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Assessing Targeted Containment Policies to Fight COVID-19

by Ariadne Checo, Francesco Grigoli and Jose M. Mota

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Abstract

The large economic costs of full-blown lockdowns in response to COVID-19 outbreaks, coupled with heterogeneous mortality rates across age groups, led to question non-discriminatory containment measures. In this paper we provide an assessment of the targeted approach to containment. We propose a SIR-macro model that allows for heterogeneous agents in terms of mortality rates and contact rates, and in which the government optimally bans people from working. We find that under a targeted policy, the optimal containment reaches a larger portion of the population than under a blanket policy and is held in place for longer. Compared to a blanket policy, a targeted approach results in a smaller death count. Yet, it is not a panacea: the recession is larger under such approach as the containment policy applies to a larger fraction of people, remains in place for longer, and herd immunity is achieved later. Moreover, we find that increased interactions between low- and high-risk individuals effectively reduce the benefits of a targeted approach to containment.

Keywords: Optimal containment policies, COVID-19, heterogeneous agents, recession, voluntary social distancing.

JEL Codes: E10, H00, I10

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1 Introduction

After realizing how infectious and deadly COVID-19 is, many countries implemented a variety of non-pharmaceutical measures to contain the spread of the pandemic. These measures slowed the growth of infections and relieved some of the pressure on the health systems, effectively saving lives.[1] However, they inevitably led to a large reduction in production and spending, which quickly culminated in deep economic recessions and high levels of unemployment (Baker et al., 2020; Beland et al., 2020; Carvalho et al., 2020; Chronopoulos et al., 2020; Coibion et al., 2020; Gupta et al., 2020). At the same time, voluntary social distancing in response to rising infections also took a toll on economic activity as people feared engaging in social interactions (Caselli et al., 2020; Chetty et al., 2020; Goolsbee and Syverson, 2020; Maloney and Taskin, 2020). Months after the beginning of the pandemic, many countries are experiencing a resurge in the number of infections and the need to weight health and economic considerations continues to animate the debate about optimal containment policies (Acemoglu et al., 2020; Alvarez et al., 2020; Eichenbaum et al., 2020; Farboodi et al., 2020; Garriga et al., 2020; Hall et al., 2020; Jones et al., 2020; Piguillem and Shi, 2020; Rowthorn and Toxvaerd, 2012).

A key input in the discussion about optimal containment policy is the mortality rate associated to the virus. Due to limited testing capacity (especially at the beginning of the pandemic) and severe health complications arising from comorbidities, it is difficult to obtain an accurate estimate of the mortality rate of COVID-19 in real time.[2, 3] On March 3 the World Health Organization announced that about 3.4 percent of confirmed cases worldwide have died (WHO, 2020). However, the mortality rate varies dramatically across age groups. Data for the United States, for example indicate that the COVID-19 mortality rate increases nonlinearly in age, as shown in Figure 1. For example, the average death rate ranged between 0.04 percent for people aged 0–19 years old to 18.8 percent for people aged 85 and over. Although mortality rates vary considerably across countries, the data unequivocally suggest that the virus is deadlier for older people. In light of the large economic costs of full-blown lockdowns and the heterogeneity in mortality rates across age groups, non-discriminatory measures have been heavily questioned and targeted interventions appear to be a more attractive option.[4]

In this paper we provide a quantitative assessment of the optimal containment policy comparing a *targeted* approach—that differentiates between younger and older individuals (or low- and high-risk ones)—to a *blanket* one—which treats individuals homogeneously. We evaluate epidemiological and macroeconomic outcomes using a framework that draws from the model of Eichenbaum et al. (2020). This combines the SIR model of Kermack and McKendrick (1927) with a general equilibrium framework in which economic decisions interact with the population dynamics affected by the pandemic. We modify the original model

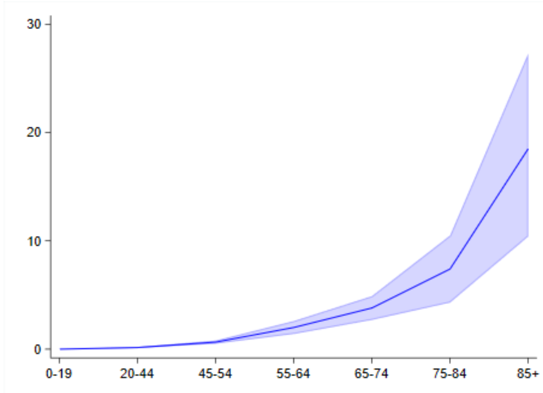
[1] On the effectiveness of lockdown measures to contain infections, see Caselli et al. (2020), Chernozhukov et al. (2020), Dave et al. (2020), Fang et al. (2020), Friedson et al. (2020), Glaeser et al. (2020), Imai et al. (2020), and Jinjarak et al. (2020). On the beneficial effects of lockdowns on the health systems, see Ferguson et al. (2020) and Juranek and Zoutman (2020).

[2] Testing was initially performed predominantly on symptomatic people. This likely biased downward the mortality rate as the denominator did not include people that contracted the virus and that are asymptomatic. See Stock (2020) for a discussion of the relevance of the asymptotic rate in determining economic costs of policies that achieve the same health outcomes.

[3] Comorbidities that lead to complications include respiratory and circulatory diseases, sepsis, and diabetes, among others. As of end-June 2020, COVID-19 was mentioned as the sole cause of death in only seven percent of COVID-19 related deaths (see `https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htm`).

[4] Turkey was the first country to introduce age-based restrictions, first applying curfews to seniors older than 65 years on March 21, and to children and youth younger than 20 years on April 5.

Figure 1: COVID-19 Mortality Rate by Age Group
(Percent)



Source: Centers for Disease Control and Prevention (https://www.cdc.gov/mmwr/volumes/69/wr/mm6912e2.htm).
Notes: Based on data for the United States between February 12 and March 16, 2020. The lower bound of the shaded area is estimated by using all cases within each age group as denominators, while the upper bound is estimated by using only cases with known information on each outcome as denominators. The line denotes the middle point between the lower and upper bound.

to allow for heterogeneous agents in terms of mortality rates and contact rates, and introducing a government that maximizes social welfare by optimally banning individuals from working.[5] This framework is particularly appropriate to study the benefits of a targeted containment policy because it allows non-contained individuals to optimally change their behavior depending on the spread of the virus, for example by practicing voluntary social distancing when infections are on the rise. The model is calibrated to the United States following Eichenbaum et al. (2020), with a new set of parameters that characterize the agents' heterogeneity.

While our paper is related to Eichenbaum et al. (2020) in terms of modeling approach, it is closest to Acemoglu et al. (2020) in terms of the issues at hand. The authors explore the benefits of a targeted containment policy in a multi-group SIR framework and conclude that policies differentiating across age groups outperform blanket policies in terms of saved lives and economic losses. Here, we revisit their conclusions by allowing for the endogenous reaction of non-contained individuals to the spread of the virus. That is, people react to changes in the probability of getting infected by curtailing (increasing) consumption and working less (more) when the virus is spreading (contained). We contend that this is a key aspect of the discussion about optimal containment, as voluntary social distancing already proved to be a key factor behind the collapse in economic activity globally.

An equally important aspect of this discussion is whether targeted containment policies are practical. Government-mandated restrictions forcing people to stay at home may lead to an undesirable increase of contacts within the household, which is where most of the contacts between younger and older cohorts take place (Prem et al., 2017). Such increase could also be the result of, for example, high-risk individuals getting help from low-risk individuals at home rather than from health professionals when restrictions kick in. It is then natural to ask if, given a certain household structure, an increase in the contact rates can undermine the benefits of a targeted containment. A similar yet different issue arises from the household

[5]In the rest of the paper we use the terms "agents" and "individuals" interchangeably.

structure itself. The question in this case is whether the benefits of targeted containment vanish in a context in which, given constant contact rates, the share of contacts between low- and high-risk individuals is higher.

We find that under a targeted policy the optimal containment reaches a larger portion of the population than under a blanket policy, and that the work ban is held in place for longer. This is because, in absence of a diversification of containment across risk categories, it is costly for the government to contain more people due to the lower average mortality rate compared to the high-risk agents' mortality rate. Interestingly, the work ban applies to almost all the high-risk individuals and 27.1 percent of low-risk individuals. That is, the optimal policy contains some low-risk individuals before containing all high-risk individuals. This is because, despite the relatively higher mortality rate of the latter, (i) the value of their discounted consumption is smaller and (ii) the government knows that containing low-risk individuals leads to less deaths of high-risk ones (who can get infected by interacting within the household).

From an epidemiological standpoint a containment policy aimed at high-risk individuals results in a sizeable decline of infections and deaths for that group of individuals. At the same time, the share of low-risk infected individuals is only marginally higher, and so is the death count. Overall, our results suggest that a targeted containment saves about 167,000 more lives than a blanket one. From a macroeconomic perspective, however, a targeted policy generates the deepest initial plunge in consumption as a larger fraction of people is contained. Also, the recession lasts longer under a targeted containment, reflecting the fact that restrictions remain place for longer and herd immunity is achieved only later compared to a blanket policy, particularly for high-risk individuals who have a stronger propensity to voluntarily self-distance in response to changes in the probability of infection. Yet, despite the larger recession, the smaller death count makes the targeted policy welfare superior.[6]

Our results call for caution. Increasing the number of interactions at home—which is where most of the contacts between low- and high-risk individuals take place (Prem et al., 2017)—makes the optimal containment less targeted, effectively diminishing the benefits of differentiating between low- and high-risk agents. In particular, since individuals can now infect each other more easily, the work ban extends to all high-risk individuals and a significantly larger portion of low-risk individuals. In an alternative setting with given contact rates, a household structure featuring a higher share of contacts between low- and high-risk individuals makes it difficult for the government to implement a targeted containment due to the cross-risk category contamination at home. In this respect, we find that a sufficiently high share of contacts between low- and high-risk individuals makes the targeted policy equivalent to a blanket one.

The rest of the paper is organized as follows. Section 2 presents the heterogeneous agent SIR-macro model. Section 3 describes the model calibration and the alternative scenarios. Section 4 discusses the results. Section 5 re-assesses the results in a setting with increased interactions between low- and high-risk individuals. Section 6 concludes.

2 A heterogeneous SIR-macro model

Our model features two types of agents who differ in the probability of dying conditional on contracting COVID-19. The first type of agents consists of younger individuals, who are people with a relatively lower probability of dying. We call this group of agents *low-risk* individuals and denote them by y. The second

[6] In addition, the work ban positively affects social welfare due to the disutility of labor.

type of agents consists of older individuals with a higher probability of dying. We call this second group of agents *high-risk* individuals and denote them by ot.

Individuals of both groups are then categorized depending on their current health status. In line with the SIR model of Kermack and McKendrick (1927), all individuals are at first susceptible, S, but they can become infected, I, if they contract the virus; then, they either recover, R, or die, D. Once individuals recover, they acquire immunity and cannot become infected in the future. Hence, at any given time t, the population in the economy, P^J, with $J = \{y, ot\}$, is

$$P_t^J = S_t^J + I_t^J + R_t^J + D_t^J$$

We explicitly account for the fraction of retirees in the population, or (so that the fraction of non-retirees is $o = ot - or$). Retirees do not perform any working activities, enjoy a fixed pension income that they fully spend in consumption. Thus, these individuals are not subject to the government containment policy and do not optimize their consumption decisions according to the evolution of the pandemic.

We further differentiate across individuals based on whether they are allowed to perform working activities. That is, in each period the government optimally imposes a heterogeneous containment policy, $m_t^j \in [0, 1]$, on low-risk agents and (non-retirees) high-risk agents, with $j = \{y, o\}$. As a result, a proportion m_t^y of low-risk agents and a proportion m_t^o of non-retirees high-risk agents cannot work, and finance their consumption with government transfers.

Then, for $X = \{S, I, R, D\}$, the share of contained individuals is

$$X_t^{jk} = X_t^j m_t^j$$

and the share of working individuals is

$$X_t^{jw} = X_t^j (1 - m_t^j)$$

so that

$$X_t^y = X_t^{yw} + X_t^{yk}$$

and

$$X_t^{ot} = X_t^o + X_t^{or} = X_t^{ow} + X_t^{ok} + X_t^{or}$$

The production side of the economy is characterized by a representative firm that uses aggregate hours worked N and pays wages w to produce consumption goods C with technology A

$$C_t = AN_t = W_t N_t$$

2.1 Epidemiological dynamics

Any susceptible agent—regardless of whether she is a low- or a high-risk individual—can get infected in three ways. The first way is by consuming; during activities of consumption, susceptible individuals interact with low- and high-risk agents, which are either contained, working, or retired. The second way susceptibles can get infected is by working; at work, they interact with low- as well as high-risk agents, unless these are subject to the work ban of the government. The third way that susceptibles can get infected is through interactions that are not directly related to consumption or working activities, such as contacts at home where high- and low-risk agents interact with each other, regardless of them being contained or not. This characterization of the infection dynamics departs from the one presented in Eichenbaum et al. (2020) in that it develops the last channel and allows for low- and high-risk agents who can be either contained or working.

Formally, the number of newly infected working individuals, T_t^{jw}, can be written as

$$\begin{aligned} T_t^{jw} &= \pi_1^S(S_t{}^{jw}C_t^{Sjw})(I_t^{ow}C_t^{Iow} + I_t^{ok}C_t^{Iok} + I_t^{yw}C_t^{Iyw} + I_t^{yk}C_t^{Iyk} + I_t^{or}C_t^{Ior}) \\ &+ \pi_2^S(S_t^{jw}N_t^{Sjw})(I_t^{ow}N_t^{Iow} + I_t^{yw}N_t^{Iyw}) \\ &+ \pi_3^S S_t{}^{jw}\Psi^j\Big[\chi^j\frac{I_t^y}{P_t^y} + (1-\chi^j)\frac{I_t^{ot}}{P_t^{ot}}\Big] \end{aligned} \tag{1}$$

where C denotes consumption expenditure and N denotes the number of hours worked, while I_t^J/P_t^J denotes the probability of interacting with an infected individual of type j conditional on having an interaction. Similarly, the number of newly infected contained individuals, T_t^{jk}, is given by

$$\begin{aligned} T_t^{jk} &= \pi_1^S(S_t{}^{jk}C_t^{Sjk})(I_t^{ow}C_t^{Iow} + I_t^{ok}C_t^{Iok} + I_t^{yw}C_t^{Iyw} + I_t^{yk}C_t^{Iyk} + I_t^{or}C_t^{Ior}) \\ &+ \pi_2^S(S_t^{jk}\cdot[N_t^{Sjk}\equiv 0])(I_t^{ow}N_t^{Iow} + I_t^{yw}N_t^{Iyw}) \\ &+ \pi_3^S S_t{}^{jk}\Psi^j\Big[\chi^j\frac{I_t^y}{P_t^y} + (1-\chi^j)\frac{I_t^{ot}}{P_t^{ot}}\Big] \end{aligned} \tag{2}$$

Finally, the number of newly infected retirees, T_t^{or}, is obtained as

$$\begin{aligned} T_t^{or} &= \pi_1^S(S_t{}^{or}C_t^{Sor})(I_t^{ow}C_t^{Iow} + I_t^{ok}C_t^{Iok} + I_t^{yw}C_t^{Iyw} + I_t^{yk}C_t^{Iyk} + I_t^{or}C_t^{Ior}) \\ &+ \pi_2^S(S_t^{or}\cdot[N_t^{Sor}\equiv 0])(I_t^{ow}N_t^{Iow} + I_t^{yw}N_t^{Iyw}) \\ &+ \pi_3^S S_t{}^{or}\Psi^o\Big[\chi^o\frac{I_t^y}{P_t^y} + (1-\chi^o)\frac{I_t^{ot}}{P_t^{ot}}\Big] \end{aligned} \tag{3}$$

with

$$T_t^y = T_t^{yw} + T_t^{yk}$$

and

$$T_t^{ot} = T_t^{ow} + T_t^{ok} + T_t^{or}$$

In equations (1), (2), and (3), π_1^S, π_2^S, and π_3^S denote the sensitivities of new infections due to interactions between infected and susceptible individuals while consuming, working, and while being at home, respectively. Hence, these parameters guide the probability of the virus transmission. With respect to new infections at home, we allow for assortative mixing (i.e., more interactions between individuals of the same group) as well as for heterogeneity in the quantity of contacts of each group of individuals.[7] The assortative mixing of low-risk individuals is captured by the parameter χ^y, which represents the share of contacts of a low-risk individual with an individual of the same group. For high-risk individuals, the respective parameter is $1-\chi^o$. The heterogeneity in the contact rates is introduced to acknowledge that young people tend to have more contacts than older people, and is captured by Ψ^j with $\Psi^y > \Psi^o$. In sum, the number

[7] Assortative mixing and heterogeneity in the number of contacts are well-established facts in the literature of contact network epidemiology (Prem et al., 2017).

of infections that occur through the third channel is driven by: (i) the sensitivity parameter π_3^S; (ii) the number of susceptible people, ${S_t}^j$; (iii) the number of contacts, Ψ^j; (iv) the shares of interactions, χ^j and $(1-\chi^j)$; and (v) the probability of interacting with an infected individual of each group conditional on having an interaction with a given group, I_t^{ot}/P_t^{ot} and I_t^y/P_t^y.

The rest of the epidemiological dynamics are governed by the same equations as in Eichenbaum et al. (2020), with the exception that we allow them to differ by type of agents. Thus, the number of susceptible individuals in the following period is determined by the number of working and contained susceptibles that get infected in the current period

$$S_{t+1}^J = S_t^J - T^J$$

At any given time, the number of infected people is computed starting from the stock of infected individuals (either working or contained) in the previous period; subtracting those infected individuals who recovered with probability π_t^{RJ} and those who died with probability π^{DJ}; and adding the number of newly infected individuals, defined in equations (1), (2) and (3)

$$I_{t+1}^J = I_t^J - (\pi^{RJ} + \pi_t^{DJ})I_t^J + T_t^J$$

where the probability of recovery and the probability of death are time-varying parameters. As a pandemic is generally an unexpected event, the healthcare system gets overloaded as the number of infections rises. To account for the difficulties of the health system in dealing with the emergency posed by the pandemic, we assume that the mortality rate is a convex function of the exogenous death rate and the number of infected people

$$\pi_t^{DJ} = \pi^{DJ} + \kappa(I_t)^2$$

We then obtain the number of recovered people by adding the number of infected individuals that recovered to the number of people that were already recovered and that can be either working or contained individuals

$$R_{t+1}^J = R_t^J + \pi^{RJ} I_t^J$$

Similarly, the number of deaths is given by the stock of deaths as of the previous period, including both working and contained individuals, plus the infected people that die in the current period

$$D_{t+1}^J = D_t^J + \pi_t^{DJ} I_t^j$$

Finally, total population in each period is given by population in the previous period minus working and contained individuals that died

$$P_{t+1}^J = P_t^J - \pi_t^{DJ} I_t^J$$

The initial shock corresponds to a fraction of susceptible individuals ε getting infected, so that $I_0 = \varepsilon$; and, since population is normalized to one, the initial fraction of susceptibles is given by $S_0 = 1 - \varepsilon$.

2.2 Agents' optimization problems

Preferences are characterized by the following discounted lifetime utility

$$U_t^{Xj} = \mathbb{E}_t \sum_{\tau=t}^{\infty} \beta^{j,\tau-t} u_t(C_\tau^{Xj}, N_\tau^{Xj}) \tag{4}$$

where C denotes consumption; N denotes hours worked; and β^j is the discount factor, which varies with the risk category j as we take into account the probability of dying from factors other than COVID-19. The period utility is increasing in consumption and decreasing in hours worked

$$u_t(C_t^{Xj}, N_t^{Xj}) = ln(C_t^{Xj}) - \frac{\theta}{2}(N_t^{Xj})^2$$

As discussed, contained and retired agents do not take optimal decisions because they are not allowed to work or do not work by construction, respectively. The consumption of contained individuals is financed by the government with a lump-sum transfer, Γ_t^k, such that

$$C_t^{Xjk} = \Gamma_t^k$$

while retired agents consume a fixed amount of their pension income, Γ^r, that is

$$C^{Xor} = \Gamma^r$$

Non-contained individuals, on the other hand, maximize their lifetime utility in equation (4), choosing optimal streams of consumption and labor supply subject to the budget constraint

$$C_t^{Xjw} = W_t N_t^{Xjw} - \Gamma_t^w$$

taking as given the government containment policy, m_t^j, and the lump-sum tax, Γ_t^w. We now discuss in detail the optimization problem of each group of agents in the economy.

Susceptibles Susceptible individuals are aware that increasing consumption and working activities lead to a higher probability of getting infected. In addition, if they are allowed to work, they consider and act according to the probability of getting contained in the future, while acknowledging that they cannot affect it. Formally, these individuals maximize their utility, U_t^{Sjw}, solving the following problem

$$\begin{aligned} Max \quad U_t^{Sjw} = & \\ & u(C_t^{Sjw}, N_t^{Sjw}) + \beta^j \Bigg\{ (1-\tau_t^{jw}) \Big[(1-m_{t+1}^j) U_{t+1}^{Sjw} + m_{t+1}^j U_{t+1}^{Sjk} \Big] \\ & + \tau_t^{jw} \Big[(1-m_{t+1}^j) U_{t+1}^{Ijw} + m_{t+1}^j U_{t+1}^{Ijk} \Big] \Bigg\} \end{aligned} \tag{5}$$

subject to the probability of getting infected[8]

$$
\begin{aligned}
\tau_t^{jw} \equiv \frac{T_t^{jw}}{S_t^{jw}} &= \pi_1^S(C_t^{Sjw})(I_t^{ow}C_t^{Iow} + I_t^{ok}C_t^{Iok} + I_t^{yw}C_t^{Iyw} + I_t^{yk}C_t^{Iyk} + I_t^{or}C_t^{Ior}) \\
&+ \pi_2^S(N_t^{Sjw})(I_t^{ow}N_t^{Iow} + I_t^{yw}N_t^{Iyw}) \\
&+ \pi_3^S\Psi^J\left[\chi^j\frac{I_t^y}{P_t^y} + (1-\chi^j)\frac{I_t^{ot}}{P_t^{ot}}\right]
\end{aligned} \tag{6}
$$

and the budget constraint

$$
C_t^{Sjw} = W_tN_t^{Sjw} - \Gamma_t^w \tag{7}
$$

Substituting equations (6) and (7) into equation (5), we obtain the first order conditions with respect to N_t^{Sjw}, which can be written as

$$
\begin{aligned}
N_t^{Sjw}: \frac{W_t}{W_tN_t^{Sjw} - \Gamma_t^w} - \theta N_t^{Sjw} + \beta\Bigg\{\Big[(1-m_{t+1}^j)U_{t+1}^{Ijw} + m_{t+1}^jU_{t+1}^{Ijk}\Big] - \Big[(1-m_{t+1}^j)U_{t+1}^{Sjw} + m_{t+1}^jU_{t+1}^{Sjk}\Big]\Bigg\} \\
\Bigg\{\pi_1^SW_t\Big[I_t^{ow}C_t^{Iow} + I_t^{yw}C_t^{yow} + I_t^{ok}C_t^{Iok} + I_t^{yk}C_t^{Iyk}\Big] + \pi_2^S\Big[I_t^{yw}N_t^{Iyw} + I_t^{ow}N_t^{Iow}\Big]\Bigg\} = 0
\end{aligned}
$$

Infected Infected individuals have a lower productivity than susceptibles and recovered, that is $\phi^I < 1 = \phi^S = \phi^R$. However, similar to the case of susceptible individuals, in any period they take into account the probability of being contained and maximize their utility, U_t^{Ijw}, solving the following problem

$$
\begin{aligned}
&Max \quad U_t^{Ijw} = \\
&\quad u(C_t^{Ijw}, N_t^{Ijw}) + \beta\Bigg\{(1-m_{t+1}^j)\Big[(1-\pi^{RJ} - \pi_t^{DJ})U_{t+1}^{Ijw} + \pi^{RJ}U_{t+1}^{Rjw}\Big] \\
&\quad + m_{t+1}^j\Big[(1-\pi^{Rj} - \pi_t^{DJ})U_{t+1}^{Ijk} + \pi^{RJ}U_{t+1}^{Rjk}\Big]\Bigg\}
\end{aligned} \tag{8}
$$

subject to the budget constraint

$$
W_t\phi^IN_t^{Ijw} = C_t^{Ijw} + \Gamma_t^w \tag{9}
$$

Substituting equation (9) into equation (8), we obtain the first order condition for infected working individuals with respect to N_t^{Ijw}

$$
N_t^{Ijw}: \frac{\phi^IW_t}{\phi^IW_tN_t^{Ijw} - \Gamma_t^w} - \theta N_t^{Ijw} = 0
$$

Recovered Recovered individuals solve the following problem

$$
Max \quad U_t^{Rjw} = u(C_t^{Rjw}, N_t^{Rjw}) + \beta\Big[(1-m_{t+1}^j)U_{t+1}^{Rjw} + m_{t+1}^jU_{t+1}^{Rjk}\Big] \tag{10}
$$

subject to the budget constraint

$$
W_tN_t^{Rjw} = C_t^{Rjw} + \Gamma_t^w \tag{11}
$$

[8]Similarly, the probability of getting infected of a susceptible contained is $\tau_t^{jk} \equiv T_t^{jk}/S_t^{jk}$.

Substituting equation (11) into equation (10), we obtain the first order condition with respect to N_t^{Rjw}

$$N_t^{Rjw} : \frac{W_t}{W_t N_t^{Ijw} - \Gamma_t^w} - \theta N_t^{Ijw} = 0$$

2.3 Government's optimization problem

The decentralized equilibrium (i.e., without government intervention) is not efficient because agents do not internalize the externalities of their behavior. There are three sources of externalities driving this inefficiency. First, while consumption and working decisions of infected individuals cannot get them re-infected, their decisions still increase the probability of infection of susceptible agents. Second, low-risk susceptible individuals—with a lower mortality rate—have a stronger incentive to work and consume than high-risk susceptible individuals—with a higher mortality rate. Hence, the decisions of the former are consequential for the latter. And third, a large number of infections leads to the congestion of the healthcare system, increasing the mortality rate. In the model, government intervention aims at reducing the problem associated with such externalities.

Government preferences are characterized by an utilitarian social welfare function, with equal weights across all agents. Since at time $t = 1$ there are no deaths or recovered individuals ($D_1 = R_1 = 0$), the welfare function is[9]

$$W_1 = (S_1^y U_1^{Sy} + I_1^y U_1^{Iy}) + (S_1^{ot} U_1^{Sot} + I_1^{ot} U_1^{Iot}) \tag{12}$$

The government maximizes social welfare, W_1, using two policy tools. The first is the containment policy, $\{m_t^j\}_{t=1}^{\infty} \in [0, 1]$, which is different depending on the risk profile of the agent; the second is a stream of lump-sum taxes on workers, $\{\Gamma_t^w\}_{t=1}^{\infty}$, to finance the consumption of contained agents with lump-sum transfers, $\{\Gamma_t^k\}_{t=1}^{\infty}$. To determine the optimal policy, the government takes into consideration the optimal response of workers to such policies and the associated epidemiological dynamics.

The government budget constraint is specified as

$$\Gamma_t^k (S_t^{ok} + S_t^{yk} + I_t^{ok} + I_t^{yk} + R_t^{ok} + R_t^{yk}) + \Gamma_t^w (S_t^{ow} + S_t^{yw} + I_t^{ow} + I_t^{yw} + R_t^{ow} + R_t^{yw}) = 0 \tag{13}$$

To facilitate the numerical solution of the problem, we compute the optimal government policies using parametric functions.[10] Specifically, following Glover et al. (2020), we approximate the mitigation path by functions that are part of the parametric class of generalized logistic functions of time

$$m_t^j = \frac{\gamma_0^j}{1 + exp[-\gamma_1^j (t - \gamma_2^j)]} \tag{14}$$

where parameter γ_0^j controls the level of containment at $t = 0$, parameter γ_1^j governs when the containment is reduced, and parameter γ_2^j commands the swiftness with which containment is reduced. Note that

[9] For a given containment policy at period $t = 1$, the government welfare function becomes $W_1 = m_1^y (S_1^y U_1^{Syw} + I_1^y U_1^{Iyw}) + m_1^o (S_1^o U_1^{Sow} + I_1^o U_1^{Iow}) + (1 - m_1^y)(S_1^y U_1^{Syk} + I_1^y U_1^{Iyk}) + (1 - m_1^o)(S_1^o U_1^{Sok} + I_1^o U_1^{Iok}) + (S_1^{or} U_1^{Sor} + I_1^{or} U_1^{Ior})$.

[10] This approach reduces the number of optimization arguments from 750 to 9. The non-parametric approach requires the computation of 250 containment policies for each type of agents and 250 transfers. Since this problem is highly non-linear, the numerical solution of the non-parametric approach is very unstable. Thus, it requires a sizeable increase of computation resources to achieve an accurate solution. However, Glover et al. (2020) find very similar results with the parametric and non-parametric approach.

as t goes to infinity, m_t^j goes to zero.

The transfers path, $\{\Gamma_t^k\}_{t=1}^{250}$, is also approximated by a parametric generalized logistic function of time, which is scaled by λ to allow for levels of transfers that are not necessarily defined between 0 and 1

$$\Gamma_t^k = \frac{\phi_0 \cdot \lambda}{1 + exp[-\phi_1(t - \phi_2)]} \tag{15}$$

while Γ_t^w is determined by equations (13) and (15).

Thus, to maximize the social welfare function in equation (12), the government takes the optimal policy functions of individuals as given and chooses the set of parameters $\{\gamma_0^y, \gamma_1^y, \gamma_2^y, \gamma_0^o, \gamma_1^o, \gamma_2^o, \phi_0, \phi_1, \phi_2\}$. The optimal policy paths, $\{\Gamma_t^k, m_t^y, m_t^o\}_{t=1}^{250}$, are determined evaluating the parametric functions at the optimal parameters. When the government imposes a homogeneous policy across agents, the optimal policy is evaluated by setting the restriction $\gamma_i^y = \gamma_i^o$ for $i \in \{0, 1, 2\}$.[11]

3 Model calibration and alternative scenarios

The model is calibrated to the US and the parameters used in the calibration are reported in Table 1. We compute the share of low- and high-risk individuals in the population using population data from the US Census Bureau as of end-2019 and the COVID-19 mortality rate data from the Centers for Disease Control and Prevention.[12] Specifically, we consider low-risk individuals those aged 0–54, which are about 71 percent of the population and have a weighted mortality rate of 0.2 percent; and high-risk individuals those aged 55+, who represent 29 percent of the population and have a weighted morality rate of 4.7 percent.[13] In addition, to obtain the share of retirees, we use data from Flood et al. (2020). Specifically, we consider the proportion of the population aged 55+ that are retired, which is equal to 47.9 percent.

In line with Atkeson (2020) and Eichenbaum et al. (2020), we assume that after 18 days the person that became infected either recovers or dies from the disease. Given that the model is set at a weekly frequency, $\pi^{DJ} + \pi^{RJ} = 7/18$. The recovery rates for each group are then obtained as the difference of that quantity with the respective mortality rate.

We calibrate the parameters that guide the probabilities of transmission to match the same targets chosen by Eichenbaum et al. (2020), which in turn draw from Lee et al. (2010), Ferguson et al. (2020), and the Bureau of Labor Statistics 2018 Time Use Survey. Based on the consumption and work decision from the pre-infection economy, we choose π_1^S, π_2^S, and π_3^S to jointly match the following targets: (i) 16 percent of infections take place when performing consumption activities, (ii) 17 percent of infections take place during work activities, and (iii) at the end of the pandemic 60 percent of the population either recovers from the infection or dies. Table 1 reports the results of the calibration of these parameters, which differ from Eichenbaum et al. (2020) because our model has two types of agents and takes into account heterogeneity in contact rates.

[11] Nevertheless, if such homogeneous policy is optimal, the solution can be achieved from the heterogeneous policy problem, as the former is a special case of the latter.

[12] See https://www.census.gov/data/tables/2019/demo/age-and-sex/2019-age-sex-composition.html for the population data and https://www.cdc.gov/mmwr/volumes/69/wr/mm6912e2.htm?s_cid=mm6912e2_w for mortality rates.

[13] Ideally, the high-risk population would include individuals aged 0–54 with pre-existing conditions that could increase the chances of death if COVID-19 is contracted. However, assessing which of the pre-existing conditions are the ones that should be considered and identifying the individuals suffering from them is extremely challenging, especially when the pandemic starts and little is known about the virus. To provide a more realistic assessment of a targeted containment that a government might want to introduce when the epidemic starts, we prefer to work with age groups.

As discussed in Section 2, infections depend on heterogeneous contact rates across types of agents. To calibrate the parameters related to this transmission channel, we rely on Prem et al. (2017). In particular, we compute the average contact rate by type of individual, Ψ^j, as the population-weighted average of the number of contacts per day at home in the US. These take the value of $\Psi^y = \chi^{yy} + \chi^{yo} = 4.3$ and $\Psi^o = \chi^{oo} + \chi^{oy} = 1.1$, where $\chi^{yy}(\chi^{oo})$ denotes the average contact rate that low-risk (high-risk) individuals have among themselves, and $\chi^{yo}(\chi^{oy})$ represents the average contact rate that low-risk (high-risk) individuals have with high-risk (low-risk) individuals. We then compute the share of contacts that low-risk individuals have with people of the same group as

$$\chi^y = \frac{\chi^{yy}}{\chi^{yy} + \chi^{yo}} = \frac{3.3}{3.3 + 1.0}$$

and similarly, the share of contacts of high-risk individuals with low-risk ones is computed as

$$\chi^o = \frac{\chi^{oo}}{\chi^{oy} + \chi^{oy}} = \frac{0.2}{0.9 + 0.2}$$

so that, by construction, the proportion of other contacts that each individual has is given by $1 - \chi^j$.

Regarding the parameters that characterize the economy, in line with Eichenbaum et al. (2020), we set the discount factor of low-risk agents to $\beta^y = 0.96^{1/52}$, which corresponds to a life value of 9.3 million 2019 US dollars. As explained in Section 2, the discount factor varies with age. Hence, following Brotherhood et al. (2020), we take into account that high-risk individuals can die due to reasons unrelated to COVID-19 with probability $\iota = 0.05$.[14] This implies that the effective discount factor of high-risk individuals is smaller than the discount factor of low-risk individuals. Specifically, we define $\beta^{ot} = \beta^y \cdot (1 - \iota)^{1/52}$.

The productivity and the disutility of labor parameters are set to $A = 39.835$ and $\theta = 0.001275$, so that the representative worker works 28 hours per week and earns a weekly income of \$58,000/52 in the pre-epidemic steady state, as in Eichenbaum et al. (2020). The productivity of infected people, ϕ^I is assumed to be lower than the productivity of susceptible and recovered individuals at 0.8. This reflects that a large share of infected people are asymptomatic, as documented in Oran and Topol (2020). The pre-infection steady-state values for salary and technology are the same as in Eichenbaum et al. (2020).

Finally, we calibrate the pension income using information from the Consumer Expenditure Survey. Specifically, we compute the ratio of the average consumption expenditure of individuals aged 55+ with respect to the average consumption expenditure of individuals aged less than 55. We then use that ratio to adjust the average income per week.[15]

To assess the benefits of doing heterogeneous containment, we consider three alternative scenarios. The first is the *targeted* policy scenario, which features a government that curtails the proportion of workers allowed to work to contain the spread of the virus and does so heterogeneously for low- and high-risk individuals. That is, the proportion of individuals who are not allowed to work can be different for low- and high-risk individuals. The second scenario is the *blanket* policy one, which is characterized by a government that applies the containment policy identically across low- and high-risk individuals. The third and last scenario, which we use as a benchmark, does not feature any containment policy and we refer to it as the *no-policy* scenario. In the targeted and blanket policy scenarios, optimal containment is com-

[14] See https://www.cdc.gov/nchs/data/nvsr/nvsr68/nvsr68_07-508.pdf.
[15] See https://www.bls.gov/cex/2019/combined/sage.pdf.

Table 1: Parameters

Parameter	Notation	Value	Source
Epidemiology			
Mortality rate for low-risk individuals	p^{Dy}	0.002	CDC and US Census Bureau
Mortality rate for high-risk individuals	p^{Dot}	0.047	CDC and US Census Bureau
Non-COVID-19 mortality rate for high-risk individuals	ι	0.05	Brotherhood et al. (2020)
Days to either recover or die	$\pi^{DJ} + \pi^{RJ}$	7/18	Eichenbaum et al. (2020)
Recovery rate for low-risk individuals	p^{Ry}	$7/18 - \pi^{Dy}$	Authors' calculations
Recovery rate for high-risk individuals	p^{Rot}	$7/18 - \pi^{Dot}$	Authors' calculations
Infection sensitivity to consumption	π_1^S	8.4792×10^{-8}	Authors' calculations
Infection sensitivity to work	π_2^S	1.6376×10^{-4}	Authors' calculations
Infection sensitivity to other activities	π_3^S	0.1293	Authors' calculations
Share of recovered or dead people	$(R + D)/P$	0.6	Eichenbaum et al. (2020)
Initially infected people	$\varepsilon_{t=0}$	0.001	Eichenbaum et al. (2020)
Overloading of the health sector	κ	0.9	Eichenbaum et al. (2020)
Average contact rate for high-risk individuals	Ψ^o	1.1	Prem et al. (2017)
Average contact rate for low-risk individuals	Ψ^y	4.3	Prem et al. (2017)
Share of contacts of low-risk individuals with themselves	χ^y	$3.3/(3.3 + 1.0)$	Prem et al. (2017)
Share of contacts of high-risk individuals with low-risk	χ^o	$0.2/(0.9 + 0.2)$	Prem et al. (2017)
Economy			
Share of low-risk individuals	y	0.71	US Census Bureau
Share of high-risk individuals	ot	0.29	US Census Bureau
Share of retirees (within high-risk individuals)	or	0.48	Flood et al. (2020)
Discount factor low-risk individuals	β^y	0.9992	Eichenbaum et al. (2020)
Discount factor high-risk individuals	β^{ot}	0.9982	Authors' calculations
Disutility of labor parameter	θ	0.001275	Eichenbaum et al. (2020)
Productivity of infected individuals	ϕ^I	0.8	Oran and Topol (2020)
Productivity of susceptible and recovered individuals	ϕ^S, ϕ^R	1	Eichenbaum et al. (2020)
Hours worked per week	N	28	Eichenbaum et al. (2020)
Salary per week	W	58,000/52	Eichenbaum et al. (2020)
Retirement per week	Γ^r	$0.744W$	Consumer Expenditure Survey
Technology	A	39.835	Eichenbaum et al. (2020)

Notes: The table reports the parameters used in the model.

puted over a sequence of 250 weeks for both low- and high-risk individuals.

4 Results

We present the results starting with the optimal containment imposed by the government. As discussed in the previous sections, under the no-policy scenario the government does not impose any containment policy. On the other hand, under the blanket and the targeted policy scenarios, the government optimally bans people from working. Panel 2a of Figure 2 shows that in the blanket policy scenario the government bans 33.9 percent of people from working.[16] Such share is larger under a targeted policy, at 38.9 percent, and the restrictions are held in place for about a month and a half longer compared to a blanket policy. The difference in containment between the blanket and the targeted policy scenarios can be explained as follows: in absence of a heterogeneous containment across risk categories, it is costly for the government to contain more people due to a lower average mortality rate in the population compared to the mortality rate of high-risk agents. Or, in other words, under a targeted policy the opportunity cost of not contain-

[16]Note that the percent of contained population excludes the retirees.

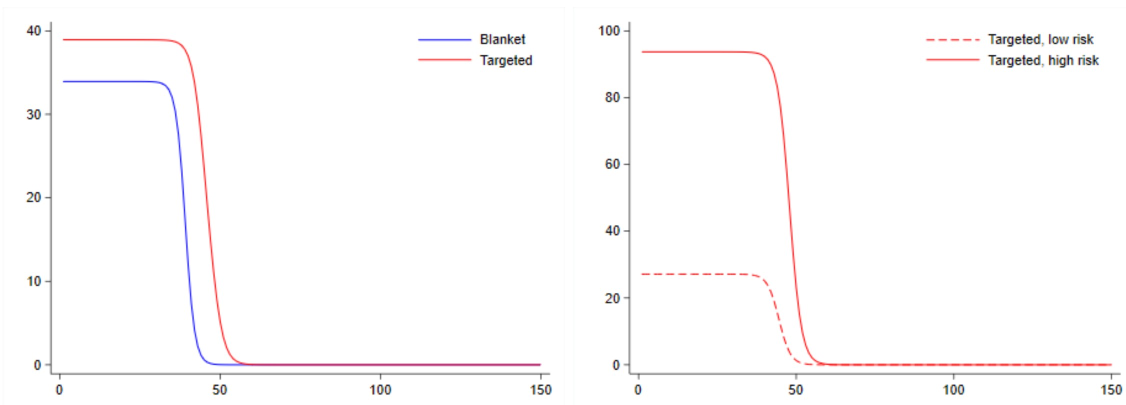
ing high-risk individuals is higher than under a blanket scenario, because in the latter the containment is applied to a pool of individuals with a lower probability of dying.

Panel 2b illustrates that the 38.9 percent of contained individuals consists of almost all the high-risk individuals and 27.1 percent of the low-risk individuals. That is, in the targeted policy scenario the government contains some low-risk individuals before containing all high-risk individuals. This is because, despite the relatively higher mortality rate of the latter, the value of their discounted consumption is smaller and the government knows that containing low-risk individuals leads to less deaths of high-risk individuals, who can get infected by interacting at work, during consumption activities, and within the household.

Figure 2: Optimal Containment

(a) Blanket and Targeted Policy (Percent of population)

(b) Targeted Policy, Low- and High-Risk Agents (Percent of population in each category)

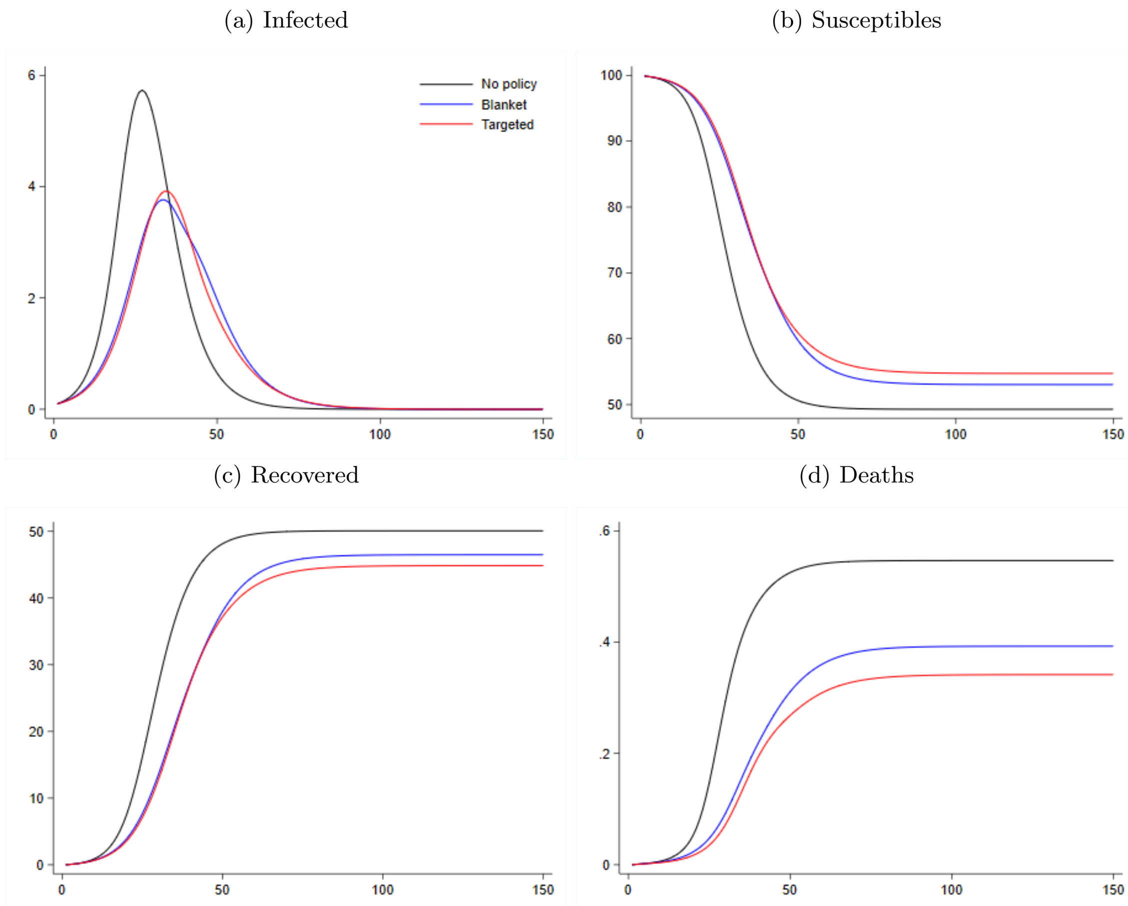


Notes: The figure shows the optimal containment over the first 150 weeks since the beginning of the pandemic for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals. In panel 2a, the share of contained people is relative to total population excluding retirees; in panel 2b, the share of contained low-risk (high-risk) individuals is relative to the population of low-risk (high-risk) individuals excluding retirees.

Figure 3 illustrates the epidemiological dynamics of the three scenarios. In the no-policy scenario infections reach their peak during week 27 at 5.7 percent of the initial population (panel 3a). This is the highest level across the three scenarios, indicating that containment policies are instrumental in containing the spread of the virus. Even in absence of policies, the share of infected individuals starts falling for two reasons: first, the number of susceptible individuals declines as the population moves towards herd immunity; second, susceptible individuals react to the pandemic by curbing consumption and working activities to reduce the probability of getting infected—effectively practicing voluntary social distancing (panel 3b). Due to the large number of infections, the share of recovered individuals ends up as high as 50 percent of the initial population (panel 3c) and deaths account for 0.55 percent of initial population (panel 3d).

Compared to the no-policy scenario, both a blanket and a targeted policy considerably flatten the infection curve. This is because the work ban reduces the chances of infection for susceptible individuals. In terms of infections, there is a marginal difference between the blanket and the targeted policy scenario, with the infection curve peaking at 3.8 and 3.9 percent of the initial population, respectively, a month and a half after compared to the no-policy scenario. The lower infection rates in the policy scenarios result in larger numbers of susceptible individuals and recovered ones and, most importantly, lower death counts. Yet, differences across the two scenarios are visible. The targeted policy scenario features a lower death rate than the blanket policy scenario—0.34 percent of initial population against 0.40 percent of initial population—which results in less recovered individuals and more susceptible ones.

Figure 3: Epidemiological Dynamics
(Percent of initial population)



(a) Infected (b) Susceptibles (c) Recovered (d) Deaths

Notes: The figure shows the epidemiological dynamics over the first 150 weeks since the beginning of the pandemic for the no-policy scenario, the blanket policy scenario, and the targeted policy scenario.

To understand the differences in the death counts between the blanket and the targeted policy scenarios vis-á-vis similar infection rates, Figure 4 presents the epidemiological dynamics splitting between low- and high-risk individuals. A containment policy aimed at high-risk individuals—as in the targeted policy scenario—leads to a sizeable decline in infections and deaths for that risk category of individuals (panels 4b and 4h, respectively). Specifically, the share of infected high-risk individuals in the blanket policy peaks at 0.34 percent in the blanket policy scenario, while it reaches 0.15 percent in the targeted policy scenario. Similarly, the share of dead high-risk individuals in the initial population is 0.25 percent under a blanket policy against 0.11 percent under a targeted policy. High-risk individuals face a small second wave of infections when the containment policy is lifted, as they return to their workplaces reactivating one of the channels through which they can get infected and infect others (panel 4b). These dynamics result in a larger share of susceptible individuals and a smaller share of recovered ones in the target policy scenario compared to the blanket policy scenario (panels 4d and 4f, respectively).

The epidemiological dynamics of low-risk individuals are similar across the two policy scenarios. The share of infected individuals is only marginally higher under a targeted policy (panel 4a), and so is the death count (panel 4g). We conclude that, compared to the blanket policy scenario, a targeted policy delivers significantly better epidemiological outcomes for high-risk individuals, and slightly worse ones for low-risk individuals. To translate these gains in terms of lives, we compute the difference in the number of deceased individuals between the blanket and the targeted policy scenarios 250 weeks after the beginning of the pandemic. Table 2 reports the results. Assuming an initial population equal to the one of the United States at the end of 2019, a targeted policy approach saves about 167,000 more lives compared to a blanket policy approach. Specifically, it saves 170,012 high-risk individuals but loses 2,423 low-risk ones.

Table 2: Death Count After the Pandemic
(Number of people)

	Blanket	Targeted	Difference
Low-risk individuals	475,687	478,110	-2,423
High-risk individuals	813,056	643,044	170,012
Total	1,288,743	1,121,154	167,589

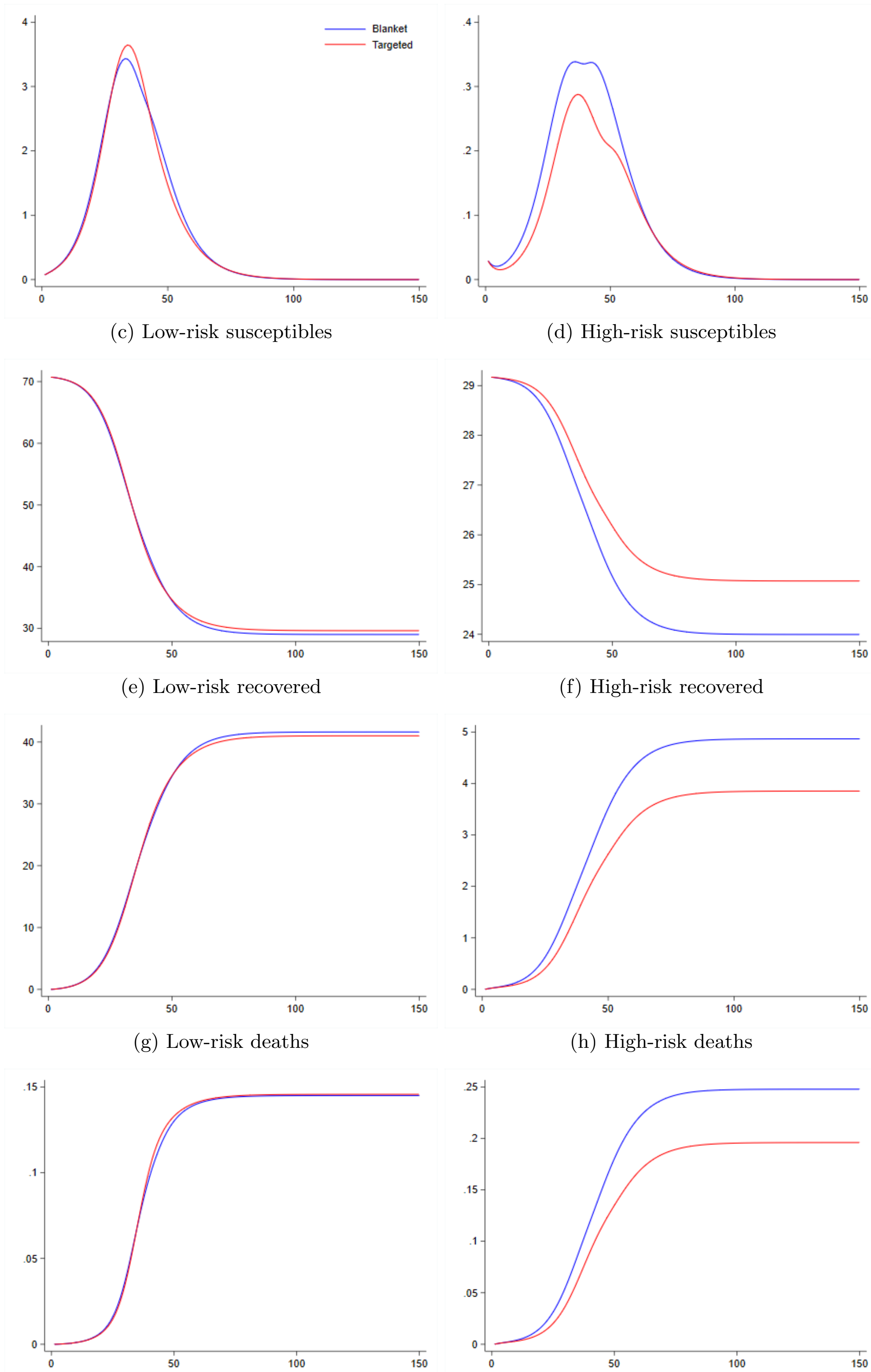
Notes: The table reports the number of deceased after 250 weeks since the start of the pandemic, separating high- and low-risk individuals. The estimates are computed based on the population of the United States in 2019.

We now turn to the macroeconomic dynamics. Panel 5a plots the percent deviation from the steady state for aggregate consumption under the three scenarios. In absence of a containment policy, a recession occurs because people voluntarily self distance in response to the rise in infections. That is, susceptible individuals curtail hours worked and consumption to reduce the chances of getting infected. However, consumption takes time to fall as infections progressively increase and people do not internalize the externality of their behavior.[17] Consumption reaches its trough when infections are at the peak, reflecting both the individuals' behavioral response and the lower productivity of infected people.

In the case of the blanket and the targeted policy scenarios, the optimal containment kicks in right at the beginning of the pandemic and leads to an immediate and abrupt plunge in the level of consumption. Since the optimal containment under a targeted policy is applied to a relatively larger share of people compared to the containment under a blanket policy, consumption falls by a larger amount. The recession is larger in the scenarios featuring some containment policy. A blanket policy leads to a 33 percent collapse in consumption at the trough, which is somewhat larger than under a targeted policy (31 percent). However, consumption remains subdued for longer in the targeted policy scenario. This occurs for two reasons: first, the optimal containment policy remains in place for almost 60 weeks in the targeted scenario, compared to 45 weeks in the blanket policy scenario; second, herd immunity is achieved earlier on under a blanket policy, particularly for high-risk individuals which are the most responsive to changes in the probability of infection. All in all, a targeted policy generates a larger recession.

[17] Infected people, in fact, do not take into consideration that their actions affect the probability of infection of susceptible people.

Figure 4: Epidemiological Dynamics of Low- and High-Risk Individuals
(Percent of initial population)



(a) Low-risk infected

(b) High-risk infected

(c) Low-risk susceptibles

(d) High-risk susceptibles

(e) Low-risk recovered

(f) High-risk recovered

(g) Low-risk deaths

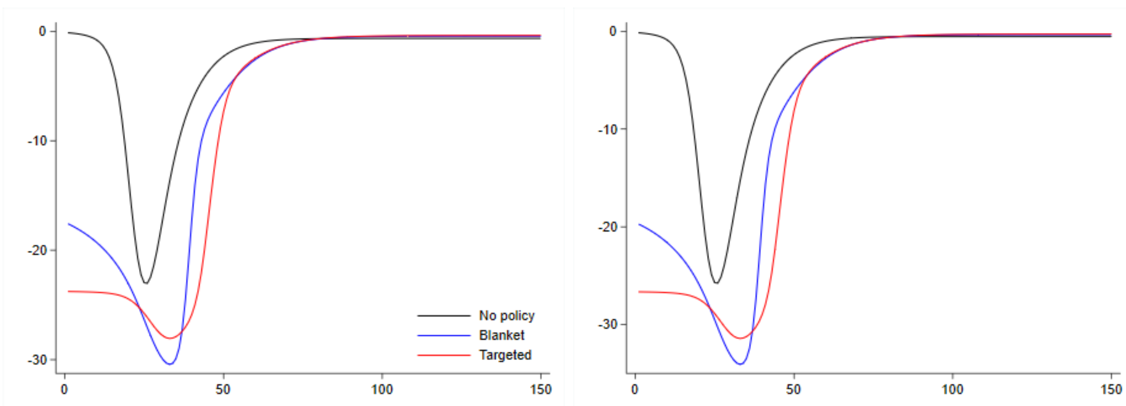
(h) High-risk deaths

Notes: The figure shows the epidemiological dynamics over the first 150 weeks since the beginning of the pandemic for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals.

Unsurprisingly, as shown in panel 5b, the consumption dynamics resemble the ones of hours worked in the no-policy scenario. This is because the production function is linear in hours worked and contained individuals receive transfers from those who are allowed to work, so that aggregate consumption moves in line with hours worked. However, while the dynamics are similar, the deviation from the steady state is smaller for hours worked than for consumption because retirees continue to consume out of their pension income (rather than labor income).[18]

Figure 5: Macroeconomic Dynamics
(Percent deviation from the steady state)

(a) Consumption (b) Hours worked



Notes: The figure shows the macroeconomic dynamics over the first 150 weeks since the beginning of the pandemic for the no-policy scenario, the blanket policy scenario, and the targeted policy scenario.

To gain further intuition about the voluntary response of individuals and how this relates to the consumption dynamics, Figure 6 shows consumption of non-contained individuals separately for low- and high-risk ones. As shown in panel 6c, in the case of the blanket policy scenario low-risk individuals work less when infections rise because they fear getting infected. As infections start to decline, they go back to work. Consistent with this, their consumption declines when infections increase and recovers when infections fall as illustrated in panel 6a. Under a targeted policy, as the pandemic starts, low-risk individuals work more hours since they know that high-risk individuals are banned from working and that, as a result, their probability of getting infected is lower. In addition, they try to compensate for the tax levied on them and sustain their consumption level.

As shown in panels 6b and 6d, the aggregate consumption and hours worked of non-contained individuals unsurprisingly collapse in the targeted scenario, as almost all these individuals are banned from working. The blanket policy scenario also shows an important decline in consumption and hours worked, reflecting the reaction of those individuals with higher mortality rates (therefore more sensitive to the rise in infections) that curb consumption and hours worked to avoid getting infected.

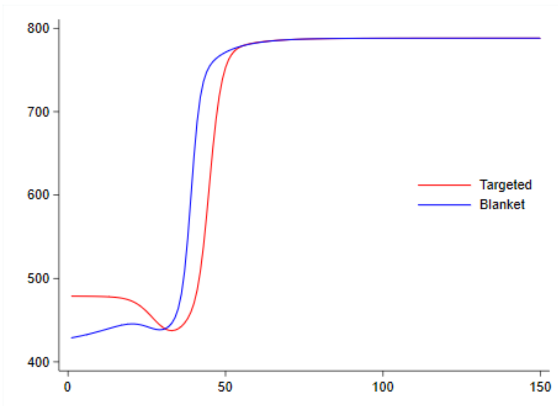
To summarize the results, we compute the present value of the welfare function for the three scenarios. By diversifying containment across risk categories and despite a more prolonged recession, a targeted approach to containment is the most rewarding one in terms of utility.[19] In other words, the government

[18] Figure 5 shows that neither consumption nor hours worked go back exactly to the steady state. This is because, after the pandemic, the population is smaller due to the loss of lives.

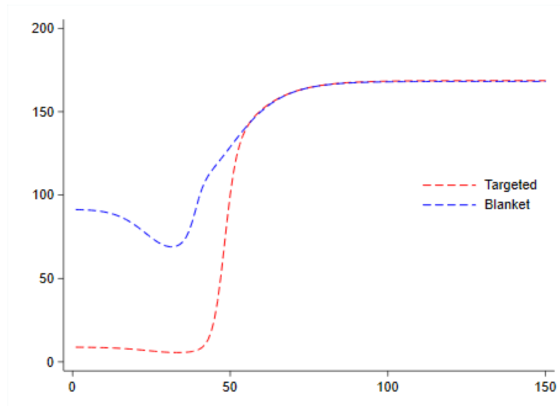
[19] Restrictions on hours worked positively affect the social welfare because the production function features disutility of

Figure 6: Macroeconomic Dynamics of Non-Contained Individuals
(Units)

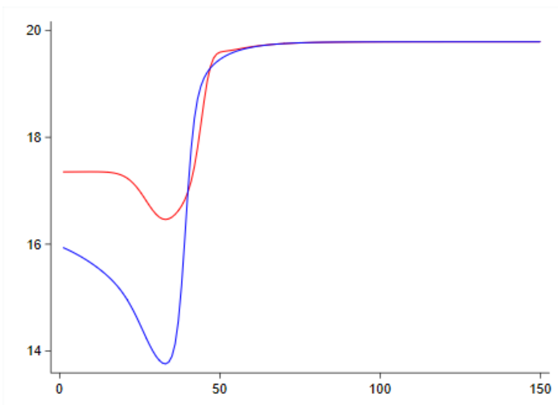
(a) Consumption, low-risk individuals



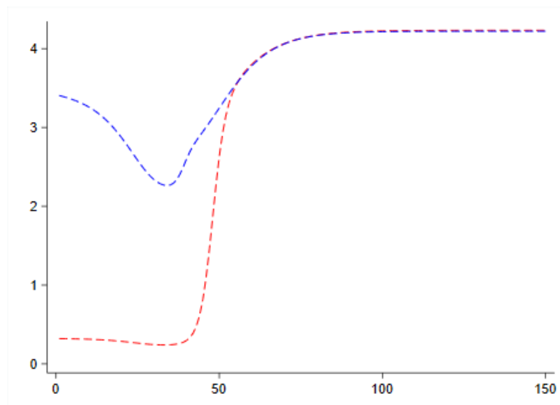
(b) Consumption, high-risk individuals



(c) Hours worked, low-risk individuals



(d) Hours worked, high-risk individuals



Notes: The figure shows the consumption dynamics over the first 150 weeks since the beginning of the pandemic of non-contained individuals for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals excluding retirees.

prefers the targeted containment policy because the reduction in deaths (and the increase in leisure) overcompensate the drop in consumption caused by a bigger recession.

5 Increased interactions

The targeted containment policy described so far is based on average contact rates at home. Yet, one could think of many reasons for which such contact rates could actually be higher during a pandemic. Government-imposed restrictions such as the ones described in this paper—i.e., banning high-risk individuals from working—could increase the number of contacts between low- and high-risk individuals within the household. This is because, *given a certain household structure*, high-risk individuals would be forced to spend more time at home, which is where most young-old contacts take place. Similarly, more vulnerable individuals may not be able to get help from health professionals as these may be banned from

labor.

work. Instead, they might have to rely on help from within the household, likely from low-risk individuals. Therefore, a natural question is how optimal containment changes when high-risk individuals become more exposed to the virus via more contacts at home with low-risk individuals.

Another equally relevant question is whether the benefits of a targeted approach depend on the household structure. Even within the US, the household composition can vary significantly, with areas in which the median household features relatively more low- and high-risk individuals living within the same household. In other words, *given the same contact rates*, the share of contacts between low- and high-risk individuals may be higher and the one between people of the same risk category may be lower than in the calibration of the model.

In this section, we re-assess benefits of a targeted approach to containment discussed in Section 4 by first presenting the results raising the contact rates and then the ones based on a higher share of contacts between low- and high-risk individuals.

5.1 Higher contact rates

We start by modifying the contact rates in equations (1), (2), and (3). Specifically, we assume that each group of agents increase its average contact rate by 10 percent relative to the initial settings, so that the new total contact rates are $\Psi^y = 4.73$ and $\Psi^o = 1.21$.[20] For this exercise we maintain the assortativity of social interactions, therefore parameters χ^j are calibrated as in Table 1.

Panel 7a of Figure 7 shows that under a blanket policy, 45.1 percent of the population gets banned from working. In other words, a 10 percent increase in the contact rates prompts the government to ban an additional 11.2 percent of people from working, since low- and high-risk individuals can now more easily infect each other. Under the targeted policy scenario, the optimal containment of the government bans 51.7 percent of the population from working, which is about 12.8 percentage points higher than in a setting with lower contact rates. As shown in panel 7b, the containment policy now applies to all high-risk individuals and it extends to a much larger fraction of low-risk individuals (42.3 percent, or 15.2 percentage points more than with lower contact rates), even if for a shorter time period. In sum, the optimal containment under a targeted scenario becomes less targeted with increased contact rates, effectively reducing the benefits of separating low-risk from high-risk individuals.

The epidemiological dynamics are qualitatively in line with the ones shown in Figure 3 and 4. In particular, the results confirm that a targeted containment continues to save more (high-risk individuals') lives than a blanket one.[21]

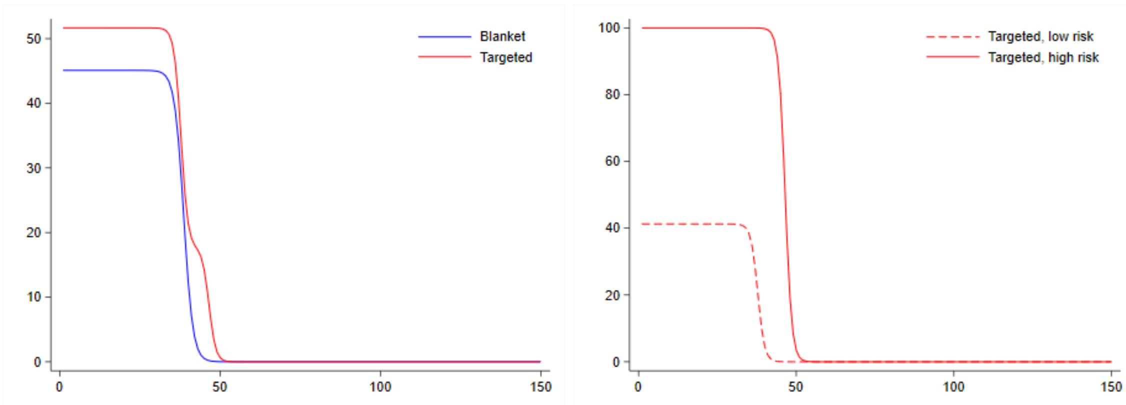
In terms of macroeconomic outcomes, the aggregate dynamics under both policies become extremely similar as shown in Figure 8. However, the dynamics of each risk-type are very different under the two policies. The initial drop in consumption and hours worked under the targeted policy reflects a containment that extends to all high-risk individuals and 42.3 percent of low-risk individuals. In contrast, under the blanket policy the containment applied to low-risk (high-risk) individuals is higher (lower) than under the targeted policy. Another key factor explaining these dynamics is that the pool of non-contained individuals under the targeted policy consists of low-risk individuals who have less incentives to voluntarily reduce their labor supply. As shown in panel 9c of Figure 9, the reduction in labor supply of non-contained

[20] There is obviously some arbitrariness in the magnitude of the increase. However, assuming a different magnitude does not affect our conclusions.

[21] See Appendix A for the epidemiological results.

Figure 7: Optimal Containment with Higher Contact Rates

(a) Blanket and Targeted Policy Scenarios (Percent of population) — (b) Low- and High-Risk Agents (Percent of population in each category)

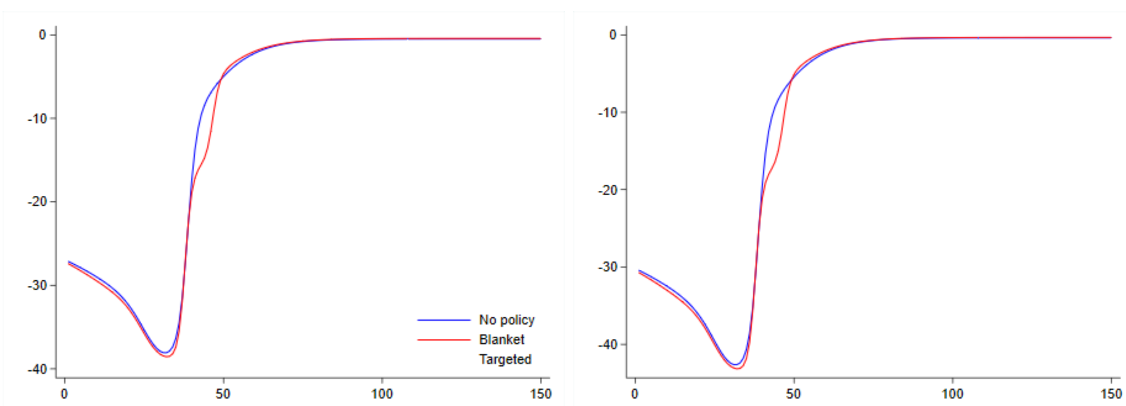


Notes: The figure shows the optimal containment over the first 150 weeks since the beginning of the pandemic for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals excluding retirees. In panel 2a, the share of contained people is relative to total population; in panel 7b, the share of contained low-risk (high-risk) individuals is relative to the population of low-risk (high-risk) individuals excluding retirees.

individuals is larger than under a targeted policy. The subsequent recovery in hours worked and consumption displayed in Figure 8 reflect the evolution of the infections and the lifting of the containment.

Figure 8: Macroeconomic Dynamics with Higher Contact Rates
(Percent deviation from the steady state)

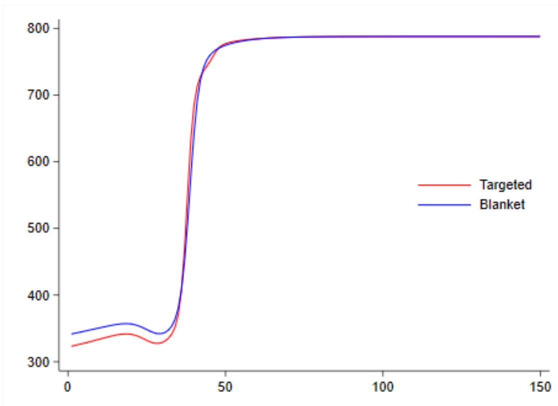
(a) Consumption — (b) Hours worked



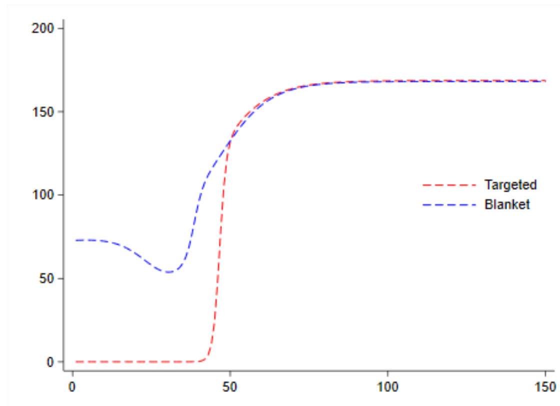
Notes: The figure shows the macroeconomic dynamics over the first 150 weeks since the beginning of the pandemic for the no-policy scenario, the blanket policy scenario, and the targeted policy scenario.

Figure 9: Macroeconomic Dynamics of Non-Contained Individuals with Higher Contact Rates (Units)

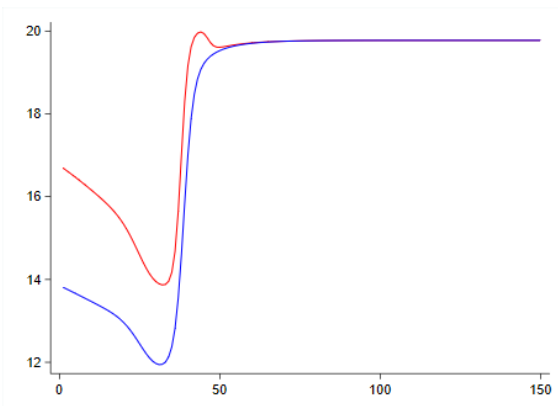
(a) Consumption, low-risk individuals



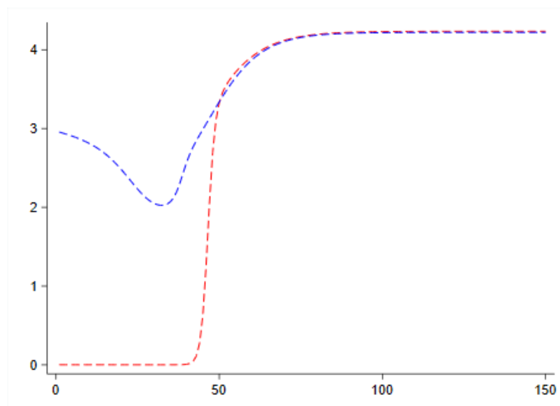
(b) Consumption, high-risk individuals



(c) Hours worked, low-risk individuals



(d) Hours worked, high-risk individuals



Notes: The figure shows the consumption dynamics over the first 150 weeks since the beginning of the pandemic of non-contained individuals for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals.

5.2 Higher share of contacts between low- and high-risk individuals

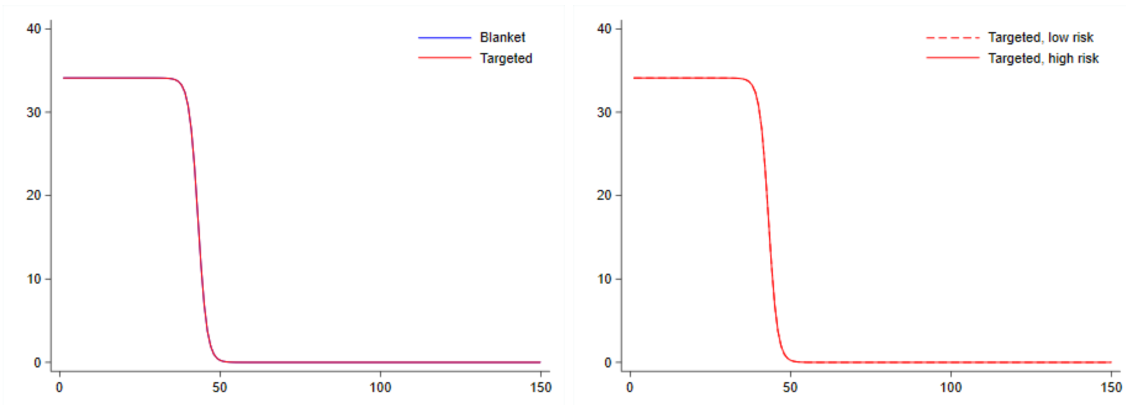
We now simulate a context in which the share of contacts between low- and high-risk individuals increases, while holding constant the number of contacts. Thus, in equations (1), (2), and (3), we set the share of contacts between low- and high-risk individuals to $\chi^j = 0.71$, so that the share of contacts of high-risk individuals with low-risk individuals increases from 0.24 to 0.71. Similarly, the share of contacts of low-risk individuals with high-risk individuals increases from 0.18 to 0.71. Hence, by construction, the share of contacts among individuals of the same risk group is reduced. This corresponds to a setting in which the share of contacts between low- and high-risk individuals is informed by the proportion of low-risk individuals in the initial population, while the contact rates Ψ^j are consistent with the calibration reported in Table 1.

As shown in Figure 10, a household structure that features a sufficiently high share of contacts between low- and high-risk individuals makes the optimal targeted approach equivalent to the optimal blanket approach. The intuition here is that, despite a work ban helps to contain infections of the individuals to which it is targeted, the government cannot fight the cross-risk category contamination happening within the household. Hence, the benefits of a targeted policy vanish.

Figure 10: Optimal Containment with Higher Share of Contacts between Low- and High-Risk Individuals

(a) Blanket and Targeted Policy Scenarios (Percent of population)

(b) Low- and High-Risk Agents (Percent of population in each category)



Notes: The figure shows the optimal containment over the first 150 weeks since the beginning of the pandemic for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals excluding retirees. In panel 2a, the share of contained people is relative to total population; in panel 7b, the share of contained low-risk (high-risk) individuals is relative to the population of low-risk (high-risk) individuals excluding retirees.

6 Conclusions

In this paper we provide an assessment of the targeted approach to containment, comparing the epidemiological and macroeconomic outcomes to the ones of a blanket policy. To do that, we propose a SIR-macro model that allows for heterogeneous agents in terms of mortality rates and contact rates, and in which the government optimally bans people from working. Importantly, the model is characterized by non-contained individuals that react optimally to the spread of the virus, for example by practicing voluntary social distancing when infections are on the rise.

Our results suggest that under a targeted policy the government optimally contains a larger portion of the population than under a blanket policy, and that the work ban is held in place for longer. In fact, when treating individuals homogeneously, it is costly for the government to contain more people due to the lower average mortality rate compared to the mortality rate of high-risk agents. Also, the optimal targeted policy contains some low-risk individuals before containing all high-risk individuals. This is because, despite the relatively higher mortality rate of high-risk individuals, (i) the value of their discounted utility is smaller and (ii) the government knows that containing low-risk individuals leads to less deaths of high-risk individuals (who can get infected by interacting within the household).

A containment policy aimed at high-risk individuals leads to a considerable decline in infections and deaths for that group of individuals, with only a marginal increase in infections and deaths for low-risk individuals. Overall, a targeted containment saves about 167,000 more lives than a blanket one. Yet, from a macroeconomic perspective, a targeted policy generates the largest initial plunge in consumption due to the wider reaching containment. Also, the recession lasts longer under a targeted policy. This is because the containment policy remains in place for longer and herd immunity is achieved only later than under a blanket policy. Despite the larger recession, the smaller number of deaths makes the targeted policy approach superior in terms of welfare.

Finally, we examine if the benefits of a targeted approach are undermined in a setting characterized by increased interactions within the household (which may occur during a pandemic) or in a setting in which the household structure is such that the share of contacts between low- and high-risk individuals is higher. The results suggest that a larger number of contacts within the household makes optimal containment less targeted, effectively diminishing the benefits of applying different restrictions to low-risk and high-risk individuals. Also, a household structure featuring a higher share of contacts between low- and high-risk individuals reduces the effectiveness of a targeted containment due to the cross-risk category contamination at home. In this respect, we find that a sufficiently high share of contacts between low- and high-risk individuals makes the targeted policy equivalent to a blanket one.

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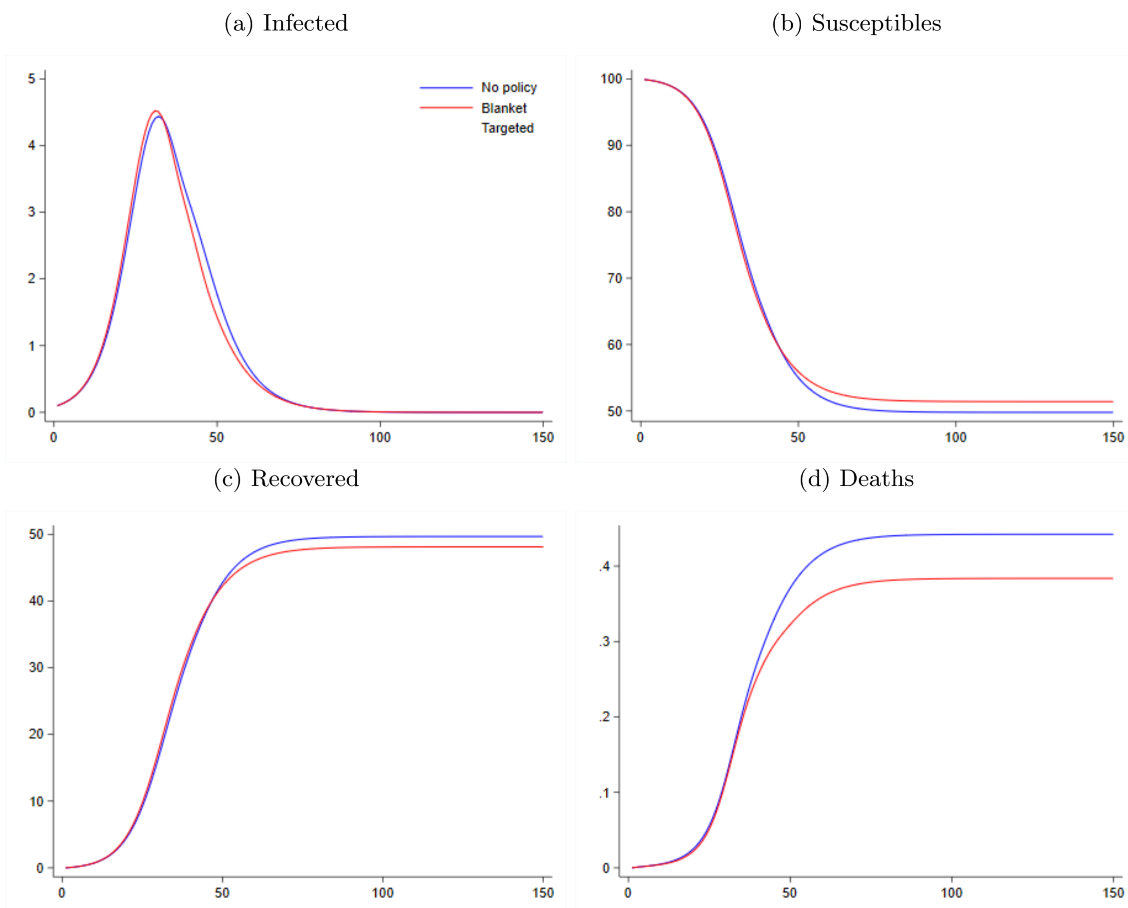
Appendix A. Additional results

Figure A.1 displays the epidemiological dynamics under a blanket and a targeted policy for the exercise featuring increased contact rates. The differences across the two scenarios are qualitatively akin to the ones in Figure 3, while magnitudes change reflecting the higher contact rates. The infection curves peak at 4.4 and 4.5 percent of initial population under a blanket policy and a targeted one, respectively, around the same week (panel A.1a). However, the death count largely favors a targeted approach, with a death rate at 0.44 percent of initial population under a blanket policy and 0.38 percent of initial population under a targeted policy (panel A.1d). As a result, there are more recovered individuals under in the blanket policy scenario (panel A.1c) and more susceptible ones under the targeted policy scenario (panel A.1b). Figure A.2 shows that, similar to the results in Figure 4, the dynamics for low-risk individuals are similar across scenarios, and that a targeted policy saves considerably more lives of high-risk individuals.

Figure A.1: Epidemiological Dynamics with Higher Contact Rates
(Percent of initial population)

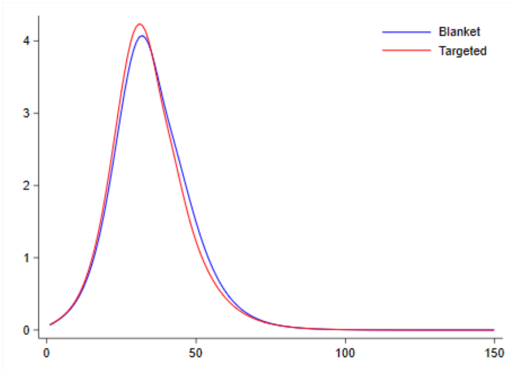


Notes: The figure shows the epidemiological dynamics over the first 150 weeks since the beginning of the pandemic for the no-policy scenario, the blanket policy scenario, and the targeted policy scenario.

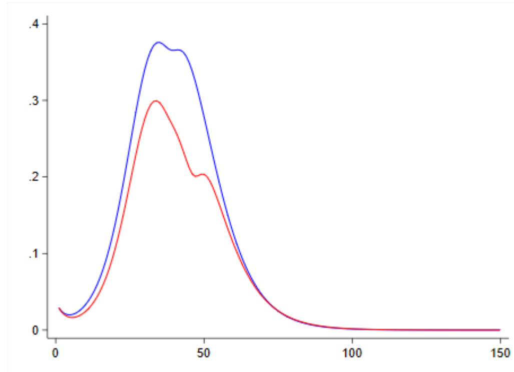
Figure A.2: Epidemiological Dynamics of Low- and High-Risk Individuals with Higher Contact Rates

(Percent of initial population)

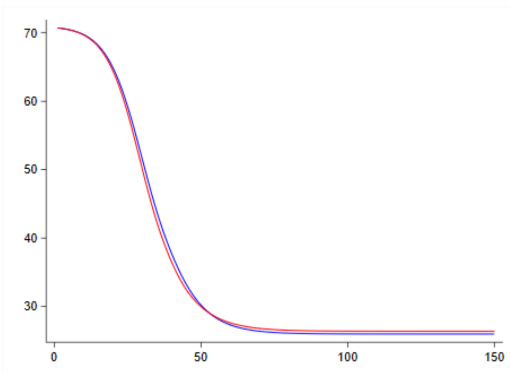
(a) Low-risk infected



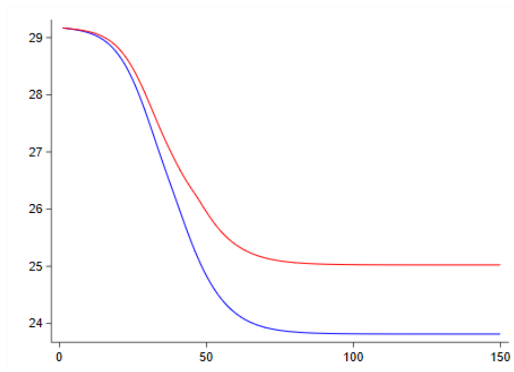
(b) High-risk infected



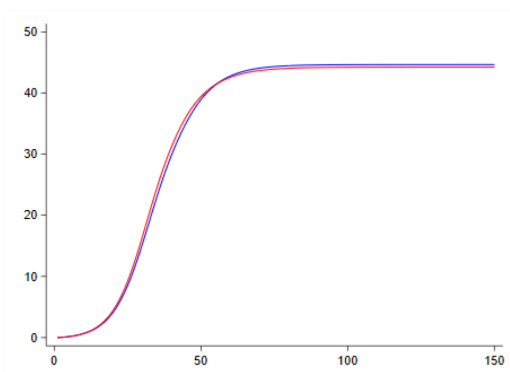
(c) Low-risk susceptibles



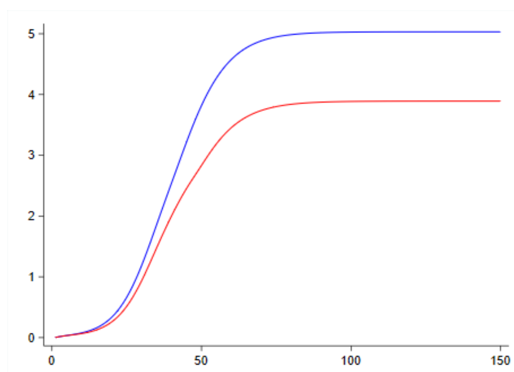
(d) High-risk susceptibles



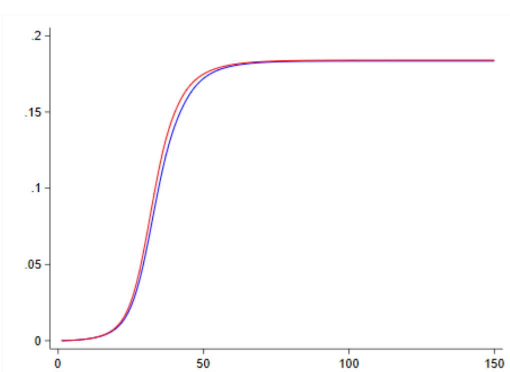
(e) Low-risk recovered



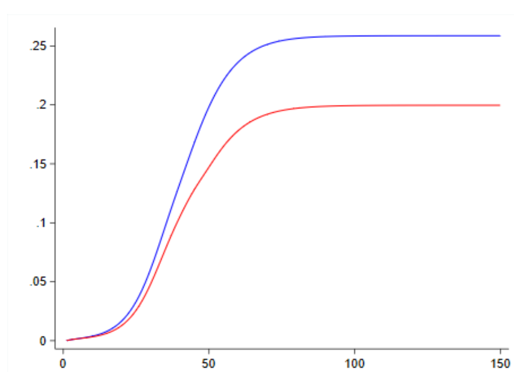
(f) High-risk recovered



(g) Low-risk deaths



(h) High-risk deaths



Notes: The figure shows the epidemiological dynamics over the first 150 weeks since the beginning of the pandemic for the blanket policy scenario and the targeted policy scenario, separating low- and high-risk individuals.