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ARTICLE

Application of an Epi-Econ-Model to Analyze COVID-19 Lockdown Policies in the Netherlands: Lessons and Limitations

Gerbert Romijn[1], Niek Stadhouders[2,3] and Johan Polder[4,5]

[1]KiM Netherlands Institute for Transport Policy Analysis, The Hague, The Netherlands
[2]Department of IQ Health, Radboud University Medical Center, Nijmegen, The Netherlands
[3]Department of Health Economics, School of Business and Economics & Talma Institute, Vrije Universiteit, Amsterdam, The Netherlands
[4]National Institute for Public Health and the Environment (RIVM), Bilthoven, The Netherlands
[5]Tilburg School of Social and Behavioral Sciences (TSB), Tranzo, Tilburg University, Tilburg, The Netherlands
Corresponding author: Niek Stadhouders; Email: niek.stadhouders@radboudumc.nl

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Abstract
Epidemiological and economic (Epi-econ) models account for endogenous interactions between the epidemic and the economy. We explore the applicability of an Epi-econ model to isolate the effects of lockdown policies during coronavirus disease 2019 in the Netherlands. To this aim, we recalibrate the seminal Epi-econ model of Eichenbaum and colleagues with updated parameters specific to the Dutch context. We find that the model performs poorly in replicating observed Epi-econ trends under baseline assumptions. Next, we explore possibilities to improve model fit by relaxing policy and transmission parameters, and by incorporating observed "random noise" in infectivity parameters. This approach spectacularly improves model performance in replicating observed trends. Finally, we test the performance of the model in simulating alternative policy scenarios. We use the Containment and Health Index from the Blavatnik School of Government to replace Dutch policy parameters with exemplary countries on opposite sides of the stringency spectrum. We find that a more stringent lockdown policy would reduce peak prevalence, while aggravating peak economic contraction, but with little effect on overall trends. Conversely, a more lenient lockdown policy was estimated to increase the peak and overall prevalence, with little effect on economic outcomes. We conclude that while rigorous adjustments to existing models were required, a combined Epi-econ model could be informative to policymakers in assessing alternative lockdown policy options.

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has had a major impact on healthcare systems and economic activity. An important question is whether there is a trade-off between health and economic interests during a pandemic. In the Netherlands, policy initially focused on dampening the impact of COVID-19 on healthcare, particularly aiming to protect intensive care unit capacity, while retaining economic activity. The focus was primarily on "flattening the curve" to prevent patient overflow in hospitals. This was pursued predominantly through lockdown policies. As in many other countries, whole sectors of society and the economy (e.g. hospitality, retail, culture, events, travel, tourism) were put in lockdown during the first COVID-19 wave. Furthermore, office work and education continued online, public transport was severely restricted, planned care was postponed, and organized sport and many other social activities were banned. A number of these interventions have been shown to reduce COVID-19 reproduction rates (Camehl & Rieth, 2021; Levelu & Sandkamp, 2022). For example, closure of nonessential shops, school closures and strictness of mass gatherings theoretically reduce infections (Wang & Ramkrishna, 2020). However, these restrictions have had major economic impacts, depending on the policy measures taken (König & Winkler, 2021b). This ignited public debate regarding the net benefits of the lockdown policy relative to the economic costs (Salgotra *et al.*, 2021). Proponents of stricter lockdowns suggested policy responses similar to countries such as Germany or South Korea, while opponents championed less restrictive policy responses of, for example, Sweden or the United Kingdom. To fully assess optimal policy responses, any social and economic costs should be weighed against presumed health benefits of lockdown policies, in comparison to alternative policy scenarios (Lasaulce *et al.*, 2020). The Netherlands could provide an interesting case study, being a densely populated, high-income open economy. An optimal balance between epidemiological and economic (Epi-econ) interests may be most relevant for the Netherlands.

A general approach to combine Epi-econ parameters is to impute economic costs of infections into a susceptible, infected, and recovered (SIR) model, including derivative models. A family of SIR models have been adjusted to incorporate economic damage by adding economic costs to infection and mortality cases (Meza, 2020; Ramírez García & Jiménez Preciado, 2021). For example, Pollinger (2020) parameterizes an epi model including the cost of infection to the Italian economy, to estimate the effect of tracing policies on Gross Domestic Product (GDP). Forsyth (2020) amends an epi model with economic costs using simple production functions, finding that the optimal lockdown strategy would be selective lockdown for symptomatic people. However, the direct effect of COVID-19 mortality on the economy is estimated to be small (Gagnon *et al.*, 2022). More elaborate SIR models incorporate economic demand models. For example, Flaschel *et al.* (2021) combine Epi-models with Keynesian demand models, allowing evaluation of different policy scenarios. Vásconez *et al.* (2023) estimate a Dynamic Stochastic General Equilibrium (DSGE)-SIR model incorporating monetary policy. These models have the potential to inform policy. For example, Andersson *et al.* (2022) constructed a simple model to study the tradeoff between health and economic production during COVID-19. They find that a social planner concerned for health would never let health capacity be exceeded, while a social planner aiming to maximize productivity would let the pandemic peak as soon as possible (Andersson *et al.*, 2022). Trotter *et al.* (2020) find the optimal timing of policies to coincide with the largest increase in infections.

However, there are convincing reasons to believe that economic damage is partly endogenous, because people may scale back economic activities on their own accord in fear of becoming infected. For example, general equilibrium models show that demand-side reductions have been shown to outweigh supply-side disturbances due to COVID-19 (Abo-Zaid & Sheng, 2020). This endogenous economic reaction dampens the epidemic: curtailing economic activities voluntarily also inhibits the spread of the virus (Di Guilmi *et al.*, 2022). The feedback loops between epidemiological trends and economic activity may

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prelude policy responses; for example, travel activity was scaled down significantly before the lockdown came into effect (Villas-Boas *et al.*, 2023; Goolsbee & Syverson, 2021). Part of the apparent effectiveness of containment policies may be attributable to endogenous behavioral reactions (Chetty *et al.*, 2020; Bodenstein *et al.*, 2021; Cardani *et al.*, 2021; Gonzalez-Eiras & Niepelt, 2022). For example, country policy responses are shown to be at most insufficient to explain large differences in economic effects (Pujol, 2020). To prevent overestimating policy effectiveness, the endogenous interaction between epidemic and economy needs to be modeled explicitly. For example, Parui (2021) extends the Epi-model with an economic supply-and-demand framework, generating a simple feedback loop. He proposes strong fiscal expansion and health capacity increases to reduce both health and economic effects (Parui, 2021).

This can be achieved by Epi-econ models that combine models of Epi evolution with a model of Econ choice behavior (Boppart *et al.*, 2025). Since the COVID-19 outbreak, Epi-econ modeling has been a fruitful topic of study. The highly cited work of Eichenbaum *et al.* (2021) extends Epi-models with economic decision-making models to render a hybrid Epi-econ model. They introduce feedback loops where economic agents scale back consumption and production when infection risk increases, limiting epidemiological spread at the cost of reduced economic production. The authors show that additional lockdown measures are required to obtain socially optimal outcomes. Their model allows dynamic policy measures to optimize welfare over time. The authors show that the model performs reasonably well in predicting actual outcomes in the United States (Eichenbaum *et al.*, 2021). Others have built upon this model by introducing asymptomatic infections (Bognanni *et al.*, 2020) or the possibility of reinfection (Iverson *et al.*, 2022). Diex de los Rios (2022) expands the Epi-econ model by introducing uncertainty surrounding infectivity and bounded-rational individuals. Pataro *et al.* (2021) endogenize time-variance in behavioral responses to policy measures. In general, models simplify reality to illustrate the main mechanisms of combining Epi-econ interactions. However, these models scarcely compare the theoretical models to the actual observed trends. We aim to research whether existing Epi-econ models, particularly the seminal model of Eichenbaum *et al.* (2021), can be calibrated to empirical data from the Netherlands and be used to gauge the effect of policy measures while controlling for endogenous behavioral responses. This renders the following research questions:

- Can the Epi-econ model developed by Eichenbaum *et al.* (2021), when applied to the Netherlands, be parameterized to realistically simulate economic and epidemiological trends observed in the Netherlands in 2020?
- What steps are required to improve model performance?
- Can this model be used to realistically simulate Epi-econ outcomes under alternative policy measures?

With this exercise, we aim to assess the usefulness of Epi-econ models in policy evaluation. The added value is twofold: first, our approach analyzes the validity and generalizability of the Epi-econ model while providing suggestions to improve parameterization. Second, we aim to show the added value of using the Epi-econ models in ex post policy evaluation. We use the Epi-econ model to estimate how much of the economic and health damage is due to policy and how much would have occurred even without policy. This may provide insight into potential tradeoffs between economic consequences and health effects. While full economic approaches could be applied to ex post policy evaluation, one potential benefit of using Epi-econ model is that it already incorporates nonlinear feedback effects between economic and epidemic trends. However, this approach depends on the ability of the Epi-econ model to

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accurately and reliably simulate observed trends. This article aims to explore the preconditions required to use Epi-econ models in policy evaluation rather than to provide a full economic evaluation of the corona policy in the Netherlands. Moreover, the article aims to explore potential improvements to the predictive capabilities of Epi-econ models.

2. Background

2.1. Epidemic, economic, and policy trends in the Netherlands

Figure 1 shows the prevalence for the Netherlands as estimated by the Dutch Institute for Public Health and the Environment (Rijksinstituut voor Volksgezondheid en Milieu, RIVM). The estimates take into account unobserved prevalence (Ainslie *et al.*, 2022). The first confirmed COVID-19 infection in the Netherlands was reported on 27 February 2020. The estimates display a first peak on 25 March 2020 at a level just below 1% of the population. A second and third peak occurred in October and December. The total number of infection throughout 2020 is estimated at 14.8 % of the population (Ainslie *et al.*, 2021).

The global economic output gap due to COVID-19 is estimated at ~6.5 % in 2020 (Rungcharoenkitkul, 2021). Similar to most countries, the Netherlands experienced sharp declines in economic activity. Figure 2 shows weekly economic activity, based on the OECD Weekly Tracker of GDP growth (OECD, 2023). Economic activity dropped sharply in March 2020, followed by a rapid recovery. The effects of the second wave in the fall of 2020 and winter of 2020/2021 are less pronounced. The estimated total loss in economic activity in 2020 is EUR 17 bn (2.1 %).[1]

COVID-19 containment policy in the Netherlands consisted of a range of policy measures and adaptions throughout 2020. The Oxford COVID-19 Government Response Tracker of

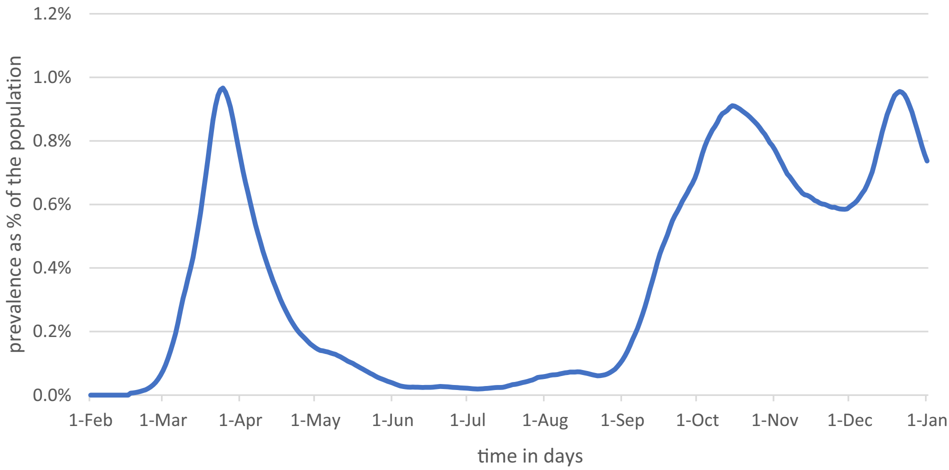

Figure 1. *Estimated prevalence of COVID-19 in the Netherlands. Source RIVM[2] and own calculations.*

[1] StatLine – Bbp, productie en bestedingen; kwartalen, waarden, nationale rekeningen (cbs.nl).
[2] https://coronadashboard.rijksoverheid.nl/landelijk/besmettelijke-mensen.

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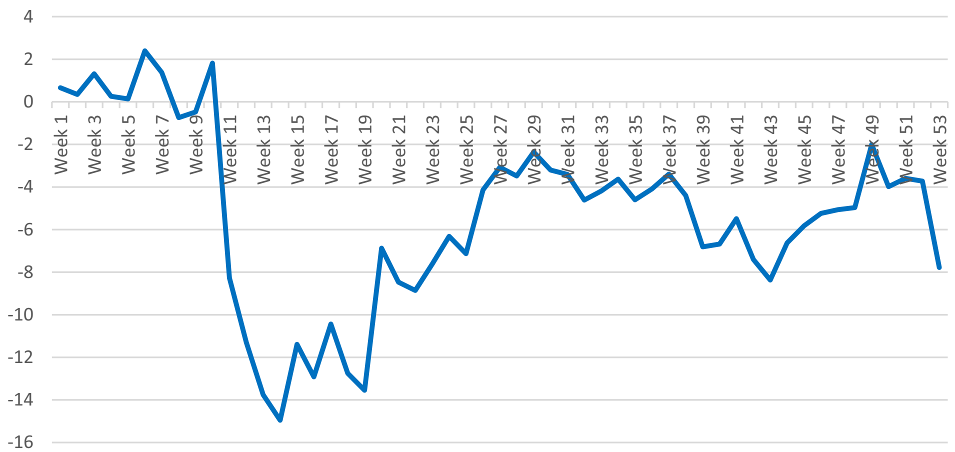

Figure 2. *OECD Tracker of economic activity in 2020 (Source: OECD (2023)). Data were downloaded on 9 September 2021.*

the Blavatnik School of Government weights individual containment measures into a Containment and Health Index (CHI) that reflects the stringency of COVID-19 containment policies (Hale *et al.*, 2020). Figure 3a displays the Dutch CHI. An attractive feature of the CHI is that similar indices have been composed for a wide range of countries, allowing for cross-country comparison of COVID-19 policies. For example, the CHI has been used to compare stock market volatility (Zhuo & Kumamoto, 2020), unemployment effects (Dreger & Gros, 2021), economic growth (Ashraf & Goodell, 2022), and tradeoffs between economic and health damage (Cross *et al.*, 2020; König & Winkler, 2021a).

3. Methods

This study adapts the Epi-econ model of Eichenbaum *et al.* (2021) to the Netherlands. The full model, including adaptations, is described in Appendix Appendix A. We pursue the following steps to assess the potential to evaluate policy options:

1. We parameterize the Eichenbaum, Rebelo and Trabandt (ERT) model to the Dutch pre-COVID economic and epidemiological situation (1a) and perform sensitivity analysis on the main parameters (1b).
2. We endeavor to reproduce observed economic and epidemiological trends by (a) a fixed-parameter calibration of policy parameters, (b) a semiflexible parameter calibration allowing policy and transmission parameters to vary over time, and (c) a fully flexible fit of the model parameters to the observed data using linear regressions
3. We simulate alternative policy responses by running CHI policy indices of a selection of countries through the model, as well as variants on the Dutch approach.

3.1. Step 1: Parameterization of the model

ERT uses fixed parameter values to define the initial prepandemic conditions. The modeling equations subsequently define how these parameters evolve over time during the pandemic. We adapt the main model parameter values to the Netherlands (Table 1). Country-specific

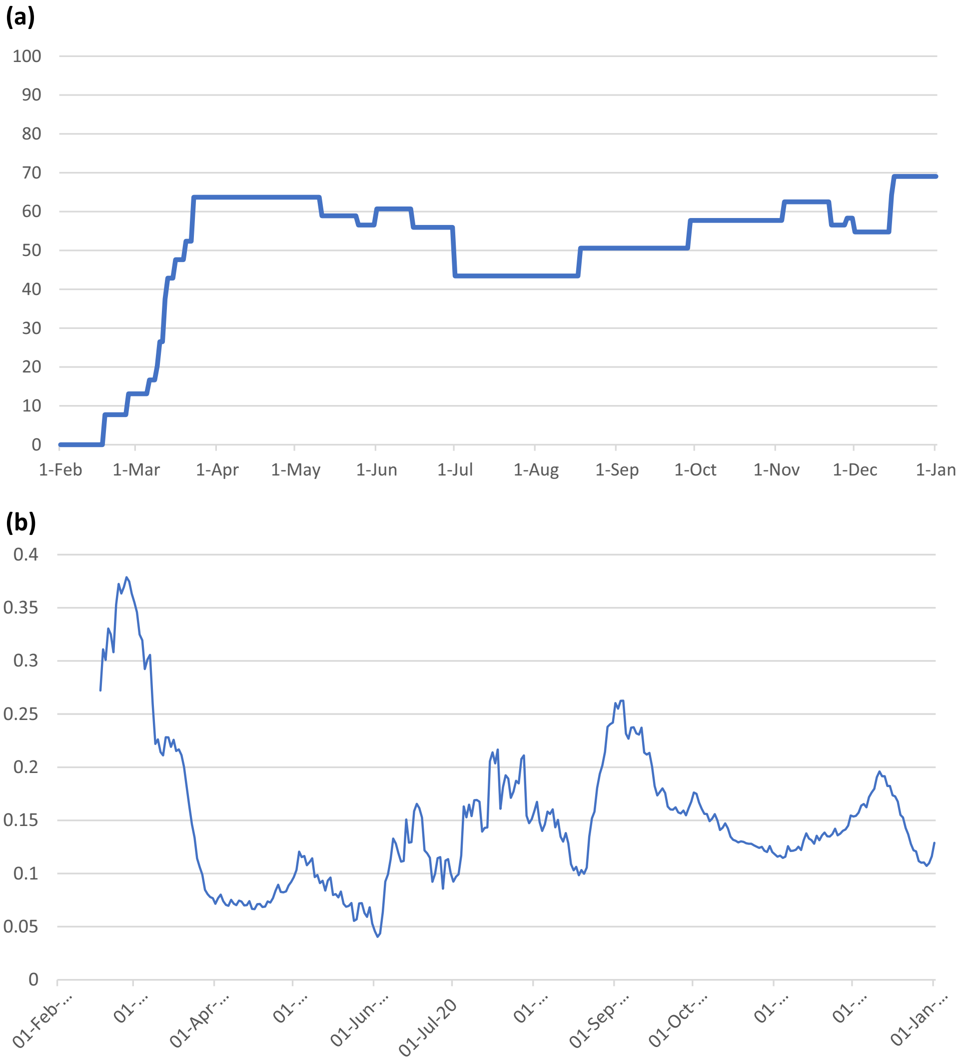

Figure 3. *(a) Oxford COVID-19 Government Response Tracker of the Blavatnik School of Government Containment and Health index of the Netherlands in 2020 (Hale et al., 2020). (b) Implied macro transmission rate (ρ_t) in the Netherlands (Source: RIVM and own calculations).*

discount rates, consumption levels, hours worked, and case fatality rates (CFRs) are taken from literature. To determine values for labor productivity A and the aversion-to-work parameter θ, data on disposable income and hours worked were used.[3] We follow Eichenbaum *et al.* (2021) and Ferguson *et al.* (2006) who argue that in a flu epidemic, 30 % of

[3] We consider the economy in steady state without a pandemic (see Appendix A), rendering the utility maximization problem: $\max_{c,n} \ln(c) - \frac{1}{2}\theta n^2$ s.t. $c = An$. It follows that $n = \sqrt{1/\theta}$ en $c = A\sqrt{1/\theta}$. With $n = 3.4$ hours and c = EUR 112, $\theta = 0.0865$, and $A = 33.1$.

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Table 1. *Calibrated model parameters*

Parameter	ERT value[a]	NL value	Notes and source (NL values)
Prepandemic consumption level (c)	USD 158.90 per day (USD 58,000 per year)[b]	EUR 112.64 per day (EUR 41,000 per year)	Estimated as net disposable income per household (CBS, 2019)
Prepandemic hours worked (n)	4.1 h per day	3.4 h per day	Based on Dutch hours worked, employed labor force, and the number of students (CBS, 2019; Roeters *et al.*, 2019)
Productivity parameter A	39.8	33.1	Own calculations based on prepandemic consumption level and hours worked (CBS, 2019; Roeters *et al.*, 2019)
Aversion to work parameter θ	0.0595	0.0865	Own calculations based on prepandemic consumption level and hours worked (CBS, 2019; Roeters *et al.*, 2019)
Daily discount rate β	$0.96^{1/365}$ per day	$0.9775^{1/365}$ per day	The Working Group on Discount Rates 2020 recommends using a default discount rate of 2¼ % per year (Werkgroep_Discontovoet, 2015). The annual discount factor is, therefore, 0.9775 per year
Mean disease duration ($1/(\pi_r + \pi_d)$)	18 days	8 days	Mean incubation period is 7.8 days (Zaki & Mohamed, 2021) Median infectious period is 6.5–9.5 days (Byrne *et al.*, 2020)
Fraction asymptomatic infectious (ϕ)	0.8	0.74	Based on Italian data (Poletti *et al.*, 2021)
Base reproduction number (R_0)	1.5	2.3	Base reproduction number estimate for the Netherlands (Ainslie *et al.*, 2022)

Table 1. *Continued*

Parameter	ERT value[a]	NL value	Notes and source (NL values)
Transmission during consumption (π_1)	5.50×10^{-7}	2.72×10^{-6}	Calibrated to ensure that 12 % of infections are related to consumption; SCP time-use survey (Ferguson *et al.*, 2006)
Transmission at work (π_2)	8.26×10^{-4}	5.47×10^{-3}	Calibrated to ensure that 22 % of infections are work-related (Ferguson *et al.*, 2006; CBS, 2019)
Transmission during leisure (π_3)	0.056	0.190	Calibrated so that the base reproduction number is 2.3 (Ainslie *et al.*, 2022)
Case fatality rate ($\pi_d/(\pi_r + \pi_d)$)	0.5 %	0.5 %	Estimates of 0.48 % (total 2020) and 0.76 % (first wave)
Initial number of infected (I_0)	0.1 %	0.0062 %	The number of infected people on 17 February 2020 (1,074) divided by the total population on 1 January 2020 (17.4 mln)[c]

[a]We have translated ERT calibration to a per day step.
[b]The average USD-EUR exchange rate during 2020 is 1.14 USD = 1 EUR (OECD). American households are on average 10-15 % larger than Dutch households (UN).
[c]https://coronadashboard.government.nl/landelijk/besmettelijke-mensen.

infections occur within a household, 33 % in the overall community, and 37 % in schools and workplaces (Ferguson *et al.*, 2006; Eichenbaum *et al.*, 2021). We use the estimated reproduction number at the beginning of the epidemic of 2.3 (Ainslie *et al.*, 2022) to calculate transmission rates.[4] We utilize survey data from the Netherlands, reporting that 38 % of leisure time involves consumptive activities (Roeters *et al.*, 2019). As 33 % of infections occur in the general community and 38 % of time spent in the general community involves consumptive activities, it follows that 12 % (0.38 × 0.33) of infections are consumption-related.[5] An estimated 10 contacts per day in education and 4 contacts per day at work (Lee *et al.*, 2010) are used to calculate infection rates at work. In the Netherlands, the working population is ~9.3 mln, while 2.6 mln people between the ages of 15 and 27 years were in education, including working students (CBS, 2019). Following Eichenbaum *et al.* (2021), 59 % of infections at work and school are attributable to work. This implies a share of infections at work of 22 % (0.59 × 0.37).[6] Next to differences in work–leisure balance, a higher base reproduction rate implies higher transmission rates for the Netherlands (e.g. 0.19 for consumption in NL vs. 0.06 in ERT). Different COVID-19 CFRs have been reported for the Netherlands, ranging from 0.76 % during the first wave and 0.48 % over 2020 (Ainslie *et al.*, 2022). We follow ERT in using a CFR of 0.5 %, and apply sensitivity analyses (Appendix C). Combined with a mean disease duration of 8 days (Byrne *et al.*, 2020; Zaki & Mohamed, 2021), the daily recovery rate π_r becomes 0.995/8 and the daily death rate $\pi_d = 0.005/8$. The sum of the recovery rate and the death rate ($\pi_r + \pi_d$) gives the percentage unsusceptible for infection (removal rate). We adjust the start number of infected persons of 0.0062 % of the population on Day 0 (17 February 2020).[7]

3.2. Step 2: Model fitting

The second step aims to calibrate the policy and transmission parameters to empirically observe Epi-econ trends (Di Bartolomeo *et al.*, 2022). Economic lockdown parameters, modeled by μ, apply constraints on consumption and economic activity, which can be tightened or relaxed over time. Transmission rates, modeled by π, are partly determined by fixed biological traits of the virus such as infectivity – although these traits may vary between virus variants – and partly by policy measures such as social distancing and protective measures. This renders two time-variant parameters (π_t and μ_t) that allow us to fit the model to the actual data (Anzum & Islam, 2021; Haw *et al.*, 2022). In a stepwise approach, we start with fixed parameter values and relax this assumption gradually. The steps are presented in Table 2.

First, we assume transmission parameters to be invariant and the policy parameter value μ to take effect at the start of the lockdown and be retained throughout the year. Next, we allow incremental changes to μ. Using trial-and-error optimization, we scale the policy parameter to the NL-CHI. Next, additional flexibility is assumed by allowing infection transmission parameters to be affected by policy (Eichenbaum *et al.*, 2022). Again, we allow incremental

[4] Using Equation (A.8) in Appendix A: $\rho_0 = \pi_1 c^2 + \pi_2 n^2 + \pi_3$.

[5] $\frac{\pi_1 c^2}{\pi_1 c^2 + \pi_2 n^2 + \pi_3} = 0.12$ implies transmission during consumption (π_1) of 2.72×10^{-6}.

[6] $\frac{\pi_2 n^2}{\pi_1 c^2 + \pi_2 n^2 + \pi_3} = 0.22$ implies transmission at work (π_2) of 5.47×10^{-3}.

[7] The original ERT simulations started the epidemic with a 0.1 % prevalence. Our simulations start at 0.0062 % of the population, as estimated by the RIVM.

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Table 2. *Parameterization steps to improve model fit to observed trends*

Scenario	Policy parameter μ	Transmission parameters π	Time variance	Method
One-time policy	μ takes effect on the first day of the lockdown at a fixed value	Fixed	Fixed	Trial-and-error optimization
CHI policy	μ is scaled according to the CHI	Fixed	Semiflexible policy, fixed transmission	Trial-and-error optimization
CHI lockdown and transmission policy	μ is scaled according to the CHI	Transmission parameters are scaled according to the CHI	Semiflexible policy and transmission	Trial-and-error optimization
CHI lockdown, fully flexible transmission rates	μ is scaled according to the CHI	Transmission rates are fitted to the CHI	Fully flexible	Linear regressions

changes over time by scaling the infection transmission rates to the CHI using trial-and-error optimization to match observed trends (Buckman *et al.*, 2020). Finally, we endogenize time-varying variables (Ho *et al.*, 2023).

To calibrate transmission parameters, we calculate the macro transmission rate ρ_t (see Appendix Appendix B for more detail). Figure 3b shows the evolution of the macro transmission rate in the Netherlands in 2020. A sharp decline during the first lockdown is followed by waves of abrupt changes and day-to-day fluctuations. The macro transmission rate is affected by a number of endogenous and exogenous factors, such as social distancing, hygiene policies, and meteorological circumstances, as well as the containment rate (Chudik *et al.*, 2021). Evidently, policies aimed at restricting contacts and reducing contact transmissibility affect the macro transmission rate. The feedback loop between economic behavior and epidemiological trends may also affect the macro transmission rate variance. The variation of the macro transmission rate can be disaggregated into a part affected by policy and an unexplained part. Using linear regression models, we estimate how ρ_{t} is affected by policy:

$$\rho_t = \beta_0 + \beta_1 \mathrm{CHI}_t + \beta_2 s_t + \varepsilon$$

where following Ainslie *et al.* (2022), we add a seasonal variable s_t[8] (Ainslie *et al.*, 2022). We incorporate the variation in ρ_t not explained by the CHI into the transmission parameters to allow daily epidemiological fluctuations in the model. We use the fitted values to estimate the effects of policy relative to endogenous effects (Appendix C). We assume that policy has a constant effect on the macro transmission rate. In reality, however, policy effects may be nonlinear, for example, larger changes in the CHI render disproportionately larger effects on the transmission parameters, on top of the existing nonlinear effects in the model. In a sensitivity analysis, we explore potential nonlinear policy effects by adding nonlinear specifications of CHI.

3.3. Step 3: Analyzing alternative policy scenarios

Next, we estimate alternative policy responses by replacing the Dutch CHI with the CHI of a selection of countries. Representing a more lenient and a more stringent approach, respectively, we chose the Swedish and the Korean CHI (Krueger *et al.*, 2022). As shown in Figure 4, Korea adopted a more stringent response, particularly in the first wave, while Sweden was less stringent in both waves (Bricco *et al.*, 2020). Korean policy would mainly simulate an earlier anticipation by the Netherlands. Interestingly, the Dutch COIVD policy was more lenient during the summer than either Sweden or Korea.

Finally, we evaluated the effects of excluding a lockdown measure from the Dutch CHI, namely the closure of "workplaces" (Figure 5). This involves closing restaurants, shops, and so forth. It does not concern the stay-at-home or work-from-home policies. The measure of workplace closings could be interchanged readily with any other measure that renders similar effects on the overall CHI, since the CHI does not discriminate between relative effects of measures. Therefore, this could be considered as a general example of a less stringent policy.

[8] The seasonal is adapted from Ainslie et al. (2022): 0.00061 × (1 + 0.14 × COS(2 × π × DayNr/365.25)). In addition, we tested for day-of-the-week effects. These proved not significant.

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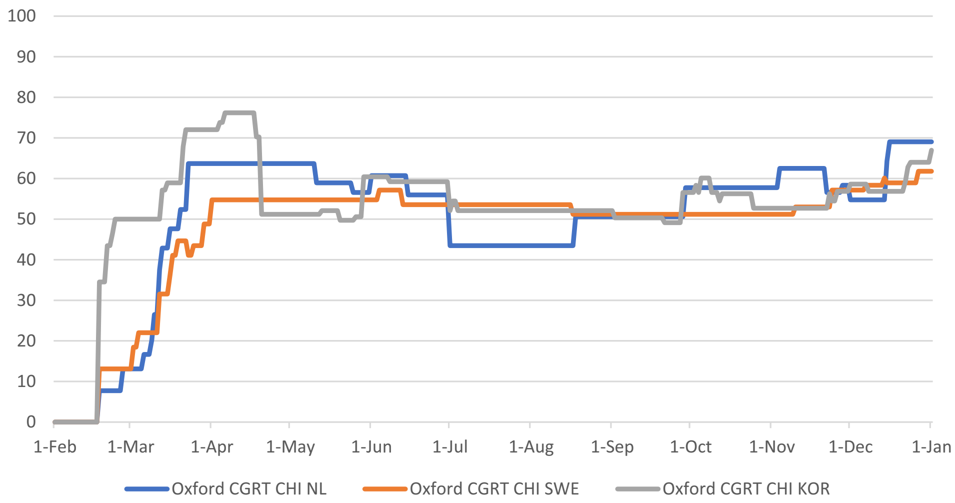

Figure 4. *Containment and health index (CHI) for the Netherlands, Sweden, and Korea (Source: Blavatnik School of Government, University of Oxford).*

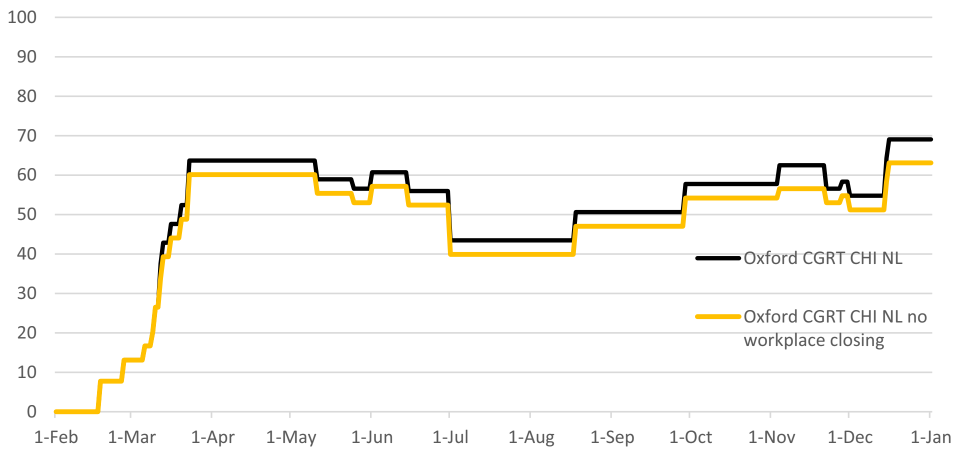

Figure 5. *Containment and health index (CHI) for the Netherlands, excluding workplace closing (Source: Blavatnik School of Government, University of Oxford, and authors' calculations).*

4. Results

4.1. Step 1: Baseline simulation

Figure 6 shows the predicted Epi-econ development in the absence of policy. The simulated epidemic prevalence peaks 69 days after the initial introduction at almost 16 % of the population. This is much later than the actual epidemic (peaking after 37 days) and significantly higher than the observed trends (under 1 %). The model predicts that over 75 % of the population will become infected after the first wave, leaving no potential for a

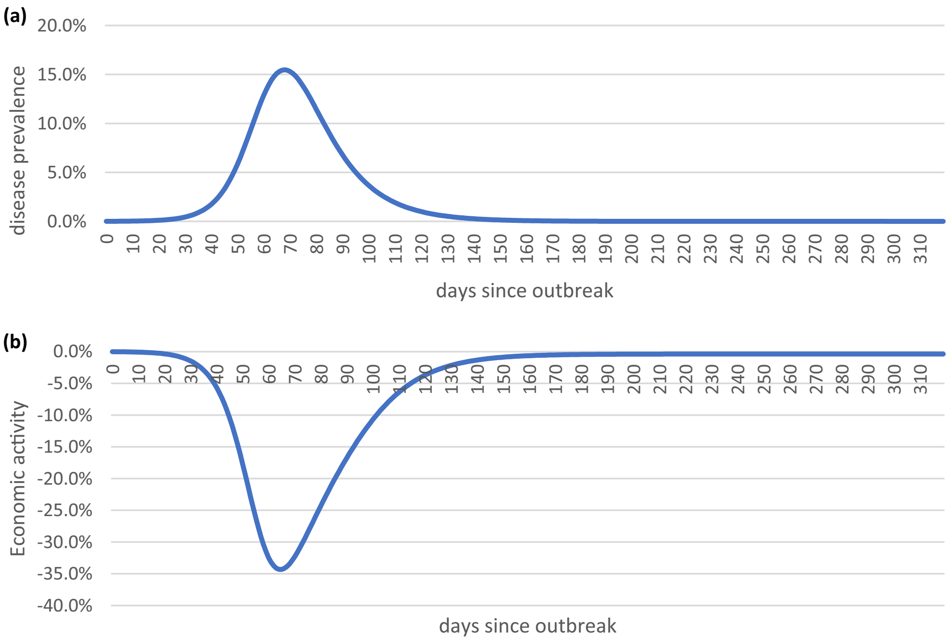

Figure 6. *Baseline simulation: (a) COVID-19 prevalence per day; (b) economic activity per day.*

second wave. Furthermore, the baseline simulation shows an initial economic contraction of almost 35 %, which is much severe than the observed trends (15 %). The simulated contraction is followed by a rapid recovery, which is also much faster than the observed trends. One explanation is that the baseline simulation does not include COVID-19 containment policies. It is noteworthy that in the baseline simulation, after 37 days, prevalence is just over 1 % of the population.

4.2. Sensitivity analyses

To gauge the effects of the Epi-econ feedback loop, we run the model without interaction between economy and epidemic (SIR) in comparison (Appendix C). Without the Epi-econ feedback loop, the predicted peak prevalence is 6 % points higher, but economic decline is much less severe, as any reduction in hours worked is only due to COVID-19 absenteeism and death.

Some model parameters were updated relative to the original model. A higher reproduction parameter of 2.3 (Ainslie *et al.*, 2022), relative to 1.5 assumed by Eichenbaum *et al.* (2021), results in a steeper and higher infection peak, with tantamount effects on the economy (Appendix C). A lower discount rate of 2.25 % per annum (Werkgroep_Discontovoet, 2015) versus 4 % per annum intensifies the economic recession and thereby dampens the epidemic (Appendix C). As a lower discount rate places additional value on future consumption, economic activity is scaled down to reduce the risk of infection and subsequent mortality. The value of the productivity parameter for infected people (ϕ^I), set at 0.74 in the baseline model, shows little

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effect on the model outcomes (Appendix C). This is due to counterbalancing effects: while reduced productivity negatively affects hours worked of susceptibles, this effect is counteracted by a reduced risk of encountering the infected individuals while consuming. The mean infection period of 8 days was subjected to sensitivity analyses (12 days, Appendix C). While a longer infection period significantly affects the length and impact of the first wave, economic effects are smaller due to the counteracting mechanisms described above. Finally, a CFR of 1 % instead of 0.5 % reduces the peak of the first wave, but significantly increases the economic decline. Evidently, working and consuming become more costly in terms of foregone expected future utility, thereby reducing economic activity, which puts a brake on the epidemic.

4.3. *Step 2: Calibrating policy parameters*

Following Eichenbaum *et al.* (2021), we introduce policy through the containment rate μ_t. We calibrate μ to attain a peak prevalence of 1 %, in accordance with observed peak prevalence. However, even at a maximum value of μ of 100 %, peak prevalence is still much higher than observed at over 11 %, while the economic contraction is over 50 %. We conclude that a fixed policy parameter μ by itself is insufficient to simulate observed developments (Figure 7).

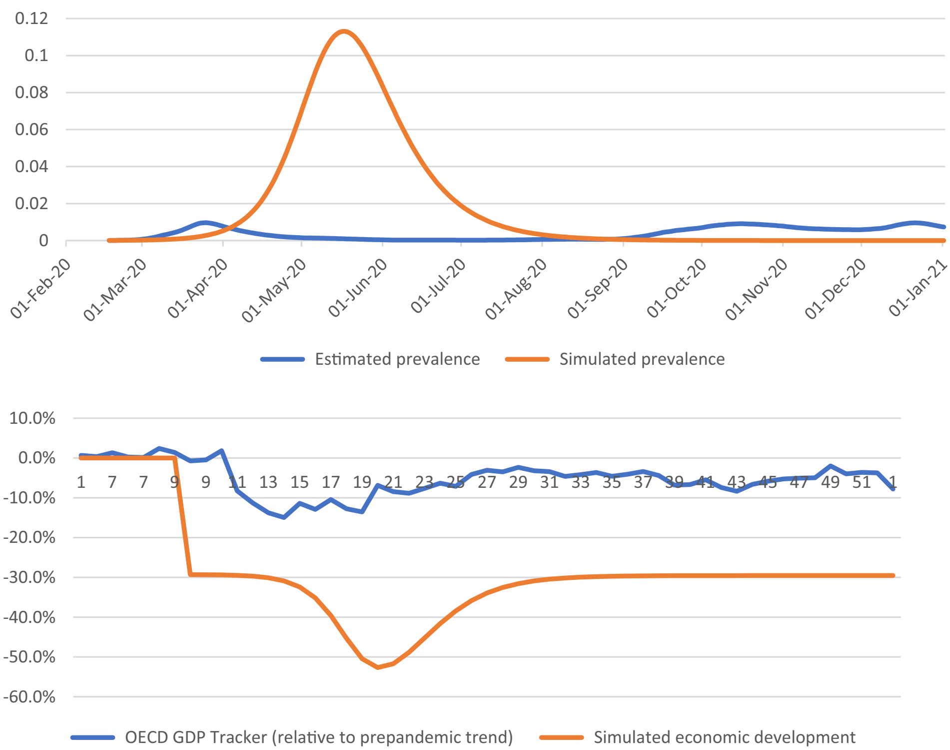

Figure 7. *Simulation results for μ = 100 %.*

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Subsequently, we assume a semiflexible time variant and scale μ_t proportionally to the CHI of the Netherlands. As the observed peak prevalence is beyond reach with any μ_t, we calibrate μ_t to match the observed economic trends in the first acute phase of the epidemic, given the actual epidemic development. The subsequent recovery of the economy may be influenced by factors outside of the model, such as fiscal support packages and increasingly efficient adaptation of economic activity to COVID-19 circumstances. The first shock, however, can only be attributed to the epidemic itself and the initial policy response to it. Using a trial-and-error fitting, a calibrated value of $\mu_t = 0.005\mathrm{CHI}_t$ is obtained.

Finally, we allow transmission parameters to be affected by policy. We calibrated the transmission parameters to the implied macro transmission rate ρ_t. This allows the model to mimic the epidemiological trends. Concurrently, we use $\mu_t = 0.005\mathrm{CHI}_t$ and add a linear trend in economic development, reflecting increasing adaptation to the circumstances (e.g. better facilities to work from home). As expected, the model closely mimics the observed epidemiological trends and produces an acceptable fit to the economic trends (Figure 8). Additional analyses reveal that this renders a policy parameter, which is relatively influential, explaining 87 % of epidemic and 70 % of economic effects relative to endogenous Epi-econ effects (Appendix C).

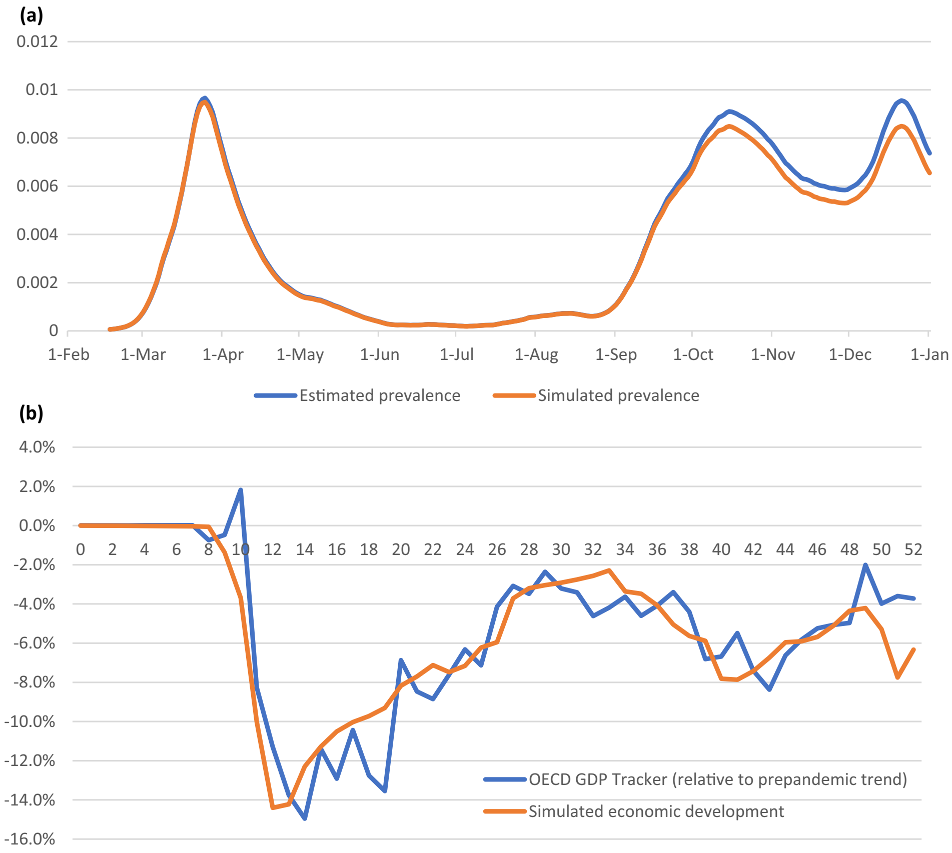

Figure 8. *Actual and simulated epidemic (a) and economic development (b).*

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Table 3. *Estimating the effect of policy on the macro transmission rate*

	Main regression	Main regression (nonlinear)	Main regression (exponential)	Regression with seasonal
CHI	−0.0039*** (0.0002)	−0.001 (0.001)	0.003 (0.002)	−0.004*** (0.0002)
CHI^2		−0.357*** (0.094)		
e^{CHI}			−0.472** (0.124)	
β^2 seasonal				350*** (37.8)
Constant	0.369*** (0.010)	0.062 (0.035)	0.537** (0.102)	0.159*** (0.024)
R^2	0.61	0.71	0.71	0.69
F-test (df1, df2)	496 (2,317)	254 (3,316)	254 (3,316)	358 (3,316)

Note: Standard errors are in parentheses. Significance: *p < .05; **p < 0.01; ***p < 0.001.

4.4. Step 3: Alternative policy simulations

We estimated the effect of policy on ρ_t using linear regression (Table 3). A significant effect is obtained, with an increase of one point on the CHI translating to a 0.0039 point reduction in ρ_t. To test the assumption that policy affects the reproduction rate in a nonlinear manner, additional linear regressions incorporating nonlinear terms and seasonal trends are estimated. The nonlinear terms are statistically significant, although with limited effects on the overall explanatory power. Marginal analysis (Appendix D) reveals that the linear term does provide a good approximation at relevant 2020 values. The seasonal trend is also significant, but its inclusion does not affect the policy coefficient. For the sake of simplicity and to avoid overfitting, we incorporate the linear term only in the model. This implies that the coefficient for CHI from the main regression model is used as a parameter to test the effect of different CHI policy evolutions.

Next, we substitute the NL-CHI for the CHI of Sweden and Korea, recalculate ρ_t and μ_t and rerun the model. Figure 9 shows that the application of the Swedish CHI to the Netherlands would increase (peak) prevalence, both during the first and second wave. At the end of 2020, this would have increased cumulative prevalence by 7 percentage points (51 %). However, economic trends are similar. This is because the economy faces two countervailing influences. More lenient policies directly stimulate economic activity. At the same time, more lenient policies increase infectivity and epidemic activity, which has a deterring effect on economic activity.

Applying the Korean CHI to the Netherlands shows significant economic decline at the start of the first wave. On the other hand, peak prevalence was reduced by a third, and while prevalence would be higher during the summer, the second peak would have been lower too, with positive effects on economic activity. At the end of 2020, this strategy was estimated to result in 0.1 percentage point lower total prevalence (0.5 %) and 0.5 percentage points of additional economic decline (10 %).

Finally, we exclude a single measure (workplace closings) from the Dutch CHI as an example to simulate a more lenient lockdown policy (Figure 10). Surprisingly, the model

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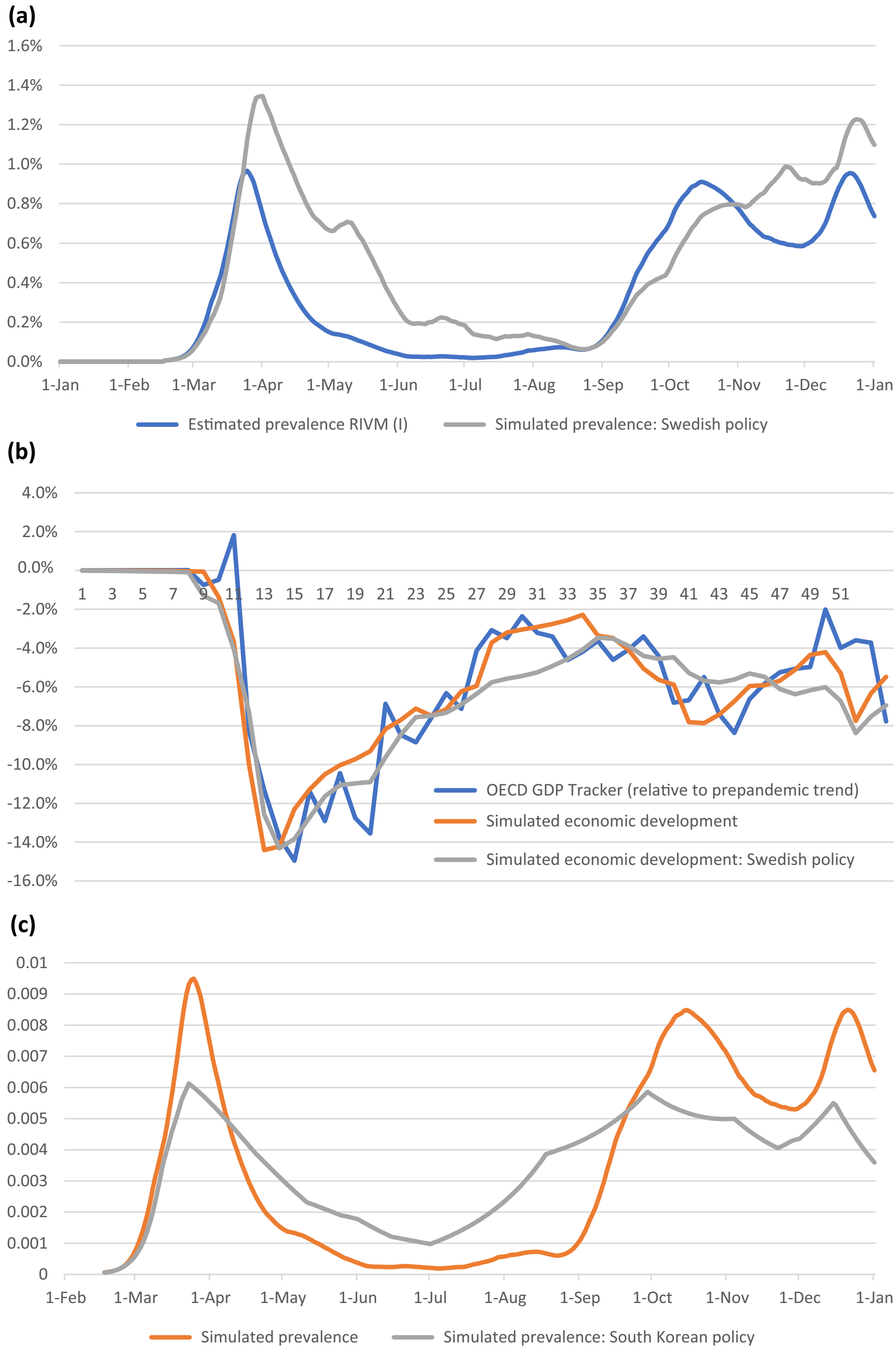

Figure 9. *Model estimates for alternative CHI of Sweden (a, b) and Korea (c, d) compared to base simulations and observed trends.*

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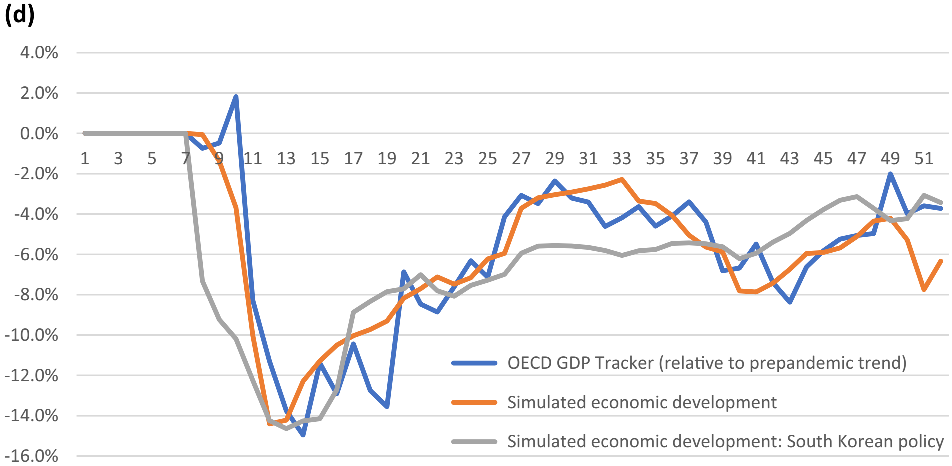

Figure 9. *(continued)*

shows limited effects during the first wave, and a very large secondary spike in COVID-19 prevalence. A large economic decline results, generated by behavioral responses to high infection rates. In the autumn of 2020, this effect would have dominated the favorable direct economic consequences of a less stringent policy. While excluding the measure (workplace closing) did reduce relative stringency slightly more during the second wave compared to the first wave, the effects are highly disproportional. This is the result of stringency during the first wave and a summer lapse. As infection rates climb, lacking the instrument of workplace closings (and putting nothing in to replace it – as we assume) shows the power of exponential growth. We also hypothesize that reduced policy adherence may be partly reflected in the unexplained part of the infectivity parameter, aggravating the effects of a less stringent policy during the second wave. This would be an interesting area for future research.

Table 4 summarizes the results in terms of the number of infected persons and economic damages in 2020. The results show that the sole SIR model is poorly equipped to estimate economic losses, and tend to overestimate the incidence of infections. The ERT model (excluding policy) better captures the tradeoffs between economic and epidemiologic activity, but tends to display marginal reductions in infections at significant economic loss. Adding policy measures tends to significantly reduce economic activity at limited gains in epidemic containment. The ERT model shows a large mismatch with observed trends. Our modifications show a significant improvement in overall fit, and a more realistic tradeoff over alternative policy scenarios. A complete cost–benefit analysis would require, besides estimating the costs of infectivity, incorporating additional policy effects (e.g. regular care delays, mental health effects of lockdowns and economic decline, etc.).

5. Conclusion and discussion

To explore the feasibility of Epi-econ models for evaluating alternative policy measures, we adopted the seminal Epi-econ model of Eichenbaum *et al.* (2021) to simulate the Dutch Epi-econ trends. We applied the Dutch parameters and updated existing parameters to the latest scientific insights. We found that the model performed poorly in simulating observed trends,

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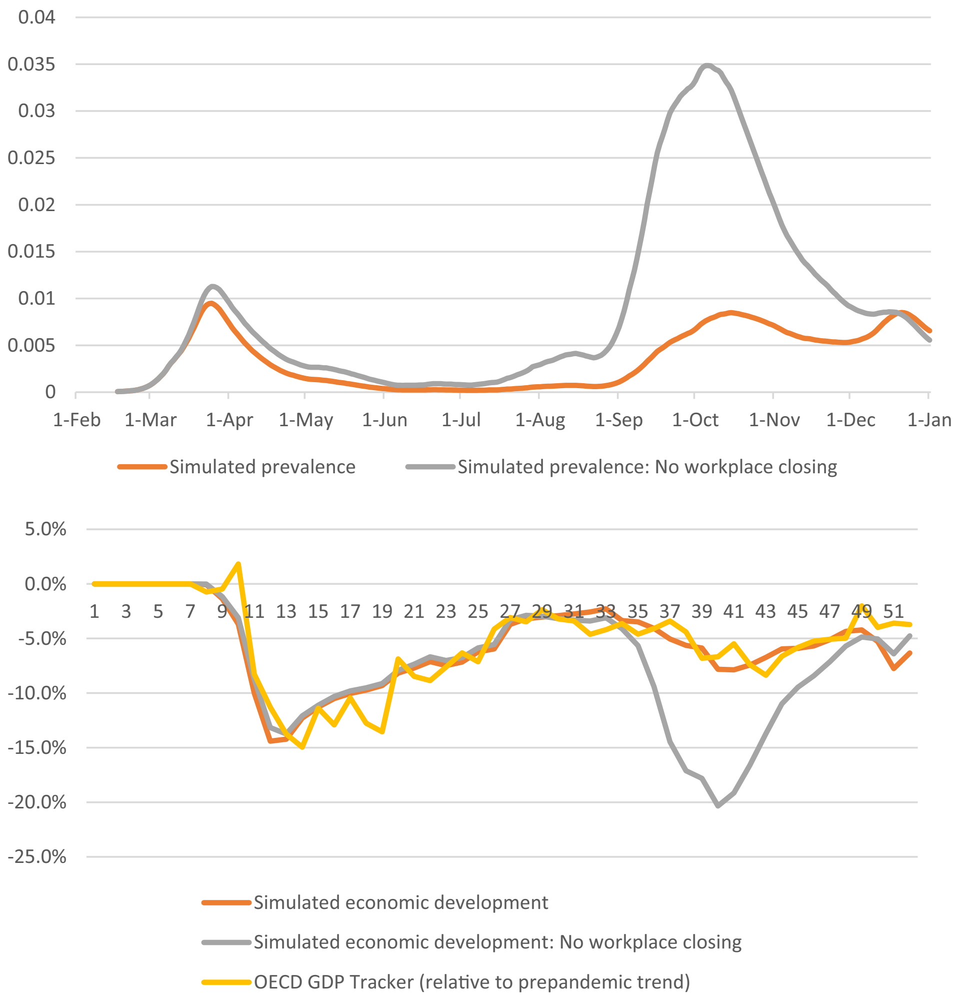

Figure 10. *Model estimates for a more lenient Dutch CHI (excluding workplace closings).*

and degrees of freedom in the model policy parameters were too small to generate realistic model outcomes. Subsequently, we systematically increased the flexibility of the model to improve fit, by first adding time flexibility to the policy parameters and, next, by adding time-variant policy influence on transmission parameters. This allowed for coupling the CHI to the model and incorporating policy responses related to voluntary mitigating behavior other than reductions in work and consumption. To further improve the model fit, linear regression estimation was used to isolate the effects of policy on transmission parameters. These rigorous alterations of the model did allow testing alternative policy scenarios in a realistic model setting with reasonable face validity. We found that a more stringent lockdown policy (e.g. as enacted by the Republic of Korea) would reduce peak prevalence and aggravate peak economic contraction, with little effect on overall trends. Conversely, more lenient lockdown policies (e.g. as enacted by Sweden) were estimated to increase peak and overall prevalence, with little effect on economic outcomes. This is due to two opposing

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Table 4. *Summary of model outcomes*

	Cumulative incidence (% of population)	Cumulative incidence (millions of infected)	GDP loss (% GDP)	GDP loss (billion euro)
Observed	15.5 %	2.70	−6.2 %	€ −51.4
SIR	87.0 %	15.14	−0.9 %	€ −7.5
EconSir	77.8 %	13.54	−5.1 %	€ −42.3
Full adjusted model, NL policy	17.6 %	3.06	−6.3 %	€ −52.3
Full adjusted model, SWE policy	28.8 %	5.01	−6.8 %	€ −56.4
Full adjusted model, KOR policy	15.1 %	2.63	−7.0 %	€ −58.1
Full adjusted model, lenient NL policy (excluding workplace closings)	38.1 %	6.63	−8.3 %	€ −68.9

forces: first, more lenient policies result in more economic activity. However, increased chances to become infected discourage economic activity. Too lenient measures, therefore, could rapidly increase overall infections and thereby harm the economy even more than stricter measures. The model allows qualitative appraisal of alternative policy scenarios and highlights complicated interrelations between economic and epidemiological trends. However, model validity declines for more impactful policy alternatives (e.g. workplace closings), as the nonlinear nature of the model makes it sensitive to underlying assumptions and parameter values, such as policy adherence.

These results are in line with other literature, finding a weak tradeoff between economic damage and infection rates and preferring stronger lockdowns (Flaschel *et al.*, 2021; Gallic *et al.*, 2022). Using a simple SIR model and a double sigmoid fitting methodology, Gallic *et al.* (2022) argue that the Netherlands and Sweden would have been better off employing a stricter lockdown policy such as that of Denmark's (Gallic *et al.*, 2022). Born *et al.* (2021) construct a counterfactual lockdown policy for Sweden, and find that a stricter lockdown would have reduced the number of deaths without significant effects on economic output. Alfano *et al.* (2022) find that the nonlinear effect on economic decline may be due to the limited capability of fiscal policy to counteract negative lockdown effects. Bognanni *et al* (2020) find that mitigation measures can have positive effects on both transmission and economic damage. Hsu *et al.* (2020) estimate real income losses of 30–37 % due to suboptimal policy in the context of the United States. Borelli and Góes (2021) apply the ERT model to the COVID-19 policy in Brazil, and found substantial divergence to the actual trends, relating to the initial percentage of infections, and the exclusion of modeling new strains. Applying DSGE economic modeling to OECD data, Cardani *et al.* (2021) find that lockdown effects are a predominant factor in explaining economic contraction. However, the authors do not distinguish between forced and voluntary lockdown behavior (Cardani *et al.*, 2021). Other authors also argue that no tradeoff between health and economic damage need to exist; for example, under specific conditions, quarantines can reduce both infections and economic damage (Goenka *et al.*, 2020). Strict social policy measures and targeted isolation may reduce both infections and damage due to shorter lockdown periods (Kahalé, 2020; Ash *et al.*, 2022).

However, a number of limitations apply. First, the model of Eichenbaum *et al.* (2021) employs a relative straightforward approach to model Epi-econ effects. For example, the SIR model employed by ERT does not account for the possibility of reinfection, international travel or viral mutations. More elaborate models are available to assess the epidemiological effects of policy measures for the Netherlands in isolation (e.g. see Ainslie *et al.*, 2022). However, it is an open question whether more advanced models have better predictive performance (Roda *et al.*, 2020). Furthermore, policy recommendations may require information on multiple interrelated outcome measures, necessitating more simplistic cross-over models. Policy recommendations also could benefit from multiple models to reduce potential idiosyncratic modeling errors (Ahn *et al.*, 2021). Ideally, the integration of specialized and generic models allows adequate incorporation of all relevant policy effects. Second, our model abstracts from fiscal policy or vaccination policies. Additional fiscal policy can reduce economic damage (Di Bartolomeo *et al.*, 2022). For example, many governments provided fiscal support to those affected by lockdown policies, to dampen long-term economic decline (Gatti & Reissl, 2020). Governments may respond to Epi-econ trends through supplementary fiscal support policies, adding a layer of complexity to the model (Siddik, 2020). The propensity of governments to provide fiscal support is likely to affect behavior, and thereby the economic and epidemiological effects of the lockdown policy. The same holds for expectations of vaccination availability and policy (Eichenbaum *et al.*, 2021; Fu *et al.*, 2022; Garriga *et al.*, 2022; Glover *et al.*, 2022; Iverson *et al.*, 2022). Third, additional information may be required to fully assess all costs and benefits of alternative policy measures. Outcomes, such as health effects due to delays in regular care, mental effects of lockdown policies, effects on education, investments, and long-term productivity, may differ between policy options and affect optimal policy (Dudine *et al.*, 2020; Oosterhoff *et al.*, 2023). Furthermore, the effects of biological changes to the severe acute respiratory syndrome coronavirus 2 virus over time (e.g. infectivity of different strains) are not taken into account. Fourth, behavioral responses are likely to be complex, being time-, context-, and path-dependent. For example, behavioral responses to mitigate infection risk may increase when the health system becomes crowded and accessibility is reduced (Hamano *et al.*, 2020). Moreover, policy compliance is likely to decrease over time. We find some evidence in our results on workplace closings that similar policy changes have highly divergent effects in different waves. Incorporating assumptions regarding declining attention to the epidemic over time was shown improve the model fit (Diez de los Rios, 2022). If future expectations are correlated to current policy measures, model outcomes may be biased. For example, a swift and strict policy response to the first wave may set a precedent for next waves and influence public expectations. Therefore, a strategy of temporal policy changes may increase effectiveness (Pataro *et al.*, 2021). We find that policy is relatively influential, contrary to some evidence suggesting the dominance of endogenous responses (Goolsbee & Syverson, 2021; Herby, 2021). Combined with the overestimations of the Epi-econ model, this could indicate an incomplete or insufficiently strong Epi-econ feedback loop. Additional research is required to distinguish between endogenous responses and policy responses (Hamilton *et al.*, 2024). Fifth, we used the CHI to model the lockdown policy under the assumption that equal changes in the CHI reflect equal-sized policy effects. The CHI is not necessarily constructed to fulfill this assumption, reducing the precision of the policy variable. However, to scale the CHI to reflect the relative size of the effect of each individual constituent policy is beyond the scope of this article. Furthermore, the effects of changes in the CHI may be nonlinear, irrespective of the underlying measures. We find evidence that larger changes in the CHI have a disproportionately larger effect. This implies that our linear approximation is mainly valid for small changes in the CHI, and for larger changes, more elaborate modeling is required. We also find that policy changes may have nonlinear effects on infectivity, although the effects at the margin seem limited. Possibly, the adjustment from weekly time steps to daily time steps in the model, combined with growth rates being modeled exponentially, could cause linear approximations to resemble nonlinear policy effects. Moreover, we assume that policy affects epidemic trends within the same time step, while the actual causal mechanism may cross multiple time steps and may include reverse causality. This is true for Epi-econ models in general. Finding the appropriate causal and temporal structure to incorporate policy measures in modeling is a promising area for future research. Last, we use the CHI of two countries as proxies for more lenient and more strict policies, while acknowledging that the CHI is a result of country-specific cultural, political, and behavioral factors. Any CHI applied to a different country is likely to produce different results. In this light, the alternative policy paths should be viewed as crude approximations that do not reflect any resemblance with the specific countries. Furthermore, it is not guaranteed that the alternative policy paths were compliant with the actual policy space of the Netherlands.

A number of potential lines of research could improve the applicability of Epi-econ models for policy evaluation. For example, the model does not stratify between important population groups, such as age groups or sectors, nor do they extent Epi-models with confounding factors such as international mobility, seasonal effects or path dependency. Differentiating between age, disease state, region, work status, employment and consumption sector, gender, or income groups could improve model validity (Campos *et al.*, 2021; Mahmoudi, 2022; Giagheddu & Papetti, 2023). Makris (2021) estimated an SIR model with multiple population groups and sectors. Other authors only use multiple age cohorts (Acemoglu *et al.*, 2020; Glover *et al.*, 2020; Jaouimaa *et al.*, 2021; La Torre *et al.*, 2022). Identifying unique groups with differing mechanisms relating infection and transmission to economic effects could improve model performance, but identifying these causal mechanisms is likely to be complicated. By incorporating "random noise," our modeling approach implicitly takes into account factors such as voluntary social-distancing behavior, as well as policy compliance, productivity at home, environmental influences, and other factors that can drive temporal variation in infectivity. However, these interactions remain implicit, and future modeling could benefit from explicit causal incorporation of these behavioral effects and policy interactions. Other potential additions include spatial modeling (Bisin & Moro, 2020, 2022; Bognanni *et al.*, 2020), uncertainty surrounding infectivity (Forsyth, 2020), and social learning (Davids *et al.*, 2023). While the model employed here has discrete time steps of a day, more elaborate infectious disease models are often specified in continuous time. Wacker and Schlüter (2020) show that a discrete-time SIR model has the same properties as a continuous-time SIR model, and that key variables (e.g. the R-number) also have a comparable interpretation (Wacker & Schlüter, 2020). Furthermore, any difference is always bounded, and decreases as the time steps of the discrete time SIR model are shorter. Alternatively, a fully empirical approach could be pursued, for example, to assume independence between Epi-econ trends and separately estimate the effects of policy measures. However, the complex, adaptive nature of both trends would likely reduce the validity of the outcomes when analyzed separately. In all cases, a common denominator needs to be constructed to compare health effects and economic effects. While COVID-19 infections could be converted to quality-adjusted life years, the incorporation of more general health effects requires additional efforts.

Despite the shortcomings, the adjusted Epi-econ model does produce policy-relevant insights. Different lockdown policy approaches would have significantly affected the epidemiological trends. More strict policies could have reduced peak prevalence, especially during the first wave. Here, timing is important to reduce both economic damage and health damage (Cross *et al.*, 2020). Pursuing a policy approach similar to that of Korea's in the Netherlands could have resulted in a more evenly distributed number of infections. Given the high strain on the Dutch healthcare system, especially during the first wave, this could have been a promising policy strategy. Especially as the model shows a weak tradeoff between epidemiology and economic development in this scenario, the expected economic decline is similar to the baseline scenario. Conversely, a less stringent policy approach similar to the Swedish strategy would have increased infection prevalence without a major effect on economic trends. Here, keeping the economy working is counterbalanced by increased disease prevalence and, as a result, endogenous reductions in economic activity. Given the large strain on the healthcare sector in the baseline scenario, a less stringent lockdown policy would have been likely undesirable, especially as the effects on the economy would have been minimal.

Differences between country lockdown policy responses were limited. When larger lockdown policy changes were assumed, for example, the removal of workplace closings from the Dutch CHI, large (negative) effects were obtained, showing nonlinear effects and high model sensitivity. However, the set of realistically attainable policy options may have been limited as well. Realistically attainable policy strategies may even be country-specific, suggesting that strategies employed by some countries may not have been a realistic option for other countries. Furthermore, uncertainty at the moment of decision-making should be taken into account (Barnett *et al.*, 2023). More research is needed to select policy options that are realistic and relevant alternatives for observed policies in a given country. The model is calibrated on the Netherlands, being a small, open economy. In theory, the model is generalizable to all countries that have sufficient data to calibrate the model. However, once calibrated, the model produces results unique to the specific country; different countries likely differ significantly in terms of epidemiological trends and policy effects.

To conclude, while Epi-econ models generate relevant insights into the interaction between Epi-econ trends, the models are ill-suited to quantitatively evaluate alternative policy options. We propose a number of fitting steps to improve the usability of Epi-econ models for this purpose, and show that the model can produce improved qualitative predictions of alternative policy effects. This could have significant benefits in policy evaluation: the adjusted model produced a more accurate estimate of economic damages and number of infected and a more realistic tradeoff between the two main outcomes. Additional steps are required to produce a valid quantitative prediction. Specifically, the challenge is to incorporate complex behavioral effects into relatively simple models. Furthermore, useful policy evaluation requires additional outcomes besides Epi-econ trends, such as the general health effects of the lockdown policy. The adjusted model could serve as a bridge model to connect more complex models that focus on a specific outcome (e.g. number of infected or economic activity). This could render a set of models that would enable a full assessment of costs and benefits of the lockdown policy. Nevertheless, using relatively simple adjustments to existing Epi-econ models, we show that the Netherlands could have benefited from slightly more stringent policy measures, especially during the first wave.

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A. Appendix A: Epi-econ model description

A.1. Epidemiological SIR model

The epidemiological SIR model describes how an epidemic spreads through a population (Weiss, 2013). It has four epidemiological stages: susceptible, infected, recovered, and deceased. Initially, the full population is susceptible, and then a small number of individuals become infected and start infecting others at reproduction rate R. Infected people either recover from their infection and enter the "recovered" category, or they die and enter the deceased category. A simplifying assumption is made that recovered people are unable to become infected again. The model of Eichenbaum *et al.* (2021) employed a time step of 1 week. To simulate the epidemic adequately, we use a time step of 1 day. The epidemiological SIR model can be described by the following equations:

$$S_{t+1} = S_t - T_t \qquad \text{(susceptibles)} \tag{A.1}$$

$$I_{t+1} = I_t + T_t - \pi_r I_t - \pi_d I_t \qquad \text{(infected; prevalence)} \tag{A.2}$$

$$R_{t+1} = R_t + \pi_r I_t \qquad \text{(recovered)} \tag{A.3}$$

$$D_{t+1} = D_t + \pi_d I_t \qquad \text{(deceased)} \tag{A.4}$$

$$T_t = \rho_t S_t I_t \qquad \text{(newly infected; incidence)} \tag{A.5}$$

$$\rho_t = \pi_1 c_t^S c_t^I + \pi_2 n_t^S n_t^I + \pi_3 \qquad \text{(transmission rate)} \tag{A.6}$$

Equation (A.1) states that the number of susceptible people (S_t) decreases by the number of new infections (T_t). In Equation (A.2), the number of newly infected people (I_{t+1}) is equal to the number of people infected in period t (I_t) plus the new infections (T_t), minus the recovered and deceased people. Infected people recover with a probability π_r per day or die with a probability π_d per day. This affects the number of people recovered (R_t; Equation (A.3)) and those who died (D_t; Equation (A.4)). The number of new infections (T_t) depends on the number of susceptible and infected people, mediated by the transmission rate (ρ_t) (Equation (A.5)). The model does not distinguish between different age groups, but it does distinguish three "settings" where infections occur, namely infections through consumption, through work and all other situations. The transmission rate depends on the chance of becoming infected during consumption (π_1), at work (π_2) or elsewhere (π_3). Equation (A.6) represents the average transmission rate (ρ_t) over the entire population ("macro transmission rate"). Through explicitly modeling the infection risk at work and during consumption, the Epi-model interacts with the economy: the more time people spend consuming or working, the faster the epidemic spreads through the population.

For further analysis, it is useful to define two additional quantities:

$$\tau_t = T_t/S_t = \pi_1\left[\left(c_t^S\right)\left(c_t^I I_t\right)\right] + \pi_2\left[\left(n_t^S\right)\left(n_t^I I_t\right)\right] + \pi_3 I_t \tag{A.7}$$

$$R_t^e = \frac{\rho_t S_t}{\pi_r + \pi_d} \tag{A.8}$$

τ_t is the so-called force of infection. It represents the risk of infection of a susceptible person. R^e is the reproduction number of the Epi-econ model.

A.2. Economic choice model

In the economic choice model, a representative consumer chooses work hours and consumption based on a representative utility function:

$$u_t^j = u\left(c_t^j, n_t^j\right) = \ln c_t^j - \frac{1}{2}\theta\left(n_t^j\right)^2 \tag{A.9}$$

The representative consumer faces a budget constraint that implies that to consume (c_t^j), income earned by working n_t^j hours is required. Spending is restricted by a budget restriction:

$$c_t^j = \frac{A n_t^j \phi^j + \Gamma_t}{(1+\mu_t)} \tag{A.10}$$

Here, A reflects someone's productivity, that is, wage. A simple representative business sector produces C_t consumer goods and services according to the production technology $C_t = AN_t$, with N_t the labor demand by companies. The representative company maximizes its profit $AN_t - w_t N_t$. From this follows $w_t = A$. The factor ϕ^j reflects productivity loss due to COVID-19 infections, where $\phi^S = \phi^R = 1$ en $0 < \phi^I < 1$. In addition, everyone receives a lump-sum benefit Γ_t. Disposable income ($A\phi^j n_t^j + \Gamma_t$) is taxed at the rate μ_t. By channeling the proceeds of the lump-sum tax back to consumers, the combination of μ_t and Γ_t acts as an approximation for the restrictive measures in the economy that the government is taking to slow down the spread of COVID-19.[9] This means that the government also has a budget restriction: $\mu_t\left(S_t c_t^S + I_t c_t^I + R_t c_t^R\right) = \Gamma_t(S_t + I_t + R_t)$. Finally, there is equilibrium in the labor market and in the market for goods and services.

People maximize their expected lifetime utility by choosing an optimal level of work and consumption in each period t. The expected lifetime utility of a susceptible person is given as:

$$U_t^S = u_t^S + \beta\left[(1-\tau_t)U_{t+1}^S + \tau_t U_{t+1}^I\right] \tag{A.11}$$

with β as the discount factor. Equation (A.11) states that the expected lifetime utility of a susceptible person is equal to the utility of a susceptible person in the current period (u_t^S), plus the expected lifetime utility from period t + 1 discounted to the current period t. With probability τ_t (see Equation (A.7)), a susceptible person will become infected. Becoming

[9] This may come across as a somewhat indirect way of modeling the partial closure of economic sectors to fight COVID-19. In a macroeconomic perspective, however, this works the same as placing restrictions on what you can and cannot consume, that is, the restrictions raise the shadow price of consumption. An explicit tax whose lump-sum revenue is recycled as an income works the same as an implicit tax or restriction on consumption.

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infected may reduce productivity during the period that a person is ill, and thus reduce consumption opportunities. Moreover, becoming infected may lead to death, which also reduces future consumption opportunities.

The expected lifetime utility of an infected person is given as follows:

$$U_t^I = u_t^I + \beta\left[(1-\pi_r-\pi_d)U_{t+1}^I + \pi_r U_{t+1}^R + \pi_d \cdot 0\right] \tag{A.12}$$

An infected person dies from COVID-19 with probability π_d and the expected lifetime utility of a deceased person is zero. In addition, with probability π_r, the infected person will recover. The probability that an infected person remains infected is $(1-\pi_r-\pi_d)$. The economic behavior of an infected person in the current period does not affect his future epidemiological status. Choices with regard to consumption and work of an infected person, therefore, only affect utility in the current period u_t^I.

Similarly, the current choices of recovered persons do not affect his future epidemiological status. The expected lifetime utility of a recovered person is given as follows:

$$U_t^R = u_t^R + \beta U_{t+1}^R \tag{A.13}$$

Because the representative consumer values future utility, susceptible individuals take into account that their economic activities (consuming and working) are associated with an increased likelihood of infection. Thus, even without policy intervention, it is expected that economic activity will decline when the infection rate increases. This also has consequences for the course of the epidemic. The drop in consumption and hours worked of susceptibles also leads to a drop in the macro transmission rate, and thus to a drop in the number of new infections T_t. These two mechanisms form the interaction between epidemiology and economics.

COVID-19 policy is incorporated into the model along two channels. First, preventative policies such as social distancing, washing hands, wearing face masks, and limiting group sizes lower the transmission parameters (π_1, π_2, π_3). Second, lockdown policies, such as closing parts of the economy, are modeled as an explicit tax on consumption (μ_t). This tax reduces the attractiveness of consuming, inhibits the level of economic activity, reduces the number of contacts in consumption and work, and thus slows down the epidemic.

B. Appendix B: Calculating the implied macro transmission rate

By combining prevalence with the SIR part of the Epi-econ model (Equations (A.1)–(A.8) of Appendix A), we can reverse calculate the macro transmission rate ρ. Next, rewriting Equation (A.2) as:

$$T_t = I_{t+1} - I_t + \pi_r I_t + \pi_d I_t \tag{B.1}$$

The first two terms at the right-hand side of Equation (B.1) are the prevalence on Day $t+1$ and the prevalence on Day t. We solve for the number of people recovering from infection on Day t using the calibrated value of π_r (0.124, see Table 1). As the number of recovered people (R) is zero at the start of the pandemic, the trend in the number of recovered people (R_t) in 2020 can be reverse calculated. Analogously, for the number of deaths, we use $\pi_r = 6.25 \times 10\text{E} - 4$.[10]

[10] In principle, we can also use the recorded number of Corona deaths. That would imply a time-varying π_d. Although interesting insights arise from that in itself (the CFR peaks at the beginning of the epidemic), a time-varying π_d has no significant effect on the development of prevalence.

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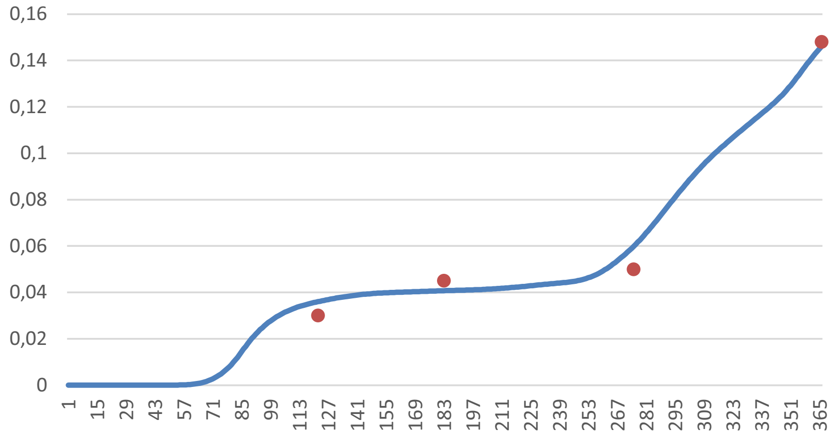

Figure B1. *The number of recovered persons (R_t) modeled (blue line) compared to official measurements (red). The x-axis shows the days of 2020.*

As a robustness check, we compare the implied recovery rate to the estimated seroprevalence from the different rounds of the Pienter Corona survey and end-of-the-year estimates from the RIVM (Figure B1). These external measurements are in accordance with the implied recovery rate from our model.

Next, we calculate the implied number of new infections (T_t, incidence), the population share of susceptible people (S_t), and the evolution of ρ_t in 2020. If we run the Epi-econ model with $\pi_1 = \pi_2 = 0$ (i.e. no interaction between the economy and the epidemic) with the observed macro transmission rate as input for π_3, then the model exactly simulates the observed prevalence and the simulated transmission rate is also equal to the observed macro transmission rate. After all, this is how the macro transmission rate is calculated.

C. Appendix C: sensitivity analyses

Figure C1 shows the results when $\pi_1 = \pi_2 = 0$, implying no feedback loop between epidemiology and the economy. The value of π_3 was adjusted to compensate for the omission of other transmission channels. As expected, prevalence is higher and economic decline lower, implying that the economy reduces infectivity through voluntary action at the cost of economic activity.

Next, we examine how the outcomes of the model change if we choose a lower value for the transmission rate (ρ), a lower value for the discount factor (β), a higher value for the productivity loss of infected (ϕ_I), a lower value for the removal rate ($\pi_r + \pi_d$), and a higher value for the CFR ($\pi_d/(\pi_r + \pi_d)$).

C.1. Transmission rate

Using the base reproduction rate of 1.5 of Eichenbaum *et al.* (2021) implies a transmission rate ρ of 0.1875. Using the best estimate of 2.3 for the Netherlands, a transmission rate of 0.2875 is obtained. A lower transmission rate reduces peak prevalence and economic damage (Figure C2a).

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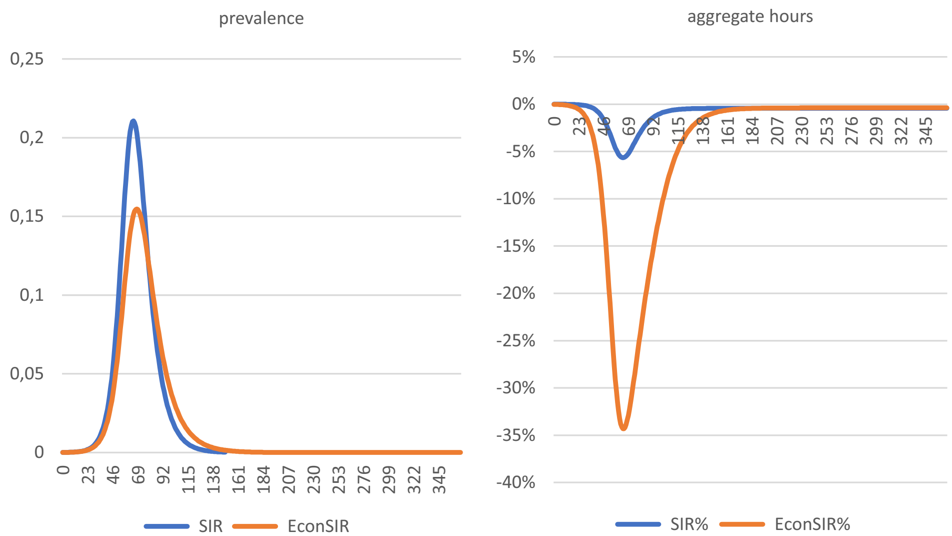

Figure C1. *The influence of interaction between epidemic and economy on economic and epidemiological development (the horizontal axis is the number of days since the start of the pandemic).*

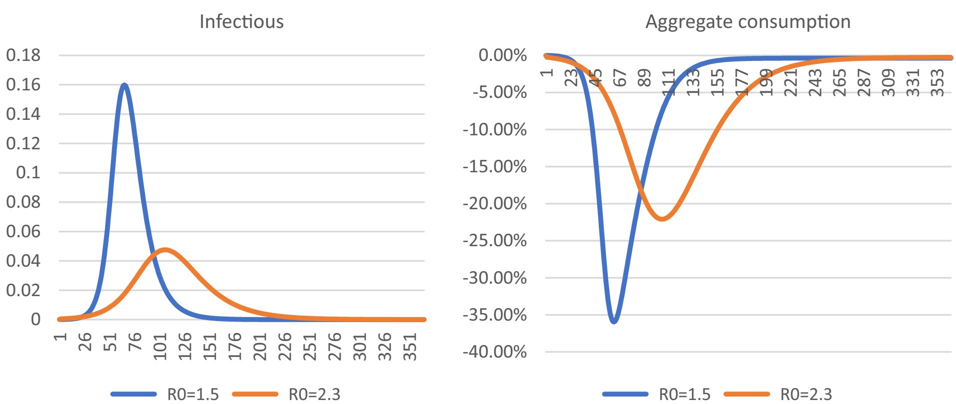

Figure C2. *Simulation of the number of infectious persons (a) and aggregate consumption (b) using a base reproduction rate of 1.5 compared to the baseline model. The horizontal axis is the number of days since the start of the pandemic.*

C.2. Discount rate

Using the original discount rate of 4 % from Eichenbaum *et al.* (2021) results in a less deep recession (Figure C3). It follows that the epidemic is somewhat more severe. The difference is small, implying a weak elasticity of the epidemiological growth to economic decline.

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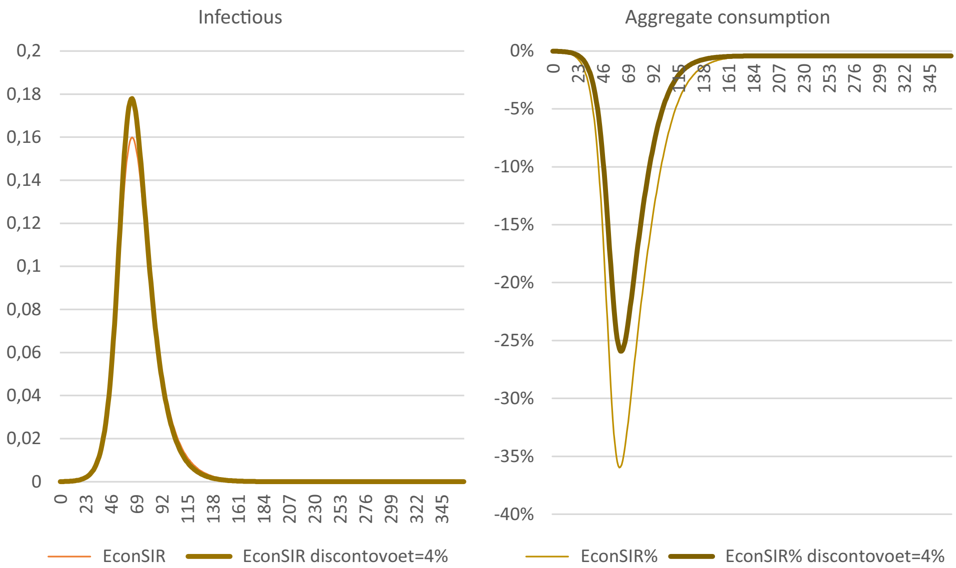

Figure C3. *Using a 4 % discount rate. The horizontal axis is the number of days since the start of the pandemic.*

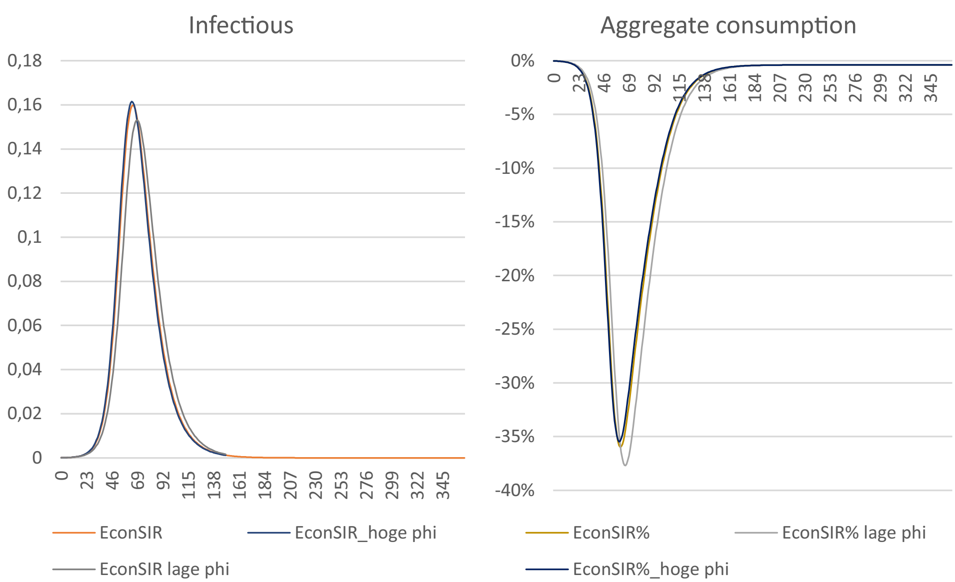

Figure C4. *Using productivity when infected of 0.5 and 0.8. The horizontal axis is the number of days since the start of the pandemic.*

C.3. Productivity loss of infected persons

The productivity loss of those infected (ϕ_I) is calibrated at 26 % for the Epi-econ model. A lower (20 %) or substantially higher (50 %) productivity loss when infected has a very limited effect on model outcomes (Figure C4). This is due to counteracting effects: on the

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one hand, a larger loss of productivity means that infected persons experience a larger consumption loss and a larger utility loss than in the original calibration. This implies that it becomes more costly for susceptible individuals to become infected. On the other hand, the reduced consumption of infected people also means that the probability of a susceptible person meeting an infected person reduces. Thus, the consequences of getting infected are more severe, but the probability of becoming infected is reduced (see Box C1 for details).

Box C1. *The influence of ϕ^I on* c_s*: an exercise in comparative statics.*

In this box, we analyze the effect of productivity loss of infected persons ϕ^I on the consumption of susceptibles c_s using comparative statics. For simplicity, we do not consider policy: $\mu_t = \Gamma_t = 0$. For notational convenience, we replace ϕ^I by ϕ. It is useful to note that in this box, we analyze an *increase* in ϕ ($d\phi$>0), which amounts to higher productivity of infected persons and fewer hours lost due to illness. Furthermore, in this box, we refer to Lagrange multipliers (the λ's). These reflect the shadow prices of the restrictions, such as budget constraints (λ_b for each consumer type S, I, or R) and the intertemporal restriction implied by the epidemic (λ_τ).

First, we assess how ϕ affects the behavior and utility of the infected persons. An infected person maximizes utility $u^I = \ln(c^I) - ½\theta(n^I)^2$ with a budget constraint $c^I = An^I$. First-order conditions are $n^I = c^I/\phi A$, $c^I = 1/\lambda_b{}^I$ en $\lambda_b{}^I = \theta n^I/\phi A$. This yields expressions for n^I, c^I , and $\lambda_b{}^I$ and their derivatives to ϕ:

$$c^I = \frac{\phi A}{\sqrt{\theta}} \Longrightarrow \frac{dc^I}{d\phi} = \frac{A}{\sqrt{\theta}}, \quad n^I = \frac{1}{\sqrt{\theta}} \Longrightarrow \frac{dn^I}{d\phi} = 0, \quad \text{and} \quad \lambda_b^I = \frac{1}{A\phi\sqrt{\theta}} \Longrightarrow \frac{d\lambda_b^I}{d\phi} = -\frac{1}{A\phi^2\sqrt{\theta}}$$

Rearranging implies that $du^I/d\phi = 1/\phi$. Lifetime utility $U^I{}_t = u^I{}_t + \beta(1-\pi_r-\pi_d)U^I{}_{t+1} + \beta\pi_r U^R{}_{t+1}$ implies that $\frac{dU_t^I}{d\phi} = \frac{1}{\phi[1-\beta(1-\pi_r-\pi_d)]} > 0$ is time independent (NB $dU^R/d\phi = 0$). Using these insights, we turn to susceptibles. First-order conditions and their derivatives to ϕ are:

$$\frac{1}{c^S} = \lambda_b^S - \lambda_\tau \pi_1 I c^I \Longrightarrow \frac{dc^S}{d\phi} = -\left(c^S\right)^2 \frac{d\frac{1}{c^S}}{d\phi} = -\left(c^S\right)^2 \left[\frac{d\lambda_b^S}{d\phi} - \frac{d\lambda_\tau}{d\phi}\pi_1 I c^I - \lambda_\tau \pi_1 I \frac{dc^I}{d\phi}\right],$$

$$n^S = \frac{c^S}{A} \Longrightarrow \frac{dn^S}{d\phi} = \frac{1}{A}\frac{dc^S}{d\phi},$$

$$\lambda_b^S = \frac{\theta n^S - \lambda_\tau \pi_2 I n^I}{A} \Longrightarrow \frac{d\lambda_b^S}{d\phi} = \frac{\theta}{A}\frac{dn^S}{d\phi} = \frac{\theta}{A^2}\frac{dc^S}{d\phi}, \quad \text{using} \frac{dn^I}{d\phi} = 0 \quad \text{and}$$

$$\lambda_\tau = \beta\left(U_{t+1}^I - U_{t+1}^S\right) \Longrightarrow \frac{d\lambda_\tau}{d\phi} = \frac{\beta}{\phi[1-\beta(1-\pi_r-\pi_d)]} - \beta\frac{dU_{t+1}^S}{d\phi}$$

Substitution of the expression for $\frac{d\lambda_b^S}{d\phi}$ in $\frac{dc^S}{d\phi}$ yields $\frac{dc^S}{d\phi} = -\left(c^S\right)^2 \frac{\theta}{A^2}\frac{dc^S}{d\phi} + \left(c^S\right)^2 \left[\frac{d\lambda_\tau}{d\phi}\pi_1 I c^I + \lambda_\tau \pi_1 I \frac{dc^I}{d\phi}\right]$. Define $\sigma = \frac{\left(c^S\right)^2}{1+\left(c^S\right)^2\left(\frac{\theta}{A^2}\right)} > 0$[a]. It follows that $\frac{dc^S}{d\phi} = \sigma\left[\frac{d\lambda_\tau}{d\phi}\pi_1 I c^I + \lambda_\tau \pi_1 I \frac{dc^I}{d\phi}\right]$.

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The second term within the square brackets of this last expression shows how a change in the consumption of infected persons affects the consumption of susceptible people. This effect is negative because $\lambda_\tau < 0$. In other words, a higher ϕ leads to a higher consumption by infected persons ($\frac{dc^I}{d\phi} = \frac{A}{\sqrt{\theta}} > 0$), which suppresses the consumption of susceptibles. And that, in turn, is because higher consumption of infected persons increases the likelihood of infection through the consumption channel, which will make susceptible people more cautious.

The first term within the square brackets shows that a higher ϕ reduces the expected loss of utility ($\lambda_\tau = \beta\left(U^I_{t+1} - U^S_{t+1}\right)$) due to infection ($\frac{d\lambda_\tau}{d\phi} > 0$). This stimulates the consumption of susceptibles as the cost of getting infected decreases.

In short, a rise of ϕ increases the risk of becoming infected ($c^S \downarrow$) but reduces the consequences ($c^S \uparrow$). Which of these two counteracting effects dominates overall is an empirical matter. To our knowledge, conclusive empirical evidence is still lacking.

[a]Please note that σ is not a constant but we suppress the time index to simplify notation.

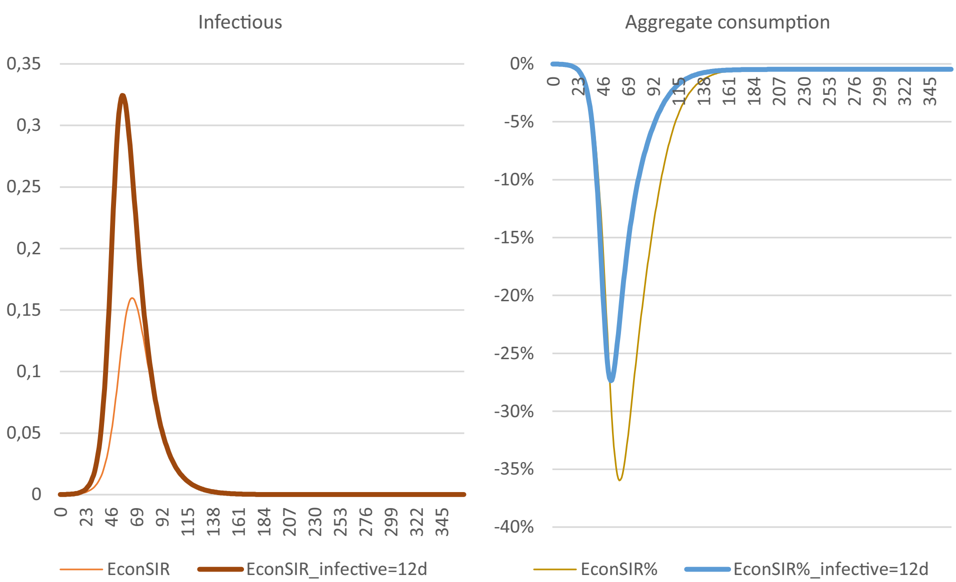

Figure C5. *The effect of a longer infectious period (12 days instead of 8 days). The horizontal axis is the number of days since the start of the pandemic.*

C.4. Removal rate

The removal rate is calibrated at 1/8, which signifies that an infected person stays infectious for 8 days on average and then recovers or dies. Figure C5 shows the effect of an increase in mean infectivity from 8 to 12 days, as assumed by Eichenbaum *et al.* (2021). A significant increase in peak prevalence results, while the economic effects are smaller. The reason for this is that although there are more infected persons, which increases the likelihood of

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becoming infected in general, but because infected persons work and consume less, the chance of getting infected while consuming or working is actually less.

C.5. Case fatality rate

The CFR is calibrated at 0.5 %, c.q. Eichenbaum *et al.* (2021). A higher CFR reduces peak prevalence at the cost of a bigger recession (Figure C6). This is because the cost of contracting an infection is now greater and, therefore, people are scaling back their economic activities of their own accord.

C.6. Disaggregation of endogenous effects and policy effects

Figure C7 shows the effects of (a) epi only, (b) Epi-econ and (c) Epi-econ + policy, with equal parameters otherwise. This allows gauging the relative contribution of policy on outcomes. Figure C7a shows that mean annual infections were 1.90, 1.71 and 0.35 %, respectively, indicating that policy contributed 87 % to the reduction in infectivity, and endogenous responses contributed 13 %. Figure C7b shows that mean annual consumption declined by −0.85, −4.62, and −13.50 %, respectively. This translates to policy contributing 70 % to economic decline and endogenous responses contributing 30 %.

D. Appendix D: nonlinear policy effects

To assess the effect of nonlinear policy effects at the margin, we evaluate the derivatives ($d\rho$/dCHI) at CHI 2020 data mean, median, and double-sided 10 and 25 % intervals.

Table D1 suggests that, compared to the quadratic model, the linear model overstates effects of policy somewhat. It also interesting to note that the quadratic model hardly differentiates across the spectrum of policy interventions in terms of its effect on outcomes.

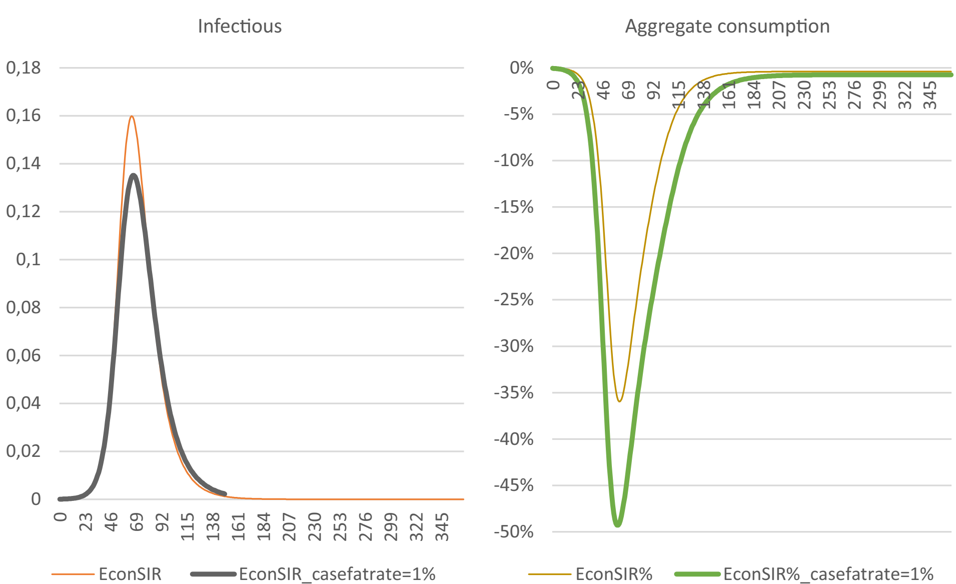

Figure C6. *The impact of a higher case fatality rate. The horizontal axis is the number of days since the start of the pandemic.*

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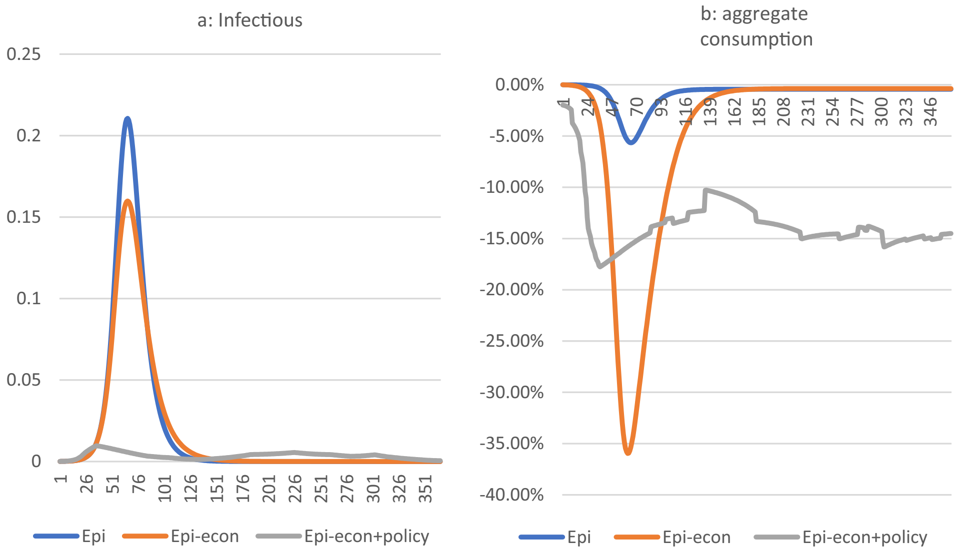

Figure C7. *Simulation of the number of infectious people (a) and aggregate consumption (b), comparing the epi-model with the epi-econ model void of policy and the epi-econ model including policy measures .*

Table D1. *Effect of CHI on ρ for different models at different positions in the frequency distribution of CHI*

		Derivative of CHI		
	Population values	1. Linear effect only	2. Squared nonlinear effect	3. Exponential nonlinear effect
Regression equation		−0.004	−0.001 to 0.00357 CHI/100	0.003–0.00472 $e^{\mathrm{CHI}/100}$
CHI mean	0.527	−0.004	−0.003	−0.005
CHI median	0.566	−0.004	−0.003	−0.005
10 % interval	0.435	−0.004	−0.003	−0.004
25 % interval	0.499	−0.004	−0.003	−0.005
75 % interval	0.625	−0.004	−0.003	−0.006
90 % interval	0.637	−0.004	−0.003	−0.006

Also interesting is that the exponential specification implies a slightly more responsive reaction of outcomes to policy and with responses higher at the higher end of the interventions. Differences are small across the spectrum. The different nonlinear approaches point to higher or lower elasticities compared to a linear model.

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