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# Covid-19 contagion, economic activity and business reopening protocols☆

Alexandre Janiak*, Caio Machado, Javier Turén

*Instituto de Economía, Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago, Chile*

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ABSTRACT

This paper studies the impact of sanitary protocols aimed at reducing the contagion by Covid-19 during the production and consumption of goods and services. We augment a heterogeneous SIR model with a two-way feedback between contagion and economic activity, allowing for firm and sector heterogeneity. While protocols are a burden for firms (especially SMEs), they may enhance economic activity by avoiding infections that reduce the labor supply. Using Chilean data, we calibrate the model and assess the impact of recommended firm protocols on contagion and economic activity in the after-lockdown period. Our quantitative results suggest that: (i) A second wave of infections is likely in the absence of protocols; (ii) Protocols targeted at some sectors can reduce deaths while at the same time improving economic conditions; (iii) Protocols applied widely have a negative effect on the economy. We also find that applying strict protocols to a few sectors is generally preferable to applying milder protocols to a larger number of sectors, both in terms of health and economic benefits.



## 1. Introduction

The year 2020 has seen many economies choosing lockdown as a strict short-run policy response to the hospital overcrowding caused by the rapid spread of Covid-19. Once ‘the curve has been flattened’, several economies have started a reopening process, but with the fear of a second wave of contagion as activity resumes. Sanitary protocols have been put in place in an attempt to reduce contagion risk as agents restart social and economic interactions. However, many of those protocols require businesses to adjust their operations and physical infrastructure. The implementation costs of such protocols can be especially harmful for the economy since firms must face this extra burden on top of an already depressed demand. This is particularly relevant for small and medium enterprises since firm protocol costs often include a large fixed component that businesses are willing to pay only if they can achieve a large enough scale. Otherwise, they have to shut down. In Chile, for example, Gallego et al. (2020) document that the average monthly cost of implementing a set of

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* Corresponding author.
*E-mail addresses:* ajaniak@gmail.com (A. Janiak), caio.machado@uc.cl (C. Machado), jturen@uc.cl (J. Turén).

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recommended protocols is about $117,000 Chilean pesos per worker for a five-worker firm, while it is about $39,000 in the case of a firm with 500 employees (36% of the minimum wage versus 12%).[1]

While protocols impose an additional layer of costs to firms, they can have benefits for aggregate economic performance since by reducing the risk of contagion they allow employees to go back to work. Hence, firm protocols do not necessarily produce a tradeoff between economic performance and health as often argued in the case of lockdowns (Auray and Eyquem, 2020; Alvarez et al., 2020; Eichenbaum et al., 2020a; Kaplan et al., 2020). Some studies have even suggested that lockdowns, if one takes a broader view of their impact on health, have had rather negative consequences for aspects of health unrelated to the spread of the virus.[2] In a situation where sanitary emergencies might become recurrent in the future, an evaluation of the impact of alternative policy tools—such as Covid-related firm protocols—is of utmost importance.

This paper aims to quantify the impact of business operating protocols on both economic performance and the rate by which the virus spreads. We extend an otherwise standard SIR model with a two-way feedback between economic activity and contagion. In the model, a spread in contagion has a negative impact on output because sick agents cannot work. At the same time, a drop in consumption tends to limit contagion, since the consumption and production of goods both require social interactions. The epidemiological block is what ultimately causes propagation in the real economy, as firms' production decisions are static. We also allow for industry and firm heterogeneity, which helps us better understand the differentiated impact of protocols on firms depending on their size and how much social interaction their activities require.

While the economic consequences of Covid-19 has attracted lots of attention, we shed light on the unexplored macroeconomic consequences of a widely adopted measure for containing the virus, namely business operating protocols. Although such protocols have been imposed to firms in many countries, studies on their aggregate impact on the economy is scant. This, we conjecture, is partly due to the difficulty of computing their specific—fixed and variable—costs along with the challenge of pinning down how much they reduce social interactions that could lead to new infections. We circumvent the first problem by relying on the estimates of the monetary cost of firm protocols computed by Gallego et al. (2020) for Chile. With respect to the latter challenge, we explore the consequences of protocols for a wide array of scenarios regarding the effect of protocols on social interactions that happen within businesses.

We calibrate the model to the Chilean economy using industry-level data on physical proximity at work from Gallego et al. (2020) and social contacts from Béraud et al. (2005). This allows us to quantify the importance of contagion through different channels (work, leisure and consumption) in different sectors. We study scenarios with and without protocols and with different levels of protocol effectiveness in reducing contact rates.

We show that economy-wide protocols prevent a second wave of contagion for scenarios where they directly reduce the social interactions induced by consumption and production by at least 50%. For scenarios where their effectiveness is only about 30–40%, the model predicts a second wave of contagion, although much less intense than without protocols. In the absence of protocols, the increase in the infection rate is large and the economy experiences a collapse in aggregate output over the first three months as a result of sick workers dropping out of the labor force. The scenarios with protocols still feature a lower present discounted value of consumption because of the magnitude of their costs, which leads several firms to close down (especially the small ones).

We also assess the potential benefits of applying protocols only to a subset of sectors which concentrate the largest risk of contagion. Our results suggest that such a policy can decrease the number of deaths while simultaneously yielding a larger value of consumption relative to a situation without firm protocols. In our benchmark simulations, if protocols are applied to a number of sectors covering about two thirds of aggregate employment, then the spread of the virus is sufficiently contained to avoid a collapse in aggregate output, while preventing firms in sectors with a lower risk of contagion from suffering the burden of protocols. Hence, imposing no protocols is Pareto dominated by imposing protocols to a few sectors in the sense that an economy with no protocols has worse economic and health outcomes.

Finally, we study protocols in a context where policymakers are constrained in their ability to impose sanitary protocols to all firms. This captures situations where the resources needed to implement protocols are fixed in the short run and/or protocols require some costly and scarce monitoring effort from public authorities to guarantee compliance. We show that when the ability of the policymaker to apply protocols is sufficiently limited, targeting the application of protocols to the sectors with the highest contact rates leads to both better economic and health outcomes than applying economy-wide protocols. Therefore, economy-wide protocols are a Pareto dominated policy when the ability to implement those is sufficiently limited.

Our findings are in line with other papers which have shown that targeted sanitary policies can improve aggregate economic performance without necessarily exacerbating the spread of the virus. Acemoglu et al. (2020) consider a SIR model with heterogeneity in infection, hospitalization and fatality rates across age groups. They show that strict lockdown applied

[1] Gallego et al. (2020) analyze the cost of 60 recommended measures ranging from the use of supplies such as masks, alcohol and thermometers, to fixing panels and signs to indicate minimum distances between customers, among many others. The measures also include, for instance, the need of a bus to transport employees to the workplace in the case of large firms. See Section 4.3 for more details on this data.

[2] The argument stems from the observation of an increase in the incidence of other diseases after lockdowns were implemented. The lockdown period is associated with an increase in mental health issues, including a considerable increase in symptoms of anxiety disorder, depressive disorder and an increase in substance abuse (Czeisler et al., 2020), and a significant increase in suicides (Reger et al., 2020; Gunnell et al., 2020). Cronin and Evans (2020) suggest that protecting the elderly in some nursing homes successfully reduced the risk of death related to Covid, but it largely increased the risk of dying of other diseases such as Alzheimer, for example. Also, there was a reduction in infant vaccination during that period in the US (Santoli, 2020). Finally, (Baron et al., 2020) show that school closures implied that significantly less child maltreatment incidents were reported.

to the most vulnerable groups allows to consider less strict policies for the lower-risk groups. Berger et al. (2020) quantitatively analyze the benefits from frequent testing and targeted lockdown as compared to widespread lockdown. Their results suggest that this type of policy can reduce cumulative output losses by 90 percent in the case of weekly testing, without increasing the long-run level of deaths in the US. Chari et al. (2020) find that targeted testing and isolation policies deliver substantial welfare gains. Eichenbaum et al. (2020b) study the effect of policies similar to Berger et al. (2020) in a context where individuals can be infected because they are involved in both economic and non-economic interactions—two channels that we also consider in our model with firm protocols. We contribute to this recent literature by studying the effects of economy-wide and sector-specific business operating protocols. Our results lend support to the general idea that there are large benefits of targeting policies aimed at containing the virus.

Our paper is also related to the macro literature that studies the heterogeneous impact of distortions across firms of different sizes.[3] This literature generally shows that the costs implied by several types of regulation tend to lower aggregate economic performance because they either force some firms out of the market or expand the scale of low-productivity firms at the expense of high-productivity ones. While there is a channel through which firm protocols have a negative impact on aggregate output in our model—as they make small firms less likely to survive—we show that they can also mitigate the drop in labor supply brought by the virus, even offsetting the former negative effect when protocols are applied to some key sectors only.

The remainder of the paper is organized as follows. Section 2 describes the model. The equilibrium conditions are presented in Section 3. Our benchmark calibration is discussed in Section 4. Section 5 presents the results of our simulations, considering the benchmark parametrization as well as alternative scenarios. Finally, Section 6 concludes.

## 2. Model

Time is continuous and indexed by $t \geq 0$. There are $N$ sectors (industries) indexed by $j \in \{0, 1, 2, \ldots, N\}$ and a continuum of workers with unit mass, each worker being associated to one industry. At each date, workers can be in one of five states: Susceptible ($S$), Infected ($I$), Resolving ($R$), recoVered ($V$) and Deceased ($D$). The total mass of workers of sector $j$ in states $S$, $I$, $R$, $V$ and $D$ at date $t$ are denoted by $S_{jt}$, $I_{jt}$, $R_{jt}$, $V_{jt}$ and $D_{jt}$, respectively. Each worker in states $S$, $I$ and $V$ inelastically supplies one hour of labor to its respective sector, and the mass of workers in each sector is denoted by $m_j$. We interpret the state $R$ as patients that have Covid-19, have been tested for it and are therefore isolated at home, while agents in state $I$ are infected but still unaware of their condition. Goods and labor markets are competitive.

### 2.1. Consumption

Workers own all firms in the economy and are part of a large household. Consumption requires social interactions, as will be detailed later when we explain the epidemiological block of the model. Workers in states $R$ and $D$ cannot purchase goods from firms, since we interpret that the former is quarantined at home, and the latter is deceased. At each period, all the labor income and profits are equally distributed across all active workers (i.e., in states $S$, $I$ or $V$) who then make consumption decisions. The instantaneous utility of each worker, $C_t$, is given by

$$C_t = \prod_{j=1}^{N} c_{jt}^{\theta_j}, \tag{1}$$

where $c_{jt}$ denotes the consumption of the good produced by firms in sector $j$, and $\theta_j$ represents the fraction of wealth spent in each good, with $\sum_j \theta_j = 1$. Workers discount their utility at a rate $\rho > 0$.

### 2.2. Production

Each sector $j \in \{1, 2 \ldots, N\}$ produces a different good $j$, and in each sector there is a unit mass continuum of firms. Within each sector all firms produce the same good, and the only difference across firms is their productivity $a$, so we index firms by $a$. The distribution of $a$ in sector $j$ is given by a distribution $F_j(a)$. The total amount produced by firm $a$ in sector $j$ is given by $y_{jt}(a) = a\tilde{n}_{jt}(a)^{\alpha_j}$, with $\alpha_j \in (0, 1)$ and where $\tilde{n}_{jt}(a)$ denotes the total number of *effective* hours of labor used to produce variety $j$ (as detailed below). At each date, firms in each sector $j$ have to pay a fixed cost that requires $\chi_j$ units of labor to produce positive quantities.

Firms need to comply with mandatory protocols to operate. We will later detail how those protocols affect contagion by Covid-19 within the firm and among its consumers. We summarize the protocols in place for sector $j$ by a variable $b_j$. Complying with protocols requires paying an additional fixed cost of $\eta_j = \eta_j(b_j) \geq 0$ units of labor that is a function of $b_j$. Also, protocols may reduce the marginal productivity of labor. Specifically, let $n_{jt}(a)$ be the total units of labor used to produce good $j$.[4] We assume that the number of effective hours of labor is given by $\tilde{n}_{jt}(a) = n_{jt}(a)/\tau_j$, where $\tau_j = \tau_j(b_j) \geq 1$

[3] The literature considers the impact of policies that have an explicit relation between firm productivity and the magnitude of the distortion, as in Restuccia and Rogerson (2008), Guner et al. (2008), Bento and Restuccia (2017), Poschke (2018) and Escobar et al. (2020), among others. It also includes the impact of policies that implicitly have a heterogeneous effect across firms. For example, Kohn et al. (2020) study the heterogeneous impact of currency devaluations, while Andreasen et al. (2019) analyze the effect of capital controls.

[4] This does not include the hours of labor devoted to paying fixed costs.

is a function of $b_j$ and represents the variable costs of the protocol. The functions $\tau_j(b_j)$ and $\eta_j(b_j)$ are possibly different across sectors. Firms that choose not to produce ($n_{jt}(a) = 0$) do not need to pay any of those costs. Hence, the profit of firm $a$ in sector $j$ is given by

$$\pi_{jt}(a) = \begin{cases} p_{jt}a\left(\frac{n_{jt}(a)}{\tau_j}\right)^{\alpha_j} - w_{jt}n_{jt}(a) - w_{jt}\left(\chi_j + \eta_j\right) & \text{if } n_{jt}(a) > 0, \\ 0 & \text{if } n_{jt}(a) = 0, \end{cases}$$

where $w_{jt}$ denotes the wage in sector $j$, and $p_{jt}$ is the price of good $j$.

### 2.3. Social contact

Only agents in the susceptible, infected and recovered states interact with other agents, work and consume. We say that agents in those states are part of the active population, and define $A_{jt} = S_{jt} + I_{jt} + V_{jt}$ as the mass of active agents belonging to sector $j$, and $\bar{A}_t = \sum_{j=1}^{N} A_{jt}$ as the total active population. Agents in the resolving state are isolated at home and do not buy goods produced by firms (as if they only consumed goods produced at home, which imply no contagion).

At each period, a mass of workers $A_{jt}$ and a mass $\bar{A}_t$ of consumers attend industry $j$ to work and shop, respectively. In equilibrium, each consumer purchases the same amount of goods $c_{jt}$, which equals total production $y_{jt}$ in sector $j$. All agents attending industry $j$ to consume or work may get matched to another agent, in which case there is a social interaction. The mass of matches that occur in sector $j$ in a small interval of length $dt$ is proportional to the total amount produced and consumed of good $j$ ($c_{jt}$) and is given by $\phi_j c_{jt} dt$. The parameter $\phi_j$ measures how much social contact the activities of firms in sector $j$ require per unit produced, and we often write $\phi_j = \phi_j(b_j)$ to emphasize that it can depend on the protocols in place.

Conditional on a social interaction happening at industry $j$ there are three possibilities: The interaction is between two workers, between two consumers, or between a worker and a consumer. We use a standard uniform matching technology to model those meetings. In particular, among the pool of agents that have an interaction at industry $j$, a fraction $\omega_j$ are workers and a fraction $1 - \omega_j$ are consumers. Hence, the fraction of worker-worker meetings is $z_j^{ww} \equiv {\omega_j}^2$, the fraction consumer-consumer meetings is $z_j^{cc} \equiv (1 - \omega_j)^2$ and the fraction of consumer-worker meetings is $z_j^{wc} \equiv 2\omega_j(1 - \omega_j)$. The parameter $\omega_j$ is a measure of how much workers in industry $j$ are exposed to social contacts relative to consumers of that industry.

Our matching technology for social contacts implies that, for an infinitesimal time interval of length $dt$, a worker of sector $j$ gets matched to a consumer with probability $\phi_j c_{jt} z_j^{wc} dt / A_{jt}$. Consumers of sector $j$ get matched to a worker with probability $\phi_j c_{jt} z_j^{wc} dt / \bar{A}_t$. A worker gets matched to another worker with probability $2\phi_j c_{jt} z_j^{ww} dt / A_{jt}$. Finally, a consumer gets matched to another consumer with probability $2\phi_j c_{jt} z_j^{cc} dt / \bar{A}_t$. Conditional on meeting a consumer, the probability that this consumer is of a given group $i$ is equal to the share of that group in the active population, $A_{it}/\bar{A}_t$.

We also assume that at every small time interval of length $dt$ agents meet another agent for leisure related reasons with probability $\xi dt$, and conditional on meeting someone during leisure the probability of meeting an agent of group $i$ is equal to $A_{it}/A_t$.

We can now write the probability of contact between two agents. The probability that an agent of sector $j$ meets an agent of sector $i$ in a small interval $(t, t + dt)$ is given $\beta_{jit} dt$, where

$$\beta_{jit} = \begin{cases} \left(\frac{A_{it}}{\bar{A}_t}\right)\left[\sum_{k=1}^{N}\left(\frac{2\phi_k c_{kt} z_k^{cc}}{\bar{A}_t}\right) + \frac{\phi_j c_{jt} z_j^{wc}}{A_{jt}} + \xi\right] + \frac{\phi_i c_{it} z_i^{wc}}{\bar{A}_t} & \text{if } i \neq j, \\ \left(\frac{A_{it}}{\bar{A}_t}\right)\left[\sum_{k=1}^{N}\left(\frac{2\phi_k c_{kt} z_k^{cc}}{\bar{A}_t}\right) + \frac{\phi_j c_{jt} z_j^{wc}}{A_{jt}} + \xi\right] + \frac{\phi_i c_{it} z_i^{wc}}{\bar{A}_t} + \frac{2\phi_j c_{jt} z_j^{ww}}{A_{jt}} & \text{if } i = j. \end{cases} \tag{2}$$

The first term inside the brackets of both cases above captures the interactions with other consumers during the consumption of each good $k$. The term $\phi_j c_{jt} z_j^{wc}/A_{jt}$ represents interactions with consumers one can have in the workplace. $\xi$ represents the leisure interactions, and $\phi_i c_{it} z_i^{wc}/\bar{A}_t$ represents meetings with workers of sector $i$ one may have during consumption of good $i$. The term $2\phi_j c_{jt} z_j^{ww}/A_{jt}$ in the second case represents meetings that happen between workers of the same sector.

### 2.4. State transitions

Whenever a susceptible agent meets an infected agents, she gets infected.[5] Agents move from the infected state to the resolving state at a rate $\gamma$. Moreover, agents leave the resolving state at a rate $\delta$. A fraction $\nu$ of agents leaving the resolving

[5] That is, what we call a meeting or interaction is a social exchange that leads to an infection whenever one agent is infected and the other is susceptible, as usual in SIR models.

state dies and a fraction $1-\nu$ recovers. We can then write the law of motions for each group $j$:

$$\begin{aligned}\dot{S}_{jt} &= -S_{jt}\sum_{i=1}^{N}\beta_{jit}\left(\frac{I_{it}}{S_{it}+I_{it}+V_{it}}\right),\\ \dot{I}_{jt} &= S_{jt}\sum_{i=1}^{N}\beta_{jit}\left(\frac{I_{it}}{S_{it}+I_{it}+V_{it}}\right)-\gamma I_{jt},\\ \dot{R}_{jt} &= \gamma I_{jt}-\delta R_{jt},\\ \dot{V}_{jt} &= (1-\nu)\delta R_{jt},\\ \dot{D}_{jt} &= \nu\delta R_{jt}.\end{aligned} \tag{3}$$

We conclude this section by discussing one particular aspect of our environment. Our setting focuses on the interaction of business protocols, contagion and the supply side of the economy. However, firm protocols are also likely to increase the demand of some goods and services if consumers anticipate that protocols reduce the probability of contagion during the consumption of those goods. Hence, explicitly incorporating the effect of protocols on the demand side would likely increase the overall desirability of firm protocols.

## 3. Equilibrium

### 3.1. Production

We first solve for a firm's decision once it has paid the fixed costs to operate. Then, we characterize firms' decisions of whether to operate. We refer to firms that paid the fixed costs as operating firms and we omit time subscripts to ease notation. Once a firm has paid the fixed costs, profit maximization implies that labor used in production is

$$n_j(a)=\left(\frac{ap_j\alpha_j}{w_j\tau_j^{\alpha_j}}\right)^{1/1-\alpha_j}.$$

Hence, operating firms' profits and output are

$$\tilde{\pi}_j(a)=(ap_j)^{\frac{1}{1-\alpha_j}}(w_j\tau_j)^{-\frac{\alpha_j}{1-\alpha_j}}\Omega_j-(\chi_j+\eta_j)w_j$$

and

$$y_j(a)=a^{\frac{1}{1-\alpha_j}}\left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}}, \tag{4}$$

respectively, where $\Omega_j\equiv\alpha_j^{\alpha_j/(1-\alpha_j)}-\alpha_j^{1/(1-\alpha_j)}$. Firms are willing to pay the fixed costs whenever $\tilde{\pi}_j(a)\geq 0$, which give us the cutoff $a_j^*$ above which firms decide to operate:

$$a_j^*=\left(\frac{\chi_j+\eta_j}{\Omega_j}\right)^{1-\alpha_j}\tau_j^{\alpha_j}\frac{w_j}{p_j}. \tag{5}$$

Following Melitz (2003), we define the (weighted) average productivity in sector $j$ as

$$a_j^e=\left(\int_{a_j^*}^{\infty}a^{\frac{1}{1-\alpha_j}}\frac{dF_j(a)}{1-F_j(a_j^*)}\right)^{1-\alpha_j}. \tag{6}$$

We can then write the average labor used in sector $j$ employed in production among operating firms as

$$n_j^e=\left(\frac{p_ja_j^e\alpha_j}{w_j\tau_j^{\alpha_j}}\right)^{\frac{1}{1-\alpha_j}}. \tag{7}$$

The average production of good $j$ among operating firms is then

$$y_j^e=\left(a_j^e\right)^{\frac{1}{1-\alpha_j}}\left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}}.$$

The total labor supply in sector $j$ is given by $L_j\equiv S_j+I_j+V_j$. Market clearing implies $L_j=(1-F_j(a_j^*))(n_j^e+\chi_j+\eta_j)$, which using (7) gives us:

$$L_j=(1-F(a_j^*))\left[\left(\frac{p_ja_j^e\alpha_j}{w_j\tau_j^{\alpha}}\right)^{\frac{1}{1-\alpha_j}}+\chi_j+\eta_j\right]. \tag{8}$$

Eqs. (5), (6) and (8) characterize $w_j/p_j$, $a_j^*$ and $a_j^e$ in equilibrium. The total supply of good $j$ is then given by

$$y_j = (1 - F(a_j^*))a_j^{e\,\frac{1}{1-\alpha_j}} \left( \frac{p_j \alpha_j}{w_j \tau_j} \right)^{\frac{\alpha_j}{1-\alpha_j}},$$

and market clearing implies $c_j = y_j$. Aggregate output is defined as $Y = C = \Pi_{j=1}^N c_j^{\theta_j}$.

#### 3.1.1. Special case: Pareto distribution

Suppose productivity in each sectors follows a Pareto distribution $F_j(a) = 1 - \left(\underline{a}_j/a\right)^{\epsilon_j}$, with support $[\underline{a}_j, \infty)$, and where $\underline{a}_j > 0$ and $\epsilon_j > 1/(1-\alpha_j)$. Suppose also that in equilibrium $a_j^* \geq \underline{a}_j$. We can then rewrite (6) as

$$a_j^e = \left( \frac{\epsilon_j}{\epsilon_j - \frac{1}{1-\alpha_j}} \right)^{1-\alpha_j} a_j^*.$$

Condition (8) becomes

$$\frac{w_j}{p_j} = \left( \frac{\epsilon_j}{\epsilon_j - \frac{1}{1-\alpha_j}} \right)^{1-\alpha_j} \left[ L_j \left( \frac{a_j^*}{\underline{a}_j} \right)^{\epsilon_j} - \chi_j - \eta_j \right]^{\alpha_j - 1} \frac{a_j^* \alpha_j}{\tau_j^{\alpha_j}}, \tag{9}$$

which using (5) yields

$$\left( \frac{\Omega_j}{\chi + \eta_j} \right)^{1-\alpha_j} = \left( \frac{\epsilon_j}{\epsilon_j - \frac{1}{1-\alpha_j}} \right)^{1-\alpha_j} \left[ L_j \left( \frac{a_j^*}{\underline{a}_j} \right)^{\epsilon_j} - \chi_j - \eta_j \right]^{\alpha_j - 1} \alpha_j. \tag{10}$$

Solving for $a_j^*$, the equation above characterizes $a_j^*$ in equilibrium whenever $a_j^* \geq \underline{a}_j$, yielding

$$a_j^* = \underline{a}_j \left\{ \frac{\chi_j + \eta_j}{L_j} \left[ \frac{(\alpha_j)^{1/(1-\alpha_j)}}{\Omega_j} \left( \frac{\epsilon_j}{\epsilon_j - \frac{1}{1-\alpha_j}} \right) + 1 \right] \right\}^{1/\epsilon_j}. \tag{11}$$

Total production in sector $j$ can be rewritten as

$$y_j = \frac{\epsilon_j}{\epsilon_j - \frac{1}{1-\alpha_j}} \underline{a}_j^{\epsilon_j} a_j^{*\,1-\epsilon_j} \left( \frac{\alpha_j (\chi_j + \eta_j)}{\Omega_j \tau_j} \right)^{\alpha_j}.$$

If Eq. (11) yields $a_j^* < \underline{a}_j$, we can compute $y_j$ and $a_j^e$ replacing $a_j^*$ by $\underline{a}_j$ in their respective expressions.

### 3.2. Contagion

For a given labor supply $L_{jt} = S_{jt} + I_{jt} + V_{jt}$ we obtain the equilibrium consumption in each sector $j$ as a function of $S_{jt}$, $I_{jt}$ and $V_{jt}$, as described above. Then, we use the map $(S_{jt}, I_{jt}, V_{jt}) \mapsto c_{jt}$ to replace $c_{jt}$ in (2) and numerically solve the system of ODEs given by (3), starting from some initial conditions.

## 4. Calibration

Our benchmark calibration chooses technology and preferences parameters to match the latest sectorial and aggregate data available on firms before the pandemic started in Chile. Because the epidemiological data from April to August of 2020 is contaminated by lockdowns and other social distancing policies that took place in Chile in that period, we use moments of the very beginning of the pandemic (March, 2020) to calibrate most of the contagion parameters.[6] The list of values for the calibrated parameters are summarized in Tables 2 and 3 in Appendix A.3. We then use the calibrated model to simulate the economy starting on September 1st, under different scenarios regarding firm protocols and its potential effectiveness.

[6] A disadvantage of focusing on such an early period is that we do not consider some elements that are characteristic of the after-lockdown period such as school closures or a more widespread use of telework. If these elements tend to reduce contagion, they *a fortiori* make protocols less effective. Ellison (2020) claims that the use of early data tends to overstate how rapidly the epidemic would spread. For these reasons, we present simulations in Section 5.4 under alternative parametrizations.

### 4.1. Firms and preferences parameters

The calibration of firm and sector level characteristics is done by using the last wave of the Chilean "Firms Longitudinal Survey" (year 2017), *Encuesta Longitudinal de Empresas* in Spanish, henceforth FLS. The survey contains detailed information at the firm level and it is the only publicly available firm survey in Chile that is representative across all sectors of the economy.

Originally the survey collects information across 13 different sectors. However, because we need the data to be consistent with the sectorial information we use for the calibration of the contagion parameters (see below the data from (Béraud et al., 2005)), we merge a few sectors and end up with 10 of them. Further details on the sectorial mapping are discussed in Appendix A.1.

We calibrate the income share for each sector $j$, the $\theta_j$'s parameters in the utility function, by computing the share of aggregate value in each sector in the FLS. Similarly, we use data on sectorial employment to parameterize the mass of workers in each sector, $m_j$.

The returns to scale $\alpha_j$ is a parameter that influences the economic cost of economic regulation (Atkenson et al., 1996). Indeed, when firms close and their workers are reallocated to other firms, the marginal product of labor goes down because firms get larger in size, implying a drop in aggregate output. However, when the production function is close to linear, the marginal product of labor is not significantly be affected. Hence, the lower the returns to scale, the larger the impact of protocols on aggregate performance. Because we lack estimates of the returns to scale at the sectorial level for Chile, we choose to fix returns at the standard value of 0.85, which was originally proposed by Atkeson and Kehoe (2005). This is a low value when it is compared to other calibration exercises like Gollin (2008), but using a higher value would only reinforce the result that aggregate output benefits from the application of protocols to a subset of sectors. We also set $\underline{a}_j$ in the Pareto distribution equal to one across sectors.

We calibrate the fixed operational costs, $\chi_j$, to match the median of the distribution of employment across firms within each sector in the FLS.[7] Also, we calibrate $m_j$ as the number of workers in each sector divided by the total number of workers. Following (Ghironi and Melitz, 2005), we calibrate the shape parameters of the productivity distributions, $\epsilon_j$, by targeting the standard deviation of log sales within each sector. More details are given in the Appendix A.2. Finally, we set the annualized discount rate equal to 4%, a standard value for Chile.

### 4.2. Contact parameters

There are several contagion parameters that we need to identify: the contagion rate $\phi_j$ related to production and consumption activities for each sector $j$, the relative exposure of workers as summarized by $\omega_j$, and the contagion rate from leisure activities $\xi$. Given the parameters obtained in Section 4.1, our calibration of contact rates first considers a benchmark economy in steady state with no virus. We rely on several studies from before the pandemic on proximity and social contact to parameterize most of the contact parameters in this economy. Then, given these contact parameters, we pin down the strength of the pandemic by targeting some statistical moments characterizing the first month of the pandemic in Chile. By focusing on earlier data, we can work with targeted moments that are not contaminated by confounding factors such as lockdowns or social distancing.

#### 4.2.1. Contagion at the workplace: sectorial heterogeneity

A first set of contagion parameters to calibrate is the set of $\phi_j$ rates that relates to the intensity of social contact generated by production and consumption activities in sector $j$. We rely on the calculations by Gallego et al. (2020) to identify the relative size of these parameters across sectors. In their calculations, (Gallego et al., 2020) consider the degree of physical proximity that has been documented by the Occupational Information Network (O*NET) at the occupational level for the United States and extrapolate it to Chile. In particular, physical proximity is measured as a dummy variable according to the answers to the following question: *To what extend does this job require the worker to perform tasks in close physical proximity to others?* Answers such as *"Moderately close (at arm's lenght)"* or *"Very close (near touching)"* implies physical proximity. Using data from the CASEN (2017) Chilean micro survey, Gallego et al. (2020) identify the distribution of occupations within each sector of the Chilean economy and obtain the share of workers with physical proximity for each one of these sectors.

We rely on this information to obtain the relative intensity of contagion as follows. Assume that the economy is originally in steady state, i.e., before the pandemic, with $\bar{c}_j$ and $S_i = m_i$ denoting steady state consumption and the mass of susceptible agents in sector $j = 1, \ldots, N$, respectively. Total interactions in steady state are denoted by $\Phi = \sum_{j=1}^{N} \phi_j \bar{c}_j$, where $\phi_j \bar{c}_j$ is the total number of matches in sector $j$. We define $h_i \equiv \phi_j \bar{c}_j / \Phi$ as the weight of each sector in total contagion, with $\sum_{j=1}^{N} h_j = 1$. We use the relative number of workers with physical proximity in each sector as a proxy for the $h_j$ shares. The obtained values of $h_j$ can be found in Table 3.

#### 4.2.2. Contagion through leisure versus work-related contagion

Over the last decade, the medicine literature has built databases on the distribution of interactions a given set of individuals have during a day. It has been documented that social contact data allows to improve the prediction of seroprevalence

[7] We rely on the median rather than the mean not to contaminate our estimations with outliers.

and infection of several diseases such as varicella, mumps, influenza, parvovirus B19 and pertussis (Wallinga et al., 2006; Ogunjimi et al., 2009; Rohani et al., 2010; Melegaro et al., 2011). One of the first such studies was Mossong et al. (2008), who calculated the distribution of social interactions within a sample of 7290 participants from eight European countries.

For this paper, we rely on information from Béraud et al. (2005), who specifically includes information at the sectorial level, even though the data is for France. The data also identifies if an interaction implies touching the skin of the respondent and interactions are categorized according to the context where contact occurs: home, work, school, transport, leisure and others. Given the share of interactions in each of these categories, we characterize the relative importance of contagion through firm-related activities (given by the $\phi$'s parameters) with respect to contagion from leisure (given by $\xi$). Without a clear mapping on how interactions at home affect contagion in our model, we interpret our model as aggregating a household into one person/worker and therefore exclude the "home" category for our calibration. Implicitly, we are assuming that if one member of a household is infected with Covid-19, due to impossibility of isolation, every other member that lives in the same household would also have it. Denote by $q \equiv \Phi/\xi$ the ratio of firm-to-leisure-related interactions. Our calibration implies $q = 1.64$.

We see the use of social contact data as an improvement over existing calibrations that do not rely on information about the distribution of contagion sources outside the household. For example, Eichenbaum et al. (2020a) use information from Ferguson et al. (2006), who rely on interesting data about the importance of intra-household contagion (Longini et al., 1988), but who need to make assumptions on the importance of leisure- and work-related contagion. Even though social contact data do not measure contagion directly, it improves the prediction of seroprevalence, as Béraud et al. (2005) claim.

#### 4.2.3. Contagion at the workplace: workers versus consumers

As discussed in Section 2, the technology in sector $j$ implies that, among the pool of agents that have a meeting, a share $\omega_j$ are workers. Moreover, within each sector, the conditional probability of a match is proportional to the size of each group in the matched population, therefore $z_j^{ww} = \omega_j^2$, $z_j^{cc} = (1-\omega_j)^2$ and $z_j^{wc} = 2\omega_j(1-\omega_j)$. The share of meetings that a worker of sector $j$ has during work hours in steady state, i.e. before the pandemic, is

$$s_j^w = \frac{2\phi_j \bar{c}_j \omega_j / m_j}{2\phi_j \bar{c}_j \omega_j / m_j + [\sum_{i=1}^N 2\phi_i \bar{c}_i (1-\omega_i) + \xi]}.$$

We then define $s^w = (s_1^w, s_2^w, \dots, s_N^w)$ using the contact data across sectors taken from Béraud et al. (2005). With $s^w$, $h_j$, $q$ and $\xi$, and after computing consumption in steady state, we can back out $\phi = (\phi_1, \phi_2, \dots, \phi_N)$, and with this we get $\omega = (\omega_1, \omega_2, \dots, \omega_N)$.

#### 4.2.4. Aggregate component of contagion

The previous sections describe how we calibrate the relative importance of different contagion channels, depending on the sector where contagion occurs, whether contagion occurs at the workplace or in the context of non-economic activities, and if a sector tends to affect consumers relatively more than workers. We now need to define the aggregate level of contagion, that is, how powerful is the spread of the virus. We choose to calibrate the parameter $\xi$ by targeting an initial growth rate in the number of infected agents at the first month of the pandemic consistent with the estimates of Fernández-Villaverde and Jones (2020) for Chile (given the relative size of the contact parameters as previously described). The first month of the pandemic (which is roughly March of 2020 for Chile) has the advantage that its data is not contaminated yet by the effect of lockdown or social distancing. Moreover, the growth rate of infected agents is nearly constant during the first 30 days because the share of susceptible agents in the population is not varying much yet.[8]

Using detailed information for many countries, Fernández-Villaverde and Jones (2020) estimate a basic reproduction number $R_0$ near 1.7 for Chile in the first days of the pandemic, which in their model is equivalent to stating that the number of agents in the $I$ state was growing at a rate of approximately 14% a day at the beginning of the pandemic.[9] By setting $\xi = 0.0795$ and then computing the relative contagion parameters as previously described we get a daily growth rate for the number of infected agents equal to 14% in the first 30 days of the pandemic.[10]

Finally, we also rely on Fernández-Villaverde and Jones (2020) for the following parameters: $\gamma = 0.2$, implying that one can infect others for a period of five days on average; $\delta = 0.1$, which means that, on average, one stays 10 days in the resolving state; and $\nu = 0.01$, implying a 1% mortality rate.

### 4.3. Parameterizing protocols

Protocols costs are computed using the new database constructed by Gallego et al. (2020). After the more strict lockdown was over in Chile, firms were provided with a list of measures that they should comply with to resume in-house production. The list includes 60 different measures grouped in 8 different categories. For instance, the list includes criteria related to

[8] See the set of Eq. (3) for a mathematical intuition.

[9] In a homogeneous model as the one in Fernández-Villaverde and Jones (2020), the growth rate of infected agents at the beginning of a pandemic is related to $R_0$ by the formula $\dot{I}_t/I_t \approx \gamma(R_0 - 1)$, where $I_t$ denotes the total number of agents in the $I$ state.

[10] To get a pandemic started when calibrating $\xi$, we assume that initially a small fraction of workers of the sector that generates the most social contact (with the higher $h_i$) is in the $I$ state. We get the same value of $\xi$ if we assume an equal and small fraction of workers in each sector is initially infected.

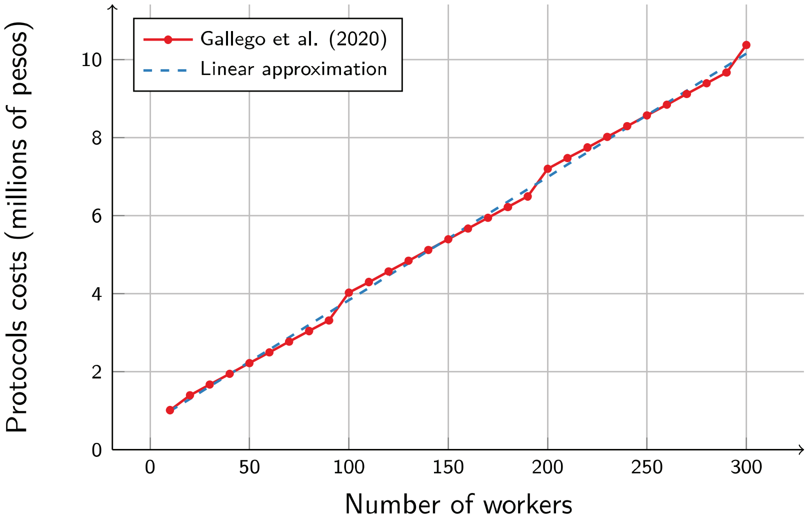



**Fig. 1.** Protocols costs.

social distancing inside the firm (e.g., the maximum number of workers allowed in a common dinning room as a function of its square meters), measures to reduce the probability of contagion during commuting (e.g. forcing firms to provide private buses for workers) and regular provision personal protective equipment and other inputs, such as gloves, masks and soap, to name a few. Gallego et al. (2020) estimate the monthly cost (in Chilean pesos) for each of the 60 measures. We rely on this novel estimates to parameterize the cost of protocols in our model.

Initially, we separate the costs of all listed protocols between variable and fixed costs.[11] For the variable costs, we distinguish between protocols that depend linearly on the total number of workers in the firm (e.g., providing masks to each worker) and measures that are binding only if total workers are above a certain threshold (e.g., for every 100 workers there must be one worker in charge of keeping track of the stock of Covid-prevention supplies). Regarding the fixed costs, we identify protocols that all firms should adopt and whose costs are independent of size. With this distinction, we compute the total cost of protocols as a function of firm size, which is shown by the solid line in Fig. 1.

We approximate the total costs of protocols by a linear function $\widehat{TC} = \widehat{\alpha} + \widehat{\beta}X$, where $\widehat{TC}$ is the approximated total costs of protocols and $X$ is the number of workers. We then interpret the obtained $\widehat{\alpha}$ and $\widehat{\beta}$ as the fixed and variable costs of protocols, respectively.

These two costs are, however, measured in Chilean pesos. Hence, we need to convert them into model-equivalent units. Let $w_j$ be the average wage (in Chilean pesos) for sector $j$. We calibrate the fixed cost (in labor units) as $\eta_j = \widehat{\alpha}/w_j$. To compute $\tau_j$, note that when protocols are in place, firms need to hire $\tau_j > 1$ hours of labor to get one hour of effective labor. Hence, protocols require hiring $(\tau_j - 1)$ additional units of labor to produce the same amount as if protocols were not required. Then, the average cost of protocols *per unit of worker* is $(\tau_j - 1)w_j$ which we can map to $\widehat{\beta} = (\tau_j - 1)w_j$, implying $\tau_j = \widehat{\beta}/w_j + 1$.

## 5. Results

We first present simulations for the calibrated benchmark economy we parameterized in Section 4, considering two alternative scenarios regarding the presence or the absence of protocols. This is done in Section 5.1. The rest of Section 5 presents several sensitivity exercises that allow us to understand the main forces at work in the model and why applying protocols only to a subset of sectors can produce a level of output that is larger than the two extreme situations where there are no protocol or where protocols are applied to the whole economy.

As for initial conditions, we try to represent the scenario in Chile at the beginning of September 2020, when the country started its reopening process after several months of lockdown. In particular, we work with the following initial conditions. We consider that 0.06% of the population is in the $D$ state (this corresponds to about 12,000 deaths). 500,000 people are in the $V$ state (this is about 2.6% of the Chilean population). 0.052% of the population is in the $I$ state and 0.1% is in the $R$ state (2,000 new infections everyday in the last 15 days). Finally, we assume that past contagion is uniform across all groups.

In our simulations, we also work with two possible scenarios regarding the impact of protocols on social interactions, assuming they can reduce $\phi_j$ by 50% or by 30%, for all $j$. We choose these two numbers because of the differentiated impact

[11] The Chilean authorities classify some measures as “mandatory” and others as “recommended”. In our calibration we assume firms comply with all the measures whenever protocols are in place.

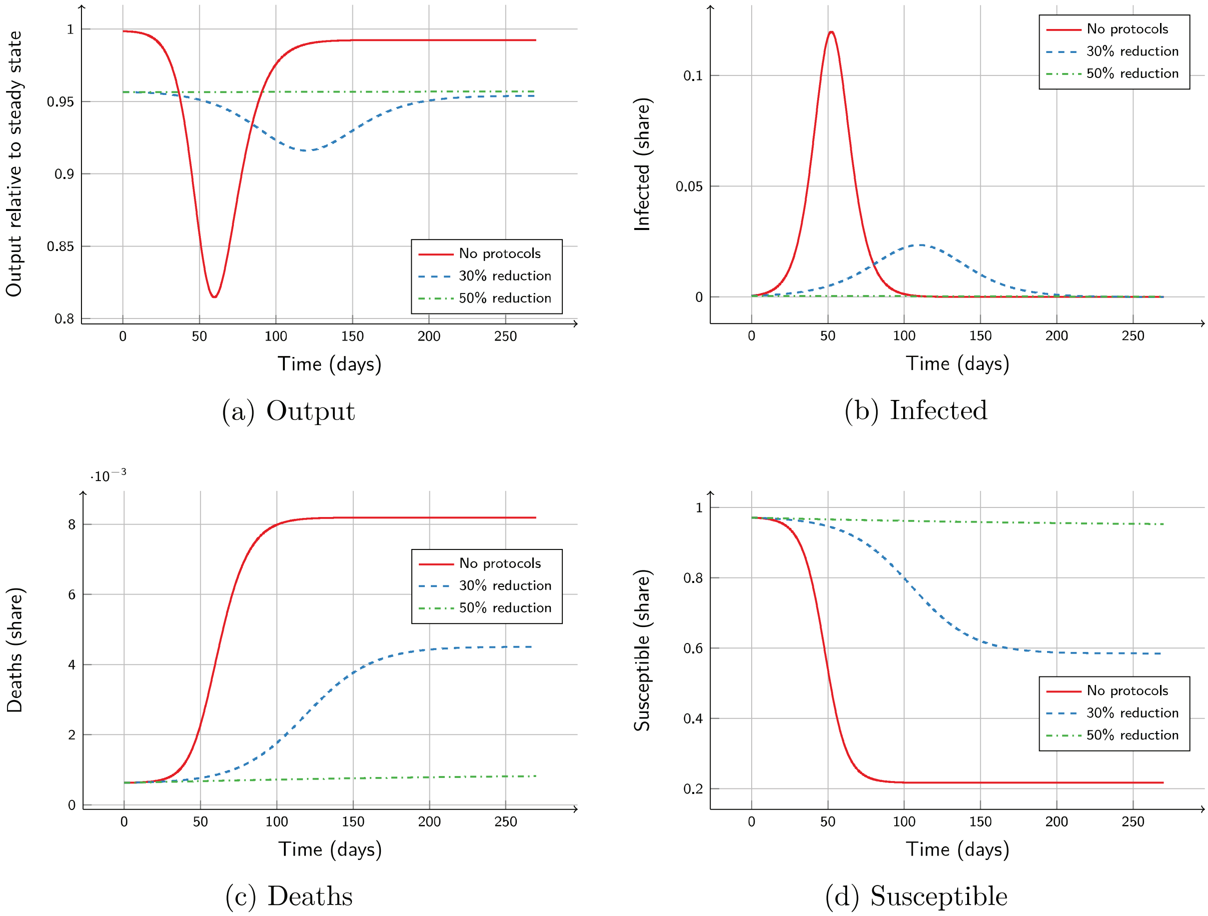



**Fig. 2.** Simulated trajectories for the benchmark economy.

they generate on economic activity. Scenarios where the reduction is above 50% all produce a similar impact on aggregate output, as shown below in Section 5.2. The reason is that SIR models may display explosive dynamics: once the effectiveness of protocols is beyond a given threshold, they are able to contain the virus and avoid a second wave.

We simulate the economy for nine months, assuming that at the beginning of June of 2021 all the population in Chile will receive immunization through a vaccine and the economy will return to its pre-Covid steady state.

### *5.1. Benchmark simulations*

Given the calibration presented in Section 4 and the initial conditions defined above, Fig. 2 displays trajectories of aggregate output and the share of infected, deceased and susceptible individuals over a time span of nine months for three different scenarios: without protocols (solid curves), when protocols reduce contagion by 30% (dashed curves) and when they reduce it by 50% (dashed-dotted curves). Panel (a), which shows the evolution of aggregate output, presents output relative to a pre-Covid steady state where all the population is active.

It is interesting to see from Panel (a) that protocols imply a tradeoff between the level of output and its volatility. On the one hand, imposing protocols reduce the initial level of output by 4% (dashed/dotted lines relative to the solid line). This is because of the importance of protocol costs, which force the low productivity firms out of the market. The remaining firms, even though they are larger in size, operate at a lower marginal product of labor, diminishing aggregate output with respect to the situation without protocols. On the other hand, in the situation without protocols, aggregate output experiences a significant collapse at the beginning that reaches about 18% after two months. The size of this collapse is far beyond the 4% reduction in the initial level of output generated by protocol costs, but output recovers two months later. This collapse is much lower and smoothed out when protocols reduce social contact by 30%, and is absent in the case where protocols reduce interactions by 50%.

The collapse in aggregate output can be explained by the dynamics presented in Panels (b)–(d), which display the time series for the share of infected, deceased and susceptible agents, respectively. In the absence of protocols, a new second

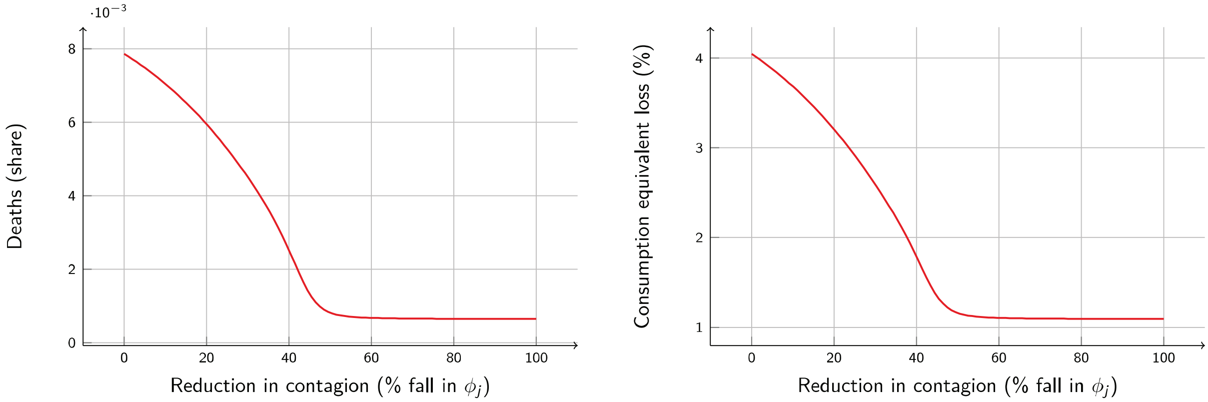



**Fig. 3.** Impact on deaths and output depending on protocol effectiveness.

wave of contagion cannot be prevented, and the amount of infected agents explodes as shown in Panel (b), leading to a posterior increase in deaths as shown in Panel (c). After three months, the boom in the amount of infected disappears as the drop in aggregate consumption endogenously reduces total contagion and herd immunity is reached. We notice from the graph that the explosion in the mass of infected is attenuated when protocols are in place. This explains why the decrease in output is lower in this case as less sick workers are forced out of the labor force. Panel (d) also shows that herd immunity is of the order of around 80% in the absence of protocols (given by one minus the level of the solid curve when it becomes flat), while it is about 40% under the scenario of protocols reducing interactions by 30%. Nevertheless, herd immunity is reached later in the latter case (six months versus three months) as protocols ‘flatten the curve’.

### *5.2. Varying the impact of protocols on social contact*

To prevent taking a stance on the effectiveness of protocols, Fig. 3 shows how the impact illustrated in Section 5.1 varies depending on the assumed drop in the $\phi$’s (Section 5.1 only considered the 30% and 50% cases). Panel (a) shows the effect on the share of deaths, while Panel (b) shows the effect on output/consumption. Throughout the paper, the impact on consumption is shown as a consumption equivalent loss during the 9 months of the simulation relative to a scenario without protocols, using the preferences defined in Section 2.1.[12]

When protocols have no impact on social contact, the amount of deaths is barely affected and the decrease in output is similar to the 4% reduction in the initial level of output shown in Panel (a) of Fig. 2. In this case protocols have an impact only through their costs. The figure shows that, as the effectiveness of protocols increases, they naturally imply less deaths and lower output losses. It is interesting to notice that, beyond a threshold of around 50%, their impact is stabilized. Intuitively, this is due to the potential explosive dynamics that the model generates: beyond a certain threshold in the effectiveness of protocols, the propagation of the virus is contained and herd immunity is immediately reached.

### *5.3. Targeting a subset of sectors*

We now extend our results to consider the possibility of partial protocols, in the sense of applying them only to a subset of sectors instead of imposing a burden on all operating firms in the economy. We order sectors according to how intensive in social contact they are, as captured by the their share of total interactions in steady state (variable $h_j$ in Table 3). We first consider a scenario where protocols are applied to the $n = 6$ sectors that create the most social contact and then generalize the results to any value of $n$. The six sectors with most contact in our benchmark calibration are “Other services”, “Real estate, administrative and financial activities”, “Wholesale and retail trade”, “Construction”, “Hotels, accommodation and food services”, “Transport and storage & information and communication”. In our data, they represent 68% of employment and 53% of output.

Fig. 4 compares the simulated trajectories when protocols are in place for all firms (solid line) with the trajectories for the case where protocols are applied to the six aforementioned sectors (dashed line). In the figure, we consider that protocols reduce contagion by 50%. According to the results, the level of output obtained in the case of partial protocols is *always* higher. This is partially because firms in four sectors are spared the costs of protocols. As a result, more firms choose to operate and a higher level of aggregate output is obtained in these particular sectors. At the same time, the regulation applied to the other six sectors seems to be enough to limit the negative consequences in terms of output due to the propagation of the virus. That is, the collapse in output observed in Fig. 2, when no regulation was in place, does not occur when only those more contact-intensive sectors are targeted by protocols. Unfortunately, the figure also shows that more

[12] That is, if the consumption equivalent loss in a given scenario is $X$%, it means that an agent is indifferent between the scenario without protocols where his consumption is cut by $X$% during the 9 months of the simulation and that scenario.

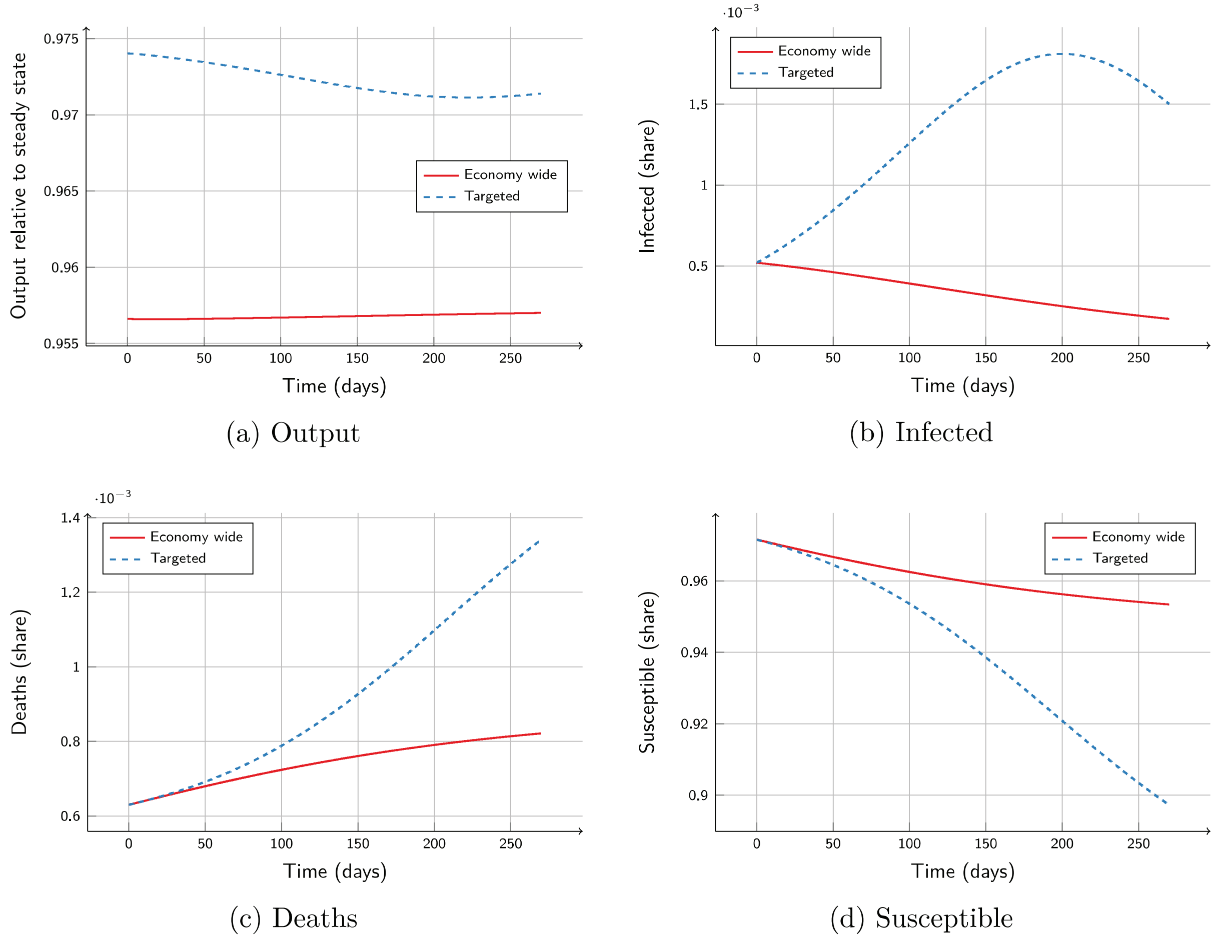



**Fig. 4.** Simulated trajectories when protocols are applied to the six sectors that concentrate most contacts.

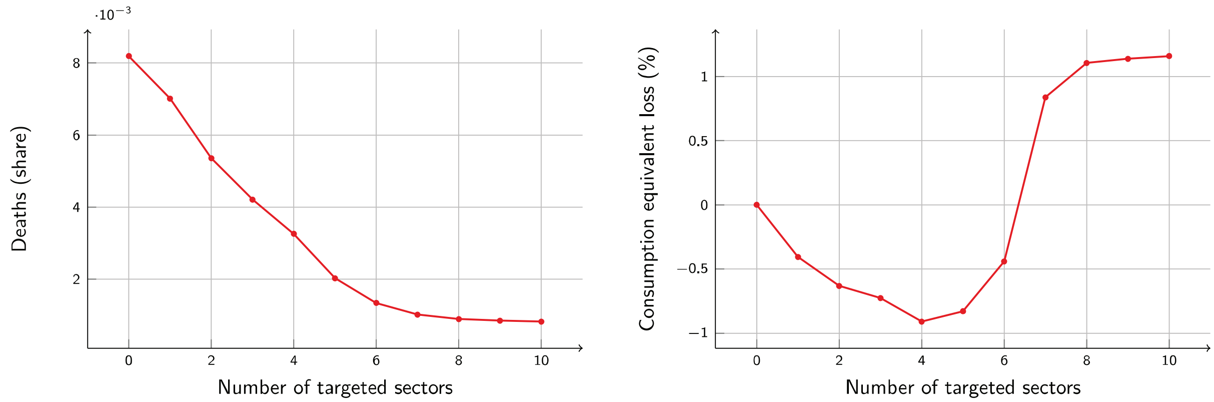



**Fig. 5.** Impact on deaths and output of the application of protocols to a subset of sectors.

contagion and deaths result from targeting only a subset of sectors with protocols, as expected. Hence, a policy aiming to reduce the number of deaths to the utmost implies imposing protocols across all sectors.

Fig. 5 generalizes the results in Fig. 4 to consider different numbers of sectors targeted by the regulation. Again, we order sectors starting from the one that creates the most interactions (in terms of their parameterized $h_j$) to the one that causes the fewer. We then start adding targeted sectors one at a time, given this ranking. The figure shows that the number of deaths diminishes with the number of targeted sectors and starts stabilizing when the number of targeted sectors is around

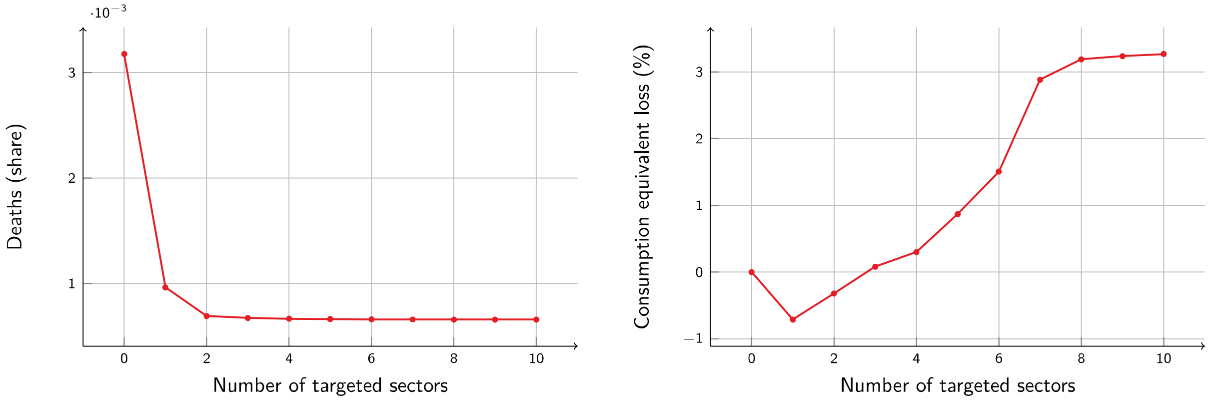



**Fig. 6.** Impact on deaths and output of the application of protocols to a subset of sectors under a low contagion parametrization.

six. This suggests that, given our benchmark parametrization, the effectiveness of protocols in reducing deaths becomes significantly lower after the first six sectors already have protocols in place.[13]

Moreover, from the right panel of Fig. 5, one can see that protocols actually have economic benefits when applied to the most contact-intensive sectors only: the consumption equivalent loss is negative when up to six sectors are targeted. As a consequence, applying protocols to an additional sector implies no tradeoff between economic and health outcomes when the number of sectors with protocols already in place is small. Hence, imposing no protocols is Pareto dominated by a policy that applies protocols to up to six sectors, in the sense that the latter leads to both better health and economic outcomes. Also, the maximum gain in terms of consumption is reached when only four sectors are targeted.

### *5.4. Some more optimistic parametrizations*

#### *5.4.1. Low contagion parametrization*

An implication of Section 5.3 is that, given our benchmark parametrization, applying protocols to some sectors can increase output in spite of the direct protocol costs. This result becomes more evident as one strengthens the level of contagion in the model since there are larger benefits from regulation. We now ask if it is still worth regulating some sectors (in terms of consumption gain) even if we consider a lower level of contagion. In particular, we modify the calibration in Section 4 by targeting a 3.5% growth rate of the number of infected agents during the first month of the pandemic, instead of the 14% mentioned in Section 4. Such a parametrization implies an initial level of contagion similar to what a homogeneous model with an $R_0$ of 1.17 would produce. The results in this case are shown on Fig. 6, where one can appreciate that, even with such a low level of contagion, regulating one or two sectors still increases the present discounted value of aggregate output when compared to a situation without protocols.

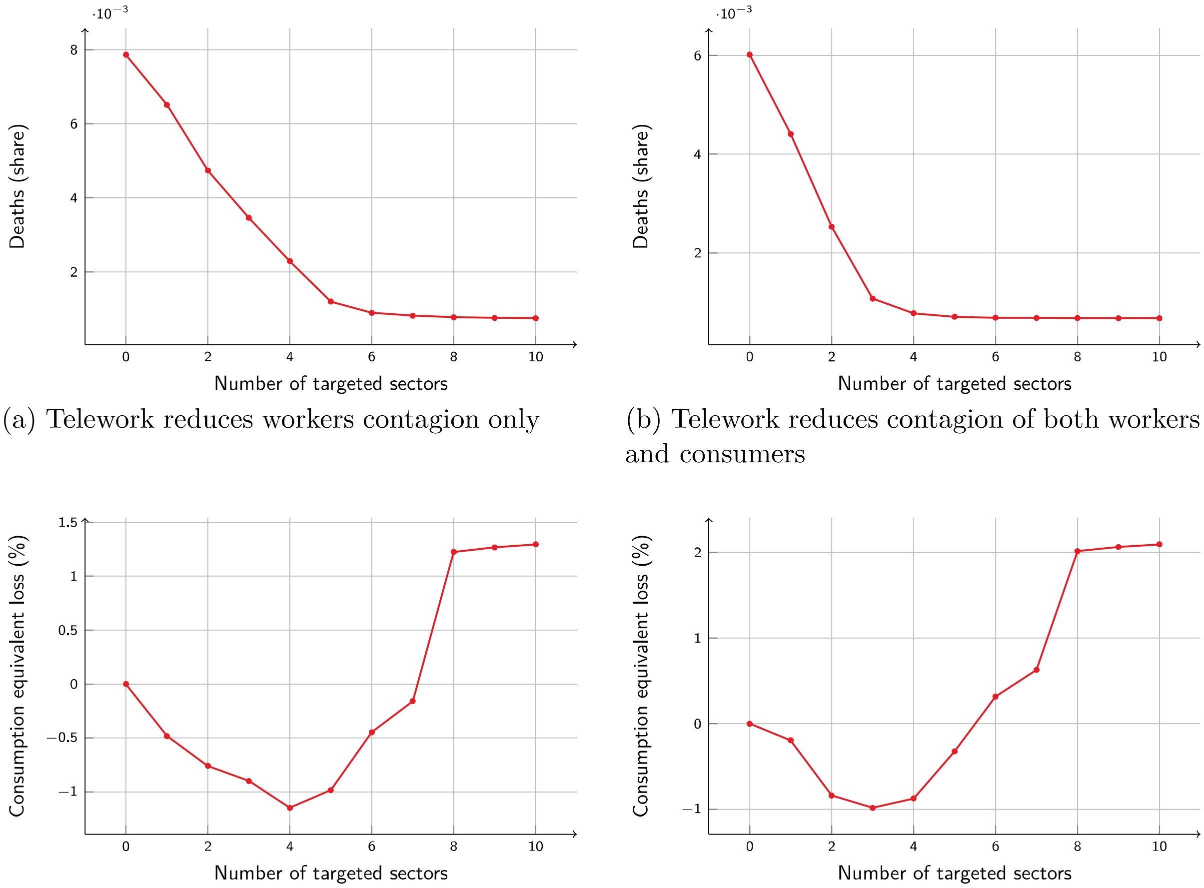
#### *5.4.2. Teleworking parametrization*

The resulting level of contagion in the benchmark calibration is admittedly large. Due to the pandemic, most people have modified their social interactions habits to reduce the risk of contagion. One common practice that has been adopted by many firms is telework. In this section, we modify the benchmark calibration to allow for this option.

Besides providing the proximity data that we use in our benchmark calibration, Gallego et al. (2020) also adjust these numbers by taking into account the fact that some occupations can be carried out remotely. They do this by using data from the Chilean CASEN 2017 survey, where participants can answer positively or negatively if their task at work could be performed remotely. They obtain the share of workers in each occupation whose work can be done remotely and then aggregate it at the sectorial level.

We incorporate this data in an alternative calibration by simply cutting the rate of social contact created by firms in the benchmark parametrization accordingly. This generates new values for $\phi_j$ and $\omega_j$ in each sector that we label as $\phi'_j$ and $\omega'_j$. Denote by $d_j$ the share of work that can be done remotely in sector $j$. A first possible assumption is that telework prevents contagion among workers only, but has no effect on contagion among consumers. In this case, the new calibrated parameters can be obtained by solving the following system of equations:

[13] Policies that allow to keep a virus outbreak within the sector where it originally occurred are effective to fight the spread of the virus and alleviate its negative impact on aggregate output. To illustrate the importance of this channel in our model, Appendix A.4.1 shows simulated trajectories when the $\omega_j$ are fixed to one, keeping the rest of the parameters as in the benchmark calibration. In this case herd immunity is lowered to about 50% instead of about 80% (in a scenario without protocols) and the collapse in aggregate output when reopening the economy is reduced by half.




(a) Telework reduces workers contagion only

(b) Telework reduces contagion of both workers and consumers

(c) Telework reduces workers contagion only

(d) Telework reduces contagion of both workers and consumers

**Fig. 7.** Impact of the application of protocols to a subset of sectors: teleworking parametrizations.

$$\phi_j'\omega_j' = \phi_j\omega_j(1-d_j),$$
$$\phi_j'(1-\omega_j') = \phi_j(1-\omega_j),$$

where we simply remove a share $d_j$ of interactions among the matched workers. In this system of equations, $\phi_j$ and $\omega_j$ correspond to the parameterized values in the benchmark calibration. Solving the system implies that

$$\omega_j' = \frac{\omega_j(1-d_j)}{\omega_j(1-d_j)+1-\omega_j} \quad \text{and} \quad \phi_j' = \phi_j\left[\omega_j(1-d_j)+1-\omega_j\right].$$

A second possibility is to assume that telework affects both workers and consumers equaly. In this case, the $\omega_j$'s simply remain the same and $\phi_j' = (1-d_j)\phi_j$.[14]

Fig. 7 reproduces the results in Fig. 5 on the impact of applying protocols to a subset of sectors, considering the two aforementioned parametrizations. The left panels use the parametrization where telework only reduces the infection of workers, while the right panels consider the parametrization where it reduces contagion for both workers and consumers. According to the figure, it is still desirable to regulate at least some sectors as a way to reduce the number of deaths and increase the level of output (as compared to a situation without protocols).

### 5.5. Protocols with limited resources

Our previous results suggest that targeting protocols to a few sectors can simultaneously increase output and reduce deaths, relative to a scenario without protocols. Now we look at the problem of targeting protocols from a different angle.

[14] The speed of the spread of the virus in this latter parametrization is similar to what an equivalent homogeneous model with an $R_0$ of 1.36 would generate.

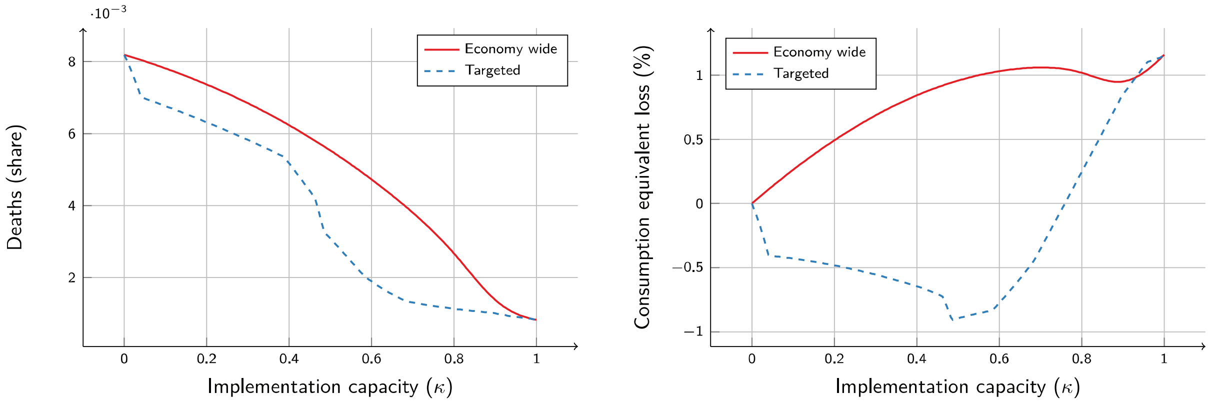



**Fig. 8.** Impact on deaths and output depending on implementation capacity.

More specifically, we try to answer: If protocols cannot be applied to all firms, how should this limited resource be allocated? Should we apply weaker protocols to all sectors or stronger protocols to a few sectors? There are many reasons why applying protocols to a large number of firms may be unfeasible. First, protocols require resources that are scarce, especially in the short run. Second, some firms may not have incentives to comply with protocols, in which case a regulator may need to enforce those through monitoring, which is costly and often difficult to implement.

To answer the proposed questions, we extend our model and assume a social planner that can only guarantee that a fraction $\kappa < 1$ of all workers are subject to protocols. We call $\kappa$ the implementation capacity. We denote by $\zeta_j$ the fraction of workers in sector $j$ that are subject to protocols. The following constraint must then be satisfied:

$$\sum_{j=1}^{N} \zeta_j m_j \leq \kappa. \tag{12}$$

In each sector, the costs of protocols and the implied reduction in interactions per unit of output are proportional to the fraction of workers subject to protocols $\zeta_j$. Therefore, the parameters $\phi_j$, $\tau_j$ and $\eta_j$ are respectively given by:

$$\phi_j' = \zeta_i \phi_j + (1 - \zeta_j)(1 - x)\phi_j, \quad \tau_j' = 1 + \zeta_j(\tau_j - 1), \quad \eta_j' = \zeta_i \eta_j,$$

where the variables $\phi_j$, $\tau_j$ and $\eta_j$ on the right-hand side of each equation represent the values obtained in our baseline calibration, and $x$ represents the percentage reduction in social interactions of a protocol applied to all workers of a sector. We assume hereafter that $x$ equals 50%, as we did before.

For a given value of $\kappa$, we consider two scenarios. In the first scenario, the social planner uses all its implementation capacity equally across sectors, that is, $\zeta_j = \kappa$ for all $j$. In the second scenario, the social planner focuses all its resources in the sectors more intensive in social contact (as captured by the variable $h_j$). Formally, in the second scenario the constraint (12) binds and $\zeta_j > 0$ only if $\zeta_i = 1$ for all $i$ such that $h_i > h_j$.

Fig. 8 shows the results in each scenario. Once again, the right panel shows the consumption equivalent loss relative to a scenario without protocols ($\zeta_j = 0$ for all $j$). Notice that, except when the implementation capacity is close to one, the policy that targets protocols in the most exposed sectors leads both to less deaths and better economic outcomes than the economy-wide policy.[15] Those results reinforce our previous conclusions in favor of targeting protocols. Moreover, it shows that, under the assumption that the social planner is sufficiently constrained in its ability to implement protocols, economy-wide protocols are a Pareto dominated policy, in the sense that they lead to worse health and economic outcomes when compared to targeted protocols.

## 6. Conclusion

This paper extends an otherwise standard SIR model by allowing for feedback between contagion and economic activity, and for industry and firm heterogeneity. We assess the impact of sanitary protocols imposed on firms aiming to prevent the propagation of Covid-19. We calibrate the model using Chilean data. While protocols impose an additional burden on firms' cost structure, they also prevent workers from temporarily exiting the labor force, which benefits total production. We show that business operating protocols, if appropriately targeted to key sectors, can simultaneously improve health and economic outcomes.

[15] Differently from the case with targeted protocols, with economy-wide protocols, the consumption equivalent loss is increasing in $\kappa$ for low values of $\kappa$. This is partially because economy-wide policies are not as effective in reducing the spread of the virus from the most contact-intensive sectors to least contact-intensive ones. See Appendix A.4.1 for a discussion of the importance of avoiding the propagation of the virus from high contact-intensity to low contact-intensity sectors.

The paper focuses on the supply side of the economy. However, the pandemic has brought changes, not only to firms' production but also to consumers' demand patterns. This latter channel is not explicitly incorporated in our analysis. We conjecture that allowing for such demand channels in the model would reinforce the potential benefits of protocols by preventing firms from facing an even larger drop in demand. This is particularly relevant in contact-intensive sectors such as wholesale, retail, and restaurants. Modelling the demand side of the economy seems like a natural extension of our paper.

As the Covid-19 pandemic unfolds, it is important to assess the economic tradeoffs of alternative containment measures such as business operating protocols. These measures are potentially beneficial as they allow the economy to reopen (as opposed to stricter measures, such as lockdowns) while keeping health outcomes relatively controlled. Therefore, such policies must be evaluated not only based on their impact on each industry or sector but also on the entire economy. While there is certainly room for further extensions, we think this paper is a step forward in this direction.

## Declarations of Competing Interest

None.

## Appendix A

### A.1. Matching sectors across databases

To calibrate the model we use information at the firm/sector level, data on the intensity of social contact within each sector, and data about the cost of protocols. As discussed in the main text, for the first group of data we use the 2017 FLS. For social contact data, we rely on both Gallego et al. (2020) and Béraud et al. (2005), while for the costs of protocols we use Gallego et al. (2020). The combination of the datasets in Gallego et al. (2020), Béraud et al. (2005) and the FLS requires unifying the definition of sectors to end up with a common definition.

Since we calibrate our model for the Chilean economy, we followed the FLS definition of sectors and we tried to naturally match each sector with the closest definition in the other two datasets. While Gallego et al. (2020) also focus on the Chilean economy, they rely on the CASEN survey (in Spanish *Encuesta de Caracterizacin Socio Economica*) to obtain proximity data at the sectorial level. However, the definition of sectors in the FLS and CASEN surveys is very similar.

**Table 1**
Matched sector.

| Corresponding sector(s) FLS | Matched with: CASEN | Matched with: Béraud et al. (2005) |
|---|---|---|
| Agriculture, forestry and fishing | Agriculture, forestry and fishing | Agriculture, forestry, fishing |
| Exploitation of Mines and Quarries | Mining | Agriculture, forestry, fishing |
| Manufacturing industries | Manufacturing industries | Other industry |
| Electricity, Gas and Water Supply | Electricity, Gas and Water | Energy |
| Construction | Construction | Construction |
| Wholesale and Retail Trade | Commerce | Trade |
| Transport and Storage & Information and communications | Transport and communication | Business services |
| Hotels, Accommodation and food service activities | Hotels and Restaurants | Services to individuals |
| Real Estate, Administrative and Financial activities | Real Estate, Business and Rental Activities | Business services and Administration |
| Other Services | Social and Personal Services | Education, Health, Social Action |

Table 1 presents how we match sectors across each survey. The first column corresponds to the sectors in the FLS, the second column represents the sectors with which they were paired from the CASEN, while the third column represents the matched sectors from Béraud et al. (2005).

In order to get a better match of sectors, we decided to merge two sectors in the original FLS data. In particular, we combined "Transport and storage" with the "Information and communications" sector, and we also pooled "Real estate and administrative activities" with the "Financial activities" sector.[16] This allowed us to get a more natural match with the remaining sectors in the other surveys.

### A.2. Calibration of the shape parameters of the Pareto distributions

Following Ghironi and Melitz (2005), we use our FLS data on the standard deviation of log sales to calibrate the shape parameters $\epsilon_j$ of the productivity distributions. Since the data is about firm size and not productivity, we need to understand how both types of distribution are related in the model.

Denote by $G_j(y)$ the distribution of output in sector $j$. This distribution can be identified by using the equilibrium relation between output and productivity in Eq. (4) together with the following:

$$F_j'(a)da = G_j'(y)dy.$$

[16] The specific description of "Real estate and administrative activities" includes services activities, real estate, administrative and service support activities. With respect to "Financial activities", it includes insurance activities as well.

Given that

$$y_j'(a) = \frac{1}{1-\alpha_j} a^{\frac{\alpha_j}{1-\alpha_j}} \left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}},$$

according to (4), we thus have

$$G_j'(y) = \frac{\epsilon_j \frac{\underline{a}_j^{\epsilon_j}}{a^{\epsilon_j+1}}}{\frac{1}{1-\alpha_j} a^{\frac{\alpha_j}{1-\alpha_j}} \left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}}},$$

which can be rewritten as

$$G_j'(y) = (1-\alpha_j) \frac{\epsilon_j \underline{a}_j^{\epsilon_j}}{\left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}}} a^{-(\frac{1}{1-\alpha_j}+\epsilon_j)}.$$

Define

$$\underline{y}_j = \underline{a}_j^{\frac{1}{1-\alpha_j}} \left(\frac{p_j\alpha_j}{w_j\tau_j}\right)^{\frac{\alpha_j}{1-\alpha_j}}.$$

Hence,

$$G_j'(y) = (1-\alpha_j) \frac{\epsilon_j}{\underline{y}_j} \left(\frac{\underline{a}_j}{a}\right)^{\left(\frac{1}{1-\alpha_j}+\epsilon_j\right)}.$$

Using again (4), one can rewrite this last equation as

$$G_j'(y) = (1-\alpha_j)\epsilon_j \underline{y}_j^{(1-\alpha_j)\epsilon_j} y^{-[(1-\alpha_j)\epsilon_j+1]}.$$

Integrating this density yeilds a Pareto distribution with shape paratemer $(1-\alpha_j)\epsilon_j$ and lower bound $\underline{y}_j$:

$$G_j(y) = 1 - \left(\frac{\underline{y}_j}{y}\right)^{(1-\alpha_j)\epsilon_j}.$$

The log of a random variable that is Pareto distributed is an exponential distribution with a rate equal to the shape parameter of the Pareto distribution. Moreover, the standard deviation is the inverse of the rate. Hence,

$$Std(log y_j) = \frac{1}{(1-\alpha_j)\epsilon_j}.$$

The equation above allows to identify the parameter $\epsilon_j$ in a given sector $j$ given data on the dispersion of log sales in this sector and a value for the returns to scale $\alpha_j$.

### A.3. Calibrated parameters

**Table 2**
Calibration of non-sector specific parameters.

| Parameter | Description | Value |
|---|---|---|
| $\rho$ | Discount rate | 4% (annual) |
| $\gamma$ | Resolving state entry rate | 0.2 |
| $\delta$ | Resolving state exit rate | 0.1 |
| $\nu$ | Death rate | 0.01 |
| $\xi$ | Infection rate through leisure | 0.0795 |
| $\alpha$ | Returns to scale | 0.85 |

**Table 3**
Calibration of sector-specific parameters.

| Sector $j$ | $\theta_j$ | $m_j$ | $\chi_j$ | $\epsilon_j$ | $\eta_j$ | $\tau_j$ | $h_j$ | $\omega_j$ |
|---|---|---|---|---|---|---|---|---|
| Agriculture, forestry and fishing | 0.056 | 0.063 | 5.080 | 13.141 | 1.086 | 1.051 | 0.027 | 0.195 |
| Exploitation of Mines and Quarries | 0.013 | 0.032 | 9.144 | 12.563 | 0.824 | 1.039 | 0.015 | 0.179 |
| Manufacturing industries | 0.104 | 0.101 | 6.470 | 12.207 | 1.285 | 1.060 | 0.054 | 0.364 |
| Electricity, Gas and Water Supply | 0.015 | 0.008 | 28.143 | 15.150 | 0.509 | 1.024 | 0.007 | 0.557 |
| Construction | 0.074 | 0.076 | 8.714 | 11.504 | 1.208 | 1.057 | 0.134 | 0.150 |
| Wholesale and Retail Trade | 0.184 | 0.347 | 17.399 | 13.567 | 0.615 | 1.029 | 0.264 | 0.247 |
| Transport and Storage & Information and communications (*) | 0.118 | 0.099 | 6.535 | 12.582 | 0.999 | 1.047 | 0.090 | 0.315 |
| Hotels, Accommodation and food service activities | 0.029 | 0.022 | 6.782 | 14.198 | 1.560 | 1.073 | 0.091 | 0.038 |
| Real Estate, Administrative and Financial activities (*) | 0.383 | 0.212 | 15.208 | 11.501 | 0.852 | 1.040 | 0.041 | 0.868 |
| Other Services | 0.024 | 0.041 | 6.641 | 13.236 | 1.171 | 1.055 | 0.278 | 0.027 |

**Table 4**
Full list of protocols.

| Categories | Protocol | Units |
|---|---|---|
| Organization and communication | Preparation of a response plan per workplace for the prevention of exposure to Covid-19 | per 100 workers |
| Organization and communication | Form a crisis gender equal committee including senior worker and other members. | per 100 workers |
| Organization and communication | Assign responsible to ensure stock of basic hygiene items. | per 100 workers |
| Organization and communication | Assign responsible for monitoring and keeping track of prevention measures, maintaining a daily record. | per 100 workers |
| Organization and communication | Assign responsible for the management of safe-passages. | per 100 workers |
| Organization and communication | Train all workers in the workplace on Covid-19, protocols and register trained workers | Number of workers |
| Prevention measures | Maintain a registry of high-risk workers (older adults, pregnant women, workers with base diseases) | per 100 workers |
| Prevention measures | Analyze the possibility of carrying out tasks in remote work or telework | Telework duties |
| Prevention measures | Distribute the workday, ensuring a maximum of 50 people sharing the same space. | % reduction in concurrent workers |
| Prevention measures | Organize spaces in the workplace to ensure social distancing (e.g. identify crowded areas, isolate large groups) | Work centers |
| Prevention measures | Make entry and exit times more flexible to avoid crowds in public transportation. | Number of workers |
| Prevention measures | Indicate mandatory use of protection items and instructions with prevention measures (hand washing) | m2 installation |
| Prevention measures | Provide masks to all workers | Number of workers |
| Prevention measures | Floor signaling at identified crowding areas | Work centers |
| Prevention measures | Install physical barriers for workers who have frequent interaction with other workers or suppliers | Number of workers |
| Prevention measures | Enable hand washing or alcohol gel in sectors where there are surfaces of common use | m2 installation |
| Prevention measures | Control access and hand washing at the entrance to main facilities or meeting rooms | Access control areas |
| Prevention measures | Have trash cans with a lid, preferably contact-less. | m2 installation |
| Prevention measures | Enable sanitary footbaths with disinfectants at the entrance to the workplace | Work centers |
| Prevention measures | Floor signaling in food preparation areas and common dining rooms | Dinning rooms |
| Prevention measures | Prepare a cleaning and disinfecting plan for the common eating areas | Dinning rooms |
| Prevention measures | Frequent dining room cleaning | m2 dinning rooms |
| Prevention measures | Control access and hand washing when entering dining rooms | Dinning rooms |
| Prevention measures | Add delimitations on bathroom floors, dressing rooms and wardrobes | Common Bathrooms |
| Prevention measures | Develop a bathroom cleaning and disinfection plan | Work centers |
| Prevention measures | Frequent bathroom cleaning | m2 bathrooms |
| Prevention measures | Ensure clean water availability in workplaces not connected to the public network | Number of duties |
| Prevention measures | Have alcohol gel before getting on and off the firm-provided bus | Number of buses |
| Prevention measures | Prepare a vehicle cleaning and disinfection plan | Work centers |
| Prevention measures | Frequent cleaning of vehicles | Number of buses |
| Prevention measures | Control access and hand washing when entering buses | Number of buses |
| Prevention measures | Install physical barrier to isolate the driver in the commuting vehicle | Number of buses |
| Prevention measures | Delimit the floor and seats of the commuting bus to ensure distance | Number of buses |

**Table 5**
Full list of protocols (continuation).

| Categories | Protocol | Units |
|---|---|---|
| Cleaning work place | Develop a "safety at work" procedure for cleaning and disinfection of workspaces and a plan for cleaning the facilities | Work centers |
| Cleaning work place | Train workers who perform cleaning tasks in the "safety at work" procedure | Number of cleaning staff |
| Cleaning work place | Ensure availability of cleaning products (quaternary ammonium, 0.1% sodium hypochlorite or 70% ethanol) | m2 installed |
| Cleaning work place | Have cleaning supplies available (disposable paper towels, fiber or microfiber cloths, mops) | Number of cleaning staff |
| Cleaning work place | Provide protection items to cleaning staff (disposable or reusable bib, gloves) | Number of cleaning staff |
| Management infected workers | Maintain a registry of infected workers, awaiting for results and close contacts | per 100 workers |
| Management infected workers | Define a procedure to implement contagion control measures for suspicious cases inside and outside the workplace | per 100 workers |
| Management infected workers | Establish two different places for the isolation of workers with suspected cases, provide them with prevention inputs | Work centers |
| Production continuity | Identify critical activities of the firm (to ensure operational continuity), workers involved in these activities and raw materials | Work centers |
| Production continuity | Implement a shift system for workers who perform critical activities | Number of critical workers |
| Production continuity | Prepare a closure plan as a result of absent workers, detailing scenarios and reopening criteria. | Work centers |
| Customer service | Ensure social distancing within customer service areas (max. capacity of 1m between people/workers) | Customer services areas |
| Customer service | Announce the social distancing measures, mandatory use of masks, maximum capacity and worker-customer distancing | Customer services areas |
| Customer service | Install physical barriers between the staff and the general public/customers | Customer services places |
| Customer service | Mark the access places/areas, provide alcohol gel at the entrance and force customers to use it before entering | Customer services areas |
| Customer service | Have a schedule for cleaning surfaces and environments in places of customer service | Customer services areas |
| Customer service | Frequent cleaning of customer services areas | m2 Customer services areas |
| Customer service | Generate time flexibility in customer service | Work centers |
| Customer service | Display products so that the shopping experience is faster (product bagging, notify unavailable products) | Work centers |
| Customer service | Promote e-commerce channels (communication campaigns) | Company |
| Delivery | Distribute protection items to workers who deliver (masks, gloves, alcohol and dispenser) | Number of delivery staff |
| Delivery | Generate instructions for cleaning and disinfection of the car/bike/motorcycle, withdrawal of products and payment | Company |
| Delivery | Implement a control system that allows establishing the route of the delivery staff to allow for possible traceability | Company |
| Waste collection | Allow frequent hand washing of waste collection staff | N. of waste collection staff |
| Waste collection | Provide prevention items to waste collection staff (sharp resistant gloves, face shield, alcohol dispenser) | N. of waste collection staff |
| Waste collection | Frequent cleaning and disinfection of the truck cabin. | N. of waste collection trucks |
| Waste collection | Generate instructions for hygiene measures that must be kept inside the truck cabin | Company |
| Waste collection | Train staff who collect waste in the use of all type of prevention measures | N. of waste collection staff |

### *A.4. Additional simulations*

*A.4.1. The importance of the consumption channel for contagion.* In this appendix, we illustrate the importance of the consumption channel for the propagation of the virus and for the dynamics of aggregate output once the economy reopens. In particular, Fig. 9 compares the simulated trajectories of aggregate output and the number of susceptible agents in the benchmark economy (as in Fig. 2) with the trajectories one obtains in the case where $\omega_j$ is equal to one for all sectors, keeping the rest of the parameters as in the benchmark calibration and considering a scenario without protocols. By setting $\omega_j = 1$, all infections at the workplace affect workers only and have no effect on consumers. This parametrization limits the spread of the virus because it partly prevents it to move to other sectors, keeping it in the original sector. This leaves the leisure channel as the only source of contagion across sectors. As one can see in Fig. 9, the herd immunity threshold becomes lower when $\omega_j$ is set equal to one (about 50% versus about 80% in the benchmark calibration) and the size of the collapse in aggregate output is reduced by half, suggesting that the consumption channel is quantitatively important.

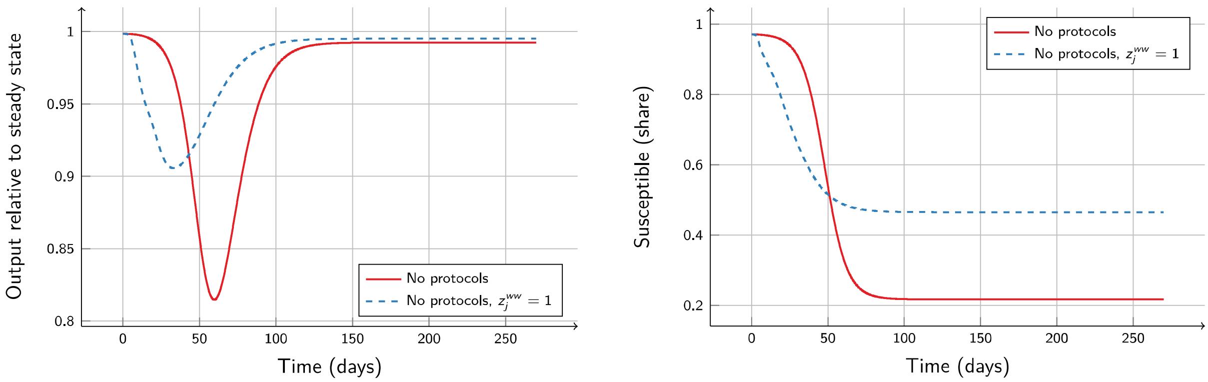



**Fig. 9.** Simulated trajectories when all $\omega_j = 1$.

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