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The Common Interests of Health Protection and the Economy: Evidence from Scenario Calculations of Covid-19 Containment Policies

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The Common Interests of Health Protection and the Economy: Evidence from Scenario Calculations of Covid-19 Containment Policies

Abstract

We develop a novel approach integrating epidemiological and economic models that allows databased simulations during a pandemic. We examine the economically optimal opening strategy that can be reconciled with the containment of a pandemic. The empirical evidence is based on data from Germany during the Sars-Cov-2 pandemic. Our empirical findings reject the view that there is necessarily a conflict between health protection and economic interests and suggest a non-linear U-shape relationship: it is in the interest of public health and the economy to balance non-pharmaceutical interventions in a manner that further reduces the incidence of infections. Our simulations suggest that a prudent strategy that leads to a reproduction number of around 0.75 is economically optimal. Too restrictive policies cause massive economic costs. Conversely, policies that are too loose lead to higher deaths tolls and higher economic costs in the long run. We suggest this finding as a guide for policymakers in balancing interests of public health and the economy during a pandemic.

JEL-Codes: C150, C540, C630, I150, I180, I190.

Keywords: Covid-19, optimal strategy, economy, deaths, integrated simulations, real-time analysis.

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A preliminary version was prepared for policy advisory purposes during the first Covid-19 wave in Germany during April and May 2020. This article elaborates on further analyses and simulations, discusses the underlying methodology, and provides guidance on how to conduct data-driven analyses in real-time during a pandemic crisis.
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Author contributions: MMH, CF, FD and MS designed the research. FD and MMH took the lead in writing the draft, with support and revisions by all authors. All authors contributed to the analysis and interpretation of the results. MS and SK prepared the final figures and tables. AP, FD, MS, TW, and SL developed the economic model and wrote the economic results. The model is based on earlier work by TW that was extended for the purposes of this study by MS. MS was responsible for the empirical implementation and simulating the policy scenarios. TW and SL estimated economic activity. PV prepared the raw data for the epidemiological model. BL provided epidemiological input for the epidemiological model and scenarios described here. TM and MMH developed the epidemiological model. SK, SB, and MMH designed the epidemiological scenarios, and SK performed the epidemiological simulations. SK, SB, and MMH interpreted and wrote the epidemiological results.

The common interests of health protection and the economy: Evidence from scenario calculations of COVID-19 containment policies

Introduction

The SARS-CoV-2 pandemic confronts the world with a rapid spread of infections and deaths associated with COVID-19. Several governments have used or are still using non-pharmaceutical interventions (NPIs) such as social distancing regulation, prohibition of public events, school closures, or restrictions of business activity to slow down and contain the pandemic. Evidence suggests that these measures indeed reduce the number of infections (1–3). At the same time, the pandemic and shutdown measures give rise to substantial economic costs (4, 5).

In the public debate, interests of public health and the economy are often presented as being in conflict (6, 7). Although this trade-off view may seem intuitive, evidence on medium- and long-run economic consequences of past epidemics suggests that an unregulated spread of a virus with larger disease burden can also have adverse effects on the economy (8–10). New infection waves, e.g. due to accelerated loosening of restrictions, could cause a large rise in absenteeism from work due to illness and could reduce trust of consumers and investors. As consequence, companies would have to shut down or to reduce their business activities again – regardless of government regulations – resulting in considerable further costs. Conversely, stricter regulations may also give rise to indirect disease burden in other areas (11). The aim is to make the fight against the pandemic sustainable and to reconcile public health and economic objectives (12).

An increasing number of studies on NPI strategies concludes that immediate shutdowns and health policy interventions is the most favorable strategy (10, 13–16). A separate question in the public debate, however, is about the optimal shutdown duration, and the timing and speed of the phasing-out of NPIs (17, 18). A conflict between health protection and economic interests arises if a strategy with lower economic costs leads to significantly higher death numbers. Such a conflict would be particularly challenging if the reduction of economic costs requires a rapid opening process. Yet, previous studies using integrated macroeconomic and epidemiological models conclude that limiting the spread of the virus is the economically optimal reopening policy (19–22). We add to this literature by examining economically optimal exit strategies that can be reconciled with public health.

We provide a novel simulation approach integrating epidemiological and economic models that allows data-driven real-time analysis during a pandemic. Using data on infection dynamics and industry-specific economic activity during the first shutdown in Germany in spring 2020, our simulation results suggest that it can be advantageous for both health and the economy to keep the effective reproduction number of infections well below one. We find that economic costs as a function of the reproduction number follow a U-shape: both an extensive opening strategy as well as a further tightening of the measures would have lead to higher economic costs compared to a prudent opening strategy with a reproduction number of around 0.75.

Our results are based on a particular time and country – SARS-CoV-2 epidemic in Germany during spring 2020 – with a given set of NPIs that have been implemented. Our quantitative results should be seen in this context, and the

optimal strategy in other pandemics, time periods or countries may be different. But the qualitative conclusion remains: our study shows that public health and the economy are not necessarily in conflict, with a non-linear relationship between the reproduction number of the virus and economic output. It is in the interest of the economy to balance NPIs in a manner that keeps the epidemic under control and further reduces the incidence of infections. Conversely, policies that are too loose also lead to higher economic costs in the long run. We suggest this finding as an orientation for policy-makers in balancing interests of public health and the economy during a pandemic.

Methods

Using Germany as a case study. We use the first COVID-19 wave and shutdown in Germany to calibrate our models. Germany's strategy during the first wave in spring 2020 with comparatively few deaths and low economic losses compared to other countries was discussed as a best practice example from an international perspective (23). Germany introduced several restrictive measures in March 2020 to contain the spread of the virus: the NPIs included travel restrictions, restrictions on gatherings, the cancellation of events, the closure of schools and universities, hotels, bars and restaurants, the recommendation of home-office and hygiene rules, as well as the ordered shutdown of several social service providers and the stationary retail industry (excluding grocery stores). Some federal states introduced curfews. The sum of these measures – and of behavioral adjustments – reduced the spread of the virus. Figure 1 plots the time-dependent reproduction number, R_{t}, and an NPI stringency index (the latter plotted with a lag of 14 days to account for the delayed impact of NPIs on the reproduction number). The stringency index is constructed from principal component analysis of all NPIs on the federal state level (24). Fig. 1 shows that, with a lag of two weeks, the stringency of Germany's first shutdown appears to inversely track R_{t}. The reproduction number fell well below one in April, and the number of daily new reported cases decreased noticeably during the shutdown. On April 20th, a gradual loosening of the restrictions was announced. With a lag of two weeks, R_{t} increased at the beginning of May.

Combining methods from epidemiology and economics to estimate the impact of reopening. The status quo of our scenario calculations represents the situation of R_{t} and economic activity in the initial shutdown phase until the gradual opening process started on April 20th. Starting from the status quo, we simulate various scenarios for a further loosening or tightening of the shutdown measures. We model the death toll and economic activity as a function of R_{t}, using an empirical relationship between R_{t} and activity at the industry sector level as well as the time until the economy fully recovers. In the model, different shutdown policies are associated with different R_{t} values; more relaxed (restrictive) restrictions yield larger (smaller) R_{t} values, implying a longer (shorter) period until the containment of the epidemic is completed. A longer period due to more relaxed restrictions is associated with larger death tolls but also with higher economic activity in the short run. However, larger R_{t} values imply that daily new infections decrease slowly (or increase) and the time until full opening of the economy is extended.

Our scenario calculations are based on a novel and unique combination of epidemiological and economic simulation models (see *SI Appendix* for detailed description). The models are connected in two ways. First, we associate the R_{t} estimates from the epidemiological model with corresponding economic activity levels in different industries for two time periods. The first time period refers to the end of the initial shutdown, and the second to the period after the implementation of several step-by-step relaxations of NPIs. That way we estimate slopes for the (linear) relationship between the severity of shutdown restrictions (R_{t}) and the corresponding activity levels for each industry. Second, the epidemiological model yields the estimated duration until the epidemic situation allows the full opening, which marks the beginning of a recovery phase in the economic model.

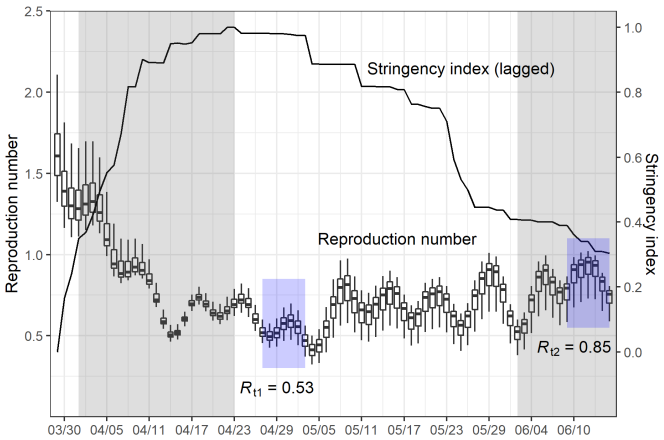

Fig. 1. Reproduction number and NPI stringency in Germany. The boxplots illustrate the distribution of the R_{t} estimates for each date (median, 25 and 75 percentile) following the model described in *SI Appendix, pp. 4–10*. The error bars denote 1.5 times the interquartile range. The stringency index is given as the first principal component from a principal component analysis based on all NPIs on the federal state level in Germany and is plotted with a lag of two weeks. Information on the NPIs are taken from the Corona Data Platform (https://corona-datenplattform.de), released by the Federal Ministry for Economic Affairs in Germany. The shaded grey areas indicate the survey periods for the ifo Business Survey in April and June 2020. The shaded blue areas indicate the time window that was used to calculate the reference R_{t} values in the status quo before and after the impact of gradual lifting of NPIs.

The reproduction number depends on the severity of shutdown restrictions. In a first step, we employ a mathematical-epidemiological model with Susceptible-Exposed-Carrier-Infected-Recovered (SECIR) components to estimate the development of R_{t} in Germany (see Fig. 1, (3), and *SI Appendix*). The estimates are based on a dynamic adaptation of the model parameters to the incidence reporting database of the Robert Koch Institute (RKI), the German government's central scientific institution for monitoring the situation on SARS-CoV-2. We specify $R_{\mathrm{t}1} = 0.53$ as reference value that refers to the estimated reproduction number in Germany just before the partial lifting of the NPIs on April 20th (Fig. 1, left blue area). Similarly, we specify $R_{\mathrm{t}2} = 0.85$ as reference value that refers to the reproduction number after the partial lifting, thus capturing the effect of lifting the NPIs on R_{t} (Fig. 1, right blue area).

Severity of shutdown determines time until control of epidemic allows full reopening. A key assumption in our analysis is that reducing the number of new infections to 300 reported

cases per day (corresponding to an incidence of 2.5 infections per 100'000 inhabitants in 7 days), would allow to fully control the epidemic through contact tracing and isolation by the approximately 400 public health offices in Germany. The remaining restrictions limiting economic activities could be completely lifted thereafter.

In a prospective study, we assume different values of R_t to reflect the severity of the shutdown restrictions and keep these values constant in the respective scenarios until the threshold of 300 daily new infections per day is reached, determining the duration of the shutdown. The fewer restrictions are imposed, the longer the restrictions need to be kept in place to reach the threshold (Figure 2B). Thus, a larger reproduction number delays a control of the epidemic. Importantly, the reproduction number impacts the period required to reach the threshold non-linearly. In addition, we consider a scenario where R_t is kept at one until a vaccine is available at large scale to vaccinate all relevant groups. In the baseline scenario, we assume that the vaccine becomes available at a large-scale on July 31st, 2021.

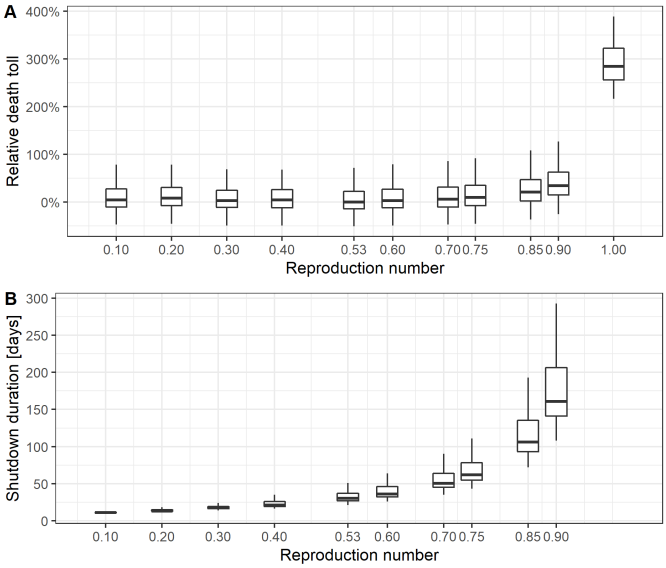

Fig. 2. **(A)** Estimation of the relative death toll accumulated between April 20th, 2020 and July 31st, 2021 with the epidemic model, in percentage difference to the median value in the reference scenario ($R_t = 0.53$). The reproduction number on the abscissa was fixed in the simulation from April 20th, 2020 until reaching 300 daily new cases per day and then set to one. **(B)** Estimation of the shutdown duration needed to reach 300 new reported cases per day for each fixed reproduction number, starting on April 20th. The boxplots illustrate the distribution of the estimates (median, 25 and 75 percentile). The error bars denote 1.5 times the interquartile range.

Economic activity depends on shutdown restrictions and speed of full reopening. In a second step, we integrate the results from the SECIR model into the economic model and simulate the economic costs at the industry level for different policy scenarios. The costs of a scenario are given as the aggregated loss of economic activity during the shutdown and economic recovery period after full reopening.

Fig. 3A illustrates the process in the economic model for the scenario where the policy-makers tolerate an increase of R_t from 0.53 to 0.85 on April 20th. This refers to the change in the reproduction number and economic activity that was empirically observed over that period of time in Germany. The model assumes that the economy starts from a pre-shutdown activity level and experiences a decline due to the shutdown imposed in March 2020. Activity levels of different industries in response to the shutdown are determined by the status quo before the exit process started on April 20th. Prior to reaching the required 300 new cases per day allowing full reopening, our model assumes that policy-makers can decide on the further course of severity of restrictions in a period of partial opening. Loosening restrictions would ceteris paribus increase economic activity in the partial opening phase (see Fig. 3A). However, it would also give rise to higher R_t values, thus increasing the duration of this phase (see Fig. 2B). Conversely, tightening restrictions would lead to a reduction in economic activity, but reduce R_t and the time needed until the number of new infections would allow a full opening. The economy slowly recovers once all shutdown measures can be fully lifted without jeopardising the containment of the epidemic because either a sufficiently low number of new infections is reached or a vaccine is available. At the end of the recovery phase, the economy returns to its pre-crisis activity level.

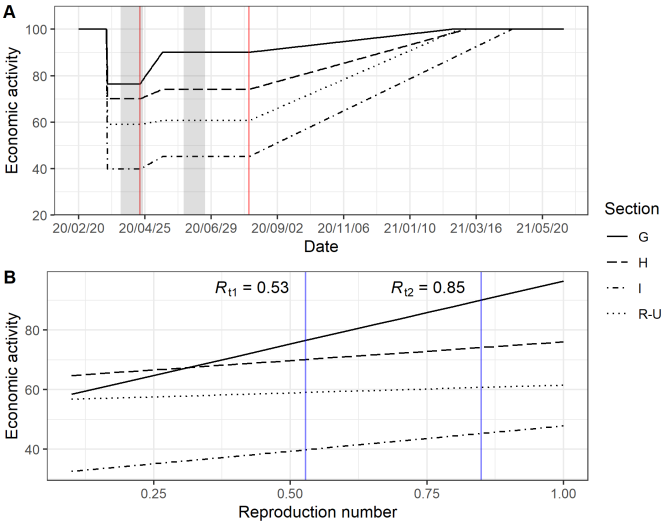

Fig. 3. **(A)** The process of economic activity for the scenario where the policy-makers increase R_t from 0.53 to 0.85. Starting from the pre-shutdown level (normalized to 100), the economy experiences a decline in activity during the shutdown. On April 20th, the policy-makers initiated a gradual lifting of NPIs (indicated with the first vertical red line). After the 300 daily new cases have been reached, the measures are lifted and the economy enters the recovery phase (indicated with the second vertical red line). The beginning of the recovery phase depends on the R_t value and the associated time period in Fig. 2B). Depicted are the activity levels for the economic sections G (wholesale and retail trade), H (transportation and storage), I (accommodation and food service activities), and R to U (entertainment and other service activities). The shaded grey areas indicate the survey periods for the ifo Business Survey in April and June. A more in-depth description of the model can be found in the supplement (see Fig. S4). **(B)** The linear relationships between changes in industry-specific economic activity and changes in the reproduction number. The vertical blue lines indicate the R_t values 0.53 and 0.85 that are used to estimate the slope.

Estimates of economic activity during shutdown. The estimates of economic activity are based on the ifo Business Survey, a monthly survey that includes roughly 9,000 responses from German firm managers in manufacturing, the service sector, trade, and construction (25, 26). Managers base their responses predominantly on information derived from their own business activities (26). During the pandemic, this informa-

tion also includes potential health-related issues, e.g. if there was a negative effect of infections on the workforce. We use the firms' assessment of their current business situation as it is highly correlated with the gross value added and several official economic activity measures (see *SI Appendix, Tab. S3 and Fig. S5*) (27).

We relate firm responses during the survey periods to different shutdown and partial opening periods as well as the corresponding R_t values from the SECIR model (see Fig. 1). Specifically, we assume a linear relationship between R_t and changes in economic activity for each industry using the April and June surveys and the corresponding reference reproduction number values, $R_{t1} = 0.53$ and $R_{t2} = 0.85$. The April survey captures the activity levels in each industry during the shutdown before partially lifting restrictions, whereas the June survey captures the activity levels after the lifting process (see *SI Appendix, Fig. S2*).

Heterogeneity and industry-specific impact of shutdown strategies. Fig. 3B shows the industry-specific linear relationship between the reproduction number and economic activity, and illustrates that elasticities in economic activity are heterogeneous across industrial sections. For example, lifting shutdown restrictions gives rise to a larger increase of economic activity in retail (G) compared to transportation industries (H). Moreover, gradual lifting of measures was more restrictive for the entertainment industries (e.g., events) and other social service activities (R–U).

Not all industries in Germany were directly affected by legal shutdown measures. The manufacturing industry or electricity firms, for example, were not included in any state order to shut down their business activities in Germany. However, these industries also experience large slumps in activity because of declined domestic and foreign demand, disrupted supply chains, or absences from work due to illness and/or quarantine. In our simulation model, we thus distinguish between exogenous and endogenous industries (see *SI Appendix, Tab. S2*). The former refer to the industries that are exogenously shut down by the government and are treated as illustrated in Fig. 3B. These include, amongst others, firms in retail trade, accommodation and food services, transportation, entertainment and recreation, and several other social service activities. Changes in activity levels in endogenous industries such as the manufacturing sector, however, are not closed by shutdown measures but affected by changes in the economic output of the treated exogenous industries. We exploit inter-industry linkages and use input-output tables for the German economy to specify to what extent the activity level in one industry is affected by changes in other industries (28). That way our approach only considers changes in economic activity of the endogenous industries that are driven by changes in treated (exogenous) industries.

We introduced a special question in the ifo Business Survey where respondents were asked about the expected duration until their business situation would return to normal once all shutdown measures are lifted. For the reference scenario ($R_t = 0.53$), we take the mean of these expectations for each industry to calibrate our model (see *SI Appendix, Tab. S4*). We assume that it takes the firms two months less to fully recover in the scenario with $R_t = 0.85$ compared to the reference scenario. That way we construct a data-based linear relationship between R_t and the time to recover to the pre-crisis level for different industries (see recovery phase in Fig. 3A).

In a globalized world, changes in NPIs and economic developments in other countries may affect domestic export-oriented industries. The manufacturing industry in Germany, which contributes about a quarter to the economic output, is particularly affected in that respect (29). We implicitly control for the effect of the developments abroad by holding the shutdown and recovery duration for endogenous sectors constant across our domestic policy scenarios. By doing so, any effects from other countries on export-oriented industries are the same in each policy scenario. Industries treated by our domestic policy scenarios, by contrast, only have a minor share in German exports (see *SI Appendix, Fig. S7*). As such, the *relative* comparison of scenarios' costs are robust to other countries' developments.

Results

Estimated COVID-19-associated death toll. Starting from the partial easing of NPIs after the first shutdown in Germany on April 20th, the calibrated simulation model projects the number of expected additional COVID-19 deaths until July 31st, 2021. The death toll rises with increasing reproduction numbers, although the differences are relatively small up to $R_t = 0.75$ and stay within a range of 10% additional deaths relative to the reference scenario with $R_t = 0.53$ (Fig. 2A). In contrast, the death toll rises sharply from $R_t = 0.9$ onward due to non-linearities. Expected additional deaths increase to around 300% compared to the reference scenario when following a policy at $R_t = 1.0$.

The long-term economic costs are minimal at intermediate reproduction numbers. The total economic costs of the scenarios result from the aggregated loss of economic activity among all industries over the years 2020-2022. Fig. 4A shows the development of aggregated activity in our policy scenarios as deviations from the pre-crisis activity level (normalized to 100). For instance, the scenario with $R_t = 0.1$, i.e. where the policymakers further intensify the shutdown, would further reduce economic activity. On the other hand, lifting the restrictions such that the reproduction number increases to one gives rise to larger economic activity thereafter. However, some restrictions have to be kept in place for such a long time that the pre-crisis economic activity level is not reached before 2022. Fig. 4B shows the relative costs for all scenarios compared to the reference scenario ($R_t = 0.53$). The relative costs are given as the percentage differences in total loss of economic activity. The results show that both a strategy with extending high levels of restrictions ($R_t < 0.53$) and a strategy with too aggressive loosening of measures ($R_t > 0.9$) would lead to higher relative economic costs. Compared to the strategy of keeping restrictions of the initial shutdown period ($R_t = 0.53$), costs decrease in a strategy of a slight loosening of restrictions. The long-term economic costs are minimal if the reproduction number is around 0.75.

Common interest of economy and health. We cannot identify a conflict between the economy and health protection in relation to a strong relaxation – the costs would be higher in both dimensions. Accelerated opening leads to substantially more COVID-19 deaths and increased economic costs. Our findings clearly challenge statements which suggest exit strategies

with R_t values close to one to be economically preferable (21). While strong opening policies would allow for more economic activity in the short term, our simulations suggest that the long duration of remaining restrictions would increase relative economic costs compared to alternative gradual opening strategies.

Our results suggest that a balanced strategy is in the common interest of health protection and the economy. The scenario calculations show that a slight, gradual lifting of shutdown restrictions which keeps reproduction numbers at an intermediate level and which allows to further reduce infection numbers in a significant manner is suitable to reduce the economic losses without jeopardizing medical objectives.

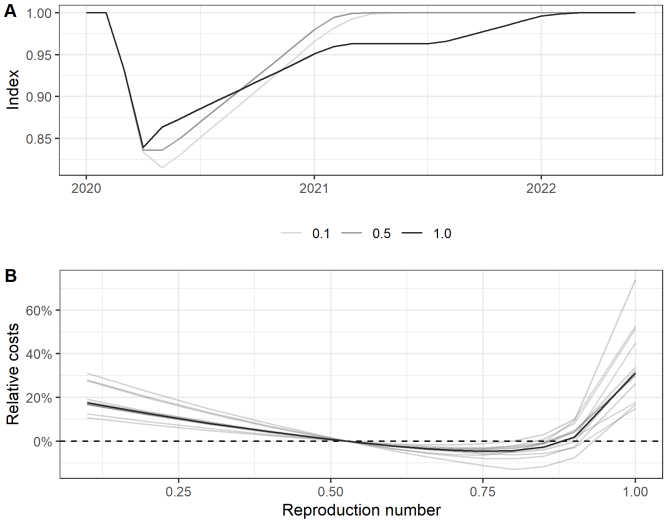

Fig. 4. (**A**) Overall economic activity over time for three baseline policy scenarios (denoted by their respective reproduction numbers, 0.1, 0.5, and 1.0). Pre-crisis economic activity is normalized to 100. (**B**) Relative costs for each policy scenario, in percentage difference to the reference scenario ($R_t = 0.53$). Economic costs are given as the aggregated loss of activity occurring as a result of the shutdown and recovery phase. The bold line indicates the baseline scenarios; the shaded grey lines indicate the results of the robustness tests. The numeric values can be found in the *SI Appendix, Tab. S3*.

Robustness of results suggests general applicability. Clearly, generalization of our results beyond Germany and across time is limited to comparable regions, situations and given NPIs. The relationship between economic activity and the reproduction number might not be the same across world regions. Moreover, the shutdown duration and final death toll are influenced by the number of new infections at the point of entering or changing shutdown measures. However, our results are robust to several sensitivity tests in assumptions regarding the relationship between the shutdown severity and economic activity, affected industries of exogenous shutdown restrictions, the duration of economic recovery, and the number of daily new cases that needs to be reached to control the epidemic. We also tested the sensitivity of our assumption on the time of large scale availability of a vaccine (see *SI Appendix, Tab. S5*).

The assumption of a linear relationship between shutdown levels and economic activities is clearly a simplification in our simulation model, although the slope of our linear relationship is based on observed data. Our robustness tests include simulations with (non-linear) isocost-curves that indicate how severely the linear assumption needs to be violated for our results to no longer be valid. The results show that it would require implausible assumptions of extreme non-linearities to invalidate our findings (see *SI Appendix, Fig. S6*). All robustness tests can be found in the supplement (*SI Appendix, Tab. S5*). Our inferences do not change. Minima of relative economic costs are between R_t values of 0.7 and 0.8 in all sensitivity tests (see light grey lines in Fig. 4B).

Discussion

We consider the qualitative statement of our results to be robust and of general nature. It is in common interest of health and the economy to implement opening policies with prudent steps and to closely monitor the respective reaction of the infection figures. Our conclusion is in line with retrospective studies of the influenza epidemic in 1918 in the USA (13, 30), and current economic studies supporting a strategy to manage the COVID-19 pandemic (19, 20). We show that it is also in the interest of the economy to balance non-pharmaceutical interventions in a manner that further reduces the incidence of infections. By contrast, NPI policies that are too loose could cause higher economic costs in the long term. We provide an additional guideline for policy-makers whether extending or easing restrictions minimizes long-term economic costs once the effective reproduction number is already below one. Using counteracting measures – such as face masks, behavioral rules, improved trace and isolation techniques, new technologies and increased testing – may limit the spread of the virus or even may help to contain the pandemic (16, 31–36) and thus creates leeway for larger opening and economic recovery. The level of economic restrictions thus depends to a large extent on technical improvements and behavioral adjustments of the population until a vaccine or effective medical treatment is available at large scale for all in need.

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Supplementary Information (SI) for

The common interests of health protection and the economy: Evidence from scenario calculations of COVID-19 containment policies

This PDF file includes:

Supplementary text

Figs. S1 to S7 and Tables S1 to S5

SI References

Supporting Information Text

Background: Containment policy in Germany during the first shutdown

In order to contain the spread of the COVID-19 epidemic in Germany, the national and federal state governments introduced restrictive measures in several stages since March 2020. These included the banning of major events, the closure of schools and day-care centres, the forced shutdown of numerous companies in the retail, catering and many (social) services sectors, and the introduction of mobility and contact restrictions (with more or less strict curfews). In addition, many companies reduced their business activities in order to protect their employees or due to reduced demand. Citizens also adapted their behavior due to the new risk situation and information policies. The sum of these measures and behavioral changes appears to have influenced the reproduction rate in Germany: R_{t} fell well below one and the number of registered new infections per day decreased during the shutdown (see Fig. S2). At the same time, however, the consequences of the COVID-19 pandemic and the shutdown measures have plunged the German economy in Q2/2020 into what is by far the deepest recession in its post-war history (1).[*] Since the German containment strategy in the spring SARS-CoV-2 wave seems to have been successful and the feared scenarios of casualties in Germany have so far failed to materialise, a growing public community called for faster loosening of restrictions in all areas. On April 20th 2020, a conference of the national and state governments agreed on a gradual, step-by-step loosening of the shutdown measures.[†]

Materials and Methods

Mathematical-epidemiological model. The development of infection dynamics has been addressed by a number of mathematical approaches based on differential equation models (7) and agent-based models (8). Our SECIR model is a deterministic ordinary differential equations (ODEs)-based model in which different stages of the infection and associated viral spreading are considered. The model structure and parameter ranges were chosen according to the specific properties of SARS-CoV-2 viral infections. The model comprises of compartments representing the individuals susceptible (S) or exposed (E) to the virus, asymptomatic carriers ($C_{\mathrm{I,R}}$) which may become symptomatic ($I_{\mathrm{H,R,X}}$), hospitalized ($H_{\mathrm{U,R}}$) or in the need of intensive care $U_{R,D}$. Infected individuals have terminal fate of recovery ($R_{\mathrm{Z,X}}$) or death (D). The carrier compartments refer to an infection state of an individual without symptoms who is able to transmit the disease to susceptible individuals, and later may or may not develop any symptoms. In this state, the transmissibility of the virus can be significant as the individual is not aware of the disease and could actively make contact with susceptible individuals. Therefore, the presence of such a compartment is crucial in the models for SARS-CoV-2 (9). A schematic representation of the model is shown in Fig. S1A. The model equations read

[*] It can be assumed that an unhindered spread of the virus would also have been associated with very high economic and health costs.

[†] The actual death toll for Germany counts around 4,500 registered COVID-19 deaths on April 20th, around 6,500 two weeks later at the beginning of May, around 8,500 at the beginning of June, and around 9,000 at the beginning of July 2020. Germany has a population of around 83 million (2). The death toll corresponds to relative numbers of around 5.3 deaths per 100k inhabitants (April 20th), 10.2 (June 1st), and 10.8 (July 1st). In comparison, two months after the start of relaxations, relative death rates have been around seven times larger in the UK, around five times larger in Sweden, and around four times larger in the USA (3–6).

$$\frac{dS}{dt} = -R_1(t)\frac{(C_I + C_R + I_X + \beta(I_H + I_R))}{N}S, \quad [1]$$

$$\frac{dE}{dt} = R_1(t)\frac{(C_I + C_R + I_X + \beta(I_H + I_R))}{N}S - R_2E, \quad [2]$$

$$\frac{dC_I}{dt} = (1-\alpha)\,R_2E - R_3C_I, \quad [3]$$

$$\frac{dC_R}{dt} = \alpha R_2E \; - R_9C_R, \quad [4]$$

$$\frac{dI_H}{dt} = \mu\rho(t)R_3C_I - R_6I_H, \quad [5]$$

$$\frac{dI_R}{dt} = \mu\,(1-\rho(t))\,R_3C_I - R_4I_R, \quad [6]$$

$$\frac{dI_X}{dt} = (1-\mu)\,R_3C_I - R_4I_X, \quad [7]$$

$$\frac{dH_U}{dt} = \vartheta(t)R_6I_H - R_7H_U, \quad [8]$$

$$\frac{dH_R}{dt} = (1-\vartheta(t))\,R_6I_H - R_5H_R, \quad [9]$$

$$\frac{dU_D}{dt} = \delta(t)R_7H_U - R_{10}U_D, \quad [10]$$

$$\frac{dU_R}{dt} = (1-\delta(t))\,R_7H_U - R_8U_R, \quad [11]$$

$$\frac{dR_Z}{dt} = R_4I_R + \; R_5H_R + \; R_8U_R, \quad [12]$$

$$\frac{dR_X}{dt} = R_9C_R + \; R_4I_X, \quad [13]$$

$$\frac{dD}{dt} = R_{10}U_D. \quad [14]$$

The rates $R_{2,\ldots,10}$ denote the inverse time of transition between the respective states and were inferred from the literature. Parameter R_1 is fitted to the course of reported case numbers in a sliding time window and, therefore, is a time-varying parameter. Parameter β determines the interaction intensity of infectious symptomatic individuals (I_H and I_R) with the susceptible population. Parameters α, μ, ρ, ϑ and δ denote fractions of individuals toward a particular fate. A complete description of the parameters' definition and value sets is given in (10). Parameters ρ, ϑ and δ have a time-varying component modelled with a logistic function

$$\rho = \rho_0\sqrt[3]{k(t)/\bar{k}}, \quad \vartheta = \vartheta_0\sqrt[3]{k(t)/\bar{k}}, \quad \delta = \delta_0\sqrt[3]{k(t)/\bar{k}}, \quad [15]$$

$$k(t) = H - (H-L)\left(\frac{1}{1+e^{-k_0(t-t_0)}}\right), \quad [16]$$

where t corresponds to the time of the year starting from January 1st 2020, $\bar{k} = \rho_0\vartheta_0\delta_0$, $H = 0.156$, $L = 0.011$, $k_0 = 0.25$, and $t_0 = 89$ are obtained from fitting the case fatality rate (CFR) ($k(t) = \rho\vartheta\delta$) which changed over the course of the epidemic in Germany. This is due to changing testing frequencies and the shifting age structure of the infected over time (11); therefore, the CFR is not completely reflecting a change in the fatality rate of the virus. The uncertainty in the parameter values was incorporated into the analysis by repeated (100 times) random sampling within the plausible ranges and obtaining the distributions of model variables.

The basic reproduction number (R_0) is defined as the expected number of secondary cases produced by a single infection in a susceptible population and is a constant characteristic of viral dissemination dynamics in a passive community. However, the dynamics of the epidemic may be under the influence of multiple time-dependent factors such as change in the individual behavior in response to policies or public awareness. Therefore, a time-dependent reproduction number (R_t) describing the expected number of secondary cases per index case at a given time of the epidemic is a more relevant quantity for an active community and reflects the multi-factorial impact of non-pharmaceutical interventions (NPIs), behavioral changes, seasonal effects, etc. on the dynamics of viral spread.

Herein, the temporal evolution of R_{t} was obtained by re-fitting the model in a sliding time-window of the data which was shifted throughout the duration of the epidemic (see Fig. S1B). This method allows to adapt the model parameter R_1 that is associated with NPIs in order to fit the data, which cannot be achieved by a fixed parameter value. The value of R_{t} corresponding to the k-th time-window is calculated based on the fitted value of R_1 by

$$R_k = R_{1,k}\frac{S_k}{N_k}\left[\frac{1-\alpha}{R_3} + \frac{(1-\alpha)\left[\beta\mu\left(1-\rho_k\right) + (1-\mu)\right]}{R_4} + \frac{\beta\mu\left(1-\alpha\right)\rho_k}{R_6} + \frac{\alpha}{R_9}\right], \quad [17]$$

where $\rho_k := \rho(t_k)$ denotes the average value of the time-varying parameter and $R_{1,k}$ is the fitted value of R_1 in the k-th time-window, $S_k := S(t_k)$ and $N_k := N_0 - D(t_k)$ are related to the first time point in the k-th time-window, and N_0 is the total population at the beginning of the epidemics. The reproduction number in (17) is derived from the SECIR model (14) using the next generation matrix method (12, 13). The cumulative reported case number is compared to the sum of infected and detected individuals, i.e. with $I_H + I_R + H_U + H_R + U_R + U_D + D + R_Z$. The parameter R_1 is estimated for each time window of 7 days using Nelder-Mead simplex algorithm (14) (see Fig. S1B).

Plausible ranges of the parameters were estimated from the literature to account for their uncertainty (see Table S1). The parameter values were then randomly sampled within these ranges 100 times to derive a quasi-empirical distribution of the R_t value.

For simulating prospective dynamics of the epidemic from a defined starting date, the state condition of the model based on available retrospective data was calculated. Then, the development of model variables was obtained by imposing fixed R_1 values corresponding to different R_ts of interest (see Fig. S1C). The assumed prospective R_ts values can be linked to different degrees of strictness of the imposed measures.

Time until new infections are under control. Following Khailaie et al. (10), we assume that the approximately 400 health authorities in Germany have sufficient capacities to control 300 new cases per day through contact tracing and isolation. For the bundles of measures with varying severity, we calculated the time it takes to reach a maximum of 300 new reported cases per day (Fig. 2B) and the number of projected COVID-19 deaths (Fig. 2A). This was calculated by obtaining the daily influx of cases to the infected and recovering compartments I_H and I_R. The analysis was also repeated for capacities of 200 and 400 new cases per day in our robustness tests to reflect the sensitivity of the impact of different assumptions in the capacity of health authorities. Once the respective assumed threshold is reached, an R_t value of 1 and a targeted isolation of identified newly infected and their contacts ($\beta = 0$) were assumed. These assumptions keep the number of new infections around the target value. Alternatively, we have considered a scenario in which the current daily infection rates are kept constant until the earliest realistic availability date of a vaccine for the entire population, i.e. R_t is assumed to be at value of 1.

The calculated duration shall be interpreted as the further time necessary to retain the shutdown or restrictive measures. Based on the reduction in economic output in the various economic sectors on April 20$^\mathrm{th}$, 2020, and the R_t value corresponding to the shutdown period (i.e. in the status quo before the first relaxation of measures on April 20$^\mathrm{th}$, 2020), the costs of maintaining the shutdown or restrictive measures until reaching 300 (or 200 or 400) new reported cases per day were estimated for each assumed scenario with $R_\mathrm{t} < 1$. For the scenario of $R_\mathrm{t} = 1$, we assume that there will be restrictive measures until a vaccine becomes generally available. The Paul Ehrlich Institute[‡] estimated in spring 2020 that combined Phase II/III trials of a vaccine could start in autumn/winter 2020. First emergency approvals were indeed licensed at the turn of the year. However, it will take several more months until the vaccine will be available at a sufficient number. For our scenario, we therefore assumed this date to be July 31$^\mathrm{st}$, 2021. In our sensitivity tests, we assume the vaccine to be available at a large scale 120 days earlier or later compared to the baseline assumption.

NPIs and their impact on R_t. In order to quantify the impact of lifting measures, we assumed a 2-weeks time delay from a person being exposed to the virus to becoming symptomatic and reported in the database. For the first openings in Germany on April 20$^\mathrm{th}$, 2020, the reporting delay assumption implies that a person exposed on the first day of lifting measures will be reported on May 4$^\mathrm{th}$. However, as the R_t value reported on each date includes the impact of 6 other days in the data retrospectively (see Fig. S1B), the R_t value calculated on May 4$^\mathrm{th}$ is biased by cases exposed before April 20$^\mathrm{th}$ (6 out of 7 data-points). With a similar reasoning, the R_t values calculated in the period of May 4$^\mathrm{th}$-May 9$^\mathrm{th}$ are contaminated with infected cases before April 20$^\mathrm{th}$, 2020. Therefore, the impact of the openings on April 20$^\mathrm{th}$ shall be inferred from May 10$^\mathrm{th}$ at the earliest. Since the obligation of wearing masks was imposed very shortly after the first openings, we considered them as a bundle of NPIs. Following the reporting delay assumption, the impact of the NPIs bundle on the R_t value is expected from May 19$^\mathrm{th}$ at the earliest. In order to take into account the seasonality observed in the data and the R_t values in the calculation of NPI impacts, we considered a pooled set of R_t values in the 1-week period of May 19$^\mathrm{th}$-May 25$^\mathrm{th}$ (see Fig. S2 and S3).

The R_t value corresponding to the complete shutdown (before April 20$^\mathrm{th}$) was calculated by excluding the contaminated period (May 4$^\mathrm{th}$-May 9$^\mathrm{th}$), following a similar reasoning. Therefore, we considered the R_t values at the latest possible week, the period of April 27$^\mathrm{th}$-May 3$^\mathrm{rd}$. The impact of the second nationwide lifting of measures was calculated by pooling the latest available week at the time of this analysis (see Fig. S2 and S3).

Economic model and empirical implementation.

Modelling economic costs. The economic costs of scenario s are given as the aggregated loss of activity occurring as a result of the shutdown. Denote y_m^s as the economic activity compared to the pre-shutdown level in scenario s and month m, with $0 \leq y_m^s \leq 100$. $y_m^s = 100$ refers to the pre-shutdown activity level, and $y_m^s = 0$ to an economy with zero production. Total costs of scenario s can be written as:

$$C^s = \sum_{m=1}^{M} 100 - y_m^s,$$

[‡] The Paul Ehrlich Institute is a German research institution and medical regulatory body, and is the German federal institute for vaccines and biomedicines.

where M is the time horizon under consideration, i.e. the total number of months that are taken into account in the analysis. Denote C^{ref} as the cost of a reference scenario. The relative costs of s are then given as $\Delta C^s = (C^s/C^{ref}) - 1$, such that $\Delta C^s > 0$, indicates scenarios with higher costs and lower aggregate economic activity compared to the reference.

The key challenge is to model y_m^s. We assume that $y_m^s = 100$ prior to the implementation of the measures, $0 \leq y_m^s \leq 100$ during the shutdown and the recovery phase, and $y_m^s = 100$ after the recovery phase. In other words, starting from the pre-shutdown activity level, activity drops during the shutdown, and recovers once the measures are lifted until the economy has returned to its pre-epidemic activity level.

Taking into account that the impact of the shutdown varies across industries, we explicitly model activity at the industry level. Denote $y_m^{s,j}$ as the activity for scenario s, month m, and industry j. y_m^s is then given as the average of each industry-specific activity, weighted by the share of the industry in total output, denoted as α_j:

$$y_m^s = \sum_{j=1}^{J} \alpha_j y_m^{s,j},$$

where J is the total number of industries in the economy.

For each s and j, the process of $y_m^{s,j}$ over m is modelled as follows. Denote $y_d^{s,j}$ as the activity on day d, with $0 \leq y_d^{s,j} \leq 100$ and $d \in \{1, \ldots, D\}$, where D is the last calendar day in the last year of observation. $y_m^{s,j}$ is given as

$$y_m^{s,j} = \frac{\sum_{d=1}^{D} y_m^{s,j} I_d^m I_d^w}{\sum_{d=1}^{D} I_d^m I_d^w} \times 100,$$

where I_d^m is an indicator variable equal to one if calendar day d belongs to calendar month m, and zero otherwise. Similarly, I_d^w indicates whether the calendar day is a working day or not (i.e. whether it falls on a weekend or a public holiday). This notation implies that the distribution of holidays across the calendar year is relevant for the cost of a scenario. That is, the shutdown is less costly when it is in place during months with few working days.

Furthermore, denote B as the calendar day when shutdown measures were implemented first, S as the day when a new policy is introduced (changing the severity of the measures), and $R^{s,j}$ as the day when the measures are lifted. $R^{s,j}$ is determined by the epidemiological model and describes the calendar day during which a certain daily case number has been reached. The superscripts indicate that there is heterogeneity across scenarios and industries. After the introduction of the new policy at S, the economy adjusts over the period $s^{s,j}$, after which the new activity level is reached. After the prescribed number of new infections is reached and the shutdown is fully lifted, i.e. for $d > R$, the economy slowly recovers and returns to its pre-shutdown activity. We assume that economic activity increases linearly from S to $S + s^{s,j}$ and from $R^{s,j}$ to $R^{s,j} + r^{s,j}$. $r^{s,j}$ denotes the industry-specific duration of the recovery period (in calendar days). For each day d, the activity in each scenario s and sector j is then given as follows:

$$y_m^{s,j} = \begin{cases} 1 & \text{for } d < B \\ y^{b,j} & \text{for } B \leq d < S \\ y^{b,j} + (d - S + 1)\frac{y^{s,j} - y^{b,j}}{s^{s,j}+1} & \text{for } S \leq d < S + s^{s,j} \\ y^{s,j} & \text{for } S + s^{s,j} \leq d < R^{s,j} \\ y^{s,j} + (d - R^{s,j} + 1)\frac{1 - y^{s,j}}{r^{s,j}+1} & \text{for } R^{s,j} \leq d < R^{s,j} + r^{s,j} \\ 1 & \text{for } d \geq R^{s,j} + r^{s,j} \end{cases}$$

$y^{b,j}$ and $y^{s,j}$ refer to the activity after the first introduction of shutdown measures and after the policy change, respectively. Figure S4 illustrates the process of $y_d^{s,j}$ over d.

Implementing the economic model. Implementing the economic model requires estimates for $y^{b,j}$, $y^{s,j}$, $R^{s,j}$, and $r^{s,j}$. B, S, and $s^{s,j}$ are determined exogenously. For our application, we specify March 19th, 2020 as the introduction date of the shutdown measures (i.e. $B = 79$). S refers to April 20th, when the national and state governments agreed on a gradual, step-by-step loosening of the shutdown measures (i.e. $S = 111$). $s^{s,j}$ is set to 21. That is, we assume that it takes an industry three weeks to adjust and reach the new activity level. The specification of $s^{s,j}$ is arguably ad-hoc, but the results are robust to different specifications. $R^{s,j}$ is estimated with the SECIR model and refers to the number of days until the infection numbers allow full opening. The recovery speed depends on the reproduction number R_{t}. In general, a higher (smaller) R_{t} value is associated with a higher (smaller) $R^{s,j}$,

Estimates for $y^{b,j}$, $y^{s,j}$, and $r^{s,j}$ are obtained from the ifo Business Survey, a long-running monthly panel survey of roughly 9,000 German firms (15) which covers the most important industries of the German economy as defined by the NACE Rev. 2 classification.[§] Economic activity, $y^{b,j}$ and $y^{s,j}$, is approximated by the companies' assessment of their own current business situation, which they can describe as "good", "satisfactory", or "poor". According to a meta survey, the information used by managers to assess their business situation is mainly firm-specific (16). Respondents of the ifo Business Survey view their profit

[§]The survey excludes public services (public administration, defence, compulsory social security, education, human health and social work activities) summarized by sections O, P and Q, as well some small industries which play virtually no role for economic fluctuations (A: agriculture, forestry and fishing; B: mining and quarrying; D: electricity, gas, steam and air conditioning supply; E: water supply, sewerage, waste management and remediation activities; K: financial and insurance activities; U: activities of extraterritorial organisations and bodies). Public services account for 18.2% of total gross value added, the other excluded industries for 7.8%.

situation, demand, sales, and orders as most important for determining their business situation, while economic policy and industry or economy-wide sentiments are considered less relevant. The responses are summarized as balance statistics, which are calculated as the difference in the percentage shares of the responses "good" and "poor".

The main advantage of the survey-based measures is that they are available on a monthly basis and with no publication lag. Table S2 shows that traditional activity measures (gross value added and turnover) are only published either on a quarterly basis (if at all), or with a substantial lag. During a pandemic, where timely data availability is paramount for real-time analyses and decision-making under uncertainty, gross value added and turnover are inferior compared to the business situation from the ifo Business Survey.

This notwithstanding, the survey-based measures must show a high correlation with the traditional measures of activity provided by the Federal Statistical Office of Germany (17). To show this, we run the following regressions for each industry j:

$$\Delta \ln(Y_{j,t}) = c_0 + c_1 \Delta B_{j,t} + \varepsilon_{j,t},$$

where $B_{j,t}$ denotes the ifo business situation and $Y_{j,t}$ gross value added in quarter t. Industries are aggregated to the level of economic sections (i.e. the one-digit level). The results of the regressions are summarized in Table S3; Figure S5 visualizes the results for the first column, i.e. the overall economy.[¶] Most of the elasticities of gross value added with respect to the ifo business situation (c_1) are positive and statistically significant, implying that changes in the business situation are sufficiently precise and timely indicators for current output changes.

While $y^{b,j}$ is constant across all scenarios, $y^{s,j}$ is allowed to vary. We start by normalizing the activity level of the model prior to the shutdown on March 19th to zero. The activity prior to the shutdown refers to the average of the balance statistics of the business situation in January and February 2020. We refer to this as the baseline business situation. To obtain an estimate of $y^{b,j}$, for each industry, we first compute the difference between the balance statistic of the business situation during the shutdown in April 2020 and the baseline business situation (see Table S4). We then apply the following transformation to the balance point differences, ensuring that $0 \leq y^{b,j} \leq 100$:

$$y^{b,j} = \frac{x^{b,j} + 200}{200} \times 100,$$

where $x^{b,j}$ are the balance point differences. Note that the balance point differences are not meant to reflect absolute differences of gross value added. Instead, they indicate the relative degree to which industries are hit during the shutdown and how they perform thereafter. The transformation such that $y^{b,j}$ is between 0 and 100 captures the intuition that economic capacity can range from zero to full capacity.

The activity level after the introduction of the new policy, $y^{s,j}$, is estimated in several steps. We first calculate the difference between the balance statistic of the business situation in June 2020 and the baseline business situation (see Table S4), and again apply the transformation described above. This yields the change in economic activity that is associated with the gradual lifting of the shutdown measured in Germany after April 20th. We obtain two corresponding R_{t} values from the SECIR model, one referring to the reproduction number before ($R_{\text{t}} = 0.53$) and one after the lifting ($R_{\text{t}} = 0.85$). To obtain estimates for $y^{s,j}$ for all values of R_{t}, we assume the relationships between the observed change in R_{t} and the industry-specific changes in economic activity to be linear. For instance, in a scenario where we simulate an increase of R_{t} that is twice as much compared to the observed change from 0.53 to 0.85, economic activity in each industry also increases twice as much.

Note that in the case of Germany, not all industries were affected exogenously by the shutdown measures in the sense that the measures were imposed by the government. For instance, the shutdown of businesses in mid-March did not apply to manufacturing firms, yet we observe a drop in production of these firms. This is due to an endogenous reaction to sluggish demand, disrupted supply chains, or a shortage in labor supply. We take this into account and distinguish between exogenous and endogenous industries (see Table S4). For *exogenous* industries, $y^{s,j}$ is estimated as described above. For *endogenous* industries, we calculate the activity level based on an input-output matrix, which specifies to what extent the production in one industry is affected by changes in production in another industry (18). We use the input-output matrix to calculate the change in activity level for each endogenous industry, Δy_i, based on the changes in activity levels in all exogenous industries:

$$\Delta y_i = \frac{1}{\alpha_i} \sum_{j=1}^{J} \Delta y_j \alpha_j l_{ij} I_j^e,$$

for $i \neq j$. l_{ij} specifies the change in output in industry i that is due to a one unit change in output in industry j. α_i and α_j are the respective industry's shares in total economic output. I_j^e is an indicator variable equal to one if industry j is an exogenous industry, and zero otherwise. We additionally assume the shutdown duration to be constant across all endogenous industries and scenarios. Specifically, we set the shutdown duration $R^{s,j} - S = 30$, i.e. the duration in the reference scenario.

Finally, the estimate for $r^{s,j}$, the duration of the recovery period of industry j in scenario s, is based on a special question in the ifo Business Survey in May. Respondents were asked about the expected duration until their business situation would return to normal once the shutdown measures were lifted. For the reference scenario ($R_{\text{t}} = 0.53$), we take the mean of these expectations for each industry, as well as the mean of their expected best and worst case durations for robustness tests (see Table S4). Similar to $y^{s,j}$, all other scenarios assume a linear relationship between R_{t} and $r^{s,j}$. To estimate the linear

[¶] While gross value added measures economic activity of all industry sections from A to U, the ifo Business Survey only covers roughly three quarters of the total economy.

relationship between R_t and the recovery time, we assume that in the scenario with $R_t = 0.85$ it takes the firms two months less to fully recover. For all scenarios (including the reference scenario), we aggregate the recovery durations to a weekly frequency to prevent weekday effects (i.e. the changes in durations between the scenarios are always multiples of seven days). For the endogenous industries, we assume the recovery periods to be constant across scenarios (but not across industries) and set the recovery duration equal to the durations in the reference scenario.

Robustness tests. To evaluate the robustness of our baseline result, we run a battery of sensitivity tests where we individually vary each model parameter. The results are shown in Table S5. Overall, we find that the baseline result is highly robust, confirming our main finding. In all robustness tests, costs are lowest in the scenarios with slight, step-wise loosening. The minima are all between R_t values of 0.7 and 0.8. Thus, from an economic point of view, a tightening as well as a too strong loosening of the shutdown measures is not the optimal strategy.

In the first two robustness tests, we vary the linear-relationship assumption between the reproduction number and economic activity (columns 1 and 2 in Table S5). We re-scale the estimated coefficient slope for each industry by the factors 2 and 0.5, respectively. That is, we assume that the change in activity when changing the reproduction number is double (half) in magnitude compared to the baseline. Similarly, we vary the linear-relationship assumption between the reproduction number and the duration of the recovery period (columns 2 and 3). Again, we re-scale the coefficient slope by the factor 2 (0.5), i.e. it takes each industry double (half) the time to fully recover from the shutdown.

Further robustness tests vary the assumptions about the shutdown duration or the exogenously affected industries. First, we change the threshold of new cases per day from 300 to 200 and 400, respectively (columns 5 and 6). This captures the intuition that policy-makers might aim at lower or higher daily case numbers. Second, since the estimated duration to reach 300 daily cases for each R_t value is subject to sampling uncertainty, we additionally calibrate our model using the 2.5^{th} and 97.5^{th} percentile of the distribution, i.e. assuming that it took less and more days to reach the 300 cases (columns 7 and 8). Third, we specify all service industries (sections J to Q in Table S4) to be exogenously affected by the shutdown measures (column 9). This controls for the potential issue that the government might have more control over economic activity than we assume in the baseline. Finally, we vary the period when a vaccine becomes available at large scale by shifting the date forward and backward by 120 days compared to the baseline (columns 10 and 11).

In two final robustness tests, we adjust the recovery durations in each section (see Table S4). Instead of relying on the mean of the expected (likeliest) duration, we use the expected best- and worst-case durations (columns 12 and 13).

Isocost curves. The assumption of a linear relationship between the reproduction number and economic activity is arguably a strong one. To test whether our result crucially depends on this assumption, we calculate isocost curves for the baseline scenario. For each reproduction number, the isocost curve specifies the activity level that would be required such that the resulting costs are equal to the costs of the reference scenario ($R_t = 0.53$).

The results are shown in Figure S6. For each economic section, the black line represents the assumed linear relationship, and the red line the isocost curve. For $R_t < 0.53$, economic activity would have to *increase* in order to yield the same costs as the reference scenario. Intuitively, the recovery duration increases with lower values of R_t, but the reduction in the shutdown period is not sufficient to compensate. It is unlikely that a more restrictive shutdown leads to an increase in economic activity, thus strengthening our finding that further tightening the measures leads to higher costs.

For $R_t > 0.53$, the results are twofold. For reproduction numbers slightly above the reference scenario, activity would have to *fall* to yield the same costs. Again, it is unlikely that this is the case in reality. For $R_t > 0.85$, the activities would have to be significantly higher than linearity in sections H, I, and $R - U$. Taken at face value, this would indicate that the optimal reproduction number might be higher than what we find in our baseline scenario. However, it is more likely that the non-linearity goes in the other direction, i.e. that there are diminishing returns to loosening the shutdown, such that the activity levels would lie *below* linearity for R_t values close to one. In fact, diminishing returns would speak even more in favour of our baseline result.

International development and industry-specific export shares. Foreign countries may affect the economy in Germany either via the activity level during the shutdown, or via the recovery path thereafter. Effects on the former are captured by the ifo Business Survey by default, as respondents are asked about their own business activity, taking into account the economic conditions of their trading partners.[‖] In our baseline specification, we calibrate the recovery duration for each sector by exploiting the respondents' expected time until their firm has fully recovered after the lockdown. Their answer reflects their expectation about economic conditions in foreign countries.

To get an intuition about the relevance of foreign countries for our results and potential effects not captured by the ifo Business Survey, we calculate the export shares for each section (see Figure S7, panel **(A)**). The shares are calibrated via the Leontief input-output matrix and calculated as the share of each section's exports to their sum of household and government consumption, investment, and exports (18). While most exogenous industries, which are directly affected by domestic shutdown policies, only have little export shares and are thus less affected by the economic conditions in foreign countries, the endogenous industries mainly consist of firms from the export-oriented German manufacturing industries. The shutdown and recovery durations for endogenous sectors are held constant across the different scenarios to retain comparability. Thus, the economic activity in the endogenous (including export-heavy) industries in our scenarios are only indirectly affected by domestic policy

[‖] In the April survey (starting point of our policy scenarios), we consider responses of all managers to estimate the initial economic shutdown situation in several industries. However, to calibrate the relationship between domestic opening policies and economic activity, we only use responses of firm managers of the exogenous sectors in the second survey in June.

measures (via domestic input-output-linkages in the supply chain). We explicitly control for the effect of the international developments of the pandemic and shutdown restrictions abroad.

As most exogenous sectors only have little export shares within their sectors (except e.g. tourism), they are less affected by the economic conditions in foreign countries. Note that although e.g. section H has a rather high export share of almost 40%, the section is small compared to e.g. section C in terms of economic output. Panel **(B)** therefore additionally shows the shares for each section's exports to the overall output of the total economy. In total, exports of the exogenous sections contribute 4.8% percent to the overall output in Germany, whereas exports of endogenous sections contribute by 26.9%. Thus, our simulation model controls for around 95 percent of overall economic output (18).

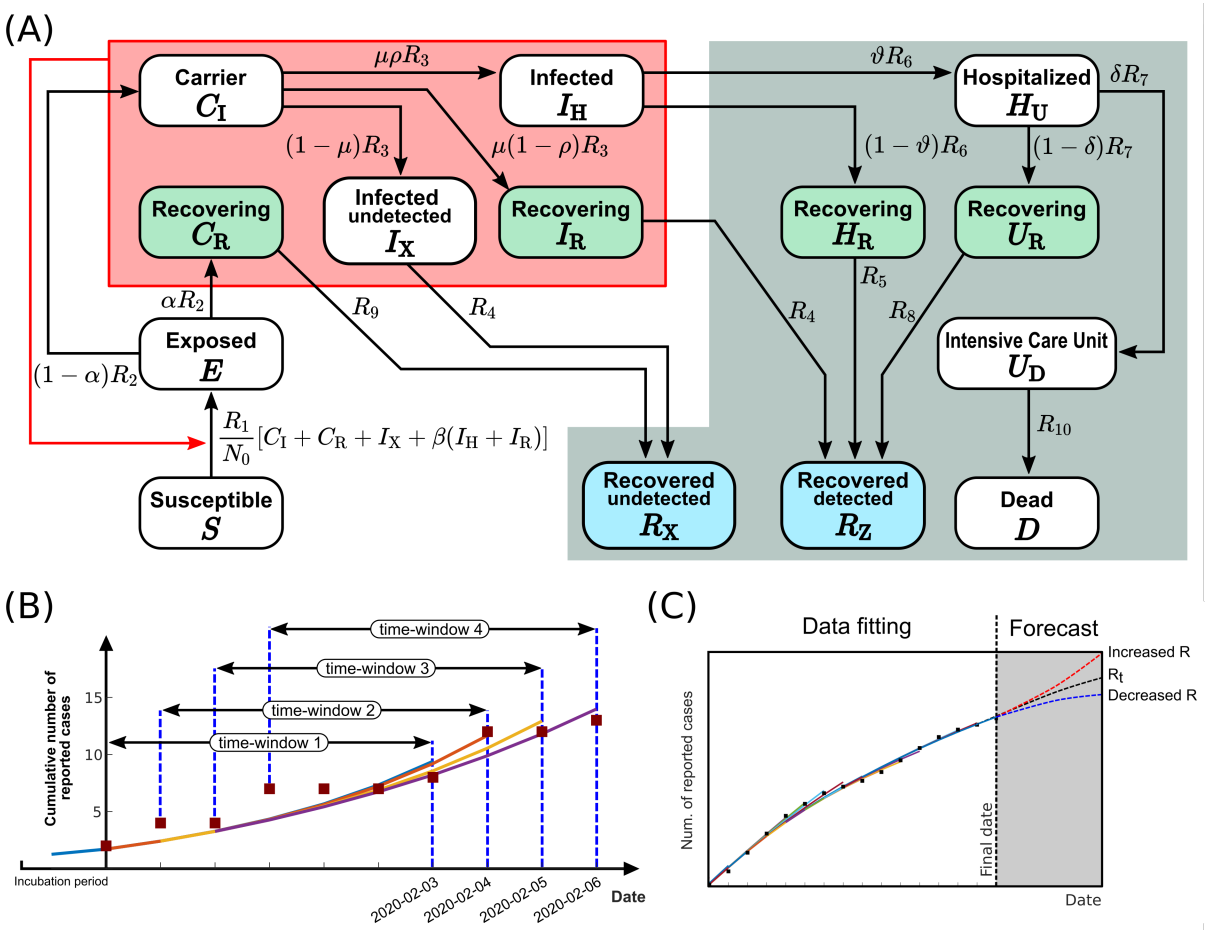

Fig. S1. (A) The scheme of the SECIR model. The model distinguishes susceptible (S), healthy individuals without immune memory of CoV, exposed (E), who carry the virus but are not yet infectious to others, carriers ($C_{I,R}$), who carry the virus and are infectious to others but do not yet show symptoms, infected ($I_{H,R,X}$), who carry the virus with symptoms and are infectious to others, hospitalized ($H_{U,R}$), who experience a severe development of the disease, transferred to intensive care unit ($U_{R,D}$), dead (D), and recovered ($R_{D,X}$), who acquired immune memory and cannot be infected again. Recovery happens from each of the states C_R, I_X, I_R, H_R, U_R. See Table S1 for parameter values. (B) Algorithm of calculating time-varying reproduction number with sliding time-window. Starting from an exposed population based on the initial case reports, the parameter R_1 was fitted to the 1-week time window in the data and the corresponding R_t value was calculated. Next, starting from the state condition of the model at the first time-point, the fitting process was repeated for the time-window shifted by 1 day. This process was repeated for the whole duration of the epidemic. The calculated R_t value was reported for the final date of each time-window. (C) Scheme of prospective simulations. Time evolution of the model variables was obtained from the case reports until the starting date of the prospective study. Then, starting from the last state condition of the model, the numerical simulation was continued with imposed fixed values of R_1 that correspond to the R_t values of interest.

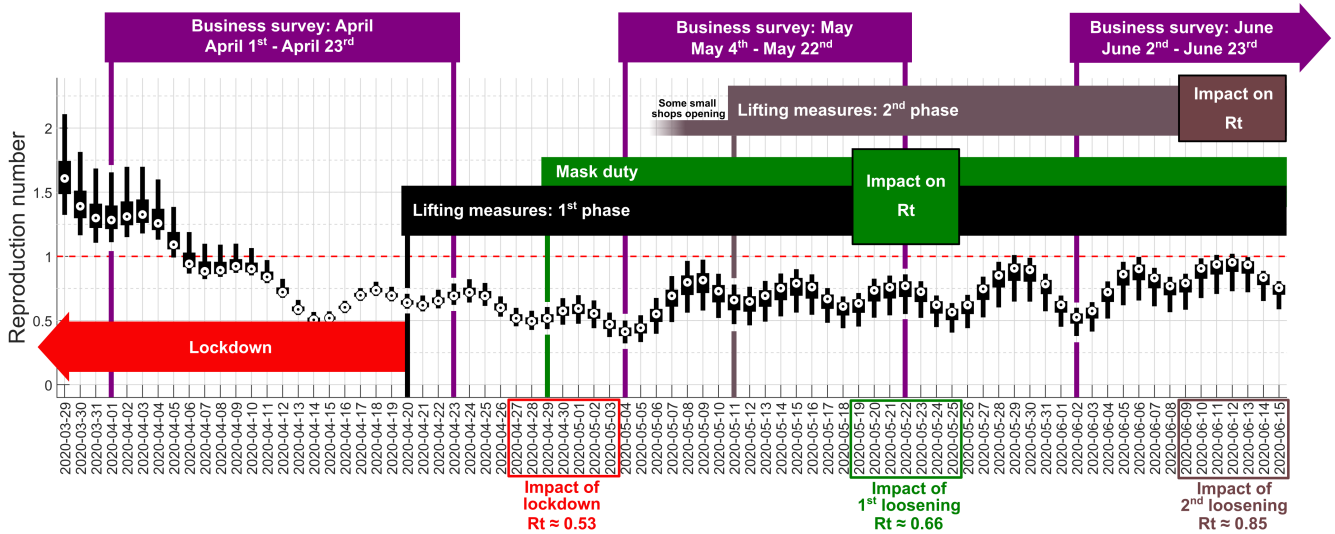

Fig. S2. Time evolution of reproduction number in Germany. The timeline of business surveys and NPIs are marked. The time-windows used for pooling R_t values associated with each NPI is shown on the horizontal axis. The boxplots illustrate the median, 25- and 75-percentiles, maximum and minimum values.

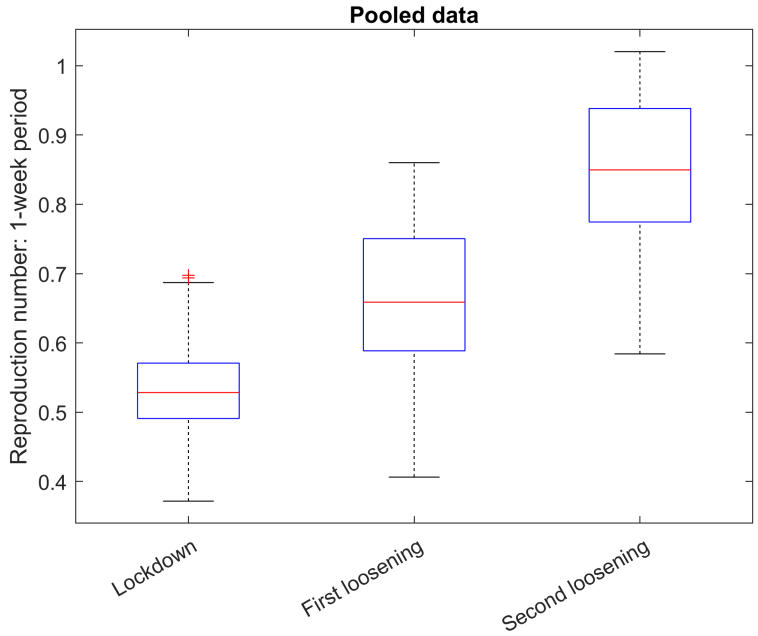

Fig. S3. Distribution of R_{t} values associated with NPIs. Each scenario and corresponding time-window for pooling the data are shown in Fig. S2. The boxplots illustrate the median, 25- and 75-percentiles, maximum and minimum values. The median was used for the economical model.

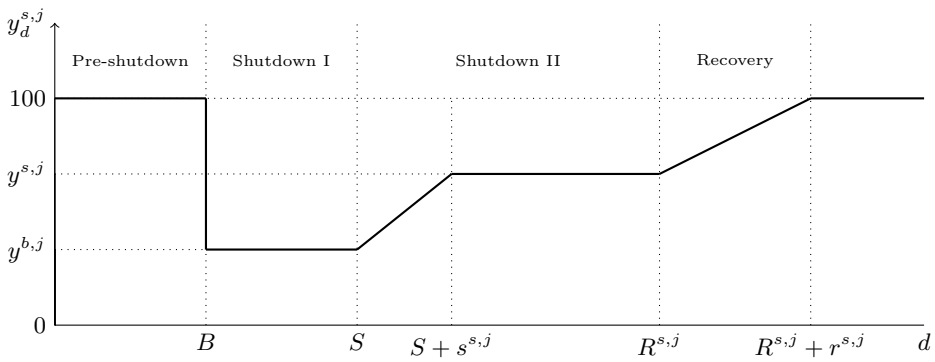

Fig. S4. The figure illustrates the process of economic activity in the model. Starting from a pre-shutdown level, the economy experiences a decline in activity during the shutdown (from 100 to $y^{b,j}$). While the measures are in place, the policy-makers may adjust their severity (from $y^{b,j}$ to $y^{s,j}$). During the recovery phase, the economy slowly returns to its pre-shutdown level (from $y^{s,j}$ to 100).

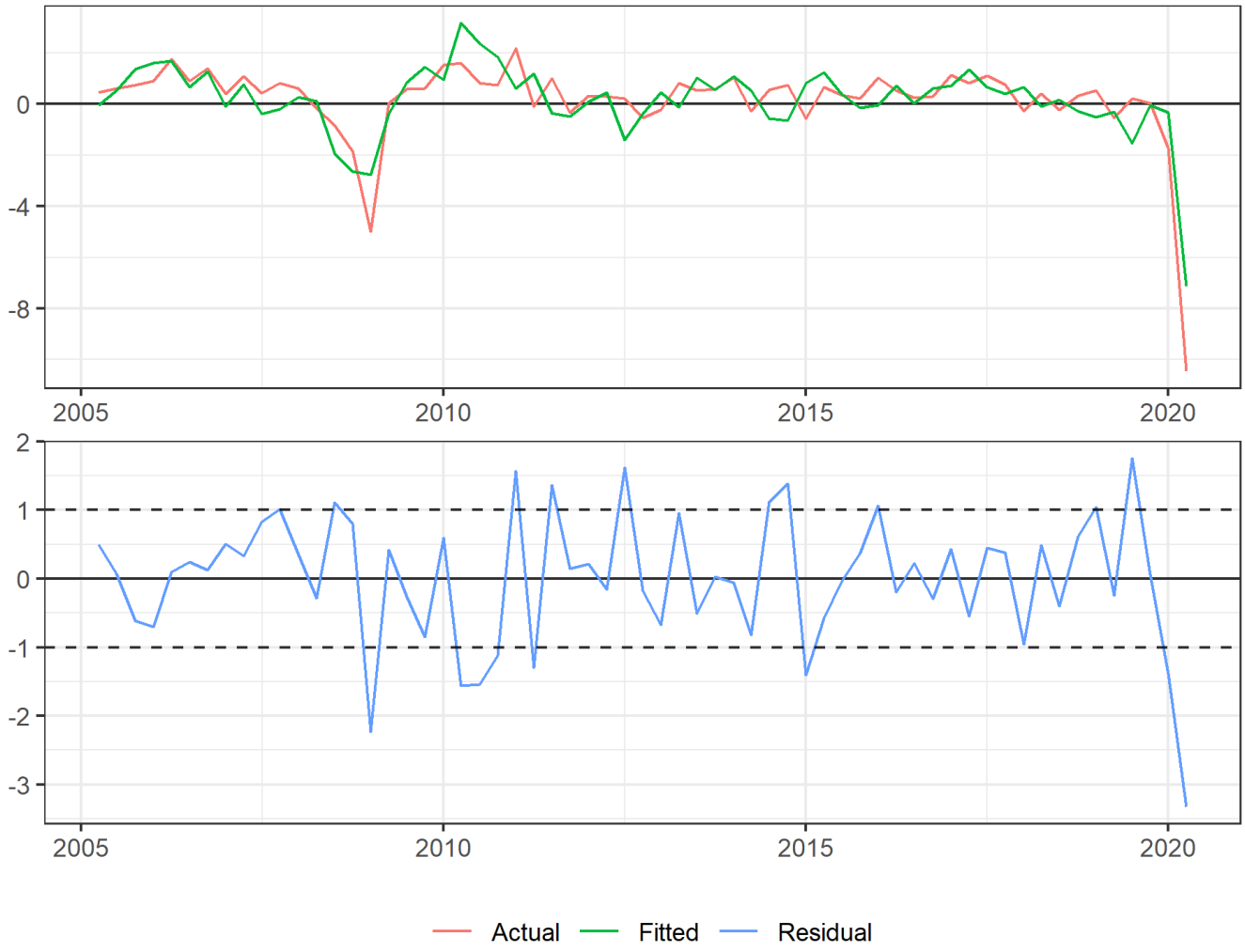

Fig. S5. Regression output

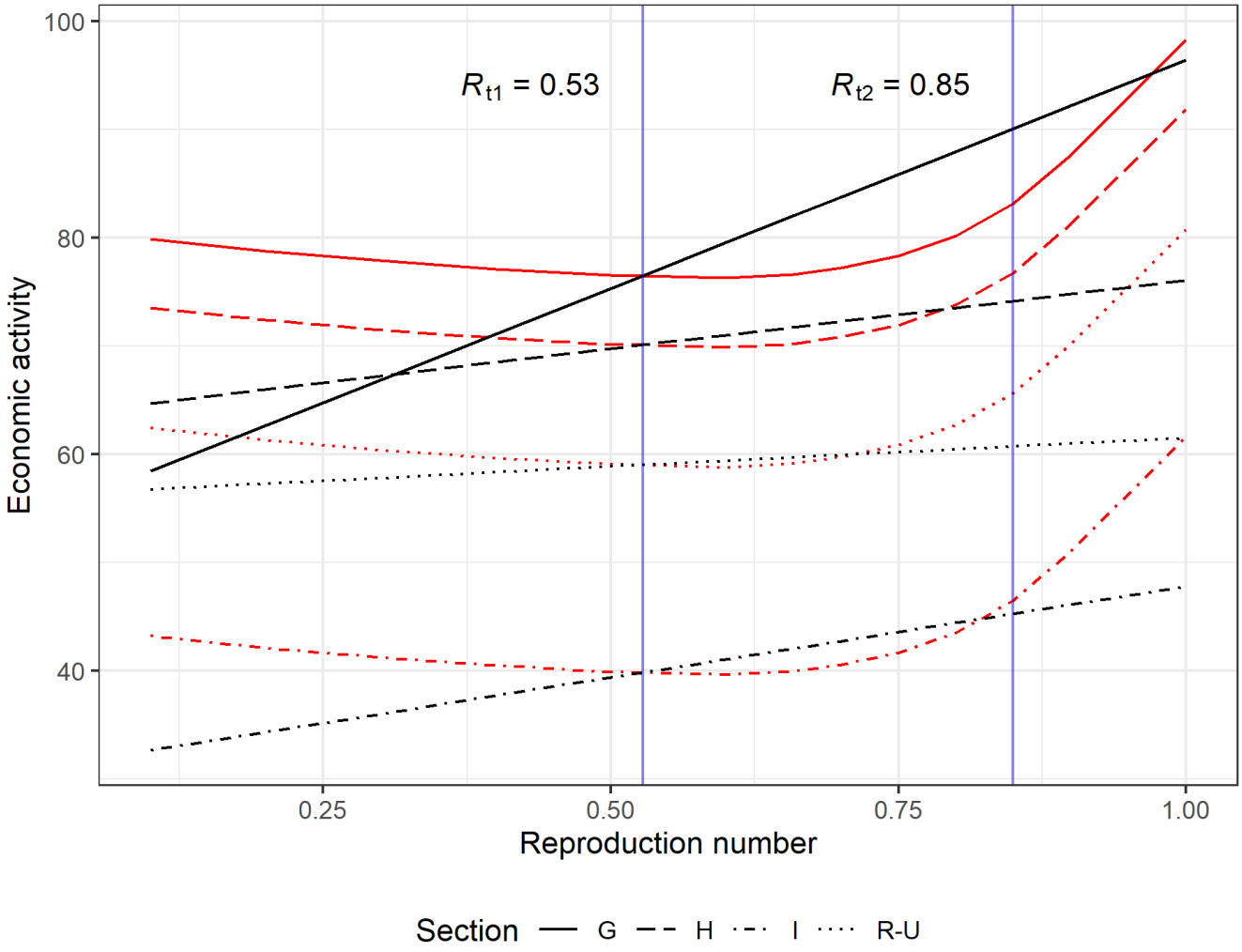

Fig. S6. The black lines show the linear relationships between changes in industry-specific economic activity and changes in the reproduction number. The vertical blue lines indicate the R_t values 0.53 and 0.85 that are used to estimate the slope. The red lines are isocost curves and specify the activity level that would be required such that the resulting costs are equal to the costs of the reference scenario ($R_t = 0.53$)

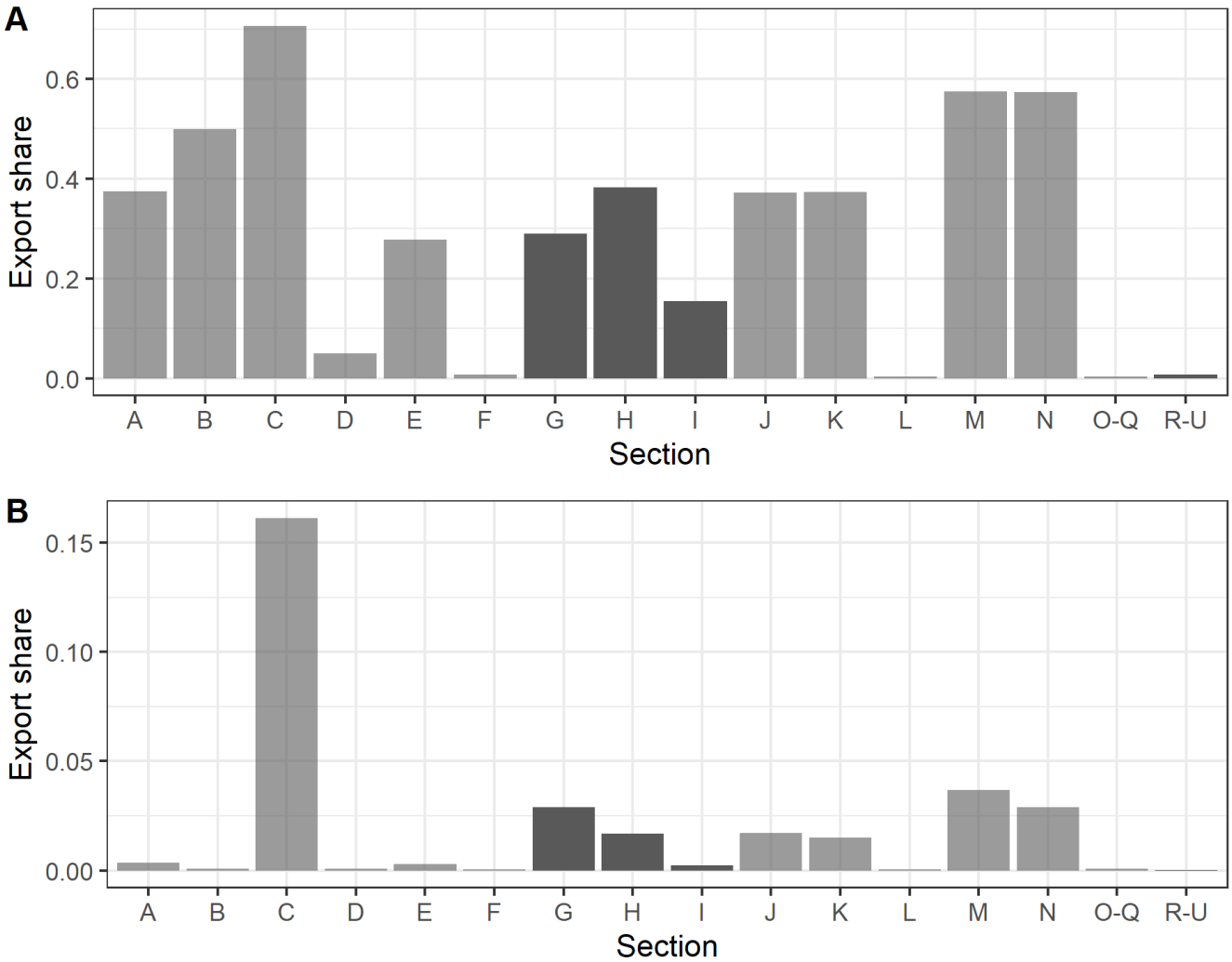

Fig. S7. Panel $(\mathbf{A})$ shows the export shares for each section. The shares are calculated as the share of each section's exports to their sum of household and government consumption, investment, and exports. Panel $(\mathbf{B})$ shows the shares for each section's exports to overall output. Exogenous sections are indicated by dark-grey bars, and endogenous sections by light-grey bars. The data is taken from the Leontief input-output matrix (18)

Table S1. Parameter sets of the SECIR model.

Parameter	References	Ranges	
		Minimum	Maximum
R_1	Variable; fitted.		
R_2	$1/R_2 = 5.2 - 1/R_3$; median incubation period is 5.2 days (19).		
R_3	(20, 21)	$\frac{1}{4.2}$	$\frac{2}{5.2}$
R_4	(22)	$\frac{1}{14}$	$\frac{1}{4}$
R_5	(23, 24)	$\frac{1}{16}$	$\frac{1}{7}$
R_6	(25, 26)	$\frac{1}{7}$	$\frac{1}{2.5}$
R_7	(23, 27)	$\frac{1}{14}$	$\frac{1}{4}$
R_8	(24)	$\frac{1}{16}$	$\frac{1}{5}$
R_9	$\frac{1}{R_9} = \frac{1}{R_3} + \left(0.5 \times \frac{1}{R_4}\right)$		
R_{10}	(23)	$\frac{1}{7.5}$	$\frac{1}{3.5}$
δ_0	(24, 28)	0.15	0.77
α	(29)	0.01	0.5
β	Assumed	0.05	1
ρ_0	(28, 30)	0.1	0.35
ϑ_0	(23, 28)	0.15	0.4
μ	Assumed; fixed value $\mu = 1$.		

Table S2. Data Availability

	Section								
	C	F	G	H	I	J	L	M-N	R-T
Gross Value Added									
Frequency	q	q	q	q	q	q	q	q	q
Publication lag	$T+55$	$T+55$	$T+55$	$T+55$	$T+55$	$T+55$	$T+55$	$T+55$	$T+55$
Turnover									
Frequency	m	m	m/q	q	m	q	-	q	-
Publication lag	$T+35$	$T+70$	$T+60$ / $T+60$	$T+70$	$T+60$	$T+70$	-	$T+70$	-
ifo Business Situation									
Frequency	m	m	m	m	m	m	m	m	m
Publication lag	$T-5$	$T-5$	$T-5$	$T-5$	$T-5$	$T-5$	$T-5$	$T-5$	$T-5$

Note: The frequency with which the data is published is either monthly (m) or quarterly (q). $T+n$ denotes the publication lag, where T is the month / quarter to which the indicator refers to, and n the days after the end of the month / quarter. The ifo Business Survey is conducted in the first half of each month and is published about five days before the end of the month.

Table S3. Regression results

j	A-U	C	F	G	H	I	J	L	M,N	R,S,T
c_0	0.21^{*}	0.16	-0.13	0.39^{**}	0.25	-0.50	1.14^{***}	0.26^{**}	0.22	-0.24
	(0.12)	(0.15)	(0.19)	(0.15)	(0.22)	(0.65)	(0.21)	(0.11)	(0.18)	(0.23)
c_1	0.19^{***}	0.26^{***}	0.14^{***}	0.12^{***}	0.13^{***}	0.69^{***}	0.11^{***}	0.01	0.25^{***}	0.30
	(0.02)	(0.04)	(0.05)	(0.03)	(0.04)	(0.17)	(0.03)	(0.02)	(0.06)	(0.19)
Obs.	61	117	117	117	61	61	61	61	61	61
R^2	0.68	0.59	0.05	0.16	0.42	0.74	0.18	0.00	0.59	0.36

Note: The sample period ranges from the second quarter 1991 (2005) to the second quarter 2020. Heteroskedasticity- and autocorrelation-consistent standard errors are shown in parentheses. *** / ** / * denotes significance at the 1 / 5 / 10 % level.

Table S4. Model Assumptions

Section	Name	α	Activity: April	Activity: June	Recovery	Recovery: best	Recovery: worst	Exogenous (yes / no)
A	Agriculture, forestry and fishing	0.9						
B	Mining and quarrying	0.1						
C	Manufacturing	22.8	-18.8	-24.3	9.2	5.2	16.1	0
D	Electricity, gas, steam and air conditioning supply	1.7						
E	Water supply; sewerage, waste management and remediation activities	1.1						
F	Construction	4.7	-8.5	-9.8	9.4	4.5	15.5	0
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	10.0	-23.5	-9.9	8.4	5.0	14.7	1
H	Transportation and storage	4.4	-29.9	-25.9	9.1	5.1	16.5	1
I	Accommodation and food service activities	1.6	-60.2	-54.8	10.5	6.3	17.5	1
J	Information and communication	4.6	-25.3	-19.1	8.2	4.4	14.9	0
K	Financial and insurance activities	4.0						
L	Real estate activities	10.6	-12.7	-11.3	9.0	5.1	16.0	0
M	Professional, scientific and technical activities	6.4	-19.0	-14.0	8.9	5.1	15.8	0
N	Administrative and support service activities	5.1	-35.2	-31.1	8.9	5.1	15.8	0
O,P,Q	Public administration and defence; compulsory social security; Education; Human health and social work activities	18.2						
R,S,T,U	Arts, entertainment and recreation; Other service activities; Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; Activities of extraterritorial organisations and bodies	3.8	-41.0	-39.3	8.8	5.0	15.3	1

Note: The table shows the model assumptions for each economic section of the NACE Rev. 2 classification. Column three with the header α shows each section's share in total economic output. Columns four and five show economic activity in April and June relative to the pre-shutdown level, which is normalized to zero. Sections A, B, D, E, O, P, and Q are set to zero due to the lack of coverage in the ifo Business Survey. Column six shows the recovery duration (in months) that it takes each industry within a section to return to its pre-shutdown level. Column seven and eight show the best-case and worst-case recovery durations, respectively. Column nine indicates which sections are specified to be exogenous.

Table S5. Robustness Tests

R_t	Baseline	Relative costs												
		Robustness tests												
		1	2	3	4	5	6	7	8	9	10	11	12	13
0.10	17.6	31.2	10.8	12.5	28.0	16.8	18.1	17.8	16.9	27.6	17.6	17.6	19.2	16.8
0.20	12.6	22.7	7.6	8.9	20.2	12.0	13.2	12.9	12.2	19.8	12.6	12.6	13.4	12.3
0.30	8.2	14.9	4.8	5.8	13.2	7.9	8.6	8.2	7.8	12.6	8.2	8.2	8.9	8.2
0.40	4.3	8.0	2.5	3.0	6.8	4.2	4.7	4.3	3.9	6.5	4.3	4.3	4.0	4.3
0.50	0.8	1.6	0.4	0.7	1.5	0.8	0.8	0.8	0.7	1.1	0.8	0.8	1.1	0.9
0.53	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.60	-2.2	-4.2	-1.2	-1.5	-3.4	-1.9	-2.2	-2.4	-2.3	-3.5	-2.2	-2.2	-2.2	-2.4
0.66	-3.5	-7.2	-1.7	-2.3	-5.5	-3.1	-3.8	-3.7	-3.3	-5.2	-3.5	-3.5	-2.8	-3.8
0.70	-4.2	-9.1	-1.7	-2.9	-6.8	-3.6	-4.5	-4.3	-3.7	-6.1	-4.2	-4.2	-3.3	-4.7
0.75	-4.6	-11.2	-1.3	-3.0	-7.8	-3.6	-5.1	-4.8	-4.0	-6.4	-4.6	-4.6	-3.5	-5.8
0.80	-4.3	-12.9	0.0	-2.4	-8.0	-3.0	-5.2	-4.7	-3.4	-4.8	-4.3	-4.3	-2.2	-6.2
0.85	-2.7	-11.7	3.0	-0.7	-6.9	-0.9	-4.0	-3.2	-1.3	-0.7	-2.7	-2.7	0.9	-5.6
0.90	2.0	-7.6	10.0	4.3	-2.5	4.9	-0.2	1.4	4.2	9.5	2.0	2.0	8.3	-3.0
1.00	31.3	16.8	52.9	33.9	26.4	29.9	32.6	31.6	30.6	74.0	17.7	45.0	51.4	15.0

Note: The table shows shows the relative costs for the baseline and the robustness tests. Relative costs are given as the percentage differences in total loss of economic activity compared to the reference scenario ($R_t = 0.53$). In columns 1 and 2, we vary the linear-relationship assumption between the reproduction number and economic activity. In columns 3 and 4, we vary the linear-relationship assumption between the reproduction number and the duration of the recovery period. In columns 5 and 6, we change the threshold of new cases per day from 300 to 200 and 400, respectively. In columns 7 and 8, we calibrate the model using the 2.5^{th} and 97.5^{th} percentile of the duration distribution. In column 9, we specify all service industries to be exogenously affected by the shutdown measures. In columns 10 and 11, we vary the period when a vaccine becomes available at large scale by shifting the date forward and backward by 120 days compared to the baseline. In columns 12 and 13, we use the expected best- and worst-case recovery durations instead of the mean of the expected (likeliest) duration.

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