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How to design virus containment polices? A joint analysis of economic and epidemic dynamics under the COVID-19 pandemic

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Abstract

We analyze the impact of different designs of COVID-19 related lockdown policies on economic loss and mortality using a micro-level simulation model, which combines a multi-sectoral closed economy with an epidemic transmission model. In particular, the model captures explicitly the (stochastic) effect of interactions between heterogeneous agents during different economic activities on virus transmissions. The empirical validity of the model is established using data on economic and pandemic dynamics in Germany in the first six months after the COVID-19 outbreak. We show that a policy inducing switches between a strict lockdown and a full opening-up of economic activity is strictly dominated by alternative policies, which implement either a much more cautious opening at the end of the lockdown or a more or less continuous light lockdown with only minor restrictions of economic activity. Furthermore, also the ex-ante variance of the economic loss suffered during the pandemic is substantially lower under these policies. Keeping the other policy parameters fixed, a variation of the consumption restrictions during the lockdown induces a trade-off between GDP loss and mortality. Finally, we study the robustness of these findings with respect to the occurrence of a more infectious virus mutation.

JEL Classification: C63, E17, H12, I18

Key Words: COVID-19, economic loss, containment policy, variance of policy effects, agent-based modeling

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1 Introduction

The ongoing COVID-19 pandemic has caused a global health crisis resulting in more than 80 million reported cases and 1.800.000 casualties, as of the end of the year 2020. Policy makers in many countries have responded to the pandemic by introducing a large variety of containment measures (see Cheng et al., 2020; Haug et al., 2020). Many of these measures have substantial implications for economic activity confronting policy makers with a trade-off between a rapid containment of the pandemic and the prevention of severe economic disruptions. Finding a balanced policy mix resolving this trade-off is a major political challenge, for which it is crucial to develop a thorough understanding of the joint epidemic (number of infected, mortality) and economic (GDP loss, sectoral unemployment) effects of different measures. Whereas well-established epidemiological models can be employed to address the first of these issues (e.g., Kissler et al., 2020; Giordano et al., 2020; Ferretti et al., 2020; Britton et al., 2020), rigorous approaches for studying both dynamics simultaneously are still sparse. Considering these two aspects in an integrated framework is important not only because many containment measures have direct economic effects, but also because several main infection channels are directly related to economic activity (Chang et al., 2020).

The growing economic literature investigating the COVID-19 pandemic on a theoretical level mainly builds upon the standard equation-based SIR model to model the infectious disease (Kermack and McKendrick, 1927; Hethcote, 2000), and introduces some link to economic activity. Measures taken to contain the pandemic thereby typically reduce production potential or consumption and hence induce an economic shock. The interplay between containment measures and economic costs is then studied as a optimization problem from a social planners point of view (e.g., Alvarez et al., 2020; Miclo et al., 2020; Acemoglu et al., 2020), or embedded in a simple macroeconomic framework, where agents individually optimize their decisions (e.g., Eichenbaum et al., 2020; Krueger et al., 2020; Jones et al., 2020). Such abstract models rely on deterministic representations of the virus dynamics and do not capture the local and complex social interactions associated with economic activities (Epstein, 2009), which play an important role in the propagation of the coronavirus (see, e.g., Wu et al., 2020; Prather et al., 2020). Hence, these models neither take the interplay between economic structure (e.g. size and sectoral distribution of firms) and the transmission dynamics into account nor capture the stochastic variation of economic and epidemic dynamics. Although there exists a wide range of stochastic SIR-type epidemic models, these approaches have not been incorporated in economic models so far.[1]

The main contribution of this paper is to examine economic and epidemic effects of lockdown measures using a calibrated micro-founded stochastic macroeconomic model, which explicitly captures the role different economic activities play with respect to the spread of the coronavirus. In particular, our model captures virus transmissions at the workplace, transmissions caused by interactions between consumers and producers, and transmissions via private contacts. Furthermore, we consider an age-structured population, allowing us to capture age-specific differences with respect to economic activities (e.g. working vs. retired population) and the case fatality rate of COVID-19. In addition to capturing relevant transmission channels, the detailed representation of socioeconomic interaction structures allows us to implement a wide range of specific containment measures in our framework. The model is calibrated based on German micro and macro data and is capable of matching to empirical time series, both for economic and epidemiological indicators, under a policy scenario resembling measures implemented in Germany. Based on this, we investigate different lockdown scenarios by systematically varying key parameters governing the intensity of measures during a lockdown, the degree of relaxation after the lockdown and the incidence thresholds used to end/reintroduce the lockdown measures.

We show that a policy combining strict lockdown measures with a full opening-up of the economy between lockdowns and a high incidence threshold[2] for (re)entering lockdowns is strictly dominated by alternative policies, which implement either a much more cautious opening or a rather continuous light lockdown with only minor restrictions.[3] The reason that policies alternating between strict lockdowns and full opening perform worse not only with respect to the expected number of casualties, but also with respect to economic losses, is that they induce a higher degree of volatility into the economy. In light of frictions on the labor and product market this generates high economic losses. Similar to others (Acemoglu et al., 2020; Alvarez et al., 2020; Atkeson, 2020), we find that there exists a trade-off between economic losses and infection numbers when varying lockdown intensity given a fixed incidence threshold. We also demonstrate that the policies differ substantially with respect to the uncertainty about the induced economic loss. In particular, the policies which are at the efficiency frontier also tend to give rise to substantially lower variation. Understanding the implications of different

[1]To our knowledge the only exception in this respect is Federico and Ferrari (2020), where the optimal lockdown policy of a social planner trying to minimize expected discounted social costs is characterized in the framework of a SIR model with a stochastic transition rate.

[2]Incidence is measured as the reported number of newly infected over 7 days per 100.000 households.

[3]This strategy has been called *the Hammer and the Dance* (Pueyo, 2020) and has been found to be optimal also in other settings (Hellwig et al., 2020; Farboodi et al., 2020).

policy choices for the variance of policy results seems particularly important in an area like virus containment, where the effectiveness of chosen measures also depends on the policies' acceptance by the general public. In such a setting bad initial outcomes might have a detrimental effect on public acceptance of the policy, deteriorating its future effectiveness (Bargain and Aminjonov, 2020; Altig et al., 2020). To our knowledge, this paper is the first economic analysis of lockdown policies, explicitly addressing the relationship between policy properties and variance of the resulting economic and epidemiological dynamics. In the last part of our analysis we show that most of our qualitative insights, in particular the appeal of a policy combining a strict lockdown with weak opening, still apply in a scenario where at some point in time the virus mutates to a more infectious variant, which then spreads in the population simultaneously to the original version. A key difference between our default scenario and that with such a mutation is however, that the mortality associated with continuous light lockdown policies substantially grows, such that these policies no longer dominate a policy characterized by strict lockdowns, full opening and a high incidence threshold for entering lockdowns.

In light of the mechanisms underlying our insights, our qualitative results can be transferred to countries with a health system and economic structure comparable to Germany. In addition, the flexibility of the framework allows the modeller to adjust the parameters related to Covid-19 to analyse potential future pandemics. In fact, the model can easily be re-calibrated to data from other countries or from different pandemics in order to analyse appropriate policies under alternative structural conditions.

Methodologically, our approach combines a SIR-type simulation model with an agent-based macroeconomic model. Agent-based models have been used to assess the effectiveness of containment policies in purely epidemiological studies (e.g., Adam, 2020; Ferguson et al., 2020; Silva et al., 2020) and the approach has been applied to address a large variety of macroeconomic research questions and policy analyses in recent years (see, e.g., Foley and Farmer, 2009; Dawid and Delli Gatti, 2018; Dosi and Roventini, 2019, for dicussions). By explicitly linking economic activities and transactions to contacts between agents, agent-based economic models are particularly suited for studying the dynamics of virus transmissions in an economy. Only a few other studies have used a unified agent-based model, combining an economic framework with an epidemiological structure in the context of COVID-19 (Delli Gatti and Reissl, 2020; Sharma et al., 2020; Mellacher, 2020; Silva et al., 2020). However, this is the first paper using a such unified framework for the evaluation of average economic and pandemic effects as well as the associated uncertainty about outcomes under different policy responses to the outbreak of the COVID-19 pandemic.

The paper is organized as follows. In Section 2 we provide a short description of the model (a detailed description is given in Appendix B) and in Section 3 we describe the set of containment policies considered in our analysis. In Section 4 we discuss the calibration of the model and demonstrate the good fit of the model output with time series data from Germany. The main insights from our policy analysis are discussed in Section 5 and we end with conclusions and an outlook on potential extensions of the analysis in Section 6. In addition to the detailed description of the baseline model and the version with a virus mutation, the Appendix contains some results with respect to additional policy variations, statistical test results underlying our findings and lists of model variables and of parameter values.

2 The model

In this section, we provide a short description of our model, which highlights the overall structure of the economy as well as the crucial assumptions and mechanisms driving the economic and pandemic dynamics. A more detailed and technical presentation of the model is given in Appendix B.

2.1 Economy

The economy consists of firms as well as young and old households. Young households constitute the labor supply of the economy, whereas old households live on a pension that is paid through a pay-as-you-go system. There are three private and one public sector in the economy. We explicitly represent these different sectors in the model in order to be able to capture sectoral differences with respect to firm size and the number of contacts a households has by consuming a product of a particular sector, as well as to analyze the effects of sector specific reductions in consumption and economic activity due to lockdown measures.[4] The basic time unit in our model is one day and activities of agents take place daily or periodically, e.g. once a week (household consumption, firm production planing,..).

[4]In particular, we include the public sector in our model to capture that employment in this sector is not affected by lock-down measures.

Firms

Firms are distributed across three private sectors: manufacturing (M), service (S) and food (F), where the latter represents all essential products for daily life. A firm i is characterized by a firm-specific productivity level A_i and employs $L_{i,t}$ workers in period t to produce a weekly output $Q_{i,t}$ according to the linear production function $Q_{i,t} = A_i \, L_{i,t}$.[5] The firms' activity and planning cycle is one week and each firm plans and carries out its production at the beginning of each week. The produced quantity replenishes the firm's inventory stock at the sector-specific mall. At the mall all producers in that sector offer their product at posted prices. In particular, the firm carries out the following steps:

1) The firm determines the target level of inventory at the beginning of the week based on its adaptive demand expectation and size of a sector-specific safety buffer, which is determined based on estimated demand volatility. The resulting planned production quantity determines the desired size of the firm's workforce. If the size of the firm's current workforce is larger than the desired number of employees, the firm dismisses the appropriate number of randomly picked workers.

2) If the firm needs to increase its workforce it opens vacancies and unemployed job seekers skilled to work in the firm's sector apply. Firms announce their openings in random order and hire on a first-come-first-serve basis. If there are no job seekers at the time of the announcement, the firm is rationed and can only hire again in the following week.

3) Production of output $Q_{i,t}$ takes place. Products are offered in the sector-specific mall at posted prices. Firms set prices $p_{i,t}$ by applying mark-up pricing with an endogenous mark-up on unit costs. The mark-up adaptively evolves over time within a fixed interval and depends positively on the firm's market share.

4) Firms pay wages w_i, which are sector-specific and proportional to the average productivity in the sector, as well as taxes and dividends. Dividends are determined as a fraction ζ of net profits, where $\zeta = 1$ if the firm's liquidity exceeds a threshold and $\zeta < 1$ otherwise. Dividends and the fixed costs paid by the firms are equally distributed among households

[5] Since our analysis focuses on a short time period (24 months) characterized by a severe economic crisis, we abstain from incorporating a market entry mechanism or productivity improvements into our model. Furthermore, we assume that the current crisis has no effect on the capital stock and hence do not explicitly incorporate a capital goods sector into our model.

to ensure stock-flow consistency of the model. A firm with negative liquidity declares bankruptcy and exits the market.

Households

While old households are retired, young households are active on the labor market. Each household has appropriate skills to work in one sector of the economy. The households' weekly activity sequence is as follows:

1) Unemployed households apply for open positions.

2) Housholds receive wages, unemployment benefits, pensions as well as dividends and pay taxes.

3) Households determine their consumption budget for the upcoming week according to a buffer-stock saving heuristic, see (Deaton, 1991). In particular, households spend exactly their weekly net income as long as their current wealth corresponds to a desired wealth-to-income ratio. Otherwise, consumption spending is adjusted such that the wealth-to-income level moves towards its target value. The consumption budget is allocated across the three sectors according to fixed (empirically determined) consumption shares. However, there is a lower bound on the factor by which the consumption budget for food/essential products might change between consecutive weeks.

4) Each household has a day of the week for each sector $k \in \{M, S, F\}$ at which with she considers to visit the sector-specific mall. The household visits the mall at that day with probability p_k^s, where in the absence of lockdown measures $p_k^s = 1$ for all sectors k. Upon visiting the mall the household scans the posted prices in a randomly chosen subset of firms in the sector, and chooses the firm to buy from according to a logit choice function based on these prices. The purchased quantity is determined by the household's consumption budget for that sector. If the inventory of a firm at the mall becomes zero during a week, the firm is no longer considered by households in their consumption choice until the inventory is filled up again.

Public sector

Besides the three private sectors, there is also a public sector operated by the government with a constant number of government offices. The public sector provides administrative services that are not sold on the goods market and employees a constant set of workers in the public offices. The government collects income and profit taxes to finance the wage bill of the public employees and to pay unemployment benefits, pensions and potentially lock-down related transfers to individuals and firms. The government adjusts the tax rate over time in order to keep the public account at a given target level.

2.2 Virus transmission

Virus transmission is modeled by explicitly tracking contacts between agents and potential infection chains. Following a standard SIRD approach households can be in one of the four states: susceptible, infected, recovered or deceased (see, e.g., Hethcote, 2000). A susceptible household is infected with the homogeneous infection probability p_{inf} at each contact with an infectious agent. After infection, agents first enter a homogeneous latency period of length t_{ltn}, followed by a period where the agent is infectious (length t_{inf}). Following this, agents enter the post-infectious phase, in which they either recover (giving them full immunity against reinfection) or pass away with a fatality rate depending on the agents' age group and the current state of the healthcare system. In case the intensive care units are underutilized, the fatality rate only depends on the agents age group. If, however, the demand for intensive care units exceeds the availability, the fatality rate increases proportionally to the size of the shortfall.

Social interactions

Contacts between households may take place on three different occasions, each potentially contributing to the propagation of the virus:

i) Employed households have contact to a number of co-workers at their employer every day.

ii) During their consumption activities, households have contacts to other agents visiting the same mall at the same day. For the service sector, this also includes contacts during the consumption of a service (e.g. at a restaurant or a fitness studio).

iii) Other social contacts not directly related to economic activities, where we distinguish between the frequencies of intra- and inter-generational contacts for the different age groups.

The actual number of contacts for a household is stochastic with sector- and age-specific expected values that have been informed by empirical data.

3 Policy measures

3.1 Containment measures

The containment measures addressed in our policy analysis are inspired by a set of measures implemented in different countries after the outbreak of COVID-19 (Cheng et al., 2020) and can be grouped into four categories:

i) Individual prevention measures reducing the infection probability at face-to-face contacts between an infected and a susceptible agent from p_{inf} to $(1-\xi)\ p_{inf}$ with $\xi \in (0,1)$. These measures include keeping a minimum physical distance, improved measures of sanitation, and wearing face coverings.

ii) Social distancing measures reducing social interactions in the private context either through contact restrictions imposed by the government or through a consensual change in the behavior of individuals. Studies show that there has been a substantial reduction in the number of social contacts in Germany after the outbreak of COVID-19 (e.g., Lehrer et al., 2020). In our model, social distancing is captured by a reduction of the average number of daily intra- and inter-generational social contacts.

iii) Reduction of contacts at the workplace, by allowing a sector-specific fraction of employees to work from home (see Fadinger and Schymik, 2020; Möhring et al., 2020).

iv) Reduction of consumption activities, by reducing the sector-specific weekly shopping probabilities p^s_k. Such a reduction might be induced by restrictions from the government (lockdown), or by voluntary changes in individual consumption behavior due to public information about potential infection risks. More precisely, we assume that the weekly shopping probability during lockdown is reduced to

$$p^{s,l} = (1,1,1) - \alpha^l(\Delta p^{s,l}_M, \Delta p^{s,l}_S, 0). \tag{1}$$

The parameter α^l governs the intensity of the lockdown and $\Delta p^{s,l}_M, \Delta p^{s,l}_S$ are calibrated such that the intensity of the lockdown measures taken in Germany in March 2020 correspond to $\alpha^l = 1$. Shopping probabilities in the food and essential good sector are not reduced during lockdowns. In contrast to measures i) - iii), the reduction of consumption activities has a direct negative impact on economic activity. In order to capture policies that include partial reduction in consumption also in periods without an actual lockdown in place, we introduce a second parameter α^o, governing the degree of opening. The sector specific weekly shopping probability in periods without lockdown (as long as the containment policy is active) is given by

$$p^{s,o} = (1,1,1) - \alpha^o(\Delta p_M^{s,l}, \Delta p_S^{s,l}, 0). \tag{2}$$

3.2 Economic support programs

We assume that economic support measures accompany the virus containment policies in order to counteract the economic disruptions and to keep the number of insolvencies low:

i) Under the *short-time work scheme* firms put a fraction q^{st} of employees on short-time work. Employees on short time receive a fraction $\varphi < 1$ of their regular wage paid by a transfer from the public account.

ii) Under the *bailout policy* the government bails out any firm with negative savings in a given period balancing the firms account with a transfer from the public account, thereby avoiding bankruptcy.

In our policy analysis below, we assume that both measures are activated at the time of the first lockdown, and then maintained for one year. The findings discussed in Section 5.2 carry over also to scenarios without economic support programs, see Basurto et al. (2020).

4 Model calibration

The calibration of the model is described in detail in Appendix B.4. It is based on demographic and statistical data from Germany, as well as empirical studies on age-structured social interaction patterns. We target key aggregate economic indicators e.g. per capita GDP, unemployment rate and the value of the R_0 coefficient for the coronavirus in the absence of any countermeasures.

For the economic parameter values of the model, we use German data on demographic structure, sectoral distributions of productivity and consumption spending, sector-specific fraction of workers eligible for working from home, average firm size and the average unemployment rate. Parametrization of behavioral rules are taken from the well-established models in the agent-based macroeconomic literature (see, e.g., Dawid et al., 2019). Epidemiological parameters, like fatality rates, intensive care utilization and the detection rate are taken from German data, whereas the (age-structured) number of social contacts associated with different activities are

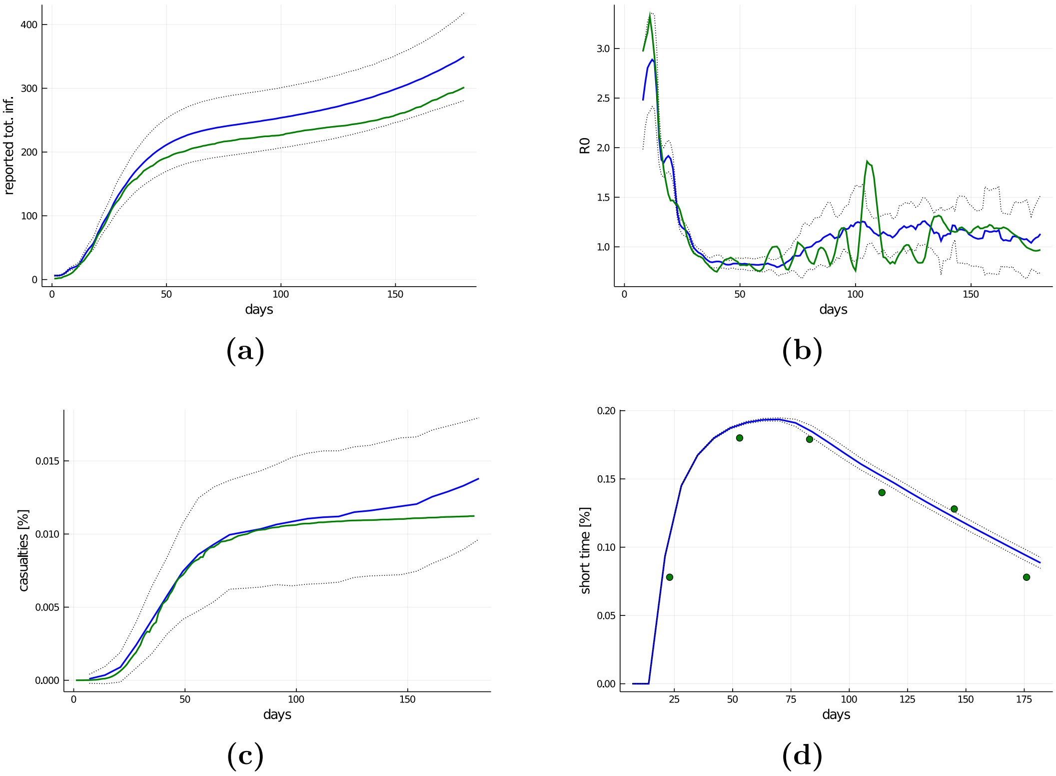


Figure 1: **Comparison of simulation output with empirical data for Germany.** Blue solid lines show the average over 20 Monte Carlo runs, black dotted lines plus-minus one standard deviation bands across Monte-Carlo runs. Green solid lines show empirical counterparts based on epidemiological data from Johns Hopkins University (Johns Hopkins University, 2020) for Germany from 9 March 2020 (day 0) to 5 September 2020 (day 180), scaled to a population of 100.000 inhabitants and adjusted by a detection rate. Containment and lockdown measures are introduced after 14 days into our simulation (corresponding to 23 March 2020) and are lifted at day 63 (11 May 2020) (Cheng et al., 2020). **(a)**, Accumulated number of infected. **(b)**, weekly smoothed R_0 value **(c)**, Casualties as a percentage of the population. **(d)**, Percentage of workers in short-time program. Green dots show estimated number of workers in short-time program relative to size of the active labor force for April to August in Germany (Bundesagentur für Arbeit, 2020).

taken from survey studies (Mossong et al., 2008). Data about the containment measures, the sector specific effects on consumption and on the reduction in contacts is based on German data on policy interventions and societal activities during and after the first lockdown in March 2020 (see Appendix B.4 for all parameter choices and sources). The individual contact infection probability p_{inf} is calibrated to match an R_0 value of 2.5 (without any containment policy), in accordance with empirical evidence (Read et al., 2020). The effectiveness of individual prevention measures ξ, for which no direct empirical observations are available, is calibrated by targeting key properties of infection dynamics in Germany over a time span of 6 months. In particular, we use two separate values for this parameter: For the first lockdown phase starting on March, 9, 2020 we use $\xi^l = 0.6$ and one for the opening-up phase after May 11 2020 we use

$\xi^o = 0.525$. In Figure 1, we compare the simulation output of the model under policies resembling German measures (blue) with actual German data (green) for the 180 days after March 9, 2020.[6] Although only three free parameters (ξ^l, ξ^o, q^{st}) were calibrated to target these empirical time series, the generated data is consistent with its empirical counterpart, both with respect to levels and dynamic patterns. This applies to infections and mortality (Fig. 1a-c) as well as to the time-series of economic indicators, like the number of workers in short-time program (Fig. 1d).

5 Policy Analysis

Having established the ability of our model to qualitatively and also quantitatively reproduce German epidemiological and economic time series under a policy scenario mirroring actual measures taken in Germany, we will now explore the epidemiological and economic implications of alternative policies. Our analysis begins in Sec. 5.1 with a policy scenario in which we only consider measures without direct economic effects. This part demonstrates that restricting attention to such policies is not sufficient to keep the number of infected at a level to avoid overutilization of ICU capacities. Based on this, we focus in our main analysis in Sec. 5.2 on lockdown policies that are associated with direct economic costs and compare the effects of different designs of such policies. In Sec. 5.3 we run the same policy analysis including the emergence of a more contagious virus mutation to assess the robustness of the derived policy results.

5.1 Policies without direct economic impact

An important question is whether the spreading of the virus can be reduced with containment measures not directly interfering with economic activities in the sense of closing stores or reducing the possibility to consume services. We consider three policy scenarios. First, a scenario where no containment measures are taken at all. Second, the introduction of only individual prevention measures, and third the combination of these individual prevention measures with working from home.

Figure 2 shows the dynamics of the percentages of the population of currently infected and of casualties. The curve of infected individuals in the absence of any measures (blue) follows a steep hump-shaped pattern well known from standard SIRD models (Hethcote, 2000). Due to herd immunity, the virus is eliminated after approximately 120 days but the associated mortality is

[6] See Table 4 in Appendix B.4 for a summary of the parameter settings underlying these simulation runs.

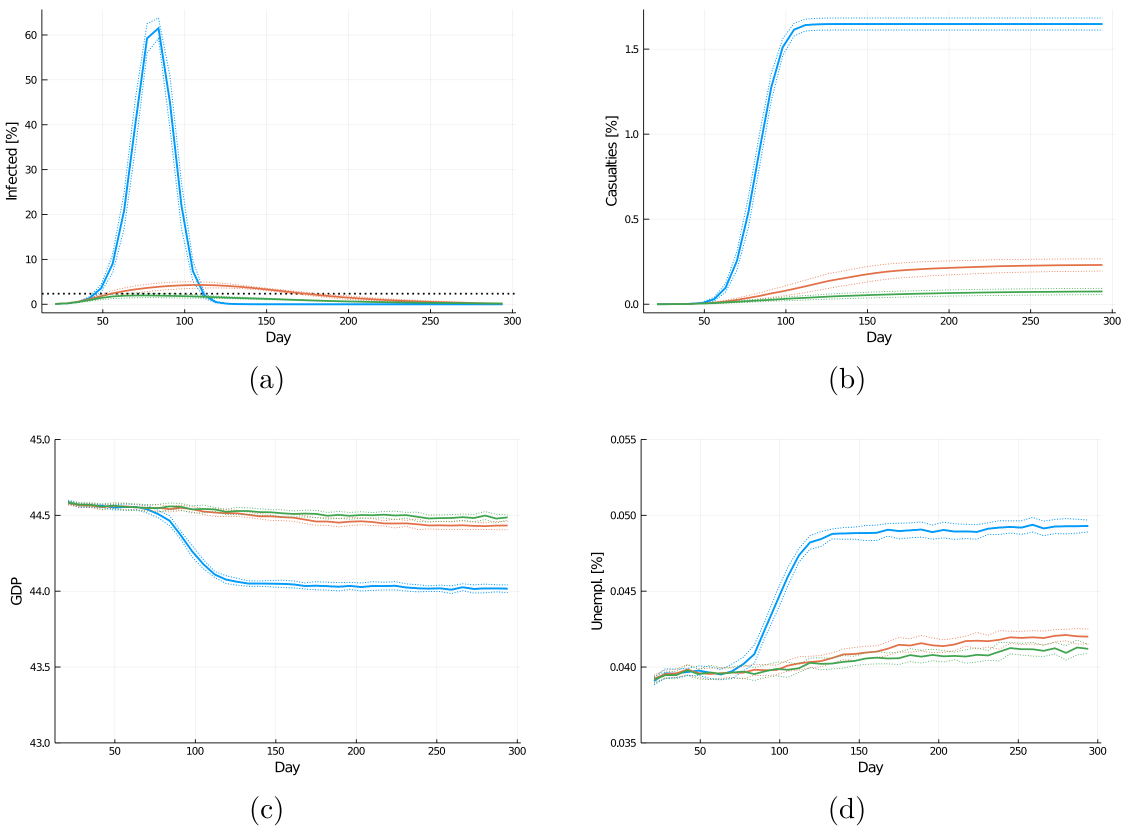


Figure 2: **Dynamics.** Solid lines show averages over 20 Monte-Carlo runs, dotted lines plus-minus one standard deviation bands across Monte-Carlo runs. **(a)** Dynamics of currently infected individuals and **(b)** total casualties as well as **(c)** GDP per capita and **(d)** unemployment rate for the scenarios with no policy measures (blue), only individual prevention measures (orange) and individual prevention measures in combination with working from home (green). The black dotted line in panel (a) indicates the upper bound on the number of infected under which the intensive care capacities are still not fully used.

about 1.6%. This illustrates that our transmission model is producing reasonable, characteristic epidemiological dynamics.

To see the effect of individual prevention measures in our model, we analyse a setup in which only ξ increases to the calibrated benchmark value of 0.6 two weeks after the appearance of the virus. The introduction of the individual prevention measures (orange) strongly reduces the speed of the diffusion of the virus and the maximum number of infected. Complementing individual prevention measures with home-office (green) reinforces these effects and average mortality can be reduced by a factor of approximately 10 compared to the scenario without any containment. Nevertheless, the simulations indicate that these measures are not sufficient to ensure that the number of infected stays below the intensive care capacity.

Considering the GDP and unemployment dynamics shown in Fig. 2 (c) and (d), it is confirmed that these measures are not associated with any direct economic costs.[7] A crucial assumption in this respect is that in our setting productivity of workers is not reduced when they work from home. The slight decrease in GDP and increase in unemployment around period 100 in the scenario without containment measures is due to the reduction in demand induced by the large mortality.

5.2 Policies with direct economic impact

In the following analysis, we focus on the design of containment measures with direct economic impact. In order to compare different policies we use two main indicators: (i) virus mortality, measured as the percentage of the population deceased due to the virus 24 months after the virus outbreak and (ii) the average percentage loss in GDP (relative to the pre-virus level) during this time interval. Similar to the default policy scenario (Fig. 1) we assume that two weeks after the initial occurrence of the virus at $t = 0$, individual preventive measures, social distancing, working from home and lockdown measures are activated.[8] The design of the lockdown policy is then characterized by the following three key parameters, which are systematically varied in our analysis:

i) Intensity of the lockdown reducing the shopping probability: α^l (see (1)).

ii) Reduction in weekly shopping probability in periods without lockdown if the virus is still active: α^o (see (2)).

iii) Incidence threshold β^l: the lockdown stage is re-activated if the reported number of weekly newly infected per 100.000 households grows above β^l.

As mentioned above, the benchmark policy resembling the German scenario in Section 4 corresponds to $(\alpha^l, \alpha^o, \beta^l) = (1, 0, 50)$. In addition, we assume that a lockdown is lifted once the incidence of newly infected falls below $\beta^o = 5$ for all policy scenarios. In Appendix C, we show that policies using larger values of β^o are dominated by those considered here. During the opening-up phase we assume that the working from home measure remains active. Moreover, all runs are based on the assumption that 18 months after the occurrence of the virus, a vaccine has been developed and a sufficient percentage of the population has been vaccinated to prevent

[7] GDP is calculated on a weekly basis and the unit of measurement on the vertical axis in Fig. 2 (c) is such that a constant flow of une unit throughout a year corresponds to an annual GDP per capita of 1000€.

[8] In Appendix C, we show that delaying the initial lockdown induces higher mortality without reducing the economic loss. Similar findings have also been obtained in a slightly different setting in Basurto et al. (2020).

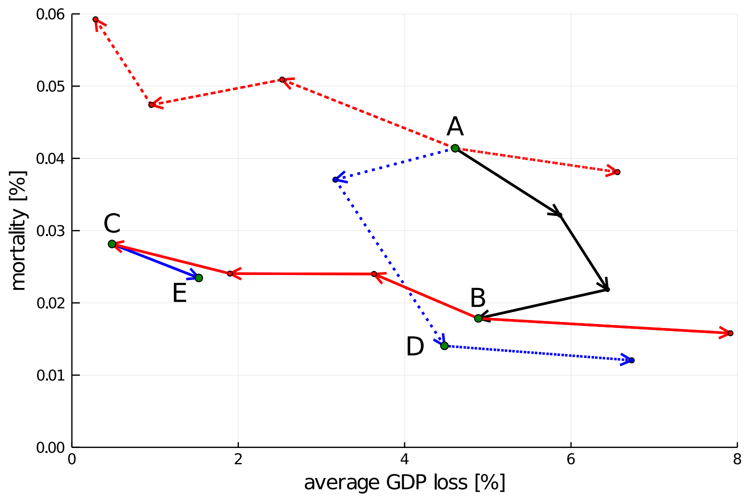
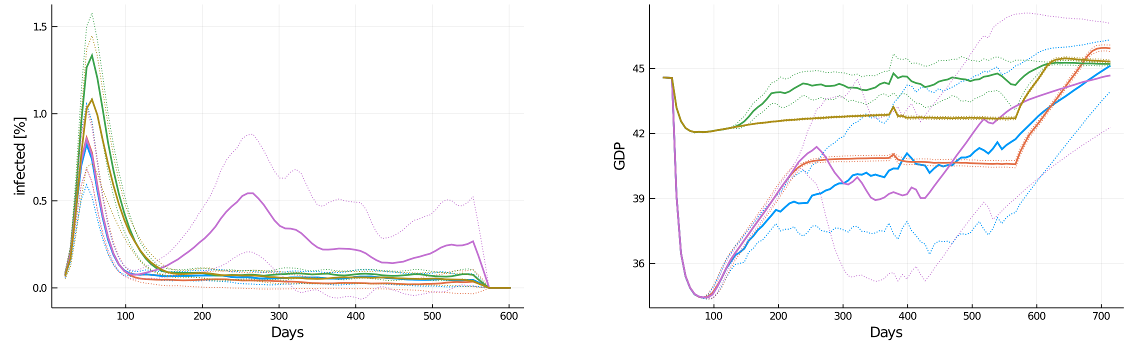


Figure 3: **Effects of variations of key policy parameters.** All points correspond to averages across the 20 runs. GDP loss [%] on the x-axis measured as weekly loss averaged over simulation time span of 728 periods (24 months) as a percentage of baseline and mortality [%] on the y-axis expressed as a percentage of population.

any further transmissions of the virus. Hence, at that point p^{inf} is set to zero and all measures are lifted. Since a full economic recovery might still need some time even after all restrictions have been removed, our analysis covers a time window of 24 months after the first introduction of lockdown measures. For each considered policy scenario we carry out 20 simulation runs of the model in order to capture the variance of the emerging dynamics.

The main results from our analysis are summarized in Figure 3, which shows the average GDP loss and total mortality after 24 months (mean over the 20 runs) under a systematic variation of the policy parameters. Starting from point A, corresponding to the calibrated German policy scenario $(1, 0, 50)$, we systematically vary the key parameters $(\alpha^l, \alpha^o, \beta^l)$. First, along the black line we decrease the threshold β^l reaching a policy $(1, 0, 5)$ in point B. Second, along red lines (solid and dashed) we decrease (left arrow) or increase (right arrow) the intensity of the lockdown, α^o with a step size of 0.25. In the following analysis we will consider in particular the policy $(0.25, 0, 5)$, labeled as C, which combines a low lockdown threshold with weak restrictions during the lockdown. Finally, along blue lines (solid and dashed) we increase the restrictions in the opening-up phase, α^l, in steps of size 0.25. Hence, point D $(1, 0.5, 50)$ corresponds to a policy with strong lockdown, a high threshold for entering a lockdown, but only weak opening. Finally, point E $(0.25, 0.25, 5)$ represents a policy of continuous weak restrictions of economic activity. Figure 4 shows the dynamics of newly infected (panel a) and per capita GDP (panel b) for the five key policy scenarios corresponding to points A-E. Table 1 contains mean values and standard



(a) **(b)**

Figure 4: **Dynamics.** Evolution of the **(a)** current number of infected and **(b)** the GDP per capita for the five policy scenarios (A: purple; B: blue; C: green; D: red; E: brown). Solid lines indicate batch run means and dotted lines means plus/minus one standard-deviation.

	A	B	C	D	E
$(\alpha^l, \alpha^o, \beta^l)$	$(1, 0, 50)$	$(1, 0, \mathbf{5})$	$(\mathbf{0.25}, 0, \mathbf{5})$	$(1, \mathbf{0.5}, 50)$	$(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$
	benchmark policy	*low threshold*	*weak lockdown*	*weak opening*	*weak lockdown+opening*
GDP loss [%]	4.61 (1.41)	4.89 (1.66)	0.48 (0.18)	4.48 (0.04)	1.53 (0.05)
Mortality [%]	0.041 (0.011)	0.018 (0.007)	0.028 (0.005)	0.014 (0.005)	0.023 (0.008)
Duration in lockdown	114.1 (56.6)	124.6 (53.2)	258.6 (120.7)	58.1 (9.1)	159.9 (28.0)
Number of lockdowns	2.0 (0.32)	7.15 (3.05)	8.1 (2.67)	1.0 (0.0)	5.5 (2.76)
Pub. Acc. Deficit [% of GDP]	3.33 (1.61)	3.03 (1.01)	1.02 (0.13)	2.45 (0.27)	1.25 (0.10)

Table 1: **Comparison of policy results.** Cells show means over 20 batch runs with standard deviation in brackets.

deviations for key indicators, such as the duration of the lockdown or the public deficit, across the batch runs for each of the five key policies. In Tables 8 and 9 in Appendix D we provide information on the statistical significance of the differences in induced GDP loss and mortality between the key policies based on Mann-Whitney-U tests.

Based on these Figures and Tables we derive four qualitative insights about the implication of different types of lockdown policies.

Result 1 *Policies with a continuous 'weak lockdown' or 'weak opening' after the initial lockdown dominate policies with switches between strong lockdown and full opening (A vs. C, D, E).*

Figure 3 shows that policy scenario A is clearly dominated by policies C and E, which both result in lower expected values of mortality and lower GDP loss. Considering the very high average lockdown duration under policy C, it is hardly surprising that the effect of this policy is close to that of policy E, which essentially implements a weak lockdown throughout the entire 18 months in which the virus is active. As can be seen in Figure 4 the main economic advantage of these policies is that, compared to a policy with strong initial lockdown, such as A, they induce a much weaker initial downturn. The reduction in economic activity caused by strong lockdown measures has immediate negative impact on firm's production planning and household's wage income. Hence, even after lockdown measures have been lifted, the adjustment of consumption spending and production plans needs time and in combination with (labor market) frictions this implies a relatively slow economic recovery. Therefore, under policies characterized by strong lockdown induced downturns, accumulated GDP loss grows in a convex way with the size of these downturns. Hence, avoiding the large costs associated with a strong initial reduction in economic activity induces smaller economic losses, even if the constraints have to be preserved for an extended period of time, as in policy E. Figure 4a shows that implementing only weak lockdown measures leads to a larger initial peak and a delayed decrease in the infection numbers, compared to a strong lockdown (A). However, the continuous application of lockdown measures prevents a second wave and hence overall mortality in policies C and E is below that of A. Combining a strong initial lockdown with a weak opening, as under policy D avoids a second lockdown, if shopping activities are sufficiently strongly reduced during the opening phase (Tab. 1). This clearly leads to lower mortality compared to policy A, but, due to the continued demand reduction also after the end of the initial lockdown, the GDP dynamics stagnates below the pre-crisis level (Fig. 4b) and fully recovers only after all measures have been lifted. Due to the reasons given above, economic losses triggered by the second sharp downturn occurring under policy A outweigh such a continuous loss, such that the total expected GDP loss under policy D is still smaller than that under policy A.[9] Finally, it should be noted that, due to the induced repeated economic downturns, policy A also results in a larger increase in the public deficit compared to policies C,D and E (Tab. 1).

Result 2 *For a given lockdown intensity α^l, decreasing the lockdown threshold β^l induces lower mortality without increasing economic losses (A vs. B).*

In terms of infection dynamics (Fig. 4a), a higher threshold causes a visible second wave which is absent for a lower threshold. A threshold of $\beta^l = 50$ results in two lockdowns for most runs (Tab. 1), which are necessary in response to resurgence of the virus. In contrast, policy B with

[9]Note that under a weak opening policy also a much smaller value of the threshold β^l could be chosen without triggering a second lockdown, such that our results obtained for policy D would apply in the same way to any policy with $\alpha^l = 1, \alpha^o = 0.5$ and $\beta^l \geq 5$.

threshold of $\beta^l = 5$ causes numerous lockdowns and accumulates a longer total duration in lockdowns over the whole time span. These repeated lockdowns keep the number of infected low, which explains the substantial reduction in mortality relative to policy A. In terms of GDP, both policies are characterized by a strong initial downturn and the trajectories only begin to deviate from each other in the recovery phase. Under a low threshold (policy B) the economy repeatedly returns into shorter lockdowns and hence recovery in general is slower compared to policy A. However, a second downturn with the associated negative effects through the demand channel and labor market frictions, as it is triggered by the second lockdown under policy A, is avoided. Hence, overall the total duration of lockdowns and also the average economic costs do not vary significantly between policies A and B (Tab. 8).

Result 3 *For a given lockdown threshold β^l, a variation of the intensity α^l results in a trade-off between mortality and GDP loss (B vs. C).*

The observation that reducing the lockdown intensity leads to lower economic losses but higher mortality can not only be derived from the comparison of policies B and C, which both have a threshold of $\beta^l = 5$, but also for $\beta^l = 50$ by considering the dotted red curve moving to the upper left from point A in Figure 3. The dynamics in Figure 4a illustrate that less reduction in consumption activity (policy C vs. B) leads to more infections and higher mortality. Considering the GDP dynamics (Fig. 4b), one can observe that the stricter lockdown of policy B imposes a strong initial shock on the economy and forces the GDP trajectory on a lower path compared to policy C over the entire course of the simulation.

Together, Results 1-3 identify a kind of 'efficiency frontier' spanned by policies of light lockdowns (C,E) and strict lockdowns with weak openings (D). As one might expect, the frontier is characterized by a trade-off between mortality and economic loss, but policies switching between strict lockdowns and full openings are above the frontier and hence seem inefficient. This is particularly true if the threshold for entering a lockdown in such policies is high (A). Whereas so far we have only considered the expected effects of the different policies, in the next result we consider the ex-ante uncertainty about mortality and GDP loss, i.e. the variance of these indicators across runs.

Result 4 *Policies differ significantly with respect to the variance of resulting GDP loss. Effects of policies with a 'weak opening' (D, E) can be predicted with higher certainty than for policies*

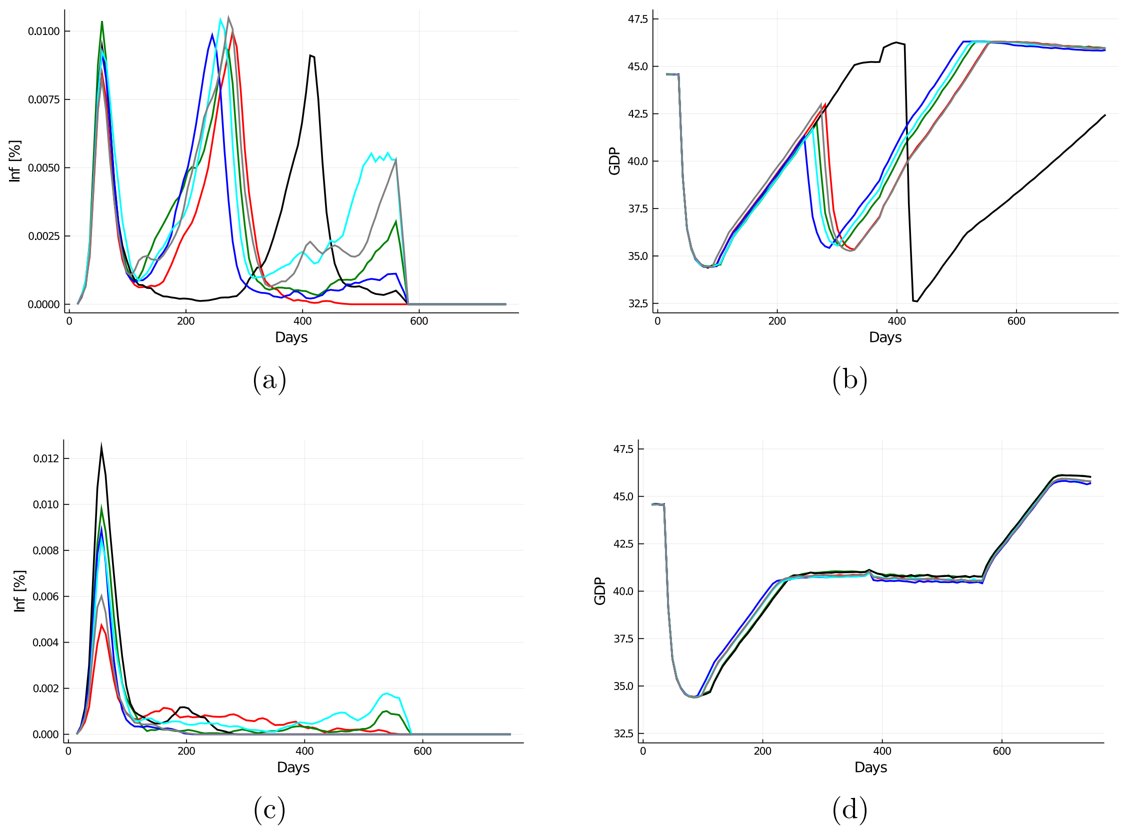


Figure 5: **Variance across Single Runs.** Dynamics of infected and per capita GDP for six random single runs under policy A (panels (a) and (b)) and policy D (panels (c) and (d)).

inducing switches between strong lockdown and full opening.

Considering the standard deviation for the different indicators across batch runs in Table 1 shows that the GDP loss induced by policies with weak opening (D,E) varies much less across runs than the GDP loss under policies A and B. Put differently, the economic implications of policies D and E are much better predictable compared to alternative approaches. The key reason for this difference is that under policies A and B the variance of the dynamics of infected is substantially larger compared to policies D and E (see in particular the size of the standard deviation bands in Figure 4a). In particular, the timing of the second respectively third wave and associated lockdowns under these policies might vary strongly across runs and, based on this also the economic effect of the induced lockdowns might differ substantially across runs. Under policies with a continuous weak lockdown (E) or a strong lockdown followed by weak opening, where a second lockdown never occurs (D), such variance in the economic policy effects is absent. For the mortality the timing of the second respectively third wave is of little importance, such

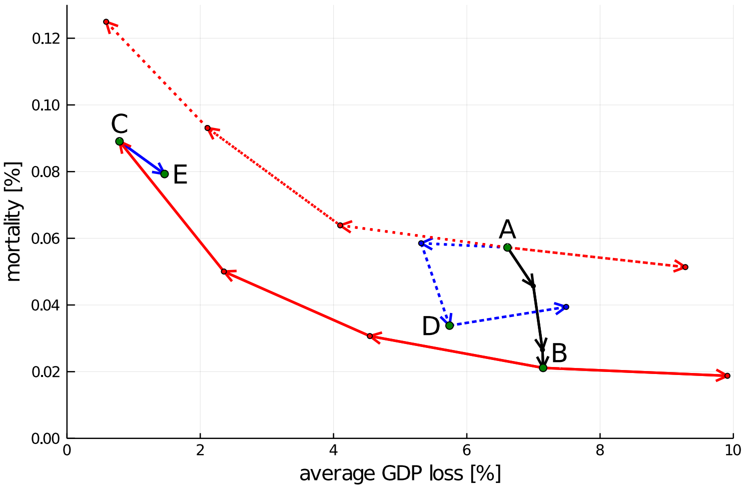


Figure 6: **Effects of variations of key policy parameters under the mutation scenario.** All points correspond to averages across the 50 runs. GDP loss [%] on the x-axis measured as weekly loss averaged over simulation time span of 728 periods (24 months) as a percentage of baseline and mortality [%] on the y-axis expressed as a percentage of population.

that the variance of mortality under policy A is comparable to that under policies D and E. We illustrate these effects in Figure 5, where we show the dynamics of six randomly picked single runs under policies A and D.

5.3 Effect of the occurrence of virus mutations

So far we have analyzed the effectiveness of the containment measures under the assumption that the virus does not mutate over time. However, it is the nature of pathogens such as the coronavirus to gradually undergo genetic change, which leads to the emergence of new variants of the virus that may enhance its transmission. In fact, in September 2020 there were first reports about the detection of a mutated and more contagious version of the coronavirus in England. This mutation quickly became the most common variant in the UK and accounted for almost two third of new cases in London by mid-December 2020 (Kirby, 2021). Other virus mutations have emerged in other areas.

In order to assess the robustness of the results of our policy analysis, we analyze the same set of policies but assume that at day $t^{mut} = 162$ a new and more contagious virus mutation emerges. In accordance with data on the English mutation (Chand et al., 2020), we assume that the individual infection probability p_{inf} of the mutant is 50% higher compared to the original virus, while the remaining epidemiological parameters are the same as for the original virus. In case the mutation is established, there are two coexisting virus strains spreading across the population, where upon being infected a household inherits the type from the infecting agent.[10]

Figure 6 summarizes the main findings of the policy experiments under the mutation scenario, the mean values and variances of the different relevant variables under the key policies are provided in Table 5 in Appendix B.5 and Tables 10, 11 and 12 in Appendix D contain the results of the tests for statistical significance of differences.[11] Comparing Figure 3 and Figure 6 yields a first qualitative insight.

Result 5 *The emergence of a more contagious virus mutation increases mortality rates and GDP loss in comparison to the benchmark scenario studied in Section 5.2. Mortality rates increase most under policies with light lockdown (C,E) while the increase in GDP loss is largest under policies with a strict lockdown in combination with full openings (A,B).*

Generally, the emergence of a more contagious virus shifts the mortality rate upwards compared to the scenario without mutation (even though this increase is not significant for policy B, see Table 12) The difference is most pronounced for the weak lockdown policies with or without weak opening (C and E). In a scenario without mutation, the advantage of these policies is to keep the number of infected low with relatively minor restrictions of economic activities. Once the virus becomes more contagious, then these minor restrictions are not sufficient to avoid a large wave of infections, which results also in a large number of casualties. In contrast, under policies associated with strict lockdowns (A and B) the economic losses substantially increase due to the occurrence of the virus. This is due to the fact that the higher infection rate of the mutated virus induces longer and/or more frequent lockdowns thereby generating more severe economic downturns. In the case of policy E, which essentially corresponds to a continuous weak lockdown, the occurrence of the mutation does not influence the restrictions of economic activity and hence the GDP loss is not affected. However, as discussed above, this comes at the cost of a strongly increased mortality.

Result 6 *Under a virus mutation, a policy with a high incidence threshold and weak opening dominates policies with strong lockdowns and full opening (D vs. A,B). All other pairwise comparisons of policies yield a trade-off between mortality and economic losses.*

[10]See Appendix B.5 for more details.

[11]Since the variance across runs substantially increases in the mutation scenario relative to the standard scenario considered above, we increase the number of runs in each batch to 50 in the mutation scenario, in order to avoid too large variance of the mean values in each batch.

Figure 6 demonstrates that the emergence of a more contagious virus mutation also changes the relation of the considered polices. While without mutation policy A, characterized by a high incidence threshold, a strict lockdown and full opening, was dominated by all other policies, this observation cannot be made under the virus mutation. In fact, policy A is now only dominated by policy D which shows that also in the presence of more contagious virus mutations a strict lockdown under a high incidence threshold is more efficient if some of the restrictions are kept during the opening phase. Comparing policies A and B, similarly to the case without mutation, a policy switching between strict lockdown and full opening with a small incidence threshold (B) substantially reduces mortality compared to the default policy A, however in the presence of the more infectious mutation the use of a lower incidence threshold comes at the cost of a relatively small but statistically significant increase in GDP loss (see Table 10). Furthermore policy B is weakly dominated by the weak opening policy D in the sense that the difference in mortality between the two policies is not statistically significant (see Table 11), while policy D induces a significantly lower GDP loss (Table 10). Closer inspection of the the set of individual simulation runs arising under policy D (not depicted here) show that in approximately half of the runs no second infection wave emerges under the weak opening policy even though the mutation spreads in the population. In these runs the outcome in terms of mortality and GDP loss is very close to the mean values reported in the scenario without mutations (i.e. Table 1). However, in the remaining runs a second infection wave emerges after the occurrence of the mutation (while the economy is in the weak opening phase) such that a second lockdown is necessary. In these runs mortality and GDP loss are substantially larger than the numbers reported for policy D in Table 1. The potential occurrence of such qualitatively very different dynamics increases the ex-ante uncertainty about the effect of the weak opening policy compared to the scenario without mutations. However, the fact that under this policy even in the case of the occurrence of a mutation a second lockdown can be avoided with a significant probability makes the policy on average perform better than policies with full opening (A,B). Finally, Figure 6 illustrates that, similar to the scenario without mutation a change in the intensity of the lockdown induces a clear trade-off between mortality and economic loss. Overall, this analysis shows that most of our insights from the baseline scenario, in particular the appeal of a policy with strict lockdown and weak opening, qualitatively stay intact also in the presence of a more infectious mutation. The performance of weak lockdown policies is most affected by the occurrence of the mutation resulting in strongly increased mortality.

6 Conclusions

In this paper, we develop an agent-based model capable of jointly describing epidemic and economic effects of measures aimed at containing the COVID-19 pandemic. We show that the calibrated model replicates the economic and epidemic dynamics in Germany in the first six months after the COVID-19 outbreak well and employ the model to compare the effects of different alternative policy approaches. Our analysis identifies an efficiency frontier of policies with respect to induced expected virus mortality and GDP loss and shows that policies on that frontier are characterized by continuous weak lockdowns or weak openings after an initial strong lockdown. Policies characterized by switches between strict lockdowns and full openings based on large incidence thresholds are strictly dominated by frontier policies and also give rise to substantially larger ex-ante uncertainty about the actual economic loss to be induced by the policy. As a robustness check, we include the emergence of a more contagious virus mutation and show that weak lockdown policies suffer from stronger increases in mortality. The combination of an initial strong lockdown and a weak opening dominates under such a scenario. Whereas these results have been obtained in a calibration of the model based on German data and the COVID 19 pandemic, the mechanisms underlying our findings clearly apply more generally such that these policy insights should carry over to other economies with similar structure as well as to other pandemics driven by similar kinds of virus transmission.

From a methodological perspective this approach, which explicitly captures individual interactions related to economic activities, allows us to jointly study the epidemiological and economic effects of different containment measures and to shed light on the interplay between economic activity and propagation of the virus. Due to the flexible microstructure of our model and the explicit representation of virus transmission through interactions between agents, our analysis can be extended in many directions, such as incorporating heterogeneity of infection probabilities across individuals, a social network structure or different vaccination strategies.

Declaration of Interest

None

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Appendix

A Data and Code Availability

The model has been implemented in Julia, the code is open source and can be downloaded from GitHub: https://github.com/ETACE/ace_covid19

B Detailed Model Description

In this appendix, we give a full description of the model and its calibration. Before we describe the economic model (Sec. B.2), we shortly summarize the timing in the model (Sec. B.1). Afterwards, we go through the transmission model (Sec. B.3). Finally, we summarize the calibration and initialization including all data sources (Sec. B.4). Some parts appear already in the main text, however, to have a consistent description we describe all parts of the model in full detail in this section.

B.1 Timing

The basic unit of time in the model is one day, denoted by $t \in \mathbb{N}_+$. The economic activities of the agents, however, take place on a weekly basis, where firms' production planning, labor market activities and delivery to the malls all take place at the first day of the week. Households' consumption is spread out during the week since each household has, for each sector, a (randomly determined) shopping day during the week. In what follows, we denote by $w \in \mathbb{N}_+$ the weeks during the simulation runs and when indexing a variable with the subscript 'w' we always refer to the first day of week w.

B.2 The Economic Model

Firms

A firm $i \in \mathbf{F}_w$ acts as a producer on the goods market and as employer on the labor market. It is assigned to one of the private sectors $k \in \{M, S, F\}$ and delivers to a sector-specific mall that only sells the products of sector k. Thus, all firms belonging to the same sector k compete on the product market and form a set of direct competitors $\mathbf{F}_{k,w}$ of size $n_{k,w}$ in week w.

A firm i is characterized by a firm-specific level of labor productivity A_i that is constant over time. The output of a firm is produced with labor as the only input. Denote by $L_{i,w}$ the number of workers employed by firm i in week w, the output of that firm is given by

$$Q_{i,w} = A_i L_{i,w}. \tag{3}$$

Production takes place on a weekly basis. All firms produce on the first day of the week. The output is delivered to the mall where each firm keeps an inventory stock. While the inventory is replenished once per week at the day of production, the products in the mall inventory can be sold every day.

The output planning of a firm is based on a simple inventory rule with adaptive demand expectations, where $\hat{D}_{i,w}$ is the expected demand, which is updated according to

$$\hat{D}_{i,w} = (1-\rho^D)\hat{D}_{i,w-1} + \rho^D\ D_{i,w-1}, \tag{4}$$

where $\rho^D \in (0,1)$ is a persistence parameter of the expectations and $D_{i,w-1}$ is the sum of the daily sales in the previous production and sales cycle. Denote by $Y_{i,w}$ the inventory stock of firm i in the mall at the end of week w. Then the planned output quantity for the current production cycle is determined by

$$\tilde{Q}_{i,w} = \begin{cases} (1+\chi_k)\hat{D}_{i,w} - (1-\delta_k)Y_{i,w-1}, & \text{if } Y_{i,w} > 0 \\ (1+\iota\cdot\chi_k)\hat{D}_{i,w} & \text{if } Y_{i,w} = 0 \end{cases} \tag{5}$$

where $\chi_k > 0$ captures the size of a sector-specific inventory buffer and $\iota > 1$ captures that firms might increase their buffer when their stock was sold out in the previous period since this is seen as a signal for an expansion in demand. Parameter $\delta_k \in [0,1]$ describes a sector-specific depreciation of the inventory at the end of the sales cycle.

For reasons of simplicity, we abstract from production time and the produced quantity is delivered to the mall at the beginning of the week before consumption starts. The inventory stock then updated every day depending on the weekly inflow of the replenishment and the daily outflow of sales. At a generic iteration t, the inventory stock in the mall changes according to

$$Y_{i,t} = \begin{cases} (1-\delta_k)(Y_{i,t-1} - X_{i,t-1}) + Q_{i,t} & \text{if } t \ mod\ 7 = 1 \\ Y_{i,t-1} - X_{i,t-1} & \text{else.} \end{cases} \tag{6}$$

Given the planned production volume and firm's production technology, the labor demand of the firm reads

$$\tilde{L}_{i,w} = \frac{\tilde{Q}_{i,w}}{A_i}. \tag{7}$$

Depending on the size of the workforce $L_{i,w-1}$ employed in the previous production cycle, the labor demand $\tilde{L}_{i,w}$ either implies to hire additional workers or to dismiss some redundant workers of the firm. In the former case, i.e. if $\tilde{L}_{i,w} > L_{i,w-1}$, the firm has $L^V_{i,w} = \tilde{L}_{i,w} - L_{i,w-1}$ vacancies from which, depending on the outcome of the labor market, $L^F_{i,w} \leq L^V_{i,w}$ will be filled. In the latter case, the firm has $L^R_{i,w} = L_{i,w-1} - \tilde{L}_{i,w}$ redundancies and the firm randomly chooses $L^R_{i,w}$ workers from the set $\mathbf{W}^F_{i,w}$ of current employees to be fired. Altogether, the size of the workforce evolves according to

$$L_{i,w} = \begin{cases} L_{i,w-1} + L^F_{i,w} & \text{if } \tilde{L}_{i,w} > L_{i,w-1} \\ L_{i,w-1} - L^R_{i,w} & \text{else.} \end{cases} \tag{8}$$

The weekly wage that paid by firms is assumed to be constant over time. It is sector-specific and proportional to the average productivity $\bar{A}_k$ of the sector k in which firm i is active, i.e.

$$w_i = w_k = \psi_k \bar{A}_k \text{ with } \psi_k = \frac{(1 - \chi_k \delta_k)}{(1 + \lambda_k)(1 + \underline{\mu}_k)} > 0, \tag{9}$$

where the sector specific wage factor ψ_k captures that the expected return from each unit of labor differs between sectors not only due to labor productivity, but also due to differences in expected depreciation of inventory stocks ($\chi_k \delta_k$), the ratio between fixed costs and labor costs (λ_k) and the mark-up (μ_k).

The firm applies mark-up pricing with an endogenous mark-up $\mu_{i,w} > 0$ on unit costs to determine the price of its product. The unit costs of a firm are determined by the variable labor costs and fixed costs c^F_i and are given by

$$c_i = \frac{w_i + \frac{c^F_i}{L_{i,w}}}{A_i(1 - \chi_k \delta_k)}. \tag{10}$$

The resulting price of a firm is given by

$$P_{i,w} = (1 + \mu_{i,w}) c_i. \tag{11}$$

The mark-up is updated at the day of production and depends on the market share of the firm. Denote by $s_{i,w}$ the market share (in terms of sold quantity) of firm i on its relevant market in week w, then the mark-up equals

$$\mu_{i,w+1} = \underline{\mu}_k + s_{i,w} \cdot (\bar{\mu}_k - \underline{\mu}_k), \tag{12}$$

where $\bar{\mu}_k$ and $\underline{\mu}_k$ are parameters determining the upper and, respectively, lower bound for the mark-up in sector k.

Accounting takes place at the day of production and is related to the previous production cycle. The profits of firm i accounted for in period w read

$$\Pi_{i,w} = P_{i,w} D_{i,t} - L_{i,w} w_i - c_i^F. \tag{13}$$

The liquidity of the firm evolves according to

$$S_{i,w} = S_{i,w-1} + \Pi_{i,w-1} - \max[0, \tau_{w-1}\Pi_{i,w-1}] - d_{i,w} - c_i^F \tag{14}$$

Here, τ_w is the tax rate for corporate taxes on (positive) profits and $d_{i,w}$ are dividends paid out to the firm's shareholders. For the dividends, we define a dividend rate $\zeta \in (0, 1)$ and a threshold savings level being proportional to the average firm revenues over the last T weeks, i.e.

$$\tilde{S}_{i,w} = \varphi_k \frac{1}{T} \sum_{\tau=0}^{T-1} P_{i,w-\tau} D_{i,w-\tau}. \tag{15}$$

Firms pay out their entire (after tax) profits as dividend once their savings are above that threshold, otherwise they put a fraction of the profits into their savings:

$$d_{i,w} = \begin{cases} (1 - \tau_w) \max[0, \Pi_{i,w}] & \text{if } S_{i,w-1} + (1 - \tau_w) \max[0, \Pi_{i,w}] > \tilde{S}_{i,w} \\ \zeta(1 - \tau_w) \max[0, \Pi_{i,w}] & \text{else,} \end{cases} \tag{16}$$

with $\zeta < 1$. The dividends as well as fixed costs are distributed equally to all households.

If a firm has a negative payment account after accounting, it has to declare bankruptcy. In this case, the firm becomes inactive and has to dismiss all workers. At the same time, the firms inventory stock is fully written off.

Households

The economy is populated by m_t households. A household $h \in \mathbf{H}_t$ acts as costumer on the goods market and, depending on her age, as an employee on the labor market.

Households are classified into a young cohort $\mathbf{H}_t^Y$ and an old cohort $\mathbf{H}_t^O$. Members of the old cohort are retired, whereas households in the young cohort constitute the labor force of the economy. A young household can be employed or unemployed. If a household is unemployed, she enters the labor market to search for a new job.

Households have work-related skills that can only be utilized in one of the sectors $k \in \{M, S, F\}$ and cannot be transferred to other sectors. Thus, households are uniquely assigned to one sector and determine the sector-specific labor supply $\mathbf{L}_{k,t}^S$. Apart from the private sectors, there is also a public sector (indexed by $k = P$) that does not produce any market goods. In this sector, the government operates n_P offices and households that work for the government as civil servants have a permanent and secure job.

We assume that, in each sector, there is a fixed proportion h_k^{WFH} of workers working on tasks that can potentially be done from home. The set composed of these workers is denoted by $\mathbf{L}_{k,t}^{WFH} \subset \mathbf{L}_{k,t}^S$.

Depending on their age and employment status, households have different income sources. Employed households earn a labor income $\omega_{h,w}$ equal to the wage w_k of the sector k in which a household is employed. Unemployed households, instead, receive unemployment benefits $u_{h,w}$ from the government that correspond to a fraction ν of her last labor income. Old households live on pensions of level w^P that are paid by the government and are uniform and constant over time for all retirees in the economy. Additionally, all households receive a capital income that correspond to an equal share of the fixed costs paid by firms and dividends distributed by the firms, i.e.

$$I_{h,w}^{Cap} = \frac{1}{m_w} \sum_{\forall i \in \mathbf{F}_w} (d_{i,w} + c_i^F). \tag{17}$$

Altogether, the overall gross income $I_{h,w}$ of household h in week w equals

$$I_{h,w} = \begin{cases} \omega_{h,w} + I_{h,w}^{Cap} & \text{if employed,} \\ u_{h,w} + I_{h,w}^{Cap} & \text{if unemployed,} \\ w^P + I_{h,w}^{Cap} & \text{if retired.} \end{cases} \tag{18}$$

All sources of income are subject to income tax. Given tax rate τ_w, the net income of household h is then

$$I_{h,w}^N = (1 - \tau_w) I_{h,w}. \tag{19}$$

On the first day of the week, the household decides on the budget $C_{h,w}$ that she plans to spend in the coming week. For the consumption and saving decision, the household takes into account an average net income

$$\bar{I}^N_{h,w} = (1-\rho^I)\bar{I}_{h,w-1} + \rho^I I^N_{h,w} \tag{20}$$

as well as her total wealth $W_{h,w}$, which consists of her money holdings. The notional consumption budget is determined according to the consumption rule

$$C_{h,w} = \bar{I}^N_{h,w} + \kappa \cdot (W_{h,w} - \Phi \cdot \bar{I}^N_{h,w}), \tag{21}$$

where the parameter Φ is the target wealth/income ratio. This formulation is motivated by the "buffer stock" theory of consumption, which is backed up by theoretical arguments and substantial empirical evidence (Deaton, 1991; Carroll and Summers, 1991). The parameter Φ describes how large the targeted buffer is relative to income, and κ indicates how sensitively consumption reacts to deviations of the actual wealth-to-income ratio to the target level.

Finally, the consumption budget $C_{h,w}$ is allocated to the different sectors. In principle, the budget that a household h tries to spend for products from sector $k \in \{M, S, F\}$ is determined by a fixed allocation across sectors, i.e.

$$\tilde{C}^S_{h,k,w} = c_k \; C_{h,w}. \tag{22}$$

However, sector $k = F$ is different from the other sectors in a way that it includes essential goods implying that households try to avoid large spending cuts for these products. Hence, the actual consumption budget allocated to the essential sector F is

$$C^S_{h,F,w} = \max\left[c_F \; C_{h,w}, \min\left[(1-\phi)C^S_{h,F,w-1}, C_{h,w}\right]\right]. \tag{23}$$

The remaining budget, instead, is distributed proportionally among the non-essential sectors $k \neq F$ according to the consumption quotas c_k such that

$$C^S_{h,k,w} = \frac{c_k}{\sum_{l \in \mathbf{K} \setminus \{k^*\}} c_l}(C_{h,w} - C^S_{h,F,w}). \tag{24}$$

The actual expenditure in a certain sector on the households sector-specific shopping day can deviate from planned ones due to rationing (see below). Denote by $E_{h,t} \geq 0$ the total expenditures for consumption on a generic day t, then the savings of household h evolve according to

$$W_{h,t} = \begin{cases} W_{h,t-1} - E_{h,t-1} + I^N_{h,t} & \text{if } t \ mod \ 7 = 1 \\ W_{h,t-1} - E_{h,t-1} & \text{else.} \end{cases} \tag{25}$$

Labor Market Interactions

The labor market is modeled as a decentralized market with separated sub markets for each sector. The labor market operates every first day of the week to match open vacancies and job seekers. All firms belonging to sector k that have open vacancies $L^V_{i,w} > 0$ try to get matched with the unemployed workers $\mathbf{U}^S_{k,w}$ searching for a job in sector k. All households $h \in \mathbf{W}^S_{P,w}$ that work in the public sector stay with their employee throughout the simulation run and are never active on the labor market.

The matching process is modeled in a way that firms open vacancies in a random sequence and unemployed job seekers with appropriate skills apply. The firm then hires on a first-come-first-serve basis. If at the time of the announcement of the job opening there are no unemployed job seekers with appropriate skills, the firm is rationed and can only hire again in the following week.

More precisely, suppose $\mathbf{V}_{k,w}$ is the randomly ordered set of firms in the queue of sector k in week w and $v_l \in \mathbf{V}_{k,w}$ is the firm ranked at the l-th position. Denote by $\tilde{L}^S_{k,w,l}$ the number of unemployed in sector k after firm v_l has been active on the labor market with $\tilde{L}^S_{k,w,0} = |\mathbf{U}^S_{k,w}|$. Then for all firms $v_l \in \mathbf{V}_{k,w}$ we have that the number of hired respectively fired workers in week w is given by

$$\begin{aligned} L^F_{i,w} &= \min[\tilde{L}_{i,w} - L_{i,w-1}, \tilde{L}^S_{k,w,l-1}] && \text{if } \tilde{L}_{i,w} \geq L_{i,w-1} \\ L^R_{i,w} &= \tilde{L}_{i,w-1} - L_{i,w} && \text{else.} \end{aligned} \tag{26}$$

The number of unemployed evolves according to

$$\tilde{L}^S_{k,w,l} = \tilde{L}^S_{k,w,l-1} - L^F_{i,w} + L^R_{i,w}.$$

Hence, a firm might be rationed on the labor market if the number of job-seekers when the firm is active on the market is below its labor demand. It might happen that firms that become active after a rationed firm can nevertheless hire because some firm in the queue in-between has fired workers.

Goods Market Interactions

Once per week, a household randomly determines a shopping day for each sector within the next 7 days. At the respective shopping day for sector k, the household h visits a mall in which those products are sold. Denote by $\mathbf{C}_{k,t}$ the ordered set of costumers shopping in sector k at day t and by $c_l \in \mathbf{C}_{k,t}$ the consumer at the l-th position in the queue. Furthermore, denote by $\tilde{Y}_{i,t,l}$ the inventory of firm i in the mall after consumer c_l has completed her shopping and by $\mathbf{A}_{t,l}$ the set of active firms at that point, i.e. those firms i for which $\tilde{Y}_{i,t,l} > 0$ holds.

Consumer c_l draws a random subset $\Omega_{c_l,k,t} \subseteq \mathbf{A}_{t,l}$ of size η of the products offered by active firms in the mall. The decision which product $i \in \Omega_{c_l,k,t}$ of sector k to purchase is based on a logit choice model. The probability to buy the product from firm i offered at price P_{i,w_t} is

$$\mathbb{P}[c_l \text{ selects } i \in \Omega_{c_l,k,t}] = \frac{\exp(-\gamma^C \log(P_{i,w_t}))}{\sum_{\forall j \in \Omega_{c_l,k,t}} \exp(-\gamma^C \log(P_{j,w_t}))}, \tag{27}$$

where γ^C is a parameter for the price sensitivity of households and w_t denotes the week of day t. The notional quantity to purchase is then

$$\mathcal{C}_{c_l,i,t} = \min\left[\frac{C^S_{c_l,k,w_t}}{P_{i,w_t}}, \tilde{Y}_{i,t,l-1}\right]. \tag{28}$$

The stock of the product of firm i still available at the mall is updated according to

$$\tilde{Y}_{i,t,l} = \tilde{Y}_{i,t,l-1} - \mathcal{C}_{c_l,i,t}. \tag{29}$$

If $\tilde{Y}_{i,t,l} = 0$, then the firm becomes inactive in the mall at this point and only becomes active again at the first day of the following week when new quantities of the product are delivered to the mall. If there are no active firms in the mall when a household h visits the mall or if the chosen firm is not able to supply to total amount demanded, i.e. $\tilde{Y}_{i,t,l-1} < \frac{C^S_{c_l,k,w_t}}{P_{i,w_t}}$, then the consumer is rationed and returns to the mall again the following day. All parts of the foreseen weekly consumption budget for sector k which have not been spent at that point, are added to the household's savings.

Government and Public Sector

The government collects income and profit taxes to fund the civil servants working in one of the n_P offices in $\mathbf{G}$ comprising the public sector, the payment of unemployment benefits and pensions to old households. Additionally, the government can pay subsidies or other financial support to households and firms as part of additional policies.

Each public sector office $g \in \mathbf{G}$ employs a set of civil servants $\mathbf{W}_g^G \subset \mathbf{H}_0^Y$ that only changes over time if an employee dies. The total number of civil servants in the economy in week w is denoted by L_w^P.

Unemployment benefits are based on the last wage of an unemployed worker with replacement rate ν. Pensions are uniform for all old households and are a percentage *pen* of the average wage in the economy. Households employed in the public sector earn a wage w^P.

Tax collection and distribution of unemployment benefits and pensions takes place at the first day of the week. The tax revenue of the government is the sum of the corporate tax revenues

$$T_w^C = \sum_{i \in \mathbf{F_w}} \max[0, \tau_w \, \Pi_{i,w}] \tag{30}$$

and the income tax revenues are

$$T_w^I = \tau_w \sum_{h \in \mathbf{W}_w} \omega_{h,w} + \tau_w \sum_{h \in \mathbf{H}_w} I_{h,w}^{Cap} + \tau_w \sum_{h \in \mathbf{U}_w} u_{h,w} + \tau_w w^P \, |\mathbf{H}_w^O|, \tag{31}$$

where $\mathbf{W}_w$ denotes the set of all employed households in the economy in week w. Denoting by $\mathbf{U}_w$ the set of unemployed workers in the economy, the public account of the government evolves according to

$$S_w^G = S_{w-1}^G + T^C + T^I - \sum_{h \in \mathbf{U}_w} u_{h,w} - w^P \, |\mathbf{H}_w^O| - w_0^S \, L^P \tag{32}$$

The government adjusts the tax rate over time in order to keep a target level of the public account. In the baseline setup, the tax rate τ_w evolves according to

$$\tau_w = (1 - \rho^T)\tau_{w-1} + \rho^T \, \hat{\tau}_w, \tag{33}$$

where $\hat{\tau}_w$ is the tax rate that would be sufficient to balance the budget on a target public account level. In particular,

$$\hat{\tau}_w = \max\left[0, \frac{\sum_{h \in \mathbf{U}_w} u_{h,w} + w^P \, |\mathbf{H}_w^O| + w_0^S \, L^P - \theta S_w^G}{\frac{T^C}{\tau} + \sum_{h \in \mathbf{W}_w} \omega_{h,w}}\right], \tag{34}$$

Note that the target level of public account and the speed of tax rate adjustment might change as part of policy.

Finally, the government compute the gross domestic product for the last week according to

$$GDP_w = w_0^S L^P + \sum_{k\in\mathbf{K}} \sum_{i\in\mathbf{F}_{k,w}} P_{i,w} Q_{i,w}. \tag{35}$$

B.3 Virus Transmission

Social Interactions

Social interactions take place on three different occasions (see Fig. 8 for a visual summary). The first type of social interactions occurs at work. Firms and public offices represent the work environment where social contacts in the professional context occur. Suppose $\mathbf{X}_{h,t} = \mathbf{W}_{i,t}^F \setminus \{h\}$ is the set of household h's colleagues at time t (or $\mathbf{X}_{h,t} = \mathbf{W}_g^G \setminus \{h\}$ for public servants). As long as she is not in the short-term program or working from home, the worker faces several potential meetings with her co-workers, where

$$\tilde{\mathbf{X}}_{h,t} = \begin{cases} \emptyset & h \in (\mathbf{W}_{i,t}^{WFH} \cup \mathbf{W}_{i,t}^{ST}), \\ \mathbf{X}_{h,t} \setminus (\mathbf{W}_{i,t}^{WFH} \cup \mathbf{W}_{i,t}^{ST}) & \text{else}, \end{cases} \tag{36}$$

is the set of co-workers worker h can potentially meet during a workday. As defined above, $\mathbf{W}_{i,t}^{WFH}$ is the set of workers working from home and $\mathbf{W}_{i,t}^{ST}$ is the set of workers on short-time work on day t. The realized number of meetings is drawn from a distribution where the maximum contact threshold n_k^w might differ across sectors. The number of colleagues $N_{h,t}^{cw}$ met by agent h is drawn from a uniform distribution with bounds $[0, n_k^w]$. The set of actually met co-workers of agent h at time t is then determined as a random subsample $\mathbf{CW}_{h,t} \subset \tilde{\mathbf{X}}_{h,t}$ of size $N_{h,t}^{cw}$.

The second possibility to interact with other households takes place during shopping. Households visit different shopping malls within a week in order to purchase or consume goods offered by the three private sectors. The maximum number of possible meetings at one shopping day is drawn from a distribution where the upper threshold n_k^c is sector specific. The actual number of people met in the specific mall is given by the fraction of the population going to that mall multiplied by the maximum number of possible meetings across the week. Thus, if one seventh of the local population is going to that mall, the number of contacts when shopping will be equal to the maximum number of possible contacts. Formally

$$N_{h,k,t}^{cs} = \bar{N}_{h,k,t}^{cs} \cdot \frac{|\mathbf{C}_{k,t}|}{|\mathbf{H}_t|} \cdot 7, \tag{37}$$

where $|\mathbf{C}_{k,t}|$ is the number of customers of sector k at time t and $\mathbf{C}_{k,t} = \sum_i \mathbf{C}_{i,t}$, $|\mathbf{H}_t|$ is the number of households at time t. $\bar{N}^{cs}_{h,k,t}$ is the upper bound number of co-shoppers met by agent h in sector k at time t and is drawn from a uniform distribution with bounds $[0, n^c_k]$. We denote by $\mathbf{CS}_{h,k,t} \subset \mathbf{C}_{k,t}$ the actual set of individuals met while shopping at the local mall, which is drawn as a subsample of size $N^{cs}_{h,k,t}$. Multiple meetings with the same household are possible.

Finally, households engage in other social activities, where those social interactions are characterized by heterogeneous cross age patterns. In particular, the number of contacts for each type of cross age meeting is drawn from a uniform distribution whose upper bound $n^p_{a,a}$ with $a \in \{y, o\}$ reflects the cross age interaction patterns. In case of a positive number of contacts for period t, potential partners are drawn among the population belonging to the specific age group. $\mathbf{H}^a_{-h,t}$ is the set of households belonging to a specific age excluding agent h at time t. We select the number of people $N^{a,a}_{h,t}$ met by agent h at time t by drawing from a uniform distribution with bounds $[0, n^p_{a,a}]$ and draw the set of actual contacts $\mathbf{SA}^a_{h,t} \subset \mathbf{H}^a_{-h,t}$ from a specific age group met by agent h at time t as a random subsample of size $N^{a,a}_{h,t}$.

Pandemic Dynamics

Households differ with respect to their health states. At every instant of time t, each household h may be in one of four states. "Susceptible", not yet been exposed to the virus and thus not immune, "Infected" already contracted the virus, "Recovered" have been infected, survived the virus and acquired immunity and "Deceased" died from the virus. In particular, we further detail the infected state into three different phases, which do matter in terms of virus transmission: We distinguish between a latency phase of length t_{lnt}, an infectious phase of length t_{inf} and a post-infectious period where one has not yet recovered. $\bar{t}_{rec}$ is the maximum number of days being infected or the recovery time. The set of households belonging to the four health states are denoted by $\mathbf{S}_t$, $\mathbf{I}_t$, $\mathbf{R}_t$ and $\mathbf{D}_t$, respectively. The set of infectious agents is denoted by $\mathbf{I}^{inf}_t \subseteq \mathbf{I}_t$ and that of newly infected people is denoted by $\mathbf{T}_t$. Thus the population of alive households evolves together with the epidemic and changes over time such that:

$$\mathbf{H}_t = \mathbf{S}_t + \mathbf{I}_t + \mathbf{R}_t. \tag{38}$$

In other words, the population decreases due to death from the disease while we abstract from other demographic dynamics such as births and other causes of death. We assume that the initial stocks of infected, recovered and deceased individuals are set equal to zero. Hence, before the outbreak of the epidemic, the entire initial population of household belongs to the susceptible group.

At period $t = t_0$, the epidemic starts. The initial infected agents are randomly selected, their state is updated and their recovery countdown starts. The rest of the population stays susceptible and is exposed to three channels through which the infection can be transmitted, social contacts at work, during consumption and other social occasions, where only meetings with infectious households might result in the contagious.

In every contact between an infectious household $h \in \mathbf{I}_t^{inf}$ and a susceptible household $\tilde{h} \in \mathbf{S}_t$ the virus is transmitted with a probability $(1-\xi)p_{inf}$, where without any policy measure $\xi = 0$. An infected agent h at each possible day has a small probability q_t^a to die from the virus. In this case, she is removed from the unemployment list if unemployed or from the list of workers of her employer if employed. Also the number of casualties is updated. After $\bar{t}_{rec}$ days of infection the household recovers and gains immunity to the virus.

The case fatality rates q_t^a with $a = \{y, o\}$ do not only depend on the age of the household, but also on the degree of utilization of intensive care units in the economy at time t. In case of an over-utilization, the rate is increasing with $|\mathbf{I}_t|$. In particular, depending on the degree of over-utilization, the age-specific fatality rate is a weighted average between a regular fatality rate $\bar{q}_l^a$ achieved with under-utilized intensive care units and a fatality rate $\bar{q}_h^a$ that would be achieved if no intensive care capacities would be available. Formally

$$q_t^a = \left[\frac{\min(n^{icu}, u^{icu} \cdot |\mathbf{I}_t|)}{u^{icu} \cdot |\mathbf{I}_t|}\right] \bar{q}_l^a + \left[1 - \frac{\min(n^{icu}, u^{icu} \cdot |\mathbf{I}_t|)}{u^{icu} \cdot |\mathbf{I}_t|}\right] \bar{q}_h^a \tag{39}$$

where n^{icu}, u^{icu}, $|\mathbf{I}_t|$ are, respectively, the number of intensive care beds available, the fraction of infected individuals in need of intensive care and the total number of actual infected.

We assume that after t_{vac} days from the beginning of the pandemic, a vaccine is available on the market and all susceptible households are assumed to receive immediate vaccination. Thus, the probability of infection p_{inf} goes to zero and the epidemic washes out as soon as infected households recover or die.

B.4 Calibration

Economic Activities

We initialize the model with $m_0 = 100.000$ households and $n_0 = 3780$ firms (private and public). The number of households is chosen to balance the trade-off between having a sufficiently large population size and technical limitations. The total number of firms, instead, has been chosen to match the relation between the size of the working population and the number of private firms in the German economy. The initial population state we use for all our simulations has been generated by running our model for a burn-in phase of 2300 periods. Without the appearance of the virus and any change in the policy parameters, the model exhibits stationary dynamics of the economic key variables like GDP and unemployment starting from this initial state.

Following German demographic data we set the fraction of young households $a_0^Y = 75\%$ capturing that the number of individuals belonging to the age group between 18 and 65 years in the German population is about three times that of individuals with an age above 65 years (Statista, 2019b,a).

The productivity level of a firm i in sector k is a random variable following a uniform distribution from an interval around a sector-specific average productivity $\bar{A}_k$ (Statistisches Bundesamt (Destatis), 2020b). Sectoral wages are proportional to the average productivity in the sector and their level is chosen such that the average price, taking into account (average) firm mark-ups and fixed costs in each sector (given the firm's markup) is equal to one. Productivity and wages are measured in units of 1.000/52 €, such that a weakly output of 1 unit corresponds to an annual GDP of 1.000 €. The parameters determining the allocation of households consumption expenditures across the three private sectors, $c_M = 21\%$ $c_S = 50\%$ $c_F = 29\%$, are based on Statistisches Bundesamt (2017). The labor supply in the three private sectors manufacturing, service and food, i.e. the fraction of the labor force with the corresponding skills, are calculated based on the allocation of consumption expenditures across the three sectors and the average labor productivity in a way to generate comparable unemployment rates across sectors. This gives $e_M = 11.70\%$, $e_S = 43.62\%$ and $e_F = 32.68\%$. The initial number of workers in sector k is $m_0 \cdot e_k$ and the initial number of firms or, respectively, offices equals $n_k = e_k\, n_0$. The properties of the sectoral structure are summarized in Table 2.

The economic parameters and the initial values of specific agent variables are calibrated to generate a stationary GDP per capita and unemployment rate that reasonably match the Ger-

	Manufacturing	Service	Food	Public
Workers with sector specific skills	11.70%	43.62%	32.68%	12.00%
Av. productivity	97	62	48	62
Productivity range	87.3 – 106.7	58.9 – 65.1	43.2 – 52.8	62
Av. wage	76.5	50.1	38.8	59.2
Consumption shares	21%	50%	29%	–

Notes: Productivity level of a firm i in sector k is a random variable following a uniform distribution from an interval around a sector-specific average productivity $\bar{A}_k$ based on German data (Statistisches Bundesamt (Destatis), 2020b). Sectoral wages are proportional to average productivity in sector and their level is chosen such that average price, taking into account (average) firm mark-ups and fixed costs in each sector (given the firm's markup) is equal to one. Productivity and wages are measured in units of 1.000/52 euro, such that a weakly output of 1 unit corresponds to an annual GDP of 1.000 euro. The parameters determining allocation of agent's consumption expenditures across three private sectors as well as employment share of public sector are based on German data (Statistisches Bundesamt (Destatis), 2020a; Grimault, 2020). Labor supply in three private sectors manufacturing, service and food, i.e. the fraction of labor force with corresponding skills, is given by estimated employment shares. These shares are calculated based on allocation of consumption expenditures across the three sectors and average labor productivity.

Table 2: **Sectoral distribution of economic values.**

man economy before the pandemic. In particular, the model generates, averaging over 20 runs, an annual GDP per capita of 43.013 euro and an unemployment rate of 3.98% compared to an annual GDP per capita (Eurostat, 2020a) of 41.350 euro and an average unemployment rate (Eurostat, 2020b) of 3.2% in 2019.

Social Interaction

Social interactions between households take place at three different occasions, which we calibrate with data reported in a survey on social contacts by Mossong et al. (2008). The actual number of contacts for an agent is a random draw from a uniform distribution between zero and a case-specific upper bound. The first one describes work-related contacts capturing that an employed agent meets co-workers. We assume that an employee meets on average four co-workers during one working day (given an interval with upper bound $n^w_k = 8$). The second occasion are social contacts that occur during shopping. For the service sector, this for example includes contacts during the visits of a restaurant or a fitness studio. The total number of shopping contacts of a households per day is sector-specific $n^c_M = 10$, $n^c_S = 28$, and $n^c_F = 10$, such that the number of potential meetings during consumption of services is considerably higher compared to the other types of goods. Finally, we model other social contacts that happen for example during leisure time. Here, we make a distinction in the frequency of social interaction between age groups. The actual number of social interactions per day across different age groups is limited by the upper bounds $n^p_{yy} = 5$, $n^p_{oo} = 2$, $n^p_{yo} = 2$, and $n^p_{oy} = 4$. This reflects that agents rather meet within their age-group.

Virus Transmission

Our model is calibrated to replicate the first six months of the pandemic of the SARS-CoV-2 virus in Germany. Since the pandemic is still ongoing, there is a considerable uncertainty around key parameters of the virus. Our choice of parameters is consistent with the current data on COVID-19. The initial fraction of population infected is based on reported number of infected in Germany on March 9, 2020. Since not all patients infected with SARS-CoV-2 show symptoms, the estimated number of infected individuals differs substantially from the detected number of cases (Bommer and Vollmer, 2020). We use the empirical infection and fatality rates (Verity et al., 2020) to estimate a detection rate in Germany. We use their result that 15% of infected are reported to link the number of infected in our model to data giving the reported number of infections. Taking this into account and scaling the number of reported infected in Germany on March 9, 2020 to our population size of 100.000 households yield an initial number of 8 young and 3 old infected households in our model.

The actual value of p_{inf}, the probability to be infected when meeting a contagious individual, is unknown in the literature. Instead, we calibrate this value such that in a scenario without any virus containment measures the average reproduction number in initial periods before herd immunity starts to play a role matches the value of $R_0 \approx 2.5$ and hence lies well within the standard range of values reported for this number (Read et al., 2020). Upon infection and after a latency period of five days ($t_{lnt} = 5$), agents are infectious for five days (t_{inf}=5) (World Health Organisation, 2020).

In case a household is infected, it takes $\bar{t}_{rec} = 21$ days to recover. During this time, the household might pass away. The calibration of the individual case fatality rate for the case of not fully utilized intensive care capacities relies on age-structured German data of casualties and reported infected as of the beginning of June 2020, where the total number of reported infected has been allocated to different age groups (Robert Koch Institut, 2020). In that case, the fatality rate for individuals below 65 years is 0.66% of reported infected. For individuals older than 65 years this rate is 16%. Taking into account that only 15 percent of infected are reported, we obtain $q_l^y = 0.099\%$ and $q_l^o = 2.4\%$. In case of a congestion of intensive care capacities, we use $q_h^y = 0.27\%$ for young and $q_h^o = 7.5\%$ for old patients. To capture the effect of a collapsing health system, we extrapolate Italian data collected during periods of over-utilization of local

Parameter from Literature	
Recovery period	21 days
Infectious period	5 days
Latency period	5 days
Detection rate	0.15
Reported infections in need of intensive care	8.5%
Intensive care units (ICU)	30 per 100.000
Fatality rates	
Below ICU capacity	
Young	0.099%
Old	2.4%
Without ICU treatment	
Young	0.27%
Old	7.5%

Notes: We use estimation from World Health Organisation (2020) for the recovery, infectious and latency period. To adjust for infected, but undetected cases we use an estimated detection rate for Germany (Bommer and Vollmer, 2020). The percentage of infected in need of intensive care units is an estimation from Rhodes et al. (2012). The actual number of intensive care units (ICU) is taken from German data (Anesi, 2020) and scaled to our population size. To get estimates for fatality rates in case the ICU capacity does not exceed its capacity, we use data from the German Robert Koch Institut (2020). Italian data (Statista, 2020a) is used for patients without ICU treatment.

Table 3: **Parameter values related to COVID-19.**

intensive care capacities (Statista, 2020a).

An infected household needs intensive care in 8.5% of the reported cases (Anesi, 2020). The assumed number of intensive care beds is 30 per 100.000 households, which is based on German data (Rhodes et al., 2012). Finally, we assume that a vaccine will be available one year after the initial spread of the virus. The pandemic related data for our calibration is summarized in Table 3.

Policy Measures

A whole set of measures has been introduced in many countries, for example in Germany in the beginning of March 2020. These measures include individual prevention measures, working from home where possible, a regulation banning meetings between more than two people in public spaces (with the exception of families), the closure of a large fraction of stores (apart from supermarkets, and stores for food and other essential products) as well as all hotels and restaurants. In the framework of our model we put all these measures together to a single lockdown policy accompanied with a phase-in period after the implementation of the policy during which the model parameters adjust to their new values.

More detailed, the lockdown is introduced two weeks after the first agents are infected. Following empirical data sector-specific working from home is introduced in manufacturing, service and public sector ($h^{ho}_M = 45\%$, $h^{ho}_S = 30\%$, $h^{ho}_P = 75\%$ of employees), but not in the food sector (Fadinger and Schymik, 2020; Möhring et al., 2020). When the working from home measure is active the sector-specific upper bounds for the number of contacts at the workplace (for those not working at home) are reduced to $n^w_M = 4$, $n^w_S = 5$, $n^w_F = 8$, $n^w_P = 2$. Furthermore, we assume that working from home does not decrease the firm's productivity level A_i. Based on survey data (Lehrer et al., 2020), we assume that, when social distancing is active, the upper bounds of social contacts are reduced to $n^p_{yy} = 2$, $n^p_{oo} = 1$, $n^p_{yo} = 1$, and $n^p_{oy} = 1$. Finally, when a lockdown is in place the upper bound of the number of contacts during each shopping trip are reduced to $n^c_M = 5$ and $n^c_S = 20$. The reduction of a household's weekly probability to carry out her activity in manufacturing and services are estimated as $\Delta p^{s,l}_M = 0.15$ and $\Delta p^{s,l}_S = 0.5$. These numbers are based on data on sector specific reduction in consumption in Germany during the lockdown in March 2020, see (Statista, 2020b), and our convention that the consumption reduction during that lockdown corresponds to an intensity of $\alpha^l = 1$.

With respect to the short-time work scheme, mirroring measures introduced in Germany, we set the ratio of short-time wage and regular wage to $\varphi = 0.7$. Furthermore, the probability that a worker not needed under the current production plan enters short-time work is calibrated to $q^{st} = 0.75$ in order to match unemployment dynamics in Germany after the introduction of the lockdown and short-time work scheme in March 2020.

Economic support measures are associated with a considerable increase in the governmental spending and, due to the mechanics of the tax rule, normally would trigger an upward adjustment of the tax rate. In order to avoid tax increases during the downturn, the adjustment of the tax rate is suspended during a lockdown.

Policy Settings for the Reproduction of German Time Series

The simulation output shown together with German data in Figure 1 has been generated under a policy setting, in which two weeks after the appearance of the virus (corresponding to March 23, 2020) individual prevention measures, social distancing, working from home are introduced together with lockdown measures of intensity $\alpha^l = 1$. These measures stay in place until the incidence value drops below $\beta^o = 5$, at which point economic activities are fully resumed (after the adjustment period), i.e. $\alpha^o = 0$. The parameter setting underlying these simulations is summarized in Table 4

	lockdown
Individual prevention measures	$\xi = 0.6$
Social Distancing	$n^{p,l}_{yy} = 2, n^{p,l}_{oo} = 0.5, n^{p,l}_{oy} = 1, n^{p,l}_{yo} = 0.5$
Working from home	Yes
Work contacts	$n^{w,l} = (4, 5, 8, 2)$
Shopping contacts	$n^{s,l} = (5, 20, 10)$
Reduction in shopping frequency	$\Delta p^{s,l} = (0.15, 0.5, 0)$
Short time work	$\varphi = 0.7,\ q^{st} = 0.75$
Bailout	Yes
lockdown intensity	$\alpha^l = 1$
Incidence threshold where lockdown is lifted	$\beta^o = 5$
Consumption reduction during opening	$\alpha^o = 0$

Table 4: Default values for lockdown policy.

B.5 Extensions

Virus Mutation

In September 2020, a mutation of the SARS-CoV-2 was detected in Great Britain (Chand et al., 2020) and afterwards has been found in other countries. With a higher infection probability, the mutation poses new challenges for health authorities. We introduce mutations in our model in the following way.

At a specific day ($t^{mut} = 162$), a number of agents ($n^{mut} = 3$) is infected by the mutation. This separates the set of infected agents $\mathbf{I}_t$ into two types of infected status, either with the original or the mutated virus $\mathbf{I}_t^{mut}$. We rely on British data to calibrate the mutation (Chand et al., 2020) and assume the transmission probability increases by 50% for a household infected with the mutated virus. Hence, in case one of the newly infected agents meets a susceptible household, the infection probability is given by $p^{mut}_{inf} = 1.5\ p_{inf}$. A household inherits the type from the infecting agent. Finally, we assume that data such as latency period or fatality rate as given in Table 3 is the same for a household infected by the mutation.

In Table 5 means and standard deviations of key indicators under the different policies are shown under the scenario with mutations. This table corresponds to Table 1 for the scenario without mutation. Since generally speaking the occurrence of a more infectious mutation increases the variance across runs the number of runs for each policy scenario was increased to 50

	A	B	C	D	E
$(\alpha^l, \alpha^o, \beta^l)$	$(1, 0, 50)$	$(1, 0, \mathbf{5})$	$(\mathbf{0.25}, 0, \mathbf{5})$	$(1, \mathbf{0.5}, 50)$	$(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$
	benchmark policy	*low threshold*	*weak lockdown*	*weak opening*	*weak lockdown+opening*
GDP loss [%]	6.61 (1.92)	7.14 (1.45)	0.79 (0.30)	5.74 (1.57)	1.46 (0.13)
Mortality [%]	0.057 (0.015)	0.021 (0.008)	0.089 (0.074)	0.034 (0.027)	0.079 (0.073)
Duration in lockdown	323.0 (196.6)	304.1 (203.8)	427.7 (214.5)	177.5 (167.4)	337.3 (239.1)
Number of lockdowns	2.54 (0.50)	7.94 (2.50)	6.74 (3.24)	1.48 (0.68)	4.68 (2.45)
Pub. Acc. Deficit [% of GDP]	6.47 (3.09)	6.16 (2.67)	1.62 (0.64)	4.63 (2.85)	1.53 (0.38)

Table 5: **Comparison of policy results in the scenario with a virus mutation.** Cells show means over 50 batch runs with standard deviation in brackets.

batch runs.

C Additional Results

In this Appendix we show that both delaying the initial lockdown and increasing the parameter β^o does not improve policy results compared to our default setting. First, we consider scenarios where also the initial lockdown is triggered by the threshold β^l rather than being started 2 weeks after the occurrence of the virus, as in our default setting. This variation is only relevant if we consider policies with $\beta^l > 5$, since this incidence threshold is already surpassed after 2 weeks. Hence, we consider policies A $(1, 0, 50)$ and D $(1, 0.5, 50)$ with $\beta^l = 50$. Table 6 shows that under both policies average mortality increases if the first lockdown is delayed relative to our benchmark setting. Under policy A also average GDP loss increases, while under policy D only a minimal effect on average GDP loss arises.

	A: (1,0,50)		**D: (1,0.5,50)**	
	default	endog.	default	endog.
GDP loss [%]	4.61 (1.41)	5.05 (2.18)	4.48 (0.04)	4.42 (0.04)
Mortality [%]	0.041 (0.011)	0.051 (0.015)	0.014 (0.005)	0.021 (0.007)

Table 6: **Comparison of scenarios with start of first lockdown 2 weeks after virus occurrence (default) and according to incidence threshold β^l for policies A and D.**

We now turn to the variation of β^o. In the main analysis in Section 5.2 we investigate the variation of β^l, the threshold for activating the lockdown measures, but keep the threshold for leaving the lockdown at a relatively low constant value of $\beta^o = 5$. In particular, for policies with relatively high thresholds for entering the lockdown, also higher values of β^o could be considered. In Table 7, we show that policies with higher values of β^o are however dominated. Again, we illustrate this observation for policies A $(1, 0, 50)$ and D $(1, 0.5, 50)$, hence for the two points with $\beta^l = 50$. Considering first policy D, it becomes clear that choosing a larger value of β^o performs worse compared to $\beta^o = 5$ in terms of mortality without producing economic gains. With respect to policy A, an increase in β^o gives rise to a trade-off between increasing mortality and decreasing GDP loss. However, comparing the values given in Table 7 with the effects of policies C and E, as depicted in Figure 3, shows that all combinations of policy A with larger values of the threshold β^o are clearly dominated by these two policies both with respect to mortality and GDP loss.

		A: (1,0,50)		
β^o	5	10	30	50
GDP loss [%]	4.61 (1.41)	4.39 (1.60)	3.72 (1.42)	2.57 (0.20)
Mortality [%]	0.041 (0.011)	0.062 (0.014)	0.083 (0.011)	0.09 (0.011)
		D: (1,0.5,50)		
β^o	5	10	30	50
GDP loss [%]	4.48 (0.04)	4.54 (0.04)	4.60 (0.01)	4.61 (0.01)
Mortality [%]	0.014 (0.005)	0.023 (0.01)	0.034 (0.01)	0.040 (0.011)

Table 7: **Variation in β^o for policies A and D.**

D Statistical Tests

This appendix provides the results from statistical tests. To verify the statistical significance for differences between points A, B, C, D and E in Figure 3 and Table 1 in mortality and average GDP loss, we use the Mann-Whitney-U test, a non-parametric test for unpaired samples. We document the p–values in Tables 8 and 9, which are based on 20 batch runs. We perform the same statistical analysis for the mutation scenario (Fig. 6 and Table 5) in Table 10 and 11 with 50 batch runs. Table 12 shows the comparison between the two scenarios mutation and without mutation documenting differences and p-values.

$(\alpha^l, \alpha^o, \beta^l)$	B $(1, 0, \mathbf{5})$ *low threshold*	C $(\mathbf{0.25}, 0, \mathbf{5})$ *weak lockdown*	D $(1, \mathbf{0.5}, 50)$ *weak opening*	E $(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$ *weak lockdown+opening*
A $(1, 0, 50)$ *benchmark policy*	0.4450	< 0.0001	0.1081	< 0.0001
B		< 0.0001	0.1081	< 0.0001
C			< 0.0001	< 0.0001
D				< 0.0001

Table 8: **Mann-Whitney-U test for GDP.** Cells show p–values over 20 batch runs.

$(\alpha^l, \alpha^o, \beta^l)$	B $(1, 0, \mathbf{5})$ *low threshold*	C $(\mathbf{0.25}, 0, \mathbf{5})$ *weak lockdown*	D $(1, \mathbf{0.5}, 50)$ *weak opening*	E $(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$ *weak lockdown+opening*
A $(1, 0, 50)$ *benchmark policy*	< 0.0001	< 0.0001	< 0.0001	< 0.0001
B		< 0.0001	0.0435	0.0527
C			< 0.0001	0.0263
D				< 0.0001

Table 9: **Mann-Whitney-U test for mortality.** Cells show p–values over 20 batch run.

$(\alpha^l, \alpha^o, \beta^l)$	B $(1, 0, \mathbf{5})$ *low threshold*	C $(\mathbf{0.25}, 0, \mathbf{5})$ *weak lockdown*	D $(1, \mathbf{0.5}, 50)$ *weak opening*	E $(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$ *weak lockdown+opening*
A $(1, 0, 50)$ *benchmark policy*	0.0383	< 0.0001	0.0652	< 0.0001
B		< 0.0001	< 0.0001	< 0.0001
C			< 0.0001	< 0.0001
D				< 0.0001

Table 10: **Mann-Whitney-U test for GDP (mutation scenario).** Cells show p–values over 50 batch runs.

$(\alpha^l, \alpha^o, \beta^l)$	B $(1, 0, \mathbf{5})$ *low threshold*	C $(\mathbf{0.25}, 0, \mathbf{5})$ *weak lockdown*	D $(1, \mathbf{0.5}, 50)$ *weak opening*	E $(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$ *weak lockdown+opening*
A $(1, 0, 50)$ *benchmark policy*	< 0.0001	0.4544	< 0.0001	0.0340
B		< 0.0001	0.8739	< 0.0001
C			< 0.0001	0.2698
D				< 0.0001

Table 11: **Mann-Whitney-U test for mortality (mutation scenario).** Cells show p–values over 50 batch run.

$(\alpha^l, \alpha^o, \beta^l)$	A $(1, 0, 50)$ *benchmark policy*	B $(1, 0, \mathbf{5})$ *low threshold*	C $(\mathbf{0.25}, 0, \mathbf{5})$ *weak lockdown*	D $(1, \mathbf{0.5}, 50)$ *weak opening*	E $(\mathbf{0.25}, \mathbf{0.25}, \mathbf{5})$ *weak lockdown+opening*
GDP [%]	2.00 (< 0.0001)	2.25 (< 0.0001)	0.31 (0.0002)	1.26 (< 0.0001)	-0.07 (0.1266)
Mortality [%]	0.016 (0.0002)	0.003 (0.1997)	0.061 (0.0040)	0.020 (0.0265)	0.056 (0.0006)

Table 12: **Differences and Mann-Whitney-U test between scenarios.** Cells show differences (mutation minus no mutation scenario) and in brackets below p–values for a comparison between the two scenario.

E Tables and Figures

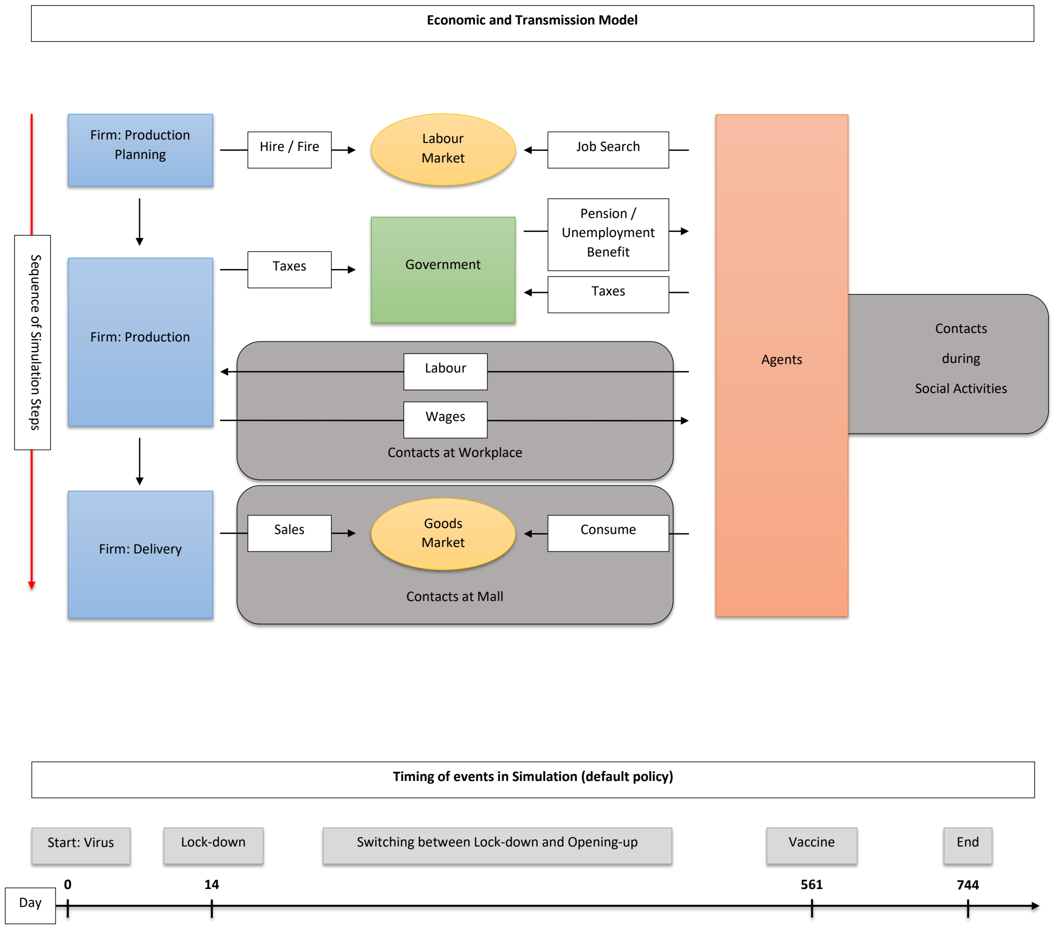

Figure 7: **Summary of model structure and timing of events (default policy).**

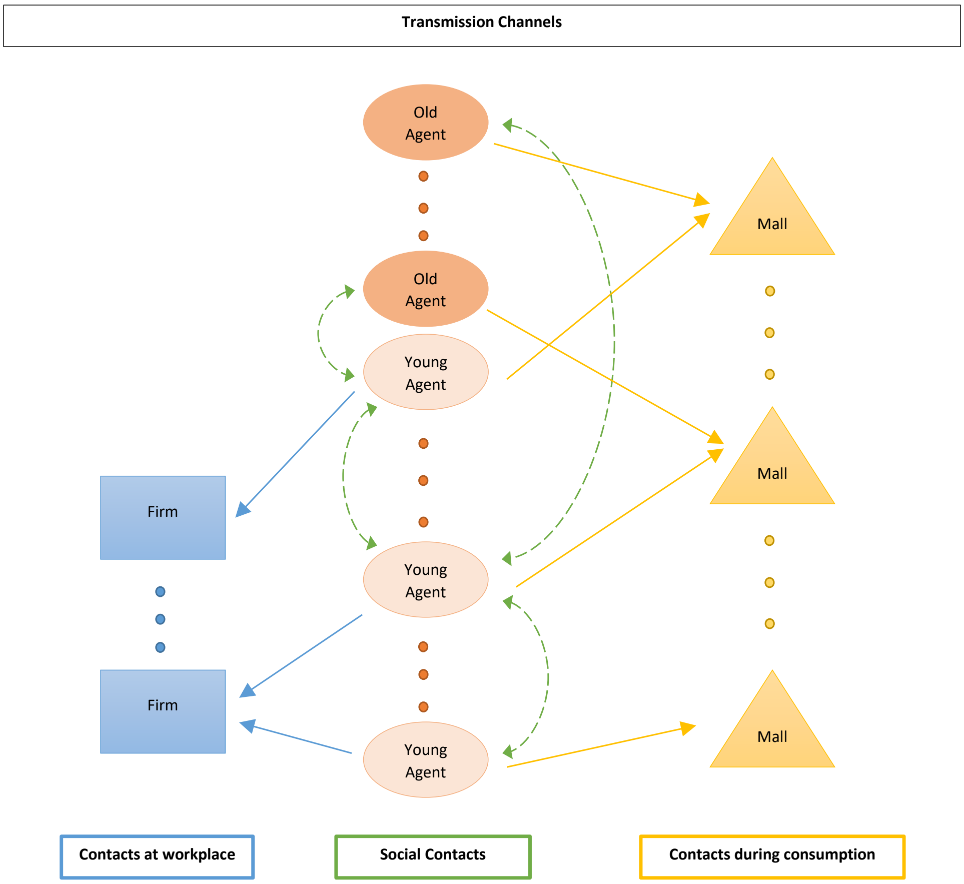

Figure 8: **Summary of transmission channels.**

Table 13: **List of variables.**

Symbol	Description
Firms	
A_i	Labor productivity
$D_{i,w}$	Sum of daily sales in the previous sales cycle
$\hat{D}_{i,w}$	Demand expectation for the production and sales cycle starting in week w
$\mathbf{F}_w$	Set of all private firms
$\mathbf{F}_{k,w}$	Set of firms in sector k
$L_{i,w}$	Labor input in the production and sales cycle starting in week w
$\tilde{L}_{i,w}$	Planned labor input for the production and sales cycle starting in week w
$L_{i,w}^V$	Open vacancies in week w
$L_{i,w}^R$	Redundancies in week w
$P_{i,w}$	Price in week w
$\Pi_{i,w}$	Profits of firm i in the previous production cycle
$Q_{i,w}$	Realized output in the production and sales cycle of week w
$\tilde{Q}_{i,w}$	Planned output for the production and sales cycle of week w
$S_{i,w}$	Available liquidity in week w
$\tilde{S}_{i,w}$	Threshold liquidity level for dividends in w
$X_{i,t}$	Sales in period t
$Y_{i,t}$	Inventory stock available for sale in period t
c_i	Unit costs
c_i^F	Fixed costs
$d_{i,w}$	Dividends paid out by firm i to its shareholders in week w
$\mu_{i,w}$	Mark-up in week w
n_t	Number of firms at time t
$n_{k,w}$	Number of firms in sector k in week w
$s_{i,w}$	Market share of firm i in week w
w_i	Wage equal to sectoral wage w_k
Households	
$C_{h,w}$	Consumption budget

Continued on next page

Table 13 – continued from previous page – List of variables

Symbol	Description
$\tilde{C}^S_{h,k,t}$	Intended consumption budget for sector k
$\mathcal{C}_{h,i,t}$	Desired quantity of product i
$C^S_{h,k,t}$	Actual consumption budget for sector k
$E_{h,t}$	Total expenditures in period t
$\mathbf{H}_t$	Set of all households at time t
$\mathbf{H}^Y_t$	Set of all young households
$\mathbf{H}^O_t$	Set of all old households
$I^{Cap}_{h,w}$	Capital income of a household
$I_{h,w}$	Total gross income of a household
$I^N_{h,w}$	Total net income of a household
$\bar{I}_{h,w}$	Smoothed average net income of a household
$W_{h,w}$	Wealth of a household
m_t	Number of households at time t
$\omega_{h,w}$	Wage of household h in week w
$u_{h,w}$	Unemployment benefits of household h in week$w$
w^P	Level of pension
Labor market	
$\mathbf{L}^S_{k,w}$	Set of workers forming the labor supply in sector k
$L^S_{k,w,}$	Number of job seekers in sector k
$\mathbf{L}^{HO}_{k,w}$	Set of workers in sector k that are eligible to work from home
$\mathbf{U}_w$	Set of all unemployed households
$\mathbf{U}^S_{k,w}$	Set of all unemployed households qualified for sector k
$\mathbf{V}_{k,w}$	Set of all firms of sector k with open vacancies
$\mathbf{W}^F_{i,w}$	Set employees of firm i in week w
$\mathbf{W}^G_g$	Set of civil servants working for the public office g
$\mathbf{W}^{HO}_{i,t}$	Set of workers able to work from home of firm i at time t
$\mathbf{W}^{ST}_{i,t}$	Set of short time workers of firm i at time t
Goods market	
$\mathbf{C}_{i,t}$	Set of clients of firm i at period t

Continued on next page

Table 13 – continued from previous page – List of variables

Symbol	Description
$\mathbf{C}_{k,t}$	Set of clients of a sectoral k mall at period t
$\Omega_{h,k,t}$	Set of products of sector k considered for consumption choice of household h
Social Interactions	
$\mathbf{CS}_{h,k,t}$	Set of co-shoppers of agent h in sector k at time t
$\mathbf{CW}_{h,t}$	Set of co-workers of agent h at time t
$N^{a,a}_{h,t}$	Number of people met during social activities by agent h at time t divided per age group
$N^{cs}_{h,k,t}$	Number of co-shoppers met by agent h while shopping in sector k at time t
$\bar{N}^{cs}_{h,k,t}$	Maximum number of co-shopper eventually met by agent h in sector k at time t
$N^{cw}_{h,t}$	Number of co-workers met by agent h at time t
$\mathbf{SA}^{a}_{h,t}$	Set of households belonging to a specific age group met by agent h at time t
$\mathbf{X}_{h,t}$	Set of colleagues of household h at time t
Government	
$\mathbf{G}$	Set of all public sector offices
GDP_w	Gross domestic product of the previous week
L^P	Number of civil servants working for the government
S^G_w	Public account
T^C_w	Corporate tax revenues
T^I_w	Income tax revenue
$\mathbf{W}^S_{P,w}$	The set of civil servants working for the government
τ_w	Tax rate
$\hat{\tau}_w$	Reference tax rate
w^S_P	Wage paid in the public sector
Pandemic	
$\mathbf{D}_t$	Set of deceased at time t
$\mathbf{I}_t$	Set of actual infected at time t
$\mathbf{I}^{inf}_t$	Set of infectious agents
$I^2_{h,t}$	Cumulative number of secondary infection caused by agent h at time t
$\mathbf{R}_t$	Set of recovered at time t

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Table 13 – continued from previous page – List of variables

Symbol	Description
$R_{0,t}$	Daily basic reproduction number
$R_{0,t}^{RKI}$	Robert Koch Institute reproduction number estimation
$\mathbf{S}_t$	Set of susceptible at time t
$\mathbf{T}_t$	Set of new infected between time t and $t+1$
q_t^a	Individual Case Fatality Rate at time t
$\mathbf{I}_t^{mut}$	Set of actual infected at time t with the mutation

Table 14: **List of parameters.**

Symbol	Description	Value
Firms		
$[\bar{A}_k]$	Sector specific average productivity	$[97, 62, 48, 62]$
$[\varphi_k]$	Target of firm savings relative to av. revenues during last 4 weeks	$[1, 0.5, 0.5, 0]$
$[\chi_k]$	Size of the sector specific weekly inventory buffer	$[0.0036, 0.0011, 0.0018, 0]$
$[\delta_k]$	Sector specific weekly depreciation rate of the inventory	$[0.01, 1.00, 0.50, 0.00]$
$[e_k]$	Estimated employment shares	$[0.1170, 0.4362, 0.3268, 0.1200]$
ι	Production boost in case of stock-out	4
$[\lambda_k]$	Weekly fixed to variable cost ratio	$[0.0752, 0.048, 0.048, 0.048]$
n_0	Initial number of private firms	3780
$[\bar{\mu}_k]$	Upper bound firm mark-up	$[0.18, 0.18, 0.18, 0]$
$[\underline{\mu}_k]$	Lower bound firm mark-up	$[0.25, 0.25, 0.25, 0]$
ρ^D	Firm demand expectation smoothing	0.5
ζ	Dividend payout ratio	0.7
q^{st}	Probability that worker enters short-time work	0.75
Households		
a_0^y	Fraction of the young households	0.75
$[c_k]$	Fixed consumption quotas	$[0.21, 0.50, 0.29]$
$[p_k^s]$	Probability of shopping $k \in \{M, S, F\}$	$[1, 1, 1]$
η	Number of products for which a household collects prices at the mall	4
γ^c	Intensity of consumer choice	16
$[h_k^{HO}]$	Sector proportion of home-office workers	$[0.45, 0.30, 0.00, 0.75]$
κ	Adjustment wealth/income ratio	0.1/4
m_0	Initial number of households	100000
$[n_k^w]$	Work contact cardinality upper bound sector specific	$[8, 8, 8, 8]$

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Table 14 – continued from previous page – List of parameters

Symbol	Description	Value
$[n^c_k]$	Shopping contact cardinality upper bound sector specific (manufacturing, service, food)	$[10, 28, 10]$
$[n^p_{a,a}]$	Cross-age contact cardinality upper bound yy,yo,oy,oo	$[5, 2, 4, 2]$
ν	Wage replacement rate	0.60
Φ	Target wealth/income ratio	32
ϕ	Adjustment parameter consumption budget for essential product	0.01
ρ^I	Income expectation smoothing	0.4
Government		
n_P	Number of public offices	600
pen	Pension as fraction of average wage	0.50
φ	Replacement rate of the short-time work program	0.7
ρ^T	Adjustment speed of the tax rate	0.05
θ	Fraction of public debt erased/added in one week	1/520
Pandemic		
δ_r	Detection rate	0.15
n^{icu}	Number of intensive care units available per agent	$30 * 10^{-5}$
p_{inf}	Infection probability in a single contact	0.0725
$[\bar{q}^a_l]_{a=y,o}$	individual fatality rate with underutilization of ICU	$[0.00099, 0.024]$
$[\bar{q}^a_h]_{a=y,o}$	individual fatality rate with overutilization of ICU	$[0.0027, 0.075]$
t_0	Starting date of the pandemic	14
t_{lnt}	Latency period of the disease	5
t_{inf}	Infectious period of the disease	5

Continued on next page

Table 14 – continued from previous page – List of parameters

Symbol	Description	Value
t_{gen}	Generation time	4
$\bar{t}_{rec}$	Maximum number of days being infected or recovery time	21
t_{vac}	Number of days after the pandemic for vaccine availability	561
u^{icu}	Fraction of infected people needing intensive care	0.01275
ξ	Reduction of infection probability coefficient default value	0
t^{mut}	Start of the mutation (only when activated)	162
n^{mut}	Number of agents initially infected by the mutation	3
p_{inf}^{mut}	Infection probability in a single contact for an agent infected by the mutation	1.5 p_{inf}