mass V_t and (6) the dead of mass D_t.

The dynamics of the model evolve as in a standard SIR epidemiological model:

$$1 = S_t + I_t + H_t + R_t + V_t + D_t, \tag{1}$$

where equation (1) describes the population composition.

In each period t, the overall mass of infectious people, I_t, is given by a sum of infected people with different virus variants and with different vaccination status. This holds true also for the overall share of hospitalized, H_t, and the overall fraction of population infected denoted K_t, which can be written as

$$I_t = \sum_a \sum_b I^b_{a,t}, \tag{2}$$

$$H_t = \sum_a \sum_b H^b_{a,t}, \tag{3}$$

$$K_t = \sum_a \sum_b K^b_{a,t}, \tag{4}$$

where $a \in \{init, A, D, O\}$ and $b \in \{u, v\}$. The upper indices u and v refer to the unvaccinated and the vaccinated status respectively. The lower indices $init$, A, D and O refer to the initial, alpha, delta and omicron strains of the COVID-19 virus.

The transmission rate in period t is unique to each of the variants and denoted correspondingly by $\beta^u_{init,t}$, $\beta^u_{A,t}$, $\beta^u_{D,t}$ and $\beta^u_{O,t}$ for the unvaccinated and β^v_t, $\beta^v_{A,t}$, $\beta^v_{D,t}$ and $\beta^v_{O,t}$ for the vaccinated. Note that the transmission rates can vary over time due to seasonality or pandemic fatigue shocks.

The daily infected evolve according to

$$K^u_{a,t} = \beta^u_{a,t} S_t I_{a,t}, \tag{5}$$

$$K^v_{a,t} = \beta^v_{a,t} V_t I_{a,t}, \tag{6}$$

where $a \in \{init, A, D, O\}$. The mass of susceptible, S_t, evolves in the following manner

$$S_{t+1} = S_t - K^u_t - \omega_t \frac{S_t}{(S_t + V^{no3rd}_t)} S_t + \Delta R_{t-\tau^R} + (1 - \omega^{3rd}) \Delta V_{t-\tau^V}, \tag{7}$$

where ω_t is a timely variable vaccination rate following an exogenously given process, $K^u_t = \sum_a K^u_{a,t}$ with $a \in \{init, A, D, O\}$, τ^R denotes the number of days of active protection after contracting the disease, τ^V after vaccination and Δ denotes the first difference. V^{no3rd}_t represents the share of population being vaccinated but not refreshing their vaccination protection with a booster. The fraction of infected people follows the flow process

$$I^b_{a,t+1} = I^b_{a,t} + K^b_{a,t} - \left(\gamma^I_t + \lambda^b_{a,t}\right) I^b_{a,t}, \tag{8}$$

where $a \in \{init, A, D, O\}$, $b \in \{u, v\}$, γ^I_t and $\lambda^b_{a,t}$ denote the recovery and the hospitalization rates of infectious people respectively. These parameters can vary over time, which we discuss in detail in the calibration section 2.2.

A certain share of infected will be hospitalized every period. The overall share of hospitalized, H_t, is given by the sum of vaccinated, H^v_t, and unvaccinated,

H_t^u, hospitalized. Their evolution reads

$$H^b_{a,t} = H^b_{a,t-1} + \lambda^b_{a,t} I^b_{a,t} - (\gamma^H_t + \delta^b_{a,t}) H^b_{a,t-1}, \tag{9}$$

in which $a \in \{init, A, D, O\}$, $b \in \{u, v\}$, γ^H_t and $\delta^b_{a,t}$ denote the recovery and the death rates of hospitalized people respectively. The parameter for the death rate differs between the vaccinated and the unvaccinated. Both parameters can vary over time.

The daily shares of admissions to hospitals, A_t, and discharges from hospitals, Dis_t, are given by

$$A_{t+1} = \sum_a \sum_b \lambda^b_{a,t} I^b_{a,t}, \tag{10}$$

$$Dis_{t+1} = \sum_a \sum_b (\delta^b_{a,t} + \gamma^H_t) H^b_{a,t} \tag{11}$$

with $a \in \{init, A, D, O\}$, $b \in \{u, v\}$.[2]

The share of recovered is given by equation (12) and the fraction of vaccinated population by equation (13):

$$R_{t+1} = R_t + \gamma^I_t I_t + \gamma^H_t H_t - \omega_t R_t - \Delta R_{t-\tau^R}, \tag{12}$$

$$V_{t+1} = V_t + \omega_t \frac{S_t}{(S_t + V_t^{no3rd})} S_t + \omega_t R_t - K^v_t - (1 - \omega^{3rd}) \Delta V_{t-\tau^V}, \tag{13}$$

where $K^v_t = \sum_a K^v_{a,t}$ with $a \in \{init, A, D, O\}$. The recovered as well as the vaccinated are assumed to keep their immunity for τ^R and tau^V number of periods respectively. However, the group of recovered is during the immunity period considered to be fully immune against the disease whereas the group of vac-

[2]Note that discharges include deaths. This assumption is made as the micro data on discharges encompass both recoveries and deaths.

cinated is not assumed to be fully immune such that there is a non-zero probability of infection. This assumption is driven by empirical observations that vaccine immunity either wanes over time or decreases subject to new emerging virus variants.

The mass of death is given by

$$D_{t+1} = D_t + \sum_a \sum_b \delta^b_{a,t} H^b_{a,t}. \tag{14}$$

The transmission rate for unvaccinated, $\beta_{a,t}$ with $a \in \{init, A, D\}$, is given by the equation 15:

$$\beta^u_{a,t} = coef^a \bar{\beta} \exp\left(-\kappa_t \sum_{i=t-20}^{t-10} H_i + \psi_t\right). \tag{15}$$

Some words about this functional form are in order. First, the transmission rate is defined as a function of parameters $coef^a$ and $\bar{\beta}$ denoting the relative severity of the variant against the initial strain and the basic transmission number in the absence of adapting behavior and seasonality respectively. Second, it is a function of two variables κ_t and ψ_{t+1} given by

$$\psi_{t+1} = \frac{seasonalsize}{2} \cos\left[(t + seasonalposition)\frac{2\pi}{365} - 1\right]. \tag{16}$$

κ_t follows an exogenously given path and models the sensibility of agents' response to the mass of hospitalized people. Hence it implicitly represents the stringency index capturing the strictness of pandemic measures by government as well as the endogenous voluntary response of households to reduce their activities. Whether this adaptation is voluntary or forced is beyond the scope of this paper. We assume that both ways lead to an endogenous decrease in the transmission rate.

ψ_{t+1} captures the seasonality of the transmission rate and follows explicitly the set-up in Atkeson (2021). $seasonalsize$ controls the magnitude of the seasonal fluctuations in the transmission rate and $seasonalposition$ controls the location of the seasonal peak (end of December) and seasonal trough (end of June) in transmission.

Third, in equation (15), given the value κ_t, the transmission rate is assumed to endogenously react to the hospitalization rate measured by a sum of hospitalized between $t - 20$ and $t - 10$.

2.1. Data sources

The data sources are the GitHub repository of The Institute for Healthcare Analyses (IZA) of the Ministry of Health of the Slovak Republic[3] and the application programming interfaces of the National health information center (NCZI).[4] Time series for hospitalizations, cases, admissions and discharges are centered 7-days moving averages.

2.2. Calibration

The model frequency is daily and the sample period starts on July 1, 2020 and ends on February 28, 2022. The calibration strategy follows Atkeson (2021) and is based on a trial-error approach. However, we take into account as much granularity of the data as possible to have clear empirical targets and discipline the model parameters as rigorously as possible. All parameters are calibrated with the goal of matching two main time series: the number of hospitalizations

[3]https://github.com/Institut-Zdravotnych-Analyz
[4]https://data.korona.gov.sk/

and the cumulative deaths. Two important notes are in order.

First, there are two sources of the number of hospitalizations in Slovakia. The first one is the number of hospitalized patients with COVID-19 reported by hospitals at the end of each day. The second source is the number of admissions and discharges which are collected via a central reporting system by the hospitals at every admission or discharge. As can be seen from Figure 1 however, there is a discrepancy between the two sources. The aggregate number of hospitalizations reported by hospitals, red dashed line, was the main indicator of the hospital utilization published publicly and therefore this series is our main empirical target. However, in order to better calibrate the values for the hospitalization, recovery and death rates, we use the underlying data paths of admissions and discharges to discipline the parameters. Data discharges consist of both discharges due to recovery and death therefore the discharges path is used to calibrate both the death rate and the recovery rate from the H status.

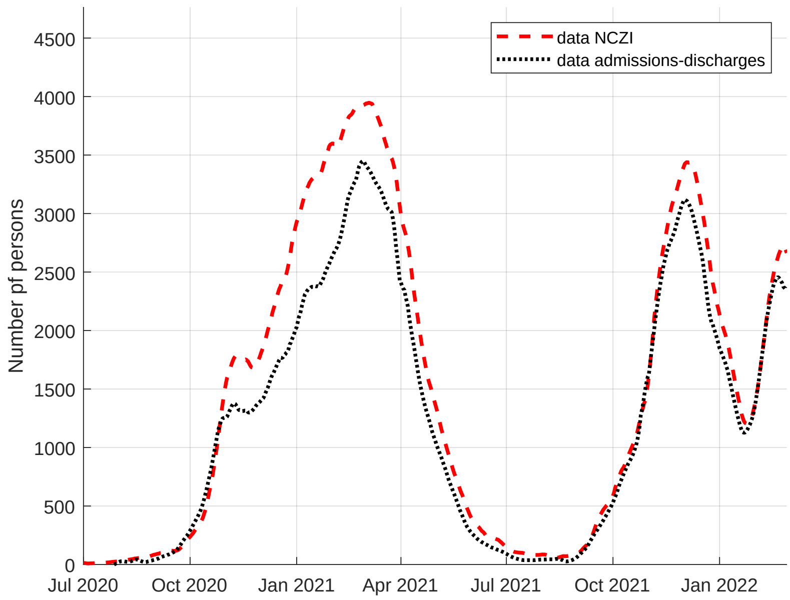


Figure 1: Differences between data sources of hospitalized patients with confirmed COVID-19

Second, the mutating nature of the virus implies that its transmission, disease severity and the course of the sickness change over time. Therefore the model parameters such as the rates of transmission, hospitalization, recovery or death eventually change as well. Since model simulations without changing parameters would not reflect the differences among virus variants and do not coincide with the realized pandemic evolution, the parameter values, in particular for the rates of hospitalization, death and recovery from hospitalization, become recalibrated over time.

Table 1 lists all used parameter values. The relation between hospitalization and death rates of vaccinated versus unvaccinated is calibrated using the evidence in Washington State Department of Health (2021).

Parameter	Description	Value
γ_t^I	recovery rate, $t <$ June 30, 2021	0.2
	recovery rate, $t \geq$ June 30, 2021	0.3
$\delta_{a,t}^u + \gamma_t^H$	rate of discharges for unvaccinated, $a \in \{init, A, D\}$, $t <$ June 30, 2021	0.093
	$t \geq$ June 30, 2021	0.125
$\delta_{O,t}^u$	omicron death rate for unvaccinated	0.015
$\delta_{a,t}^v$	death rate for vaccinated, $a \in \{init, A, D, O\}$	$\delta_{a,t}^u/13$
$coef^{init}$	transmission factor initial strain	1
$coef^A$	transmission factor A strain	1.6
$coef^D$	transmission factor D strain	2.25
$coef^O$	transmission factor O strain	3.72
$\lambda_{a,t}^u$	hospitalization rate, $a \in \{init, A, D\}$, $t <$ June 30, 2021	0.021
	hospitalization rate, $t \geq$ June 30, 2021	0.015
$\lambda_{O,t}^u$	omicron hospitalization rate	0.005
$\lambda_{a,t}^v$	hospitalization rate vaccinated, $a \in \{init, A, D, O\}$	$\lambda_{a,t}^u/3$
ω_t	vaccination rate, $t <$ January 1, 2021	0
	January 1, 2021 $\leq t <$ July 30, 2021	0.0026
	July 30, 2021 $\leq t <$ November 23, 2021	0.0026/3
	November 23, 2021 $\leq t \leq$ December 31, 2021	0.0026/2
	$t \leq$ January 1, 2022	0.0026/3
τ^R	days for loss of immunity after recovery	4000[5]
τ^V	days for loss of immunity after vaccination	$\tau^V = \tau^R$

Table 1: Baseline parametrization

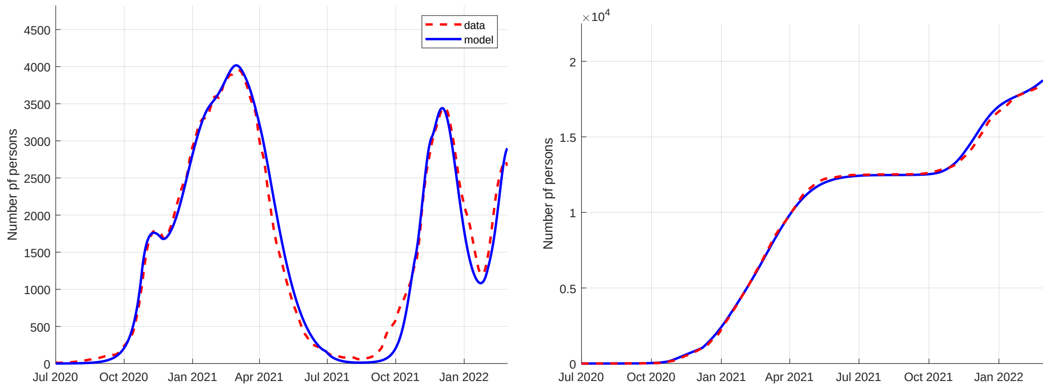
[5]This number is chosen such that loss of immunity does not play a role in the baseline model.

3. MAIN RESULTS

3.1. BASELINE

In this section we present the results for the baseline model variant featuring endogenous response of the transmission rate to the hospitalization rate, seasonality, vaccination and pandemic fatigue and tell a quantitative story of the Slovak COVID-19 pandemic.

As can be seen from Figure 2, the model can explain the empirical evolution of the COVID-19 epidemic in Slovakia remarkably well.

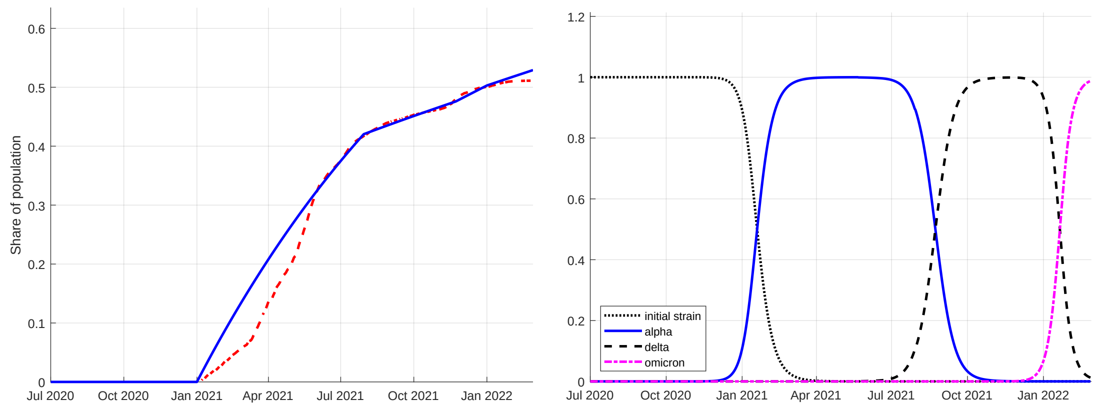


Hospitalized | Cumulative deaths

Figure 2: Empirical match of the model with (1) endogenous transmission, (2) seasonality, (3) vaccination and (4) pandemic fatigue shocks

In particular, panel A in Figure 2 shows the match of the hospitalized path, panel B the cumulative deaths. The first panel in Figure 3 depicts the share of vaccinated population with at least one dose and the second one the prevalence of various variants.

It is set lower in the forecasting exercise as loss of immunity is considered to affect future pandemic evolution significantly.

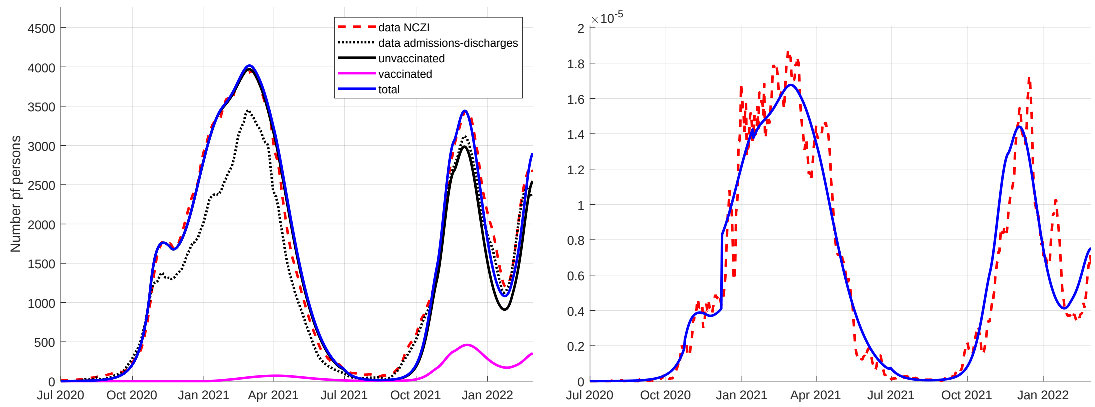


Vaccinated

Variant prevalence

Figure 3: Empirical match of the model with (1) endogenous transmission, (2) seasonality, (3) vaccination and (4) pandemic fatigue shocks

Figure 4 and Figure 5 illustrate the above-mentioned discrepancy between available time series for hospitalizations, the match of admissions, discharges and daily deaths. As discussed above, the time series for admissions and discharges are not targeted but serve to inform the calibration of epidemic parameters.



Structure of hospitalizations

Daily deaths

Figure 4: Structure of hospitalizations and daily deaths

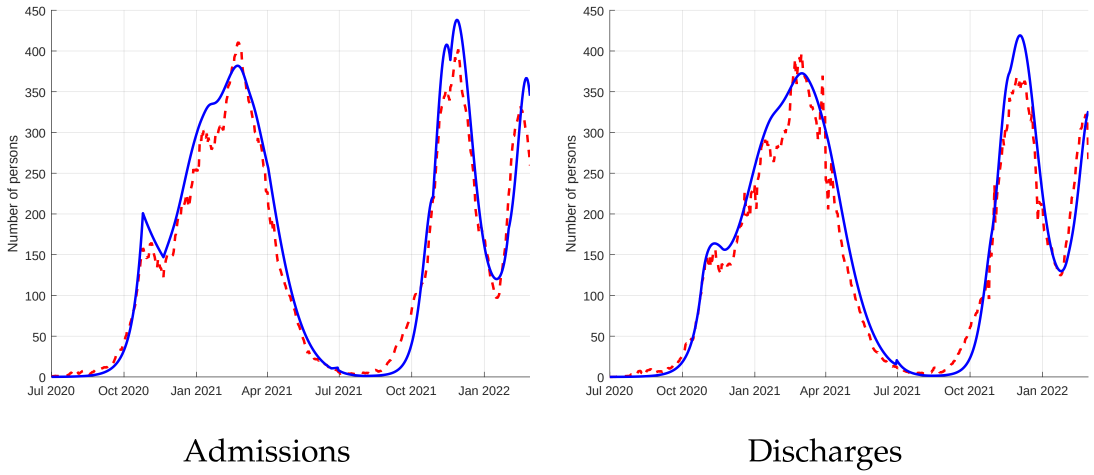


Figure 5: Disentangling hospitalizations into admissions and discharges

Story At the beginning of the sample period in autumn 2020 the pandemic evolution can be very well explained by the dynamics of a plain-vanilla SIR model without the behavioral aspect and therefore only seasonality but not the pandemic-related endogeneity in the transmission rate applies. Between October 24, and November 18, the transmission rate is exogenously reduced by 31 percentage points to model the containment measure of combining mass testing with a strict lockdown. In Section 4.3 we conduct robustness and counterfactual exercises to elaborate on the effectiveness of this policy. The endogeneity starts to apply from November 19, 2020.

The alpha variant starts to spread in the model from November 14, 2020. The pandemic wave from October 2020 to April 2021 is thus a result of two overlapping waves. The former is due to the initial strain whereas the latter is due to the alpha variant whose spread was magnified by the fatigue-related decrease in κ_t. We discuss the exogenously given path of κ_t and the pandemic fatigue shocks in detail in Section 4.2.

Between April 1, 2021 and June 20, 2021, the transmission rate is exogenously fixed at the level from the end of March, 2021. The reason is that during this time period not only a form of nationwide lockdown was imposed but it was also a requirement to be regularly tested. This resulted in a continued decrease of positive cases from spring to summer. Without this modelling assumption the model would predict a second wave with the alpha variant in April and May 2021 due to an increasing transmission rate as the number of hospitalized steadily decreased. Apparently, since this scenario did not materialize and its timing coincided exactly with the lockdown and regular mandatory testing, it can be considered to be a result of regular testing.

In late summer 2021 cases due to the delta variant started to rise causing the third wave of the pandemic in Slovakia. In the model, the delta variant starts to spread from May 5, 2021. The magnitude of the delta wave is a result of the combination of the delta emergence and pandemic fatigue whose effect is discussed in detail in Section 4.2. Following the introduction of more stringent containment measures for unvaccinated people from November 22, 2021 and the subsequent imposition of a lockdown on November 25, 2021, the number of people getting vaccinated accelerated. However, this acceleration was only of a short-term nature.

The latest wave arose due to the omicron variant which is calibrated to spread in the model from November 10, 2021. By the end of February 2022, 18,499 persons had died due to COVID-19 in Slovakia.

3.2. MODEL MECHANISMS AND DECOMPOSITION OF THE TRANSMISSION RATE

The key mechanism of the model is the endogenous reaction of the transmission rate to the pandemic evolution characterized by the cumulated number of hospitalized between periods $t-20$ and $t-10$.[6] In the following section we discuss how different components affect the transmission rate, i.e. the baseline transmission rate, differences in strains, the fatigue related shocks and seasonality.

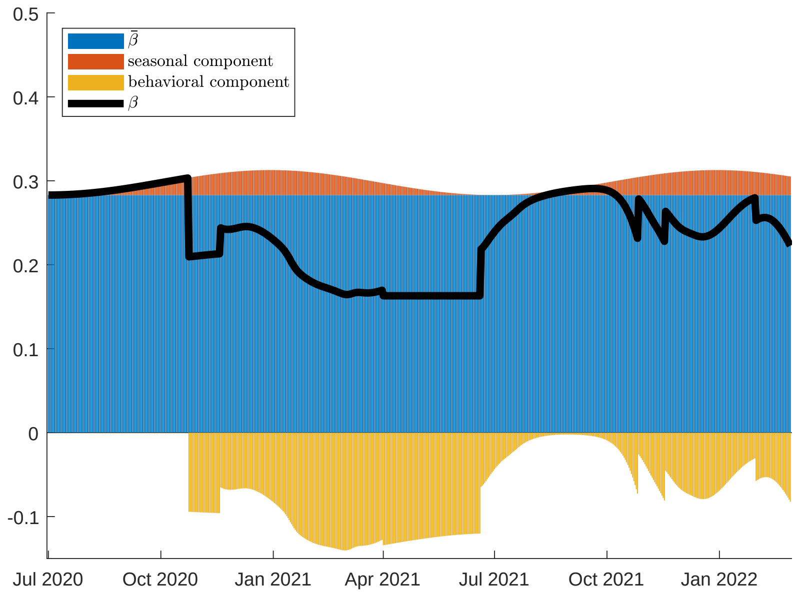


Figure 6: Decomposition of the transmission rate β_t

Figure 6 shows the building components of the transmission rate of the initial virus variant, i.e. the basic transmission number $\bar{\beta}$, from which we derive by scaling transmission rates of other virus mutations, the seasonal component and the behavioral component. The final transmission rate β_t for the initial virus strain is given by the black line. Figure 7 shows the scaling of the basic

[6]In Section D.1 we provide robustness checks for a different timing specification of the cumulative sum of hospitalized.

transmission rate for other virus strains.

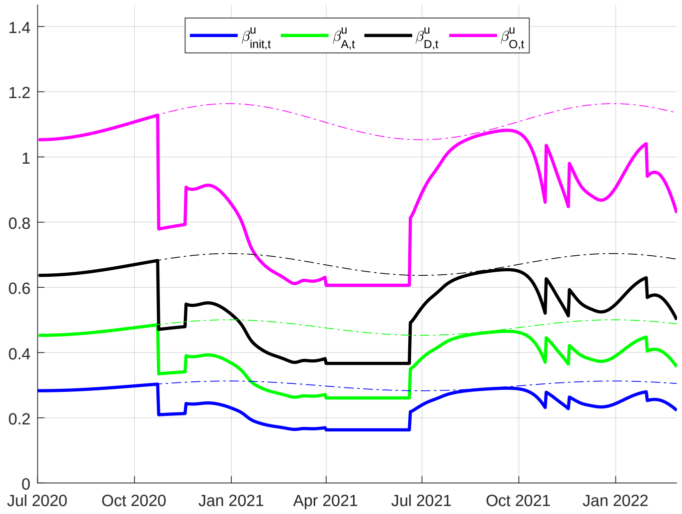


Figure 7: Transmission rates of various COVID-19 strains in Slovakia

As can be seen, the major force driving the dynamics of the transmission rate is the behavioral component describing the endogenous reaction of the society to the pandemic behavior.

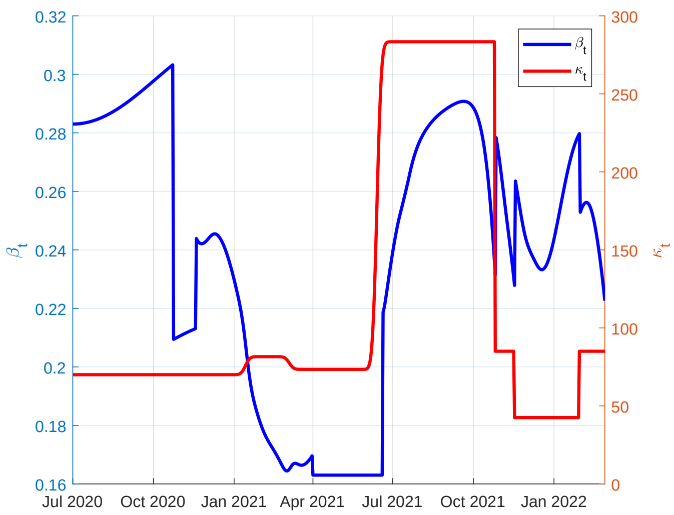
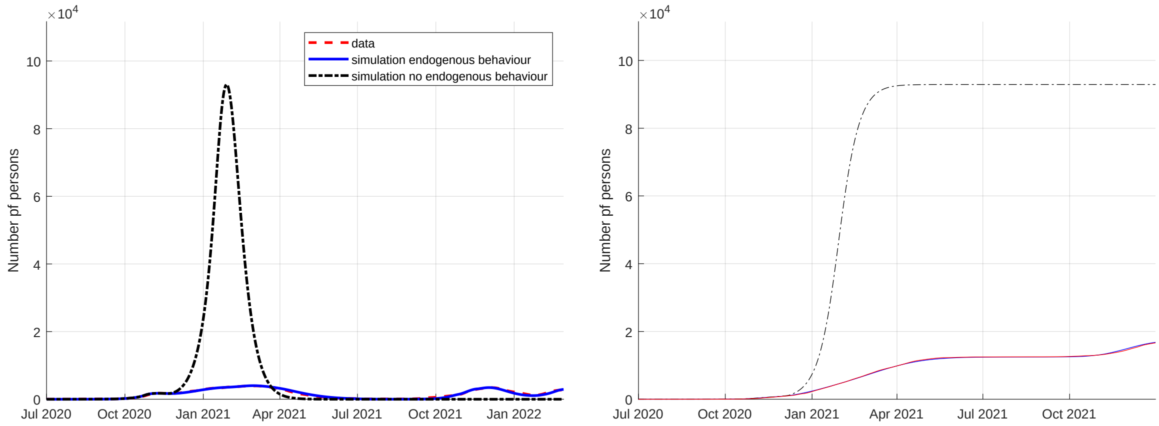


Figure 8: Endogenous component of the transmission rate and pandemic fatigue

Figure 8 illustrates the impact of fatigue shocks on the endogenous transmission rate of the initial virus variant. The fatigue shocks play the most important role in the deterioration of the delta outbreak in autumn 2021. As can be seen from the figure, the endogenous transmission rate would have been, absent the fatigue shocks, higher which could have led to a milder delta wave than observed in reality.

3.3. No endogenous transmission

Figure 9 shows the model results for the scenario without the behavioral aspect of the model, i.e. $\kappa_t = 0, \forall t$ but keeping all model aspects such as vaccination and seasonality unchanged. As we can see, without the endogeneity of the transmission rate capturing the forced as well as voluntary reduction of activities, the model would predict a much stronger wave of hospitalizations and much more deaths during the second wave. Notably, the degree of immunization would be large enough to avoid the subsequent delta and omicron waves completely under the assumption of no loss of immunity. Overall, this model variant clearly overstates the evolution of hospitalizations and deaths.



Hospitalized

Cumulative deaths

Figure 9: Baseline without the behavioral model aspect

3.4. Seasonality

Seasonality in the model might work just like a proxy for temperature. Seasonality can be considered as a proxy for weather. Figure 10 shows the relationship of the seasonality pattern and the average monthly temperature measures at the airport in Bratislava from July 1, 2020 and February 28, 2022. As can be seen, both time series shares the same cyclical behavior.

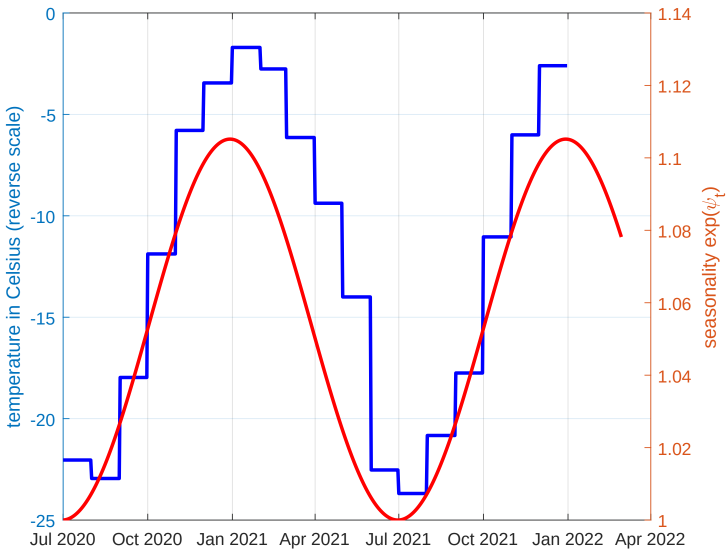


Figure 10: Seasonality as a proxy for temperature

4. Counter-factual exercises

Conducting counter-factual analysis means tackling the question of what could have happened if something different had happened in the first place. To conduct this kind of analysis for pandemic evolution in the Slovak context, we always switch off one of the channels because we would like to have counter-factual results if keeping everything else unchanged.

4.1. Vaccination strategy

What if no vaccination had been available at all or Slovakia had vaccinated at the pace of the average of the best five EU countries? The latter would mean reaching a vaccination rate with the first dose of 81.12% by the end of the year 2021, instead of only 50%. Figure 11 shows the different vaccination paths. Note that the first vaccine in Slovakia was provided on December 26, 2020.

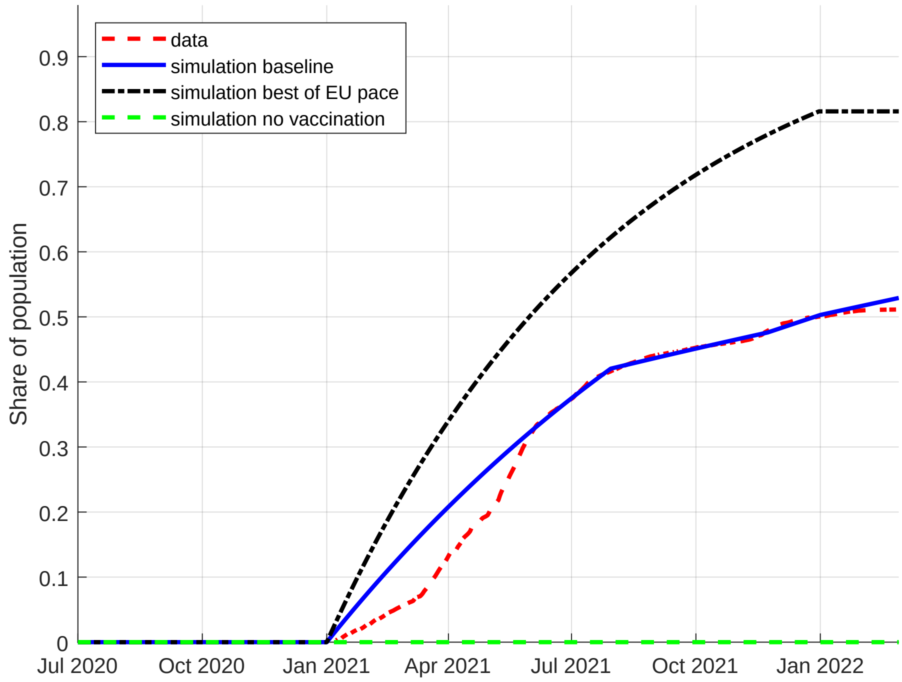


Figure 11: Vaccination paths

Figure 12 plots the counter-factual results for the number of hospitalized persons and cumulative deaths. In the scenario without any vaccination, already the second wave would have been larger and there would have been another shortly after.[7] An obvious effect is also the amplitude of the third wave due to the delta variant and the fourth wave due to the omicron variant. Admit-

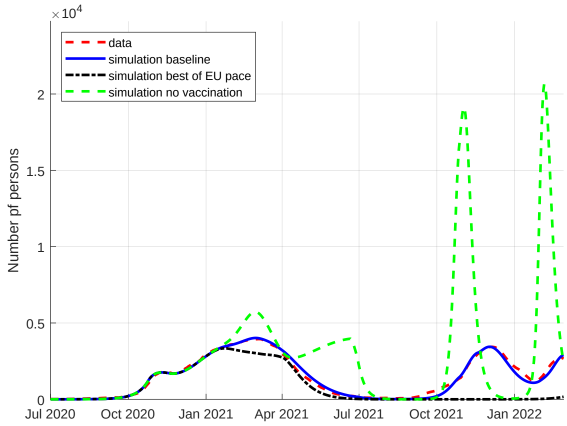
[7] Its abrupt end is caused by the assumed path of sensitivity of the transmission rate which we keep unchanged from the baseline calibration.

tedly, it is important to note that this counter-factual exercise does not assume any countrywide lockdown in addition to the ones imposed in the baseline scenario.

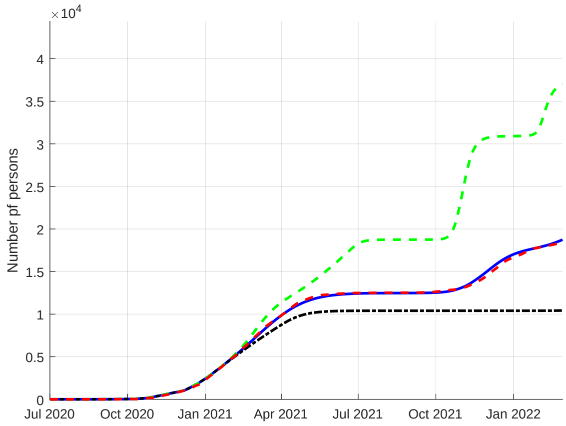
The death toll in the no vaccination scenario would have been larger by about 18,500 deaths relative to the realized path. Assuming the average pace of the five best EU countries in terms of vaccination progress (Portugal, Malta, Spain, Denmark and Italy) could have eliminated the third and the fourth wave and reduced the number of deaths by another 8,000. In other words, under the assumption of no loss of immunity and with the share of vaccinated akin to the EU countries vaccinating at the highest pace we could have almost avoided the delta and omicron wave altogether.[8] This would be in line with the empirical observations in Portugal, Malta, Spain, Denmark and Italy, where the delta wave hardly materialized and did not reach anywhere near the peaks of the waves due to previous virus variants.

However, the caveat for this analysis is the last omicron wave. As we know from Denmark, which barely imposed any measures but faced record high numbers of cases and even hospitalizations, even with very high vaccination rates the spread of the virus is not stopped. If we neglect the months of January and February in Slovakia, i.e. the omicron wave, the overall death toll would still be smaller by ca. 15,000 deaths.

[8] In terms of hospitalized.



Hospitalizations



Cumulative deaths

Figure 12: Simulation results with different vaccination paths

4.2. Pandemic fatigue

In this section we discuss in detail the role of pandemic fatigue shocks in Slovakia as introduced by Atkeson (2021). In a nutshell, a pandemic fatigue shock materializes as a decrease in the semi-elasticity of the transmission rate to the rate of hospitalized, κ_t, which results automatically in a higher number of infections. Notably, this parsimonious way of modelling the behavioral dimension captures both the voluntary and the forced activity reduction.

Figure 13 shows the time path of the semi-elasticity of the transmission rate to the hospitalization rate assumed by the baseline model.

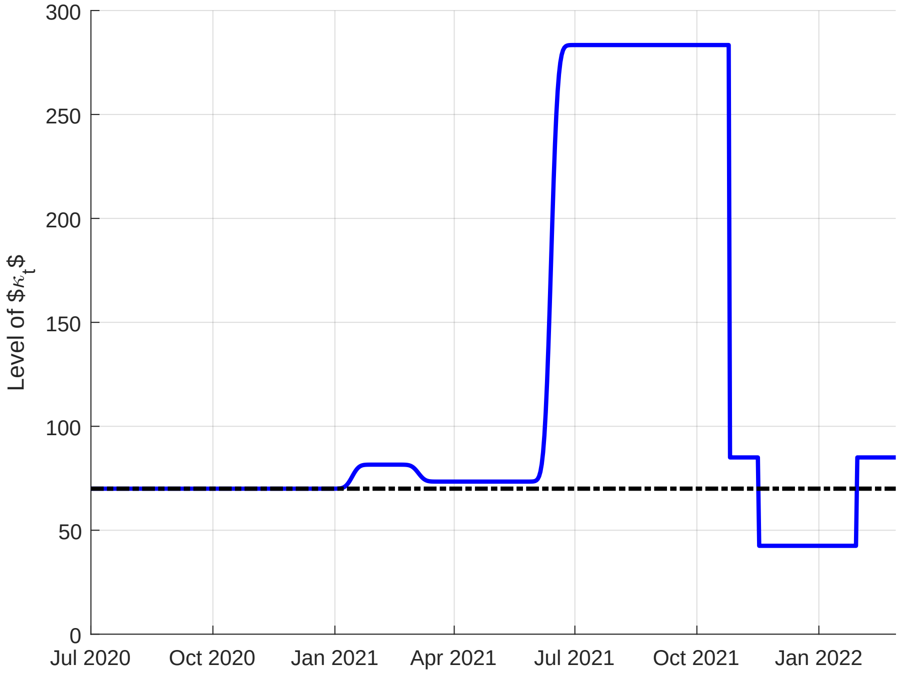


Figure 13: Imposed degrees of sensitivity to pandemic evolution over time

The basic sensibility of the transmission rate to the number of hospitalized is calibrated to 70. To match the evolution path of hospitalized, there are three increases and three decreases whereas the decreases are interpreted as pandemic fatigue shocks which are chosen to match the pandemic evolution in Slovakia. The first increase is due to imposing obligatory containment measures as captured by the stringency index followed by an unexpected decrease of the stringency index which we interpret as the first fatigue shock. In particular, we show that Slovakia lifting the mandatory pandemic measures in December 2020, after the mass testing at the beginning of November, paved the way for the alpha variant to spread and thus amplified the magnitude of the second wave.[9]

After the pandemic wave due to the initial strain and the alpha variant, in Sum-

[9] Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Cameron-Blake, Hallas, Majumdar, and Tatlow (2021) and https://ourworldindata.org/grapher/covid-stringency-index?tab=chart&country= SVK

mer 2021 the Slovak government introduced a so-called pandemic traffic light, a contingent catalogue of containment measures which were to apply regionally based on the current local epidemic situation. This is the reason for the increase of the sensitivity to a much higher level in the summer. This level is arbitrarily set to the triple of the last value.

What role does pandemic fatigue play among individuals? The results of the nationwide survey "Ako sa máte, Slovensko?" ("How are you, Slovakia?")[10] reveal that society has become over time less sensitive to the pandemic situation, as evinced by weaker compliance with pandemic measures. As the left panel of Figure 14 shows, the number of respondents who said they were not voluntarily complying with measures was higher in October 2021 than at any time since the pandemic started. This number is significantly higher among the unvaccinated (panel B in Figure 14). The effect of fatigue in non-compliance with measures, particularly among the unvaccinated, may be interpreted as one of the factors behind the higher virus transmission rate. We model it by decreasing the value of κ_t in October and November 2021.

[10] How Are You, Slovakia? survey, MNFORCE, Seesame, Institute for Sociology of the Slovak Academy of Sciences, and NBS calculations.

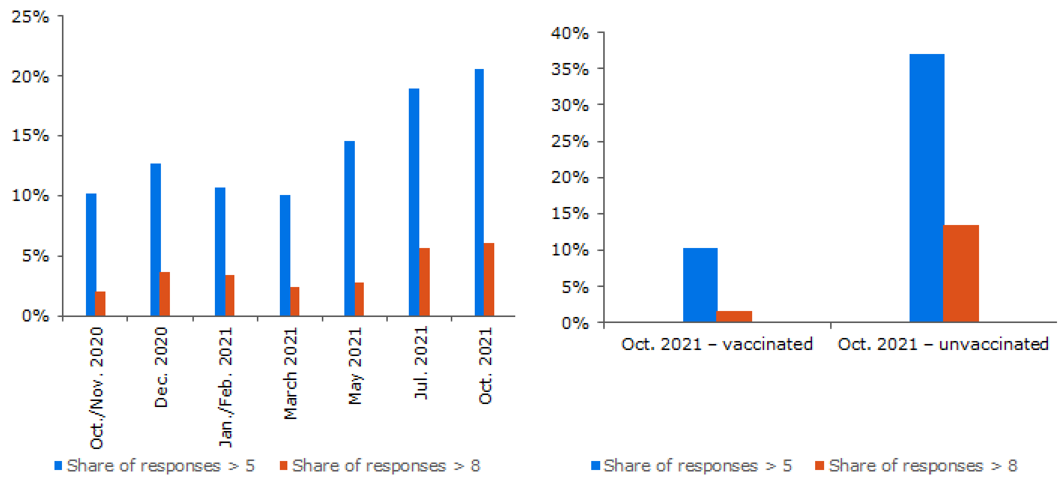
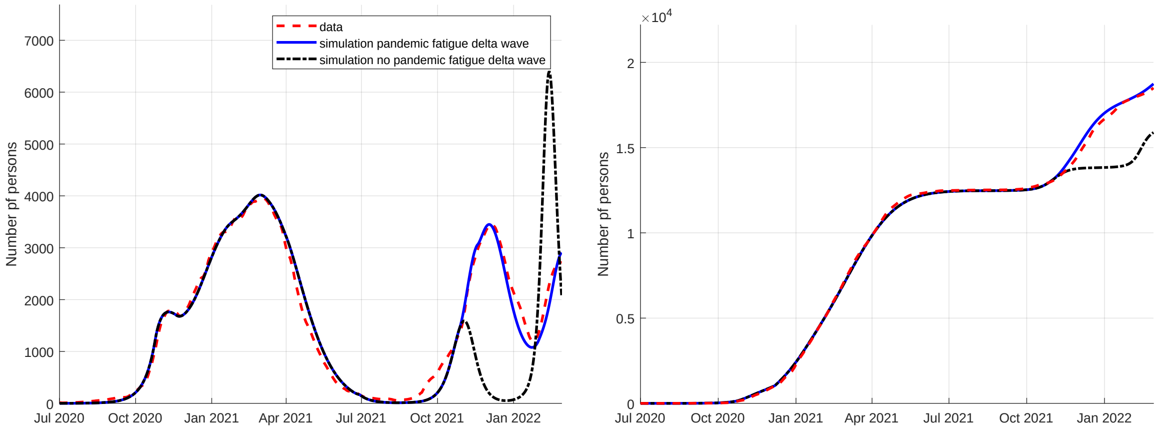


Figure 14: The How Are You, Slovakia? survey. Question: Are you complying with the current pandemic containment measures? Responses range from 1 to 10, where 1 means that the respondent is fully complying and 10 that the respondent is not complying at all.

Besides incorporating the appearance of pandemic fatigue, the path of sensitivity also takes into account a tightening of pandemic containment measures that included the imposition of a lockdown on November 25, 2021. Since the sensitivity parameter to pandemic developments includes both mandatory measures and the voluntary slackening of activities that would contain the pandemic, fatigue and lockdowns have opposing effects.

Pandemic fatigue during the delta wave As discussed above, at the beginning of the delta wave in October survey data suggests a peak in the manifestation of pandemic fatigue through a lower degree of compliance with pandemic measures among individuals. This led to a deterioration of the pandemic situation and a subsequent further increase in cases.

Figure 15 shows the results without the pandemic fatigue shocks in October and November 2021, i.e. if assuming that pandemic fatigue would not have materialized. The rapid increase in hospitalizations at the beginning of 2022 is driven by the omicron variant as we leave its outbreak in the model unchanged. The magnitude of the omicron wave is thus in this counter-factual exercise driven also by the smaller share of recovered people from the delta wave.



Hospitalizations | Cumulative deaths

Figure 15: Pandemic fatigue during the delta wave

4.3. Mass testing in October 2020

In October 2020, the second COVID-19 pandemic wave hit Slovakia. The government was one of the first in Europe to consider mass testing as a measure to contain the outbreak. This measure was highly controversial though as it was disputed whether mandatory testing is legitimate. The mass testing was preceded by a pilot testing on October 23-24, 2020, in some of the most affected regions.[11] The country-wide mass testing was conducted on October 31, 2020, and November, 1, 2020. Overall, more than 3.6 M people were tested with a

[11] In this experiment over 120.000 people were tested with a positivity rate of 3.65%.

positivity rate of 1.06%. Over the following weekend, November 7-8, 2020, the testing was repeated in regions with a positivity rate exceeding 0.69% in the first round.

One important note about modelling and evaluating the measure of mass testing is in order. In Slovakia, in October and November 2020, strict lockdown measures and mass testing were applied simultaneously. Therefore, we have two possible, yet indistinguishable, sources of the transmission reduction. Therefore, in what follows, we consider mass testing as a policy involving strict lockdown measures when referring to its efficacy.

Empirical observation suggests that the combination of mass testing and a strict lockdown efficiently stopped the outbreak, albeit only temporarily. Our simulation results show that in the period between the pilot testing and ca. two weeks after the final mass-testing round, i.e. October 24, 2020 and November 18, 2020, the transmission of the virus was reduced by 31 percentage points. Yet after this period the rise in cases after a temporarily hold continued, also due to the easing of the containment measures which was discussed above as the first pandemic fatigue shock in Slovakia, and reached the peak in February 2021.

To evaluate the measure of mass testing, it is important to identify a proper counter-factual scenario. To this end we compare the baseline results of the scenario in which endogenous transmission is in place from the very beginning, in opposition to the baseline in which endogeneity of the transmission applies only after the period of mass testing. In addition, we focus solely on a hypothetical scenario with no alpha variant emerging in winter 2020/2021 since the alpha variant emergence overlapped with an ongoing surge in cases due to the initial strain.

The results shown in Figure 16 suggest that in the absence of mass testing the pandemic wave due to the initial variant, black dashed line, would have been larger than in the baseline scenario, solid blue line. However, there would not have been a subsequent wave as in the baseline calibration which occurred due to the easing of the anti-pandemic measures after the mass testing round. The cumulative number of deaths due to the initial strain in the baseline model is lower by 760 deaths.

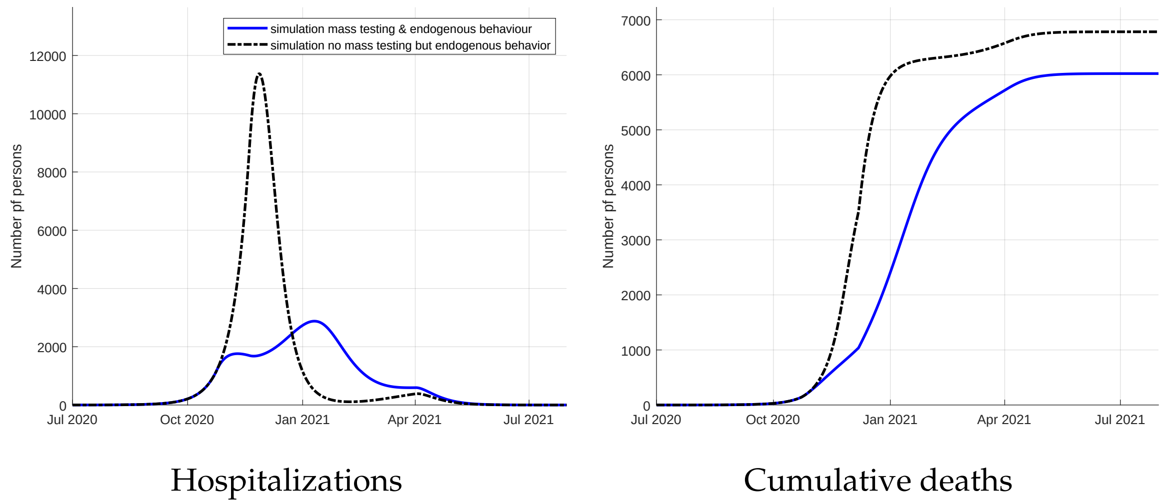


Figure 16: Simulation results without mass testing

5. Model forecast until 2025 with loss of immunity

Having discussed the model's mechanisms and its ability to explain the epidemic evolution in the past, we use it to generate model forecasts until 2025. To this end there are two important dimensions to take into account. First, the pace of vaccination, both of initial as well as booster doses. Second, the role of waning immunity.

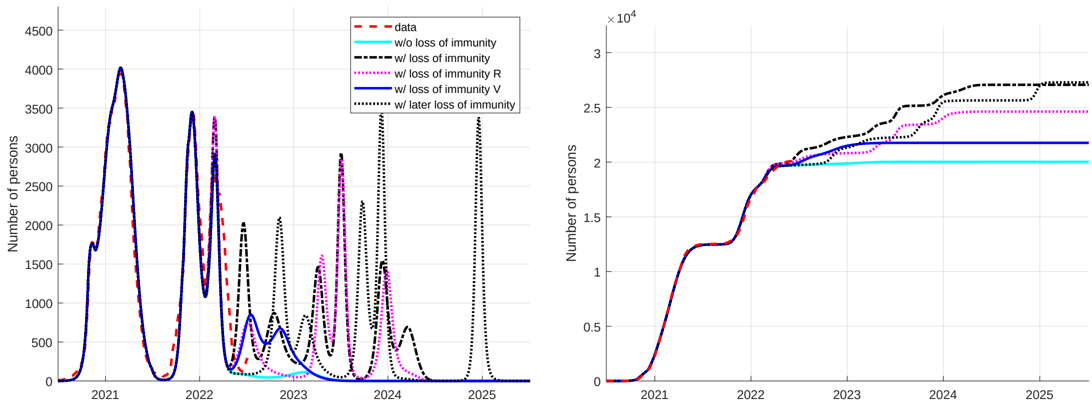
Regarding the former, we assume that the overall share of population with at least one dose will stay at the level as of March 1, 2022. This assumption is based on the observation that the rate of vaccination has already virtually come to a halt in Slovakia. The second vaccination assumption concerns the 3rd and potentially further booster doses. For simplicity we assume that each person being vaccinated initially will boost their immunity before losing it. Hence, $\omega^{3rd} = 1$.

Concerning the loss of immunity, we distinguish between two scenarios. First, without a loss of immunity after vaccination or recovery and, second, with losing the immunity protection. The number of days after which the immunity is lost for both vaccinated and recovered is assumed to be constant and equal to 450 or 600 days.[12]

Figure 17 shows the results of the forecasting exercise considering five scenarios: (1) without any loss of immunity, (2) with loss of immunity after 450 days

[12] The maturity of immunity of 450 or 600 days is, for illustrative purposes, in the simple forecasting scenario considered to be deterministic. However, it could be easily modified to be either random or that the immunity is waning over a certain period of time. See e.g. Ehrhardt, Gašper, and Kilianová (2019).

in both groups V and R, scenarios (3) and (4) are for the cases with loss of immunity after 450 days only for recovered or vaccinated and, finally, (5) for loss of immunity after 600 in both groups V and R. It is obvious that the loss of immunity is governing the occurrence of future pandemic waves.



Hospitalized

Cumulative deaths

Figure 17: Forecast till 2025

Note: *Scenario w/o loss of immunity* represents the baseline result from Section 3. *Scenario w/ loss of immunity* is the scenario with loss of immunity after 450 days in both groups V and R. *Scenario w/ loss of immunity R* is the scenario with loss of immunity after 450 days but only for the recovered. *Scenario w/ loss of immunity V* is the scenario with loss of immunity after 450 days but only for the vaccinated. *Scenario w/ later loss of immunity* is the scenario with loss of immunity after 600 in both groups V and R.

Hence, an important aspect of the results is the timing of the loss of immunity given by τ^R and τ^V. It relates strongly to the time at which the pandemic waves took place in Slovakia in the past. This is the reason why there are forecasted waves in summer 2022 or summer 2023 which might seem counter-intuitive due to the seasonality peaking in winter months.

Hence, the role of loss of immunity, as expected, will be crucial for future pandemic waves. If we manage to keep the immunity protection in tact, given the share of susceptible population in Slovakia being ca. 22-24% after the last omicron wave, it is possible not to have any COVID-19 epidemic waves in terms of hospitalizations in the future. This of course depends on further external factors such as the emergence of new variants, their severity and their hospitalization rates but also on the lack of interest in refreshing the immunity protection by repeated vaccination.

Figure 18 and Figure 19 show the results of the forecasting exercise for scenarios with a different severity level of the virus with or without the loss of immunity. In particular we consider scenarios with varying severity implying $coef^O$ being either 3.9 or 3.6 instead of the baseline calibration of 3.72.

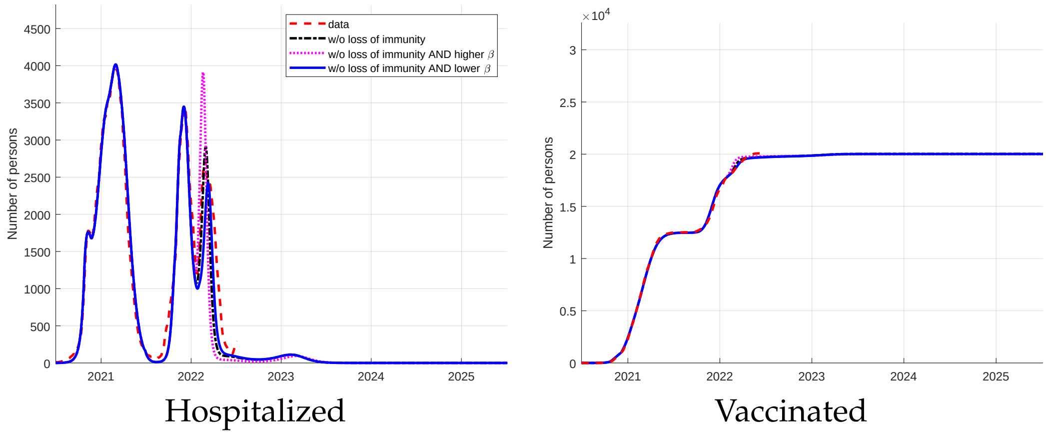
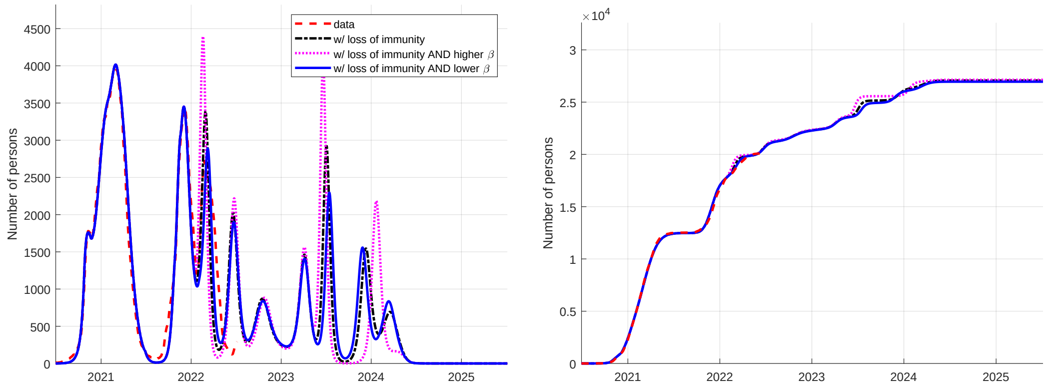


Figure 18: Forecast till 2025 without loss of immunity but varying severity

Note: *Scenario w/o loss of immunity* represents the baseline result from Section 3. *Scenario w/o loss of immunity AND higher* β is the scenario of greater severity with $coef^O = 3.9$. *Scenario w/o immunity AND lower* β is the scenario of lower severity with $coef^O = 3.6$.

The comparison between Figure 18 and Figure 19 suggests that even though the severity matters, it is especially the loss of immunity in the first place governing the occurrence of future waves. Admittedly, the hospitalization rates can change in the future as well, implying smaller waves in terms of hospitalized patients.

Finally in Figure 20 we show the results for the scenarios with a longer maturity of the immunity protection both after recovery as well as vaccination.

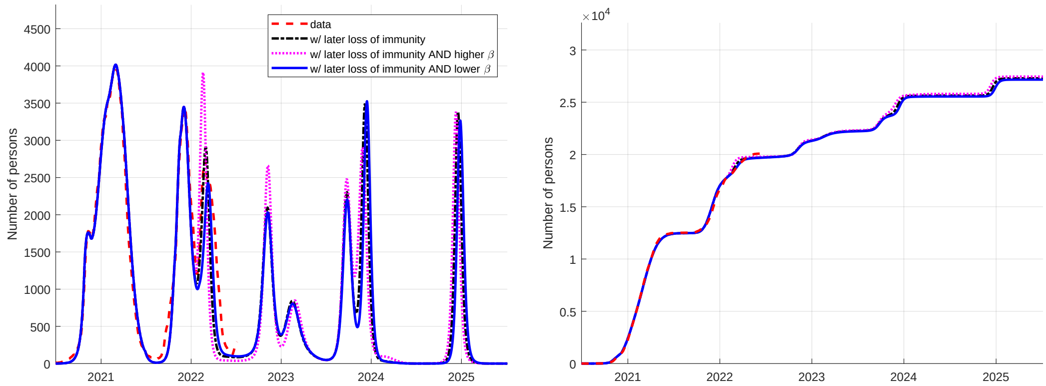


Hospitalized

Vaccinated

Figure 19: Forecast till 2025 with loss of immunity but varying severity

Note: *Scenario w/o loss of immunity* represents the baseline result from Section 3. *Scenario w/ loss of immunity* is the scenario of greater severity with $coef^O = 3.9$. *Scenario w/ loss of immunity R* is the scenario of lower severity with $coef^O = 3.6$.



Hospitalized

Vaccinated

Figure 20: Forecast till 2025 with longer immunity protection

Note: *Scenario w/o loss of immunity* represents the baseline result from Section 3. *Scenario w/ later loss of immunity AND higher* β is the scenario of greater severity with $coef^O = 3.9$. *Scenario w/ later loss of immunity AND lower* β is the scenario of lower severity with $coef^O = 3.6$.

6. Conclusion

The results presented in this paper share the same concerns as discussed in Atkeson (2021). First, calibration of the model is a result of trial-error approach. Second, the simplicity of the model comes with costs such as ignoring important heterogeneity issues in terms of population composition and regional differences. In particular the structure and location of (un)vaccinated population may drive the evolution of future epidemic waves. Third, other shocks than seasonality and pandemic fatigue could be considered as well.

However, taking into account the advantages and disadvantages of the model approach taken in this paper, it can be used as a simple but powerful tool for scenario analysis and reduced-form analysis of various policies. It could be used as a tool to inform the development of more realistic models combining geographical and demographical heterogeneity and as a benchmark for comparison purposes.

To conclude, even though highly parsimonious, this paper presents a model which matches the empirical evolution of the COVID-19 pandemic reasonably well. It provides evidence in favor of Atkeson (2021) in which seasonality and pandemic fatigue are crucial in addition to an endogenous response of the transmission rate to the rate of hospitalizations to match the patterns observed in the data. Pandemic fatigue finds empirical support in the Slovak data. And last but not least, vaccination is a crucial aspect to be taken into account in matching epidemic evolution since January 2021 and for scenario forecasts.

References

Atkeson, A. (2021, February). A Parsimonious Behavioral SEIR Model of the 2020 COVID Epidemic in the United States and the United Kingdom. Working Paper 28434, National Bureau of Economic Research.

Avery, C., W. Bossert, A. Clark, G. Ellison, and S. F. Ellison (2020, November). An economist's guide to epidemiology models of infectious disease. *Journal of Economic Perspectives 34*(4), 79–104.

Barro, R. J. (2022, March). Vaccination Rates and COVID Outcomes across U.S. States. Working Paper 29884, National Bureau of Economic Research.

Cochrane, J. (2020, May). An SIR model with behavior. https://johnhcochrane.blogspot.com/2020/05/an-sir-model-with-behavior.html.

Ehrhardt, M., J. Gašper, and S. Kilianová (2019). SIR-based mathematical modeling of infectious diseases with vaccination and waning immunity. *Journal of Computational Science 37*, 101027.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2021, April). The Macroeconomics of Epidemics. *The Review of Financial Studies*.

Hale, T., N. Angrist, R. Goldszmidt, B. Kira, A. Petherick, T. Phillips, S. Webster, E. Cameron-Blake, L. Hallas, S. Majumdar, and H. Tatlow (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour 5*, 529–538.

Johanna, N., H. Citrawijaya, and G. Wangge (2020, December). Mass screening vs lockdown vs combination of both to control COVID-19: A systematic review. *Journal of Public Health Research*.

Washington State Department of Health (2021). Covid-19 cases, hospitalizations, and deaths by vaccination status. Washington State Department of Health, Working paper.

D. Appendix

D.1. Sensitivity of the reaction function

In equation (15), given the value of κ_t, the transmission rate is assumed to endogenously react to the pandemic evolution measured by a sum of the hospitalized between $t-20$ and $t-10$.

Figure 21 shows the sensitivity to choosing a different sample. In particular, in addition to the initial simulation with $t-20$ and $t-10$ given by the blue line, the black dashed line shows the results for $t-15$ and $t-5$ and the purple dotted line for the case with $t-10$ and t. As can be seen, the results are different quantitatively but not qualitatively.

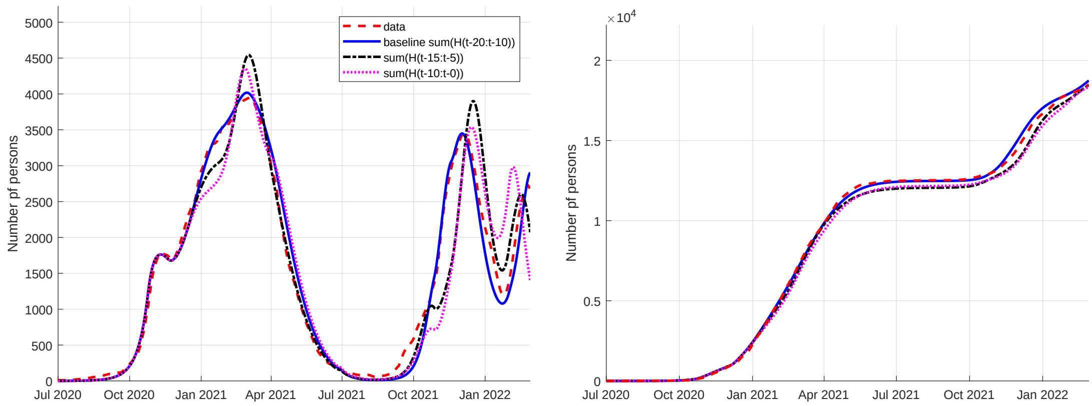
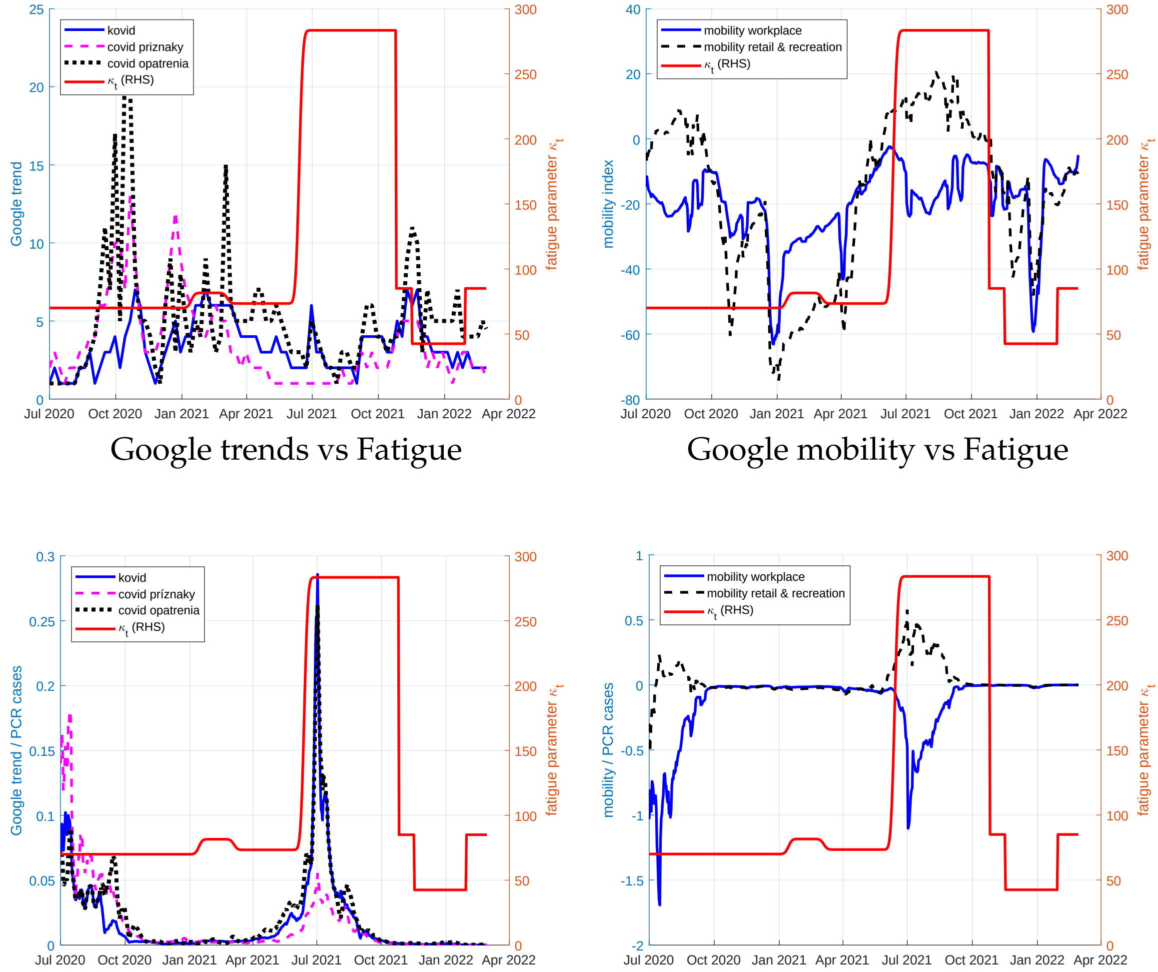


Figure 21: Robust analysis of the timing specification of the pandemic status in the reaction function of the transmission rate

D.2. People's attention towards rules

Figure 22 illustrates the co-movement of trends in Google searches for the expressions ”kovid,” ”covid priznaky” and ”covid opatrenia” and Google mobility indices for ”mobility workplace” and ”mobility retail and recreation” with the pandemic fatigue parameter κ_t. The graphs at the bottom are relative to the number of reported PCR cases.



Google trends vs Fatigue

Google mobility vs Fatigue

Google trends / cases vs Fatigue

Google mobility / cases vs Fatigue

Figure 22: Informing modelling of pandemic fatigue

Notes: Data on trends in Google searches are centered 7-days moving averages. Source: Google Trends, https://trends.google.com/trends/explore?date=2020-07-01%202022-02-28&geo=SK&q=covid%20priznaky,covid%20opatrenia,kovid.

A priori it is not clear, however, whether a pandemic fatigue should result in an increase or a decrease in Google searches. On the one hand, one could argue that given a pandemic fatigue shock, people start to be less attentive and search for covid related topics less. On the other hand, it is also possible that exactly because of the fatigue people start to search more intensively to learn how to bypass restrictions. The co-movement of Google trends and fatigue parameter κ_t seems to slightly support the latter line of argument even though the evidence is inconclusive.

Interestingly, when considered relative to the number of reported PCR cases, there is a surge in the number of Google searches at the beginning of July 2021 which supports the exogenous increase in $\bar{\kappa}$ due to the introduction of the flashlight system governing the automatic introduction of containment measures conditional on the pandemic situation.

Concerning the Google mobility indices, there is no striking evidence that at the time of the pandemic fatigue shocks in autumn 2021 mobility increased remarkably. However, when taking into account that at that time it was the Covid flashlight system in Slovakia that was supposed to automatically govern the containment measures, mobility should have decreased more strongly than was the case.