

Dorn, Florian et al.

Working Paper

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

ifo Working Paper, No. 367

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Dorn, Florian et al. (2022) : The common interests of health protection and the economy: Evidence from scenario calculations of COVID-19 containment policies, ifo Working Paper, No. 367, ifo Institute - Leibniz Institute for Economic Research at the University of Munich, Munich

This Version is available at:

<https://hdl.handle.net/10419/251446>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

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

*Florian Dorn, Sahamoddin Khaiaie, Marc Stoeckli, Sebastian C. Binder,
Tanmay Mitra, Berit Lange, Stefan Lautenbacher, Andreas Peichl, Patrizio
Vanella, Timo Wollmershäuser, Clemens Fuest, Michael Meyer-Hermann*

Imprint:

ifo Working Papers

Publisher and distributor: ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49(0)89 9224 0, Telefax +49(0)89 985369, email ifo@ifo.de

www.ifo.de

An electronic version of the paper may be downloaded from the ifo website:

www.ifo.de

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 Code: C15, C54, C63, I15, I18, I19

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

Florian Dorn^{**a,f,g,1}, Sahamoddin Khailaie^{b,1}, Marc Stoeckli^{a,f,1}, Sebastian C. Binder^b, Tanmay Mitra^b, Berit Lange^{c,d}, Stefan Lautenbacher^{a,f}, Andreas Peichl^{a,f,g}, Patrizio Vanella^{c,h}, Timo Wollmershäuser^{a,f,g}, Clemens Fuest^{a,f,g}, Michael Meyer-Hermann^{b,e}

This version has been accepted for publication in The European Journal of Health Economics.

^a ifo Institute – Leibniz Institute for Economic Research, Poschingerstr. 5, 81679 Munich, Germany

^b Department of Systems Immunology and Braunschweig Integrated Centre of Systems Biology, Helmholtz Centre for Infection Research, Rebenring 56, 38106 Braunschweig, Germany

^c Department of Epidemiology, Helmholtz Centre for Infection Research (HZI), Inhoffenstr. 7, 38124 Brunswick, Germany

^d German Center for Infection Research (DZIF), Inhoffenstr. 7, 38124 Braunschweig, Germany

^e Institute for Biochemistry, Biotechnology and Bioinformatics, Technische Universität Braunschweig, Germany

^f Economics Department, University of Munich (LMU), Ludwigstr. 28, 80539 Munich, Germany

^g CESifo Munich, Poschingerstr. 5, 81679 Munich, Germany

^h Chair of Empirical Methods in Social Science and Demography, University of Rostock, Ulmenstr. 69, 18057 Rostock, Germany

¹ FD, SK and MS contributed equally to this work as first authors in alphabetic order.

* 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.

**Corresponding author, email: dorn@ifo.de.

Acknowledgements: PSB, MMH, BL and PV received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 101003480. BL and PV were funded by the Initiative and Networking Fund of the Helmholtz Association. SB and MMH were supported by the German Federal Ministry of Education and Research within the Rapid Response Module of the National Research Network on Zoonotic Infections, project CoViDec, FKZ: 01KI20102. SK was supported by the Helmholtz Association, Zukunftsthema Immunology and Inflammation (ZT-0027). We thank Manuel Menkhoff and Sascha Möhrle for allowing us to use their NPI stringency index. The research for this interdisciplinary article was inspired by a discussion within the Anne Will talkshow on April 19th, 2020. Anne Will is the most watched German political talk show on *Das Erste* and has run since 2007. Declarations of interest: *none*.

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

Florian Dorn^{a,f,g,1}, Sahamoddin Khailaie^{b,1}, Marc Stoeckli^{a,f,1}, Sebastian C. Binder^b, Tanmay Mitra^b, Berit Lange^{c,d}, Stefan Lautenbacher^{a,f}, Andreas Peichl^{a,f,g}, Patrizio Vanella^{c,h}, Timo Wollmershäuser^{a,f,g}, Clemens Fuest^{a,f,g}, and Michael Meyer-Hermann^{b,e}

^aifo Institute – Leibniz Institute for Economic Research, Poschingerstr. 5, 81679 Munich, Germany; ^bDepartment of Systems Immunology and Braunschweig Integrated Centre of Systems Biology, Helmholtz Centre for Infection Research, Rebenring 56, 38106 Braunschweig, Germany; ^cDepartment of Epidemiology, Helmholtz Centre for Infection Research (HZI), Inhoffenstr. 7, 38124 Brunswick, Germany; ^dGerman Center for Infection Research (DZIF), Inhoffenstr. 7, 38124 Braunschweig, Germany; ^eInstitute for Biochemistry, Biotechnology and Bioinformatics, Technische Universität Braunschweig, Germany; ^fEconomics Department, University of Munich (LMU), Ludwigstr. 28, 80539 Munich, Germany; ^gCESifo Munich, Poschingerstr. 5, 81679 Munich, Germany; ^hChair of Empirical Methods in Social Science and Demography, University of Rostock, Ulmenstr. 69, 18057 Rostock, Germany; ¹FD, SK and MS contributed equally to this work as first authors in alphabetic order

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

COVID-19 | optimal strategy | economy | deaths | integrated simulations | real-time analysis

1 Introduction

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

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

28 An increasing number of studies on NPI strategies concludes
29 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 con-
clude 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 epi-
demiological 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 led 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

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

71 Methods

72 **Using Germany as a case study.** We use the first COVID-19
 73 wave and shutdown in Germany to calibrate our models. Ger-
 74 many’s strategy during the first wave in spring 2020 with
 75 comparatively few deaths and low economic losses compared
 76 to other countries was discussed as a best practice example
 77 from an international perspective (23). Germany introduced
 78 several restrictive measures in March 2020 to contain the
 79 spread of the virus: the NPIs included travel restrictions, re-
 80 strictions on gatherings, the cancellation of events, the closure
 81 of schools and universities, hotels, bars and restaurants, the
 82 recommendation of home-office and hygiene rules, as well as
 83 the ordered shutdown of several social service providers and
 84 the stationary retail industry (excluding grocery stores). Some
 85 federal states introduced curfews. The sum of these measures
 86 – and of behavioral adjustments – reduced the spread of the
 87 virus. Figure 1 plots the time-dependent reproduction number,
 88 R_t , and an NPI stringency index (the latter plotted with a lag
 89 of 14 days to account for the delayed impact of NPIs on the
 90 reproduction number). The stringency index is constructed
 91 from principal component analysis of all NPIs on the federal
 92 state level (24). Fig. 1 shows that, with a lag of two weeks,
 93 the stringency of Germany’s first shutdown appears to inversely
 94 track R_t . The reproduction number fell well below one in
 95 April, and the number of daily new reported cases decreased
 96 noticeably during the shutdown. On April 20th, a gradual
 97 loosening of the restrictions was announced. With a lag of
 98 two weeks, R_t increased at the beginning of May.

99 **Combining methods from epidemiology and economics to es-**
 100 **timate the impact of reopening.** The status quo of our scenario
 101 calculations represents the situation of R_t and economic ac-
 102 tivity in the initial shutdown phase until the gradual opening
 103 process started on April 20th. Starting from the status quo,
 104 we simulate various scenarios for a further loosening or tight-
 105 ening of the shutdown measures. We model the death toll
 106 and economic activity as a function of R_t , using an empirical
 107 relationship between R_t and activity at the industry sector
 108 level as well as the time until the economy fully recovers. In
 109 the model, different shutdown policies are associated with
 110 different R_t values; more relaxed (restrictive) restrictions yield
 111 larger (smaller) R_t values, implying a longer (shorter) period
 112 until the containment of the epidemic is completed. A longer
 113 period due to more relaxed restrictions is associated with
 114 larger death tolls but also with higher economic activity in
 115 the short run. However, larger R_t values imply that daily new
 116 infections decrease slowly (or increase) and the time until full
 117 opening of the economy is extended.

118 Our scenario calculations are based on a novel and unique

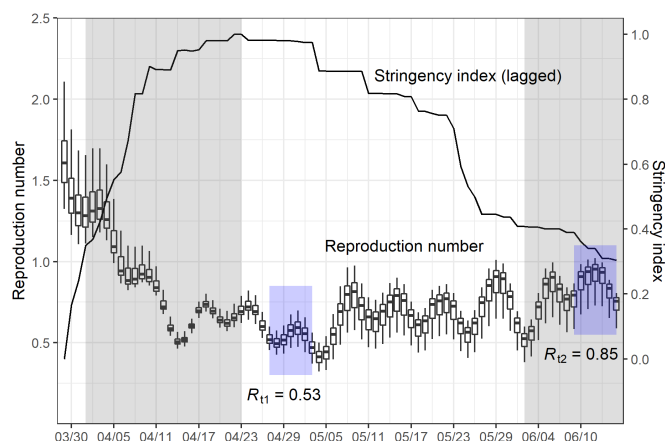


Fig. 1. Reproduction number and NPI stringency in Germany. The boxplots illustrate the distribution of the R_t estimates for each date (median, 25 and 75 percentile) following the model described in *SI Appendix*, pp. 4–10. The error bars denote 1.5 times the interquartile range. The stringency index 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.

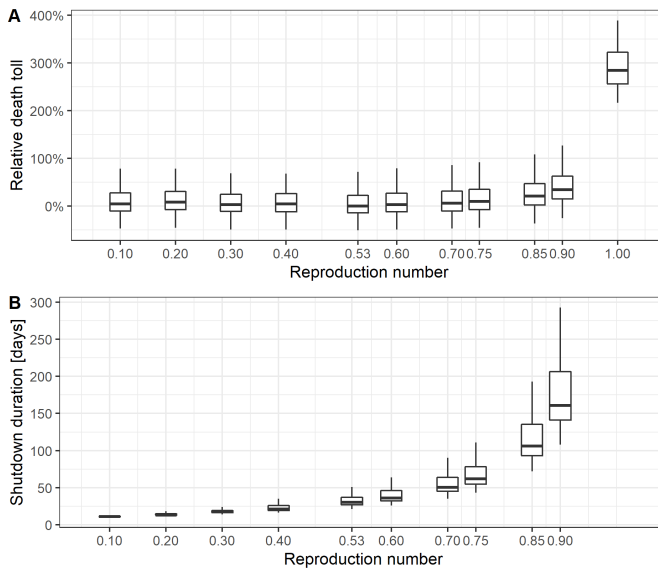
combination of epidemiological and economic simulation mod- 119
 els (see *SI Appendix* for detailed description). The models are 120
 connected in two ways. First, we associate the R_t estimates 121
 from the epidemiological model with corresponding economic 122
 activity levels in different industries for two time periods. The 123
 first time period refers to the end of the initial shutdown, and 124
 the second to the period after the implementation of several 125
 step-by-step relaxations of NPIs. That way we estimate slopes 126
 for the (linear) relationship between the severity of shutdown 127
 restrictions (R_t) and the corresponding activity levels for each 128
 industry. Second, the epidemiological model yields the esti- 129
 mated duration until the epidemic situation allows the full 130
 opening, which marks the beginning of a recovery phase in 131
 the economic model. 132

The reproduction number depends on the severity of shut- 133
down restrictions. In a first step, we employ a mathematical- 134
 epidemiological model with Susceptible-Exposed-Carrier- 135
 Infected-Recovered (SECIIR) components to estimate the de- 136
 velopment of R_t in Germany (see Fig. 1, (3), and *SI Appendix*). 137
 The estimates are based on a dynamic adaptation of the model 138
 parameters to the incidence reporting database of the Robert 139
 Koch Institute (RKI), the German government’s central scien- 140
 tific institution for monitoring the situation on SARS-CoV-2. 141
 We specify $R_{t1} = 0.53$ as reference value that refers to the 142
 estimated reproduction number in Germany just before the 143
 partial lifting of the NPIs on April 20th (Fig. 1, left blue area). 144
 Similarly, we specify $R_{t2} = 0.85$ as reference value that refers 145
 to the reproduction number after the partial lifting, thus cap- 146
 turing the effect of lifting the NPIs on R_t (Fig. 1, right blue 147
 area). 148

Severity of shutdown determines time until control of epi- 149
demic allows full reopening. A key assumption in our analysis 150
 is that reducing the number of new infections to 300 reported 151

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

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



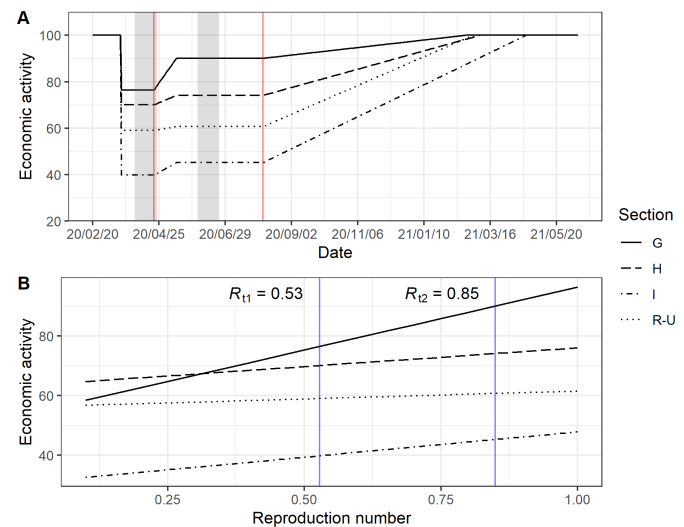
171 **Fig. 2.** (A) Estimation of the relative death toll accumulated between April 20th,
 2020 and July 31st, 2021 with the epidemic model, in percentage difference to the
 median value in the reference scenario ($R_t = 0.53$). The reproduction number on
 the abscissa was fixed in the simulation from 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.

172 **Economic activity depends on shutdown restrictions and**
 173 **speed of full reopening.**

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

179 Fig. 3A illustrates the process in the economic model for
 180 the scenario where the policy-makers tolerate an increase of
 181 R_t from 0.53 to 0.85 on April 20th. This refers to the change
 182 in the reproduction number and economic activity that was
 183 empirically observed over that period of time in Germany. The

184 model assumes that the economy starts from a pre-shutdown
 185 activity level and experiences a decline due to the shutdown
 186 imposed in March 2020. Activity levels of different industries
 187 in response to the shutdown are determined by the status quo
 188 before the exit process started on April 20th. Prior to reaching
 189 the required 300 new cases per day allowing full reopening, our
 190 model assumes that policy-makers can decide on the further
 191 course of severity of restrictions in a period of partial opening.
 192 Loosening restrictions would ceteris paribus increase economic
 193 activity in the partial opening phase (see Fig. 3A). However,
 194 it would also give rise to higher R_t values, thus increasing the
 195 duration of this phase (see Fig. 2B). Conversely, tightening
 196 restrictions would lead to a reduction in economic activity,
 197 but reduce R_t and the time needed until the number of new
 198 infections would allow a full opening. The economy slowly
 199 recovers once all shutdown measures can be fully lifted without
 200 jeopardising the containment of the epidemic because either
 201 a sufficiently low number of new infections is reached or a
 202 vaccine is available. At the end of the recovery phase, the
 economy returns to its pre-crisis activity level.



203 **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.

204 **Estimates of economic activity during shutdown.**

205 The estimates of economic activity are based on the ifo Business Survey,
 206 a monthly survey that includes roughly 9,000 responses from
 207 German firm managers in manufacturing, the service sector,
 208 trade, and construction (25, 26). Managers base their responses
 209 predominantly on information derived from their own
 210 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 policy-makers 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

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

337 Our results suggest that a balanced strategy is in the com-
 338 mon interest of health protection and the economy. The
 339 scenario calculations show that a slight, gradual lifting of shut-
 340 down restrictions which keeps reproduction numbers at an
 341 intermediate level and which allows to further reduce infec-
 342 tion numbers in a significant manner is suitable to reduce the
 economic losses without jeopardizing medical objectives.

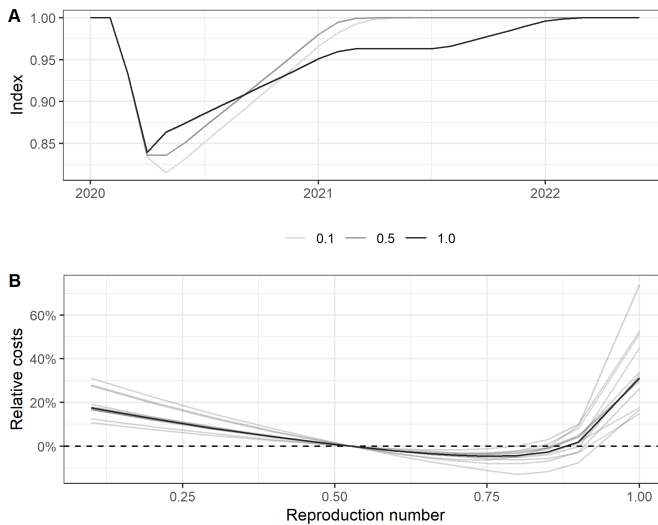


Fig. 4. (A) Overall economic activity over time for three baseline policy scenarios (denoted by their respective reproduction numbers, 0.1, 0.5, and 1.0). Pre-crisis economic activity is normalized to 100. (B) Relative costs for each policy scenario, in percentage difference to the reference scenario ($R_t = 0.53$). 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*.

343

344 **Robustness of results suggests general applicability.** Clearly,
 345 generalization of our results beyond Germany and across time
 346 is limited to comparable regions, situations and given NPIs.
 347 The relationship between economic activity and the repro-
 348 duction number might not be the same across world regions.
 349 Moreover, the shutdown duration and final death toll are influ-
 350 enced by the number of new infections at the point of entering
 351 or changing shutdown measures. However, our results are
 352 robust to several sensitivity tests in assumptions regarding
 353 the relationship between the shutdown severity and economic
 354 activity, affected industries of exogenous shutdown restrictions,
 355 the duration of economic recovery, and the number of daily
 356 new cases that needs to be reached to control the epidemic.
 357 We also tested the sensitivity of our assumption on the time
 358 of large scale availability of a vaccine (see *SI Appendix, Tab.*
 359 *S5*).

360 The assumption of a linear relationship between shutdown
 361 levels and economic activities is clearly a simplification in our
 362 simulation model, although the slope of our linear relation-
 363 ship 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 ro-
 bustness 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.

References.

1. N Ferguson, et al., Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand, (Imperial College London), Technical report (2020).
2. J Dehning, et al., Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. *Science* **369**, eabb9789 (2020).
3. S Khailaie, et al., Development of the reproduction number from coronavirus SARS-CoV-2 case data in Germany and implications for political measures. *BMC Medicine* **19** (2021).
4. F Dorn, et al., The economic costs of the coronavirus shutdown for selected European countries: A scenario calculation. *EconPol Policy Brief* **25** (2020).
5. IMF, *World Economic Outlook, April 2020: The Great Lockdown*. (International Monetary Fund), (2020).
6. MS Eichenbaum, S Rebelo, M Trabandt, The macroeconomics of epidemics. *The Rev. Financial Stud.* **34**, 5149–5187 (2021).
7. Economist, A grim calculus: COVID-19 presents stark choices between life, death and the economy. *The Econ. April 2nd* (2020).
8. RJ Barro, JF Ursua, J Weng, The coronavirus and the great influenza epidemic - lessons from the "spanish flu" for the coronavirus's potential effects on mortality and economic activity. *CESifo Work. Pap.* **8166** (2020).
9. Ó Jordà, SR Singh, AM Taylor, Longer-run economic consequences of pandemics. *Rev. Econ. Stat.* **104**, 166–175 (2022).
10. C Ma, JH Rogers, S Zhou, Global economic and financial effects of 21st century pandemics and epidemics. *Covid Econ.* **5**, 56–78 (2020).
11. F Dorn, et al., The challenge of estimating the direct and indirect effects of COVID-19 interventions – an integrated economic and epidemiological approach. *Work. Pap. mimeo* (2021).
12. A Abele-Brehm, et al., *Making the fight against the Coronavirus pandemic sustainable*. (ifo Institute), (2020).
13. S Correia, S Luck, E Verner, Pandemics depress the economy, public health interventions do not: evidence from the 1918 flu. *SSRN* (2020).
14. O Holtemöller, Integrated assessment of epidemic and economic dynamics. *IWH Discuss. Pap.* **4/2020** (2020).
15. F Alvarez, D Argente, F Lippi, A simple planning problem for COVID-19 lockdown, testing, and tracing. *Am. Econ. Rev. Insights* **3**, 367–82 (2021).

- 432 16. C Jones, T Philippon, V Venkateswaran, Optimal mitigation policies in a pandemic: Social
433 distancing and working from home. *The Rev. Financial Stud.* **34**, 5188–5223 (2021).
- 434 17. E Bertuzzo, et al., The geography of COVID-19 spread in Italy and implications for the relax-
435 ation of confinement measures. *Nat. Commun.* **11** (2020).
- 436 18. H Noorbhai, A mathematical model to guide the re-opening of economies during the COVID-
437 19 pandemic. *Annals Medicine Surger* **57** (2020).
- 438 19. D Baqaee, E Farhi, M Mina, J Stock, Reopening scenarios. *NBER Work. Pap.* **27244** (2020).
- 439 20. G Kaplan, B Moll, G Violante, The great lockdown and the big stimulus: tracing the pandemic
440 possibility frontier for the US. *NBER Work. Pap.* **27794** (2020).
- 441 21. M Farboodi, G Jarosch, R Shimer, Internal and external effects of social distancing in a
442 pandemic. *J. Econ. Theory* **196**, 105293 (2021).
- 443 22. L Miclo, D Spiro, J Weibull, Optimal epidemic suppression under an ICU constraint. *arXiv*
444 **2005.01327** (2020).
- 445 23. J Fernández-Villaverde, C Jones, Estimating and simulating a SIRD model of COVID-19 for
446 many countries, states, and cities. *NBER Work. Pap.* **27128** (2020).
- 447 24. P Vanella, Stochastic forecasting of demographic components based on principal component
448 analyses. *Athens J. Sci.* **5**, 223–246 (2018).
- 449 25. S Sauer, K Wohlrabe, *ifo Handbuch der Konjunkturumfragen.* (ifo Beiträge zur Wirtschafts-
450 forschung) No. 88, (2020).
- 451 26. S Lautenbacher, Subjective uncertainty, expectations, and firm behavior. *MPRA Work. Pap.*
452 **103516** (2020).
- 453 27. R Lehmann, The forecasting power of the ifo business survey. *CESifo Work. Pap.* **8291**
454 (2020).
- 455 28. Federal Statistical Office, *Volkswirtschaftliche Gesamtrechnungen. Input-Output-Rechnung*
456 *nach 12 Gütergruppen / Wirtschafts- und Produktionsbereichen.* (Federal Statistical Office of
457 Germany), (2020).
- 458 29. A Storza, M Steininger, Globalization in the time of COVID-19. *CESifo Work. Pap.* **8184**
459 (2020).
- 460 30. H Markel, et al., Nonpharmaceutical interventions implemented by US cities during the 1918-
461 1919 influenza pandemic. *JAMA* **298**, 644–654 (2007).
- 462 31. K Prather, C Wang, R Schooley, Reducing transmission of SARS-CoV-2. *Science* **368**, 1422–
463 1424 (2020).
- 464 32. T Mitze, R Kosfeld, J Rode, K Wälde, Face masks considerably reduce COVID-19 cases in
465 Germany. *Proc. Natl. Acad. Sci.* **117** (2020).
- 466 33. V Chernozhukov, H Kasahara, P Schrimpf, Causal impact of masks, policies, behavior on
467 early COVID-19 pandemic in the US. *J. Econom.* **220**, 23–62 (2020).
- 468 34. A Karaivanov, SE Lu, H Shigeoka, C Chen, S Pamplona, Face masks, public policies and
469 slowing the spread of COVID-19: evidence from Canada. *J. Heal. Econ.*, 102475 (2021).
- 470 35. V Grimm, F Mengel, M Schmidt, Extensions of the SEIR model for the analysis of tailored
471 social distancing and tracing approaches to cope with COVID-19. *Sci. Reports* **11** (2021).
- 472 36. JV Alipour, H Fadinger, J Schymik, My home is my castle – the benefits of working from home
473 during a pandemic crisis. *J. Public Econ.* **196** (2021).

1 Supplementary Information (SI) for

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

5
6
7
8

9 This PDF file includes:

10 Supplementary text

11 Figs. S1 to S7 and Tables S1 to S5

12 SI References

13 Supporting Information Text

14 Background: Containment policy in Germany during the first shutdown

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

28 Materials and Methods

29 **Mathematical-epidemiological model.** The development of infection dynamics has been addressed by a number of mathematical
30 approaches based on differential equation models (7) and agent-based models (8). Our SECIR model is a deterministic ordinary
31 differential equations (ODEs)-based model in which different stages of the infection and associated viral spreading are considered.
32 The model structure and parameter ranges were chosen according to the specific properties of SARS-CoV-2 viral infections.
33 The model comprises of compartments representing the individuals susceptible (S) or exposed (E) to the virus, asymptomatic
34 carriers ($C_{I,R}$) which may become symptomatic ($I_{H,R,X}$), hospitalized ($H_{U,R}$) or in the need of intensive care $U_{R,D}$. Infected
35 individuals have terminal fate of recovery ($R_{Z,X}$) or death (D). The carrier compartments refer to an infection state of an
36 individual without symptoms who is able to transmit the disease to susceptible individuals, and later may or may not develop
37 any symptoms. In this state, the transmissibility of the virus can be significant as the individual is not aware of the disease
38 and could actively make contact with susceptible individuals. Therefore, the presence of such a compartment is crucial in the
39 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).

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

$$\frac{dE}{dt} = R_1(t) \frac{(C_I + C_R + I_X + \beta(I_H + I_R))}{N} S - R_2 E, \quad [2]$$

$$\frac{dC_I}{dt} = (1 - \alpha) R_2 E - R_3 C_I, \quad [3]$$

$$\frac{dC_R}{dt} = \alpha R_2 E - R_9 C_R, \quad [4]$$

$$\frac{dI_H}{dt} = \mu \rho(t) R_3 C_I - R_6 I_H, \quad [5]$$

$$\frac{dI_R}{dt} = \mu (1 - \rho(t)) R_3 C_I - R_4 I_R, \quad [6]$$

$$\frac{dI_X}{dt} = (1 - \mu) R_3 C_I - R_4 I_X, \quad [7]$$

$$\frac{dH_U}{dt} = \vartheta(t) R_6 I_H - R_7 H_U, \quad [8]$$

$$\frac{dH_R}{dt} = (1 - \vartheta(t)) R_6 I_H - R_5 H_R, \quad [9]$$

$$\frac{dU_D}{dt} = \delta(t) R_7 H_U - R_{10} U_D, \quad [10]$$

$$\frac{dU_R}{dt} = (1 - \delta(t)) R_7 H_U - R_8 U_R, \quad [11]$$

$$\frac{dR_Z}{dt} = R_4 I_R + R_5 H_R + R_8 U_R, \quad [12]$$

$$\frac{dR_X}{dt} = R_9 C_R + R_4 I_X, \quad [13]$$

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

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

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

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

46 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
 47 $t_0 = 89$ are obtained from fitting the case fatality rate (CFR) ($k(t) = \rho \vartheta \delta$) which changed over the course of the epidemic in
 48 Germany. This is due to changing testing frequencies and the shifting age structure of the infected over time (11); therefore,
 49 the CFR is not completely reflecting a change in the fatality rate of the virus. The uncertainty in the parameter values
 50 was incorporated into the analysis by repeated (100 times) random sampling within the plausible ranges and obtaining the
 51 distributions of model variables.

52 The basic reproduction number (R_0) is defined as the expected number of secondary cases produced by a single infection in
 53 a susceptible population and is a constant characteristic of viral dissemination dynamics in a passive community. However,
 54 the dynamics of the epidemic may be under the influence of multiple time-dependent factors such as change in the individual
 55 behavior in response to policies or public awareness. Therefore, a time-dependent reproduction number (R_t) describing the
 56 expected number of secondary cases per index case at a given time of the epidemic is a more relevant quantity for an active
 57 community and reflects the multi-factorial impact of non-pharmaceutical interventions (NPIs), behavioral changes, seasonal
 58 effects, etc. on the dynamics of viral spread.
 59 Herein, the temporal evolution of R_t was obtained by re-fitting the model in a sliding time-window of the data which was
 60 shifted throughout the duration of the epidemic (see Fig. S1B). This method allows to adapt the model parameter R_1 that
 61 is associated with NPIs in order to fit the data, which cannot be achieved by a fixed parameter value. The value of R_t
 62 corresponding to the k -th time-window is calculated based on the fitted value of R_1 by

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

64 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
65 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
66 total population at the beginning of the epidemics. The reproduction number in (17) is derived from the SECIR model (14)
67 using the next generation matrix method (12, 13). The cumulative reported case number is compared to the sum of infected
68 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
69 window of 7 days using Nelder-Mead simplex algorithm (14) (see Fig. S1B).

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

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

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

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

97 **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
98 being exposed to the virus to becoming symptomatic and reported in the database. For the first openings in Germany on April
99 20th, 2020, the reporting delay assumption implies that a person exposed on the first day of lifting measures will be reported
100 on May 4th. However, as the R_t value reported on each date includes the impact of 6 other days in the data retrospectively
101 (see Fig. S1B), the R_t value calculated on May 4th is biased by cases exposed before April 20th (6 out of 7 data-points). With
102 a similar reasoning, the R_t values calculated in the period of May 4th-May 9th are contaminated with infected cases before
103 April 20th, 2020. Therefore, the impact of the openings on April 20th shall be inferred from May 10th at the earliest. Since
104 the obligation of wearing masks was imposed very shortly after the first openings, we considered them as a bundle of NPIs.
105 Following the reporting delay assumption, the impact of the NPIs bundle on the R_t value is expected from May 19th at the
106 earliest. In order to take into account the seasonality observed in the data and the R_t values in the calculation of NPI impacts,
107 we considered a pooled set of R_t values in the 1-week period of May 19th-May 25th (see Fig. S2 and S3).

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

112 Economic model and empirical implementation.

113 **Modelling economic costs.** The economic costs of scenario s are given as the aggregated loss of activity occurring as a result
114 of the shutdown. Denote y_m^s as the economic activity compared to the pre-shutdown level in scenario s and month m , with
115 $0 \leq y_m^s \leq 100$. $y_m^s = 100$ refers to the pre-shutdown activity level, and $y_m^s = 0$ to an economy with zero production. Total
116 costs of scenario s can be written as:

$$117 \quad C^s = \sum_{m=1}^M 100 - y_m^s,$$

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

118 where M is the time horizon under consideration, i.e. the total number of months that are taken into account in the analysis.
 119 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
 120 $\Delta C^s > 0$, indicates scenarios with higher costs and lower aggregate economic activity compared to the reference.

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

125 Taking into account that the impact of the shutdown varies across industries, we explicitly model activity at the industry level.
 126 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
 127 activity, weighted by the share of the industry in total output, denoted as α_j :

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

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

130 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 $0 \leq y_d^{s,j} \leq 100$
 131 and $d \in \{1, \dots, D\}$, where D is the last calendar day in the last year of observation. $y_m^{s,j}$ is given as

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

133 where I_d^m is an indicator variable equal to one if calendar day d belongs to calendar month m , and zero otherwise. Similarly,
 134 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
 135 notation implies that the distribution of holidays across the calendar year is relevant for the cost of a scenario. That is, the
 136 shutdown is less costly when it is in place during months with few working days.

137 Furthermore, denote B as the calendar day when shutdown measures were implemented first, S as the day when a new policy
 138 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
 139 the epidemiological model and describes the calendar day during which a certain daily case number has been reached. The
 140 superscripts indicate that there is heterogeneity across scenarios and industries. After the introduction of the new policy
 141 at S , the economy adjusts over the period $s^{s,j}$, after which the new activity level is reached. After the prescribed number
 142 of new infections is reached and the shutdown is fully lifted, i.e. for $d > R$, the economy slowly recovers and returns to its
 143 pre-shutdown activity. We assume that economic activity increases linearly from S to $S + s^{s,j}$ and from $R^{s,j}$ to $R^{s,j} + r^{s,j}$. $r^{s,j}$
 144 denotes the industry-specific duration of the recovery period (in calendar days). For each day d , the activity in each scenario s
 145 and sector j is then given as follows:

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

147 $y^{b,j}$ and $y^{s,j}$ refer to the activity after the first introduction of shutdown measures and after the policy change, respectively.
 148 Figure S4 illustrates the process of $y_d^{s,j}$ over d .

149 **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
 150 $s^{s,j}$ are determined exogenously. For our application, we specify March 19th, 2020 as the introduction date of the shutdown
 151 measures (i.e. $B = 79$). S refers to April 20th, when the national and state governments agreed on a gradual, step-by-step
 152 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
 153 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
 154 specifications. $R^{s,j}$ is estimated with the SECIR model and refers to the number of days until the infection numbers allow full
 155 opening. The recovery speed depends on the reproduction number R_t . In general, a higher (smaller) R_t value is associated
 156 with a higher (smaller) $R^{s,j}$,

157 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
 158 9,000 German firms (15) which covers the most important industries of the German economy as defined by the NACE Rev. 2
 159 classification.[§] Economic activity, $y^{b,j}$ and $y^{s,j}$, is approximated by the companies' assessment of their own current business
 160 situation, which they can describe as "good", "satisfactory", or "poor". According to a meta survey, the information used by
 161 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.⁴ 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 ($R_t = 0.53$) and one after the lifting ($R_t = 0.85$). 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 ($R_t = 0.53$), 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

⁴ 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.

215 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
216 less to fully recover. For all scenarios (including the reference scenario), we aggregate the recovery durations to a weekly
217 frequency to prevent weekday effects (i.e. the changes in durations between the scenarios are always multiples of seven days).
218 For the endogenous industries, we assume the recovery periods to be constant across scenarios (but not across industries) and
219 set the recovery duration equal to the durations in the reference scenario.

220 **Robustness tests.** To evaluate the robustness of our baseline result, we run a battery of sensitivity tests where we individually
221 vary each model parameter. The results are shown in Table S5. Overall, we find that the baseline result is highly robust,
222 confirming our main finding. In all robustness tests, costs are lowest in the scenarios with slight, step-wise loosening. The
223 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
224 loosening of the shutdown measures is not the optimal strategy.

225 In the first two robustness tests, we vary the linear-relationship assumption between the reproduction number and economic
226 activity (columns 1 and 2 in Table S5). We re-scale the estimated coefficient slope for each industry by the factors 2 and
227 0.5, respectively. That is, we assume that the change in activity when changing the reproduction number is double (half) in
228 magnitude compared to the baseline. Similarly, we vary the linear-relationship assumption between the reproduction number
229 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
230 takes each industry double (half) the time to fully recover from the shutdown.

231 Further robustness tests vary the assumptions about the shutdown duration or the exogenously affected industries. First,
232 we change the threshold of new cases per day from 300 to 200 and 400, respectively (columns 5 and 6). This captures the
233 intuition that policy-makers might aim at lower or higher daily case numbers. Second, since the estimated duration to reach
234 300 daily cases for each R_t value is subject to sampling uncertainty, we additionally calibrate our model using the 2.5th and
235 97.5th percentile of the distribution, i.e. assuming that it took less and more days to reach the 300 cases (columns 7 and 8).
236 Third, we specify all service industries (sections J to Q in Table S4) to be exogenously affected by the shutdown measures
237 (column 9). This controls for the potential issue that the government might have more control over economic activity than we
238 assume in the baseline. Finally, we vary the period when a vaccine becomes available at large scale by shifting the date forward
239 and backward by 120 days compared to the baseline (columns 10 and 11).

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

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

246 The results are shown in Figure S6. For each economic section, the black line represents the assumed linear relationship,
247 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
248 the reference scenario. Intuitively, the recovery duration increases with lower values of R_t , but the reduction in the shutdown
249 period is not sufficient to compensate. It is unlikely that a more restrictive shutdown leads to an increase in economic activity,
250 thus strengthening our finding that further tightening the measures leads to higher costs.

251 For $R_t > 0.53$, the results are twofold. For reproduction numbers slightly above the reference scenario, activity would
252 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
253 have to be significantly higher than linearity in sections H, I, and R – U. Taken at face value, this would indicate that the
254 optimal reproduction number might be higher than what we find in our baseline scenario. However, it is more likely that the
255 non-linearity goes in the other direction, i.e. that there are diminishing returns to loosening the shutdown, such that the
256 activity levels would lie *below* linearity for R_t values close to one. In fact, diminishing returns would speak even more in favour
257 of our baseline result.

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

264 To get an intuition about the relevance of foreign countries for our results and potential effects not captured by the ifo
265 Business Survey, we calculate the export shares for each section (see Figure S7, panel (A)). The shares are calibrated via the
266 Leontief input-output matrix and calculated as the share of each section's exports to their sum of household and government
267 consumption, investment, and exports (18). While most exogenous industries, which are directly affected by domestic shutdown
268 policies, only have little export shares and are thus less affected by the economic conditions in foreign countries, the endogenous
269 industries mainly consist of firms from the export-oriented German manufacturing industries. The shutdown and recovery
270 durations for endogenous sectors are held constant across the different scenarios to retain comparability. Thus, the economic
271 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.

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

274 As most exogenous sectors only have little export shares within their sectors (except e.g. tourism), they are less affected
275 by the economic conditions in foreign countries. Note that although e.g. section *H* has a rather high export share of almost
276 40%, the section is small compared to e.g. section *C* in terms of economic output. Panel **(B)** therefore additionally shows
277 the shares for each section's exports to the overall output of the total economy. In total, exports of the exogenous sections
278 contribute 4.8% percent to the overall output in Germany, whereas exports of endogenous sections contribute by 26.9%. Thus,
279 our simulation model controls for around 95 percent of overall economic output (18).

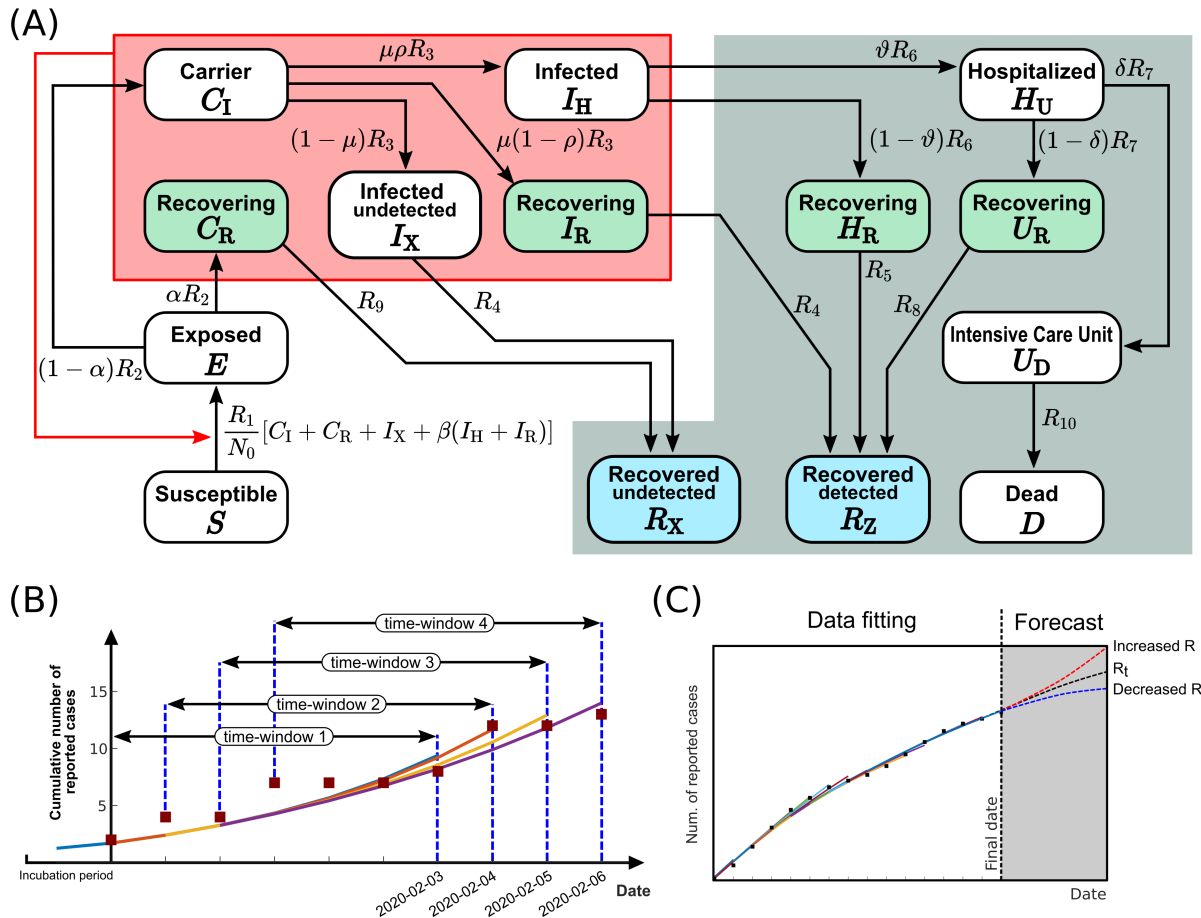


Fig. S1. (A) The scheme of the SECIR model. The model distinguishes susceptible (S), healthy individuals without immune memory of CoV, exposed (E), who carry the virus but are not yet infectious to others, carriers ($C_{I,R}$), who carry the virus and are infectious to others but do not yet show symptoms, 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.

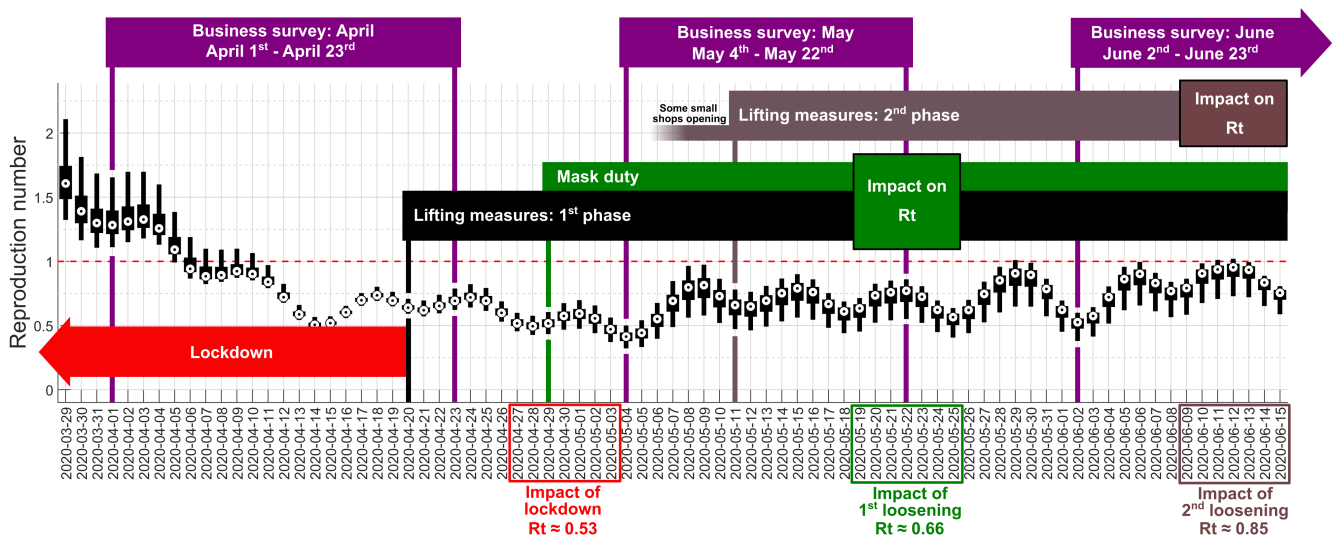


Fig. S2. Time evolution of reproduction number in Germany. The timeline of business surveys and NPIs are marked. The time-windows used for pooling R_t values associated with each NPI is shown on the horizontal axis. The boxplots illustrate the median, 25- and 75-percentiles, maximum and minimum values.

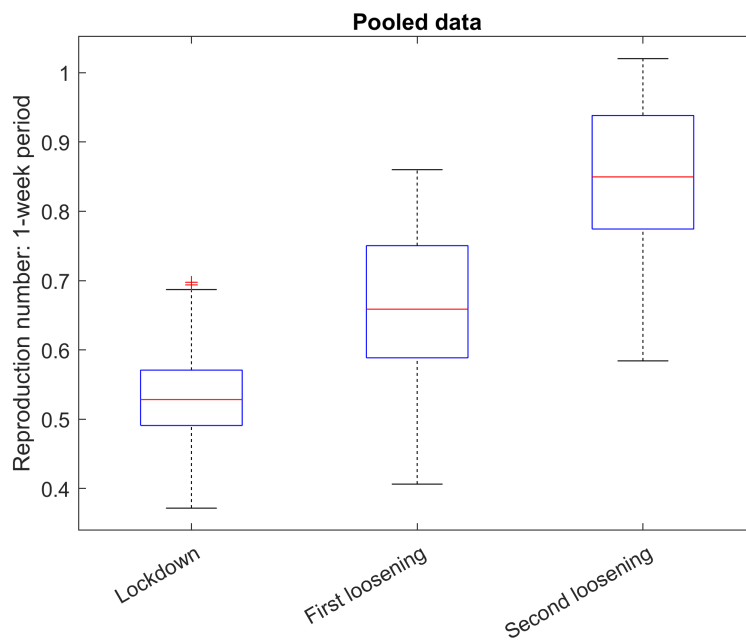


Fig. S3. Distribution of R_t values associated with NPIs. Each scenario and corresponding time-window for pooling the data are shown in Fig. S2. The boxplots illustrate the median, 25- and 75-percentiles, maximum and minimum values. The median was used for the economical model.

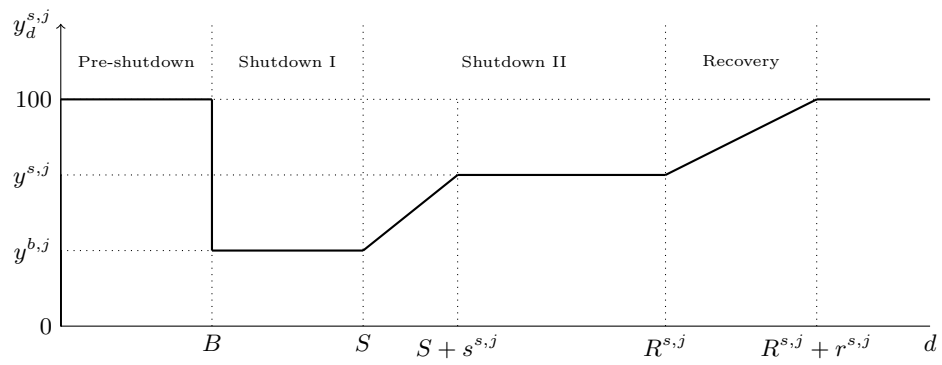


Fig. S4. The figure illustrates the process of economic activity in the model. Starting from a pre-shutdown level, the economy experiences a decline in activity during the shutdown (from 100 to $y^{b,j}$). While the measures are in place, the policy-makers may adjust their severity (from $y^{b,j}$ to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

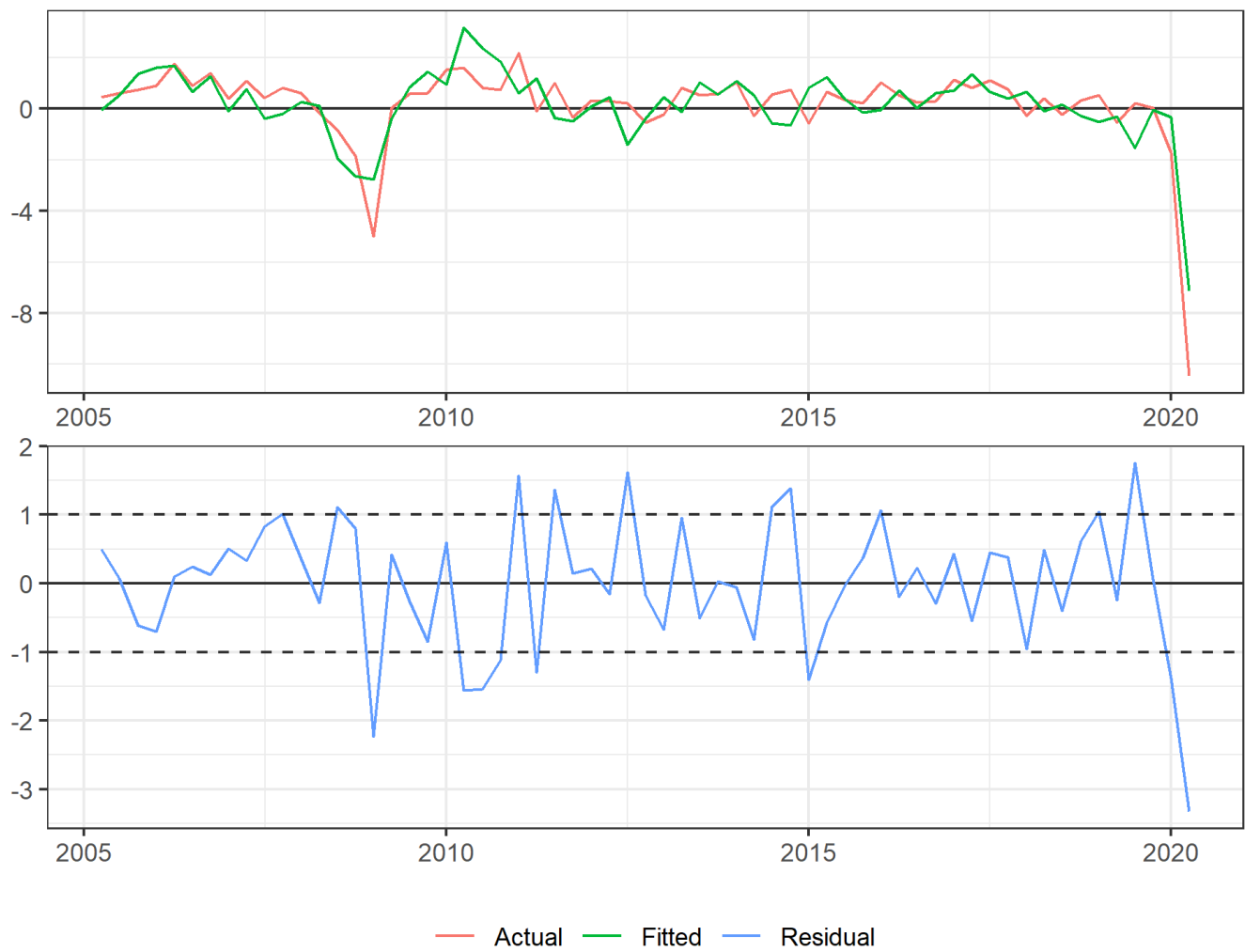


Fig. S5. Regression output

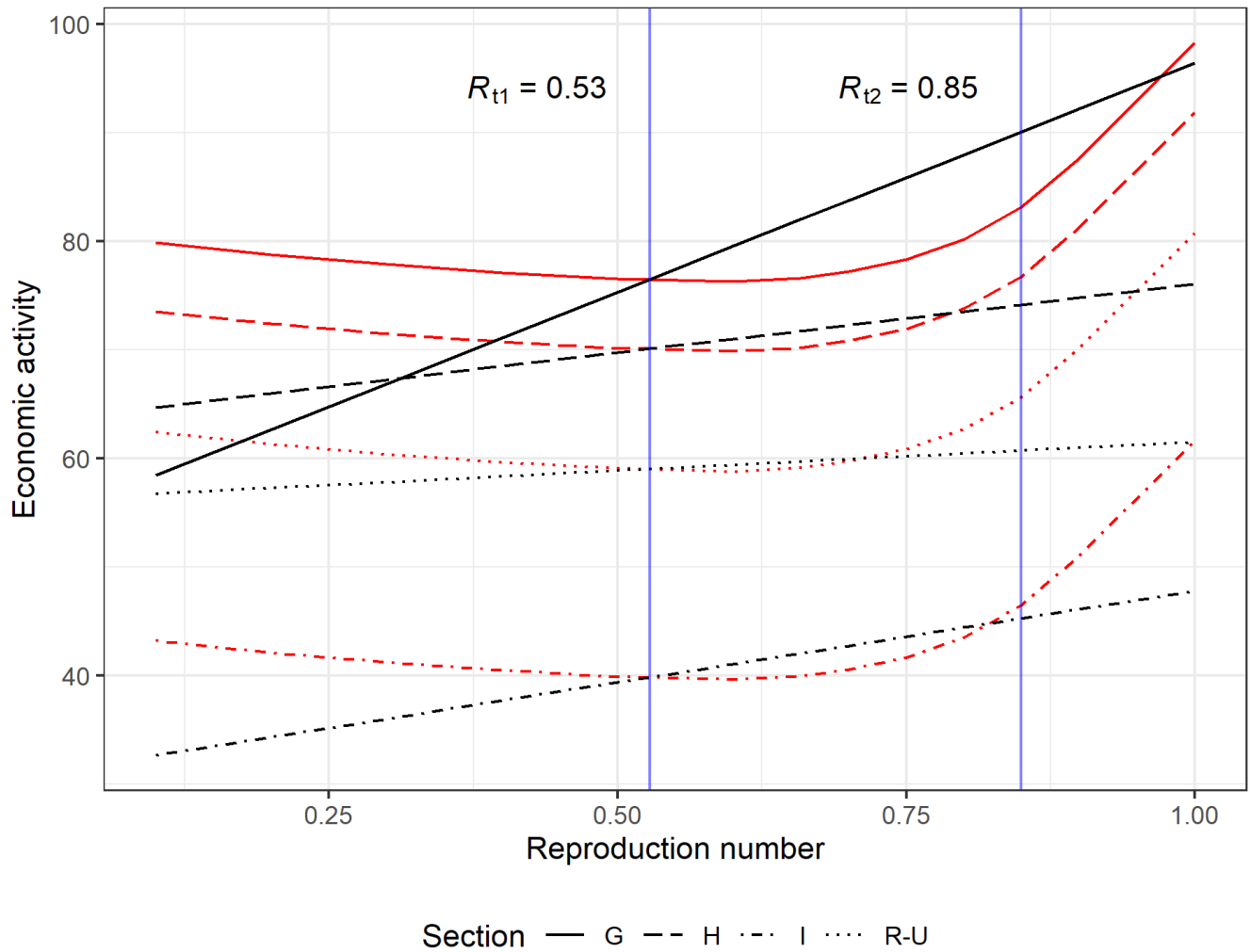


Fig. S6. The black lines show the linear relationships between changes in industry-specific economic activity and changes in the reproduction number. The vertical blue lines indicate the R_t values 0.53 and 0.85 that are used to estimate the slope. The red lines are isocost curves and specify the activity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

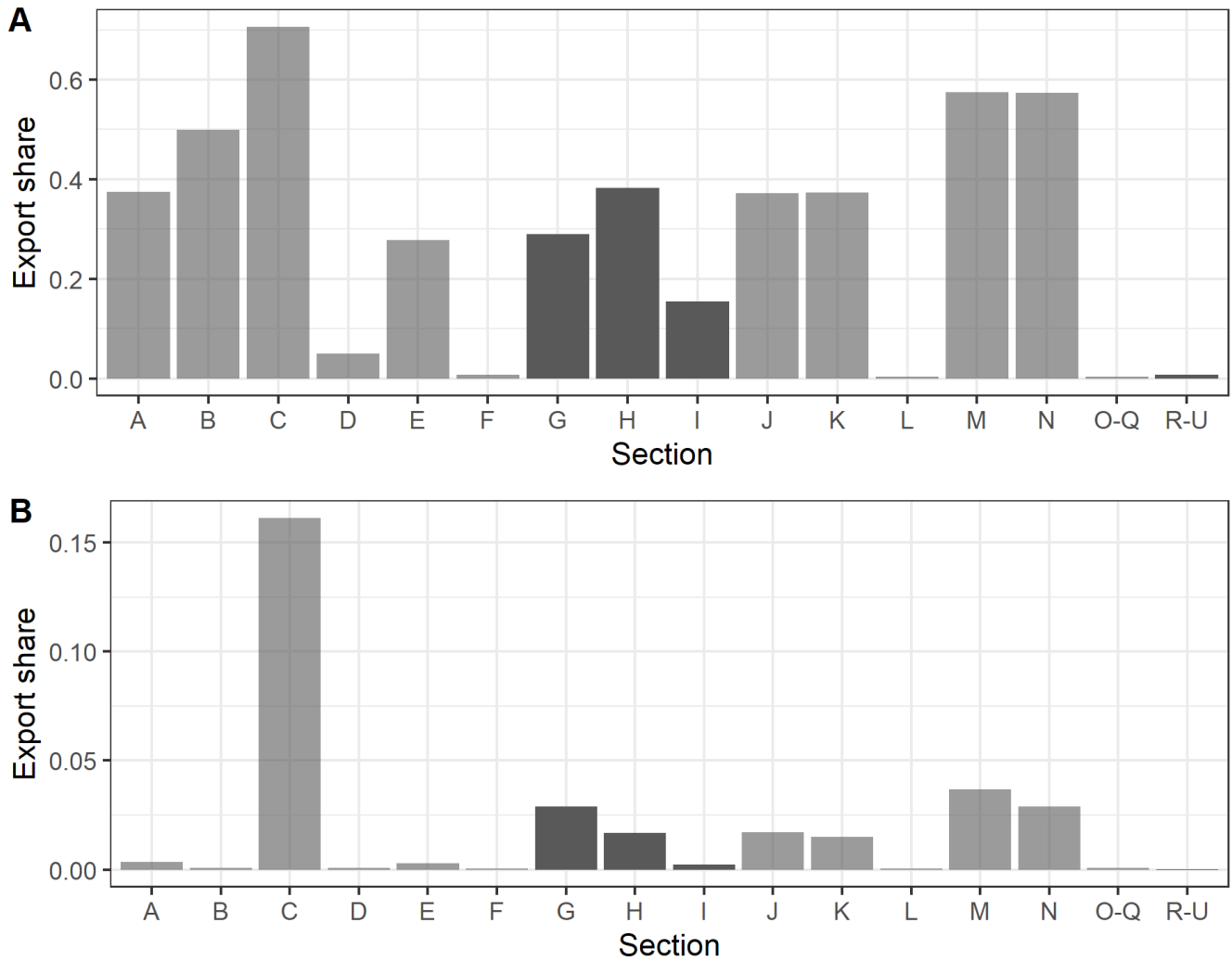


Fig. S7. Panel (A) shows the export shares for each section. The shares are calculated as the share of each section's exports to their sum of household and government consumption, investment, and exports. Panel (B) shows the shares for each section's exports to overall output. Exogenous sections are 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

<i>j</i>	A-U	C	F	G	H	I	J	L	M,N	R,S,T
c_0	0.21* (0.12)	0.16 (0.15)	-0.13 (0.19)	0.39** (0.15)	0.25 (0.22)	-0.50 (0.65)	1.14*** (0.21)	0.26** (0.11)	0.22 (0.18)	-0.24 (0.23)
c_1	0.19*** (0.02)	0.26*** (0.04)	0.14*** (0.05)	0.12*** (0.03)	0.13*** (0.04)	0.69*** (0.17)	0.11*** (0.03)	0.01 (0.02)	0.25*** (0.06)	0.30 (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	Relative costs													
	Baseline	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 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 2.5th and 97.5th 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.

280 References

- 281 1. T Wollmershäuser, et al., ifo Konjunkturprognose Sommer 2020: Deutsche Wirtschaft – es geht wieder aufwärts. *ifo*
282 *Schnelldienst* **73**, 3–58 (2020).
- 283 2. Genesis-Online, Bevölkerung, Stichtag (2020).
- 284 3. John Hopkins University, COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns
285 Hopkins University (JHU) (2020).
- 286 4. Human Mortality Database, Sweden, Population size (abridged) (2020).
- 287 5. Human Mortality Database, United Kingdom, Population size (abridged) (2020).
- 288 6. Human Mortality Database, The United States of America, Population size (abridged) (2020).
- 289 7. K Prem, et al., The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan,
290 China: a modelling study. *The Lancet Public Heal.*, e261–e270 (2020).
- 291 8. N Hoertel, et al., A stochastic agent-based model of the SARS-CoV-2 epidemic in France. *Nat. Medicine*, 1–5 (2020).
- 292 9. F Ndairou, I Area, JJ Nieto, DFM Torres, Mathematical modeling of COVID-19 transmission dynamics with a case study
293 of Wuhan. *Chaos Solitons Fractals* **135**, 109846 (2020).
- 294 10. S Khailaie, et al., Development of the reproduction number from coronavirus SARS-CoV-2 case data in Germany and
295 implications for political measures. *BMC Medicine* **19** (2021).
- 296 11. P Vanella, et al., Pitfalls and solutions in case fatality risk estimation - a multi-country analysis on the effects of
297 demographics, surveillance, time lags between reports and deaths and healthcare system capacity on COVID-19 CFR
298 estimates. *Vienna Yearb. Popul. Res.* **20** [forthcoming] (2022).
- 299 12. O Diekmann, JA Heesterbeek, JA Metz, On the definition and the computation of the basic reproduction ratio r_0 in
300 models for infectious diseases in heterogeneous populations. *J Math Biol* **28**, 365–382 (1990).
- 301 13. O Diekmann, JAP Heesterbeek, MG Roberts, The construction of next-generation matrices for compartmental epidemic
302 models. *J R Soc Interface* **7**, 873–885 (2010).
- 303 14. JC Lagarias, JA Reeds, MH Wright, PE Wright, Convergence properties of the nelder-mead simplex method in low
304 dimensions. *SIAM J Optim.* **9**, 112–147 (1998).
- 305 15. S Sauer, K Wohlrabe, *ifo Handbuch der Konjunkturumfragen*. (ifo Beiträge zur Wirtschaftsforschung) No. 88, (2020).
- 306 16. S Lautenbacher, Subjective uncertainty, expectations, and firm behavior. *MPRA Work. Pap.* **103516** (2020).
- 307 17. R Lehmann, The forecasting power of the ifo business survey. *CESifo Work. Pap.* **8291** (2020).
- 308 18. Federal Statistical Office, *Volkswirtschaftliche Gesamtrechnungen. Input-Output-Rechnung nach 12 Gütergruppen /*
309 *Wirtschafts- und Produktionsbereichen*. (Federal Statistical Office of Germany), (2020).
- 310 19. Q Li, et al., Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *N Engl J Med* **382**,
311 1199–1207 (2020).
- 312 20. H Nishiura, NM Linton, AR Akhmetzhanov, Serial interval of novel coronavirus (COVID-19) infections. *Int J Infect Dis*
313 **93**, 284–286 (2020).
- 314 21. S Zhao, et al., Estimating the serial interval of the novel coronavirus disease (COVID-19): A statistical analysis using the
315 public data in Hong Kong from January 16 to February 15, 2020. *medRxiv* (2020).
- 316 22. R Woelfel, et al., Clinical presentation and virological assessment of hospitalized cases of coronavirus disease 2019 in a
317 travel-associated transmission cluster. *medRxiv* (2020).
- 318 23. D Wang, et al., Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus-infected pneumonia in
319 Wuhan, China. *JAMA* (2020).
- 320 24. World Health Organization, Report of the WHO-China joint mission on coronavirus disease 2019 (COVID-19) (2020).
- 321 25. Q Cai, et al., 2019-nCoV pneumonia in a normal work infectious diseases hospital besides Hubei province, China. *SSRN J.*
322 (2020).
- 323 26. WJ Guan, et al., Clinical characteristics of coronavirus disease 2019 in China. *N Engl J Med* (2020).
- 324 27. Robert Koch Institut, Steckbrief zur Coronavirus-Krankheit-2019 (COVID-19) (2020).
- 325 28. Novel Coronavirus Pneumonia Emergency Response Epidemiology Team, The epidemiological characteristics of an outbreak
326 of 2019 novel coronavirus diseases (COVID-19) in China. *Zhonghua Liu Xing Bing Xue Za Zhi* **41**, 145–151 (2020).
- 327 29. Istituto Superiore di Sanità, Report sulle caratteristiche dei pazienti deceduti positivi a COVID-19 in Italia. il presente
328 report è basato sui dati aggiornati al 20 marzo 2020. (2020).
- 329 30. R Verity, et al., Estimates of the severity of COVID-19 disease. *medRxiv* (2020).