Balancing Mitigation Policies during Pandemics: Economic, Health, and Environmental Implications*

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Abstract

The strategies implemented to contain the spread of COVID-19 have clearly shown the existence of a nontrivial relation between epidemiological and environmental outcomes. On the one hand, mitigation policy generates unclear pollution effects, since social distancing measures favor a reduction in industrial emissions while health regulations and recommendations contribute to increase it. On the other hand, increased pollution exposes individuals to a higher chance of severe symptoms increasing their probability of death due to respiratory diseases. In order to understand how balancing the different goals in the design of effective containment policies we develop a normative approach to account for their consequences on the economy, health and the environment by analyzing the working mechanisms of social distancing in a pollution-extended macroeconomic-epidemiological framework with health-environment feedback effects. By limiting social contacts and thus disease incidence, social distancing favors health and environmental outcomes at the cost of a deterioration in macroeconomic conditions. We show that social distancing alone is not enough to reverse the growth pattern of both disease prevalence and pollution and thus it is optimal to reduce the disease spread even if this generates a deterioration in environmental conditions. We also extend our baseline model to account for the role of strategic interactions between neighbor economies in which both pollution and disease prevalence are transboundary. In this context we show that free-riding induces sizeable efficiency losses, quantifiable in about 5% excess disease prevalence and 10% excess pollution at the end of the epidemic management program in the case of only two interacting economies.

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1 Introduction

Sustainable development has become a very popular topic lately and in its broader definition it demands policies promoting improvements in economic, health and environmental issues (WCED, 1987; UN, 2005; UNEP, 2012). The ongoing COVID-19 pandemic has shown more clearly than ever that economy, environment and health are all interrelated and that exogenous communicable-disease-induced shocks may generate devastating effects on economic activities, health conditions and environmental outcomes at once. Indeed, since the initial outbreak of the disease in China in late 2019, it has thus far (at the time of writing, in March 2023) generated more than 430 million cases and nearly 6 million deaths at world level (Dong et al., 2020). A broad variety of policy measures have been implemented everywhere in the world in order to contain the spread of the disease, including traditional preventive and treatment measures but also lockdowns, quarantines, social distancing, limitations on mobility (Cheng et al., 2020). Such containment strategies, forcing individuals to work from home and imposing the closure of unnecessary businesses, have resulted in dramatic consequences for economic activities, in terms of drastic reductions in household income, substantial increases in unemployment rates, and increases in social inequalities (Brodeur et al., 2021; Crossley et al., 2021). However, mitigation policies have also generated important and unclear environmental consequences: on the one hand, by reducing economic activities social distancing measures (and lockdowns in particular) have favored a reduction in industrial emissions and pollution concentrations (Venter et al., 2020; Schneider et al., 2022) while, on the other hand, the growing use of plastic-material in the manufacturing of single-use medical and personal protection equipment and in the single-use packaging for food has resulted in a massive increase in waste and emissions (EEA, 2021; Peng et al., 2021). Considering also that pollution generates sizeable implications on morbidity and mortality especially when interacting with respiratory diseases (Cui, 2003; Wu et al., 2020), it is essential to understand not only the health and economic consequences of disease control strategies but also their environmental impacts in order to design effective policies aiming to minimize their social cost and support policymakers in one of the most difficult periods of the recent economic history.

The recent COVID-19 experience has pointed out the existence of a nontrivial relation between epidemiological and environmental outcomes. By limiting individuals' mobility and forcing the closure of unnecessary businesses the most widely used policy measures to contain the disease spread, namely social distancing and lockdowns, have promoted a dramatic reduction in industrial emissions benefitting environmental quality through reduced air pollution. However, by modifying the production and the delivery needs of specific products other disease containment public health regulations have contributed to deteriorate the environmental quality through increased waste and emissions. While the beneficial effects of social distancing on pollution concentrations are extensively documented and have been under everyone's eye (Brodeur et al., 2021; Dang and Trinh, 2021), less known but not less important or supported are the detrimental effects induced by public health regulations. Indeed, several studies show that one of the most important consequences of public health recommendations during the COVID-19 pandemic consists of changing individuals' purchasing habits, which have shifted towards plastic-intensive products (OECD, 2020b, EEA, 2021). Indeed, the needs of the frontline health workers and private citizens to wear protective equipment (such as face masks, gloves, and aprons) along with those of staying-home workers to increase their reliance on e-commerce and take-away food deliveries in order to minimize their mobility have resulted in a massive increase in the production, transport and consumption of plastic (EEA, 2021; Filho et al., 2021). Moreover, prolonged periods of stay-at-home conditions have increased the production of household waste (such as cleaning and disinfecting material, used or unused medical waste, but also food waste) which have put under stress recycling facilities and the health of the environment (OECD, 2020a; Hantoko et al., 2021). The increased use of plastic-based products during the COVID-19 pandemic has important environmental and climate impacts, related to resource extraction, production, transport, waste handling and littering, resulting in increased pollution on streets, in rivers, on beaches, along coasts and in the sea (Adyel, 2020; Canning-Clode et al., 2020).[1]

Apart from the effects of disease mitigation policy (both in the form of social distancing and public health regulations) on pollution, pollution in turn affects epidemiological outcomes as well. By magnifying the health risk factors increased pollution exposes individuals to a higher chance of severe symptoms increasing their probability of death. Indeed, several studies show that pollution increases people's vulnerability to the effects of respiratory infections, such as SARS and COVID-19 (Cui, 2003; Wu et al., 2020). It is well known that high pollution levels lead to several health problems especially to lung and respiratory diseases, such as triggering new cases of asthma, exacerbating previously-existing respiratory illness, and provoking the development or progression of chronic illnesses including lung cancer, chronic obstructive pulmonary disease, and emphysema (Pope et al., 1995; Katsouyanni et al., 1996; Kunzli et al., 2000). And pre-existing medical conditions, including those involving lung and respiratory impairments, increase the likelihood of severe illness and death from COVID-19 (CDC, 2021; Lacedonia et al., 2021). In particular, recent estimates show that a person exposed for decades to high levels of fine particulate matter is 15% more likely to die from COVID-19 than someone exposed to one unit less of the fine particulate pollution (Wu et al., 2020; OECD, 2020). Therefore, not only the disease mitigation measures implemented in the fight of COVID-19 affect pollution but also pollution affects the mortality associated with COVID-19, which requires to carefully account for the existence of such a bilateral relation between epidemiological and environmental outcomes in the design of effective containment policies.

However, optimally designing disease control policies is not simple at all since the effectiveness of the different measures implemented in a given economy largely depends on those implemented in other economies as well. Several papers discuss that because of the growing level of globalization, international trade, technological progress and migration, localized epidemic shocks tend to spread fast on a geographical level eventually achieving a pandemic scale (Kimball, 2006; Tatem et al., 2006; Baker et al., 2021). Such a geographical interrelation between epidemiological outcomes at single country level suggests that trying to limit the spread of an infectious disease without accounting for the policy actions in other economies is

[1] Just to give a sense of the magnitude of the problem, the number of plastic facemasks used on a daily basis at the world level is estimated to exceed 7 billion (Hantoko et al., 2021). And during the height of the epidemic in Wuhan the city has dealt with 240 tons of medical waste a day, compared to around 40 tons a day before the outbreak (Zuo, 2020). The increased consumption of face masks only during the first wave (April-September 2020) has led to the emission of 2.4-5.7 million tonnes of CO2 above the business-as-usual level in Europe, equivalent to an increase of 118% (EEA, 2021).

pointless and only international coordination may effectively allow for disease eradication (Barrett, 2003; La Torre et al., 2022). Even in the case of COVID-19, a growing number of works document that the fast spread of the disease both within and between countries is driven by mobility and trade patterns, justifying the introduction of travel bans and other policies aiming to reduce individuals' mobility at different geographical levels in order to limit the diffusion of the illness (Tayoun et al., 2020; Chang et al., 2021). This requires to critically understand the extent to which uncoordinated mitigation efforts may allow for disease containment, especially in light of the fact that the unpopularity of the most widely spread policy tools in the fight of COVID-19 (i.e., social distancing) may give rise to free-riding opportunities. Therefore, apart from introducing environmental considerations in the analysis of disease control measures, it is essential to account for strategic interactions between multiple policymakers in order to quantify the effects of free-riding on mitigation efforts.

In order to address these issues, we extend a macroeconomic-epidemiological framework to an environmental dimension to assess the extent to which pollution considerations may impact the intensity of mitigation strategies. Our work is thus related to the growing economic epidemiology literature which aims to analyze how health policies may impact economic activities both at microeconomic and macroeconomic levels (Philipson, 2000; Gersovitz and Hammer, 2003; Goenka and Liu, 2012; La Torre et al., 2020). In particular, a huge number of works has analyzed the consequences of different policies on the trade-off between economic and health objectives in the context of COVID-19, placing particular emphasis on social distancing and lockdown (Acemoglu et al., 2020; Alvarez et al., 2020; Gori et al., 2021; La Torre et al., 2021b). Several works have also examined the role of strategic interactions between different players, in terms of individual agents, individual demographic groups or individual economies, in determining the relation between the spread of COVID-19 and macroeconomic outcomes (Cui et al., 2020; Bouveret and Mandel, 2021; La Torre et al., 2021a). Most of these works discuss the macroeconomic implications of COVID-19 and the related mitigation measures, abstracting completely from their environmental impacts. To the best of our knowledge, very limited are the papers accounting for the possible environmental issues associated with disease-control strategies, and all these works abstract completely from strategic interactions (Brock and Xepapadeas, 2020; Augeraud-Veron et al., 2021; Davin et al., 2023). Brock and Xepapadeas (2020) discuss the importance to take into account environmental issues in the analysis of disease containment strategies to distinguish between short-run epidemic management objectives and long-run climate mitigation goals, but they do not derive the optimal policy. Augeraud-Veron et al. (2021) discuss how the optimal policy depends on biodiversity conservation which by decreasing the probability of an epidemic shock acts as a preventive measure of disease containment showing that biodiversity conservation is larger the more forward looking the society; however, they abstract from pollution and bidirectional feedback epidemiological-environmental effects. Davin et al. (2023) analyze the relation between fiscal policy and epidemics in a setting in which pollution affects the infectivity rate showing that public debt can help to achieve disease eradication; however, they do no rely on a normative approach and they do not quantify the consequences of infections on the environment. Different from these works, we explicitly account for the two-ways health-environment relation driven by emissions and mortality effects, discussing in particular how the optimal policy depends on environmental conditions. Moreover, we analyze the implications of strategic interactions between two-neighbor economies to understand the role of transboundary epidemiological and pollution externalities on free-riding opportunities and the optimal policy.

Specifically, we analyze a pollution-extended macroeconomic-epidemiological framework in which the spread of the disease deteriorates economic activities and affects the stock of pollution which in turn impacts the disease-induced mortality rate. Disease dynamics are described by a susceptible-infected-susceptible (SIS) model with vital dynamics, which represents a simple but general enough setting to capture the implications of epidemiological factors on the economy and the environment. Indeed, the SIS model is one of the most largely discussed frameworks in mathematical epidemiology, widely applicable to a range of diseases not conferring permanent immunity, such as the seasonal flu, some sexually transmitted diseases and some vector-borne diseases (Hethcote, 2008). Since individuals do not acquire permanent immunity from COVID-19 either through recovery or through vaccination, it is also well suited to characterize in a simplified way the spread of COVID-19 (WHO, 2020; La Torre et al., 2021b). Mitigation policies, in the form of social distancing by reducing disease incidence, favor epidemiological and environmental outcomes at the cost of a deterioration in macroeconomic conditions. The social planner needs to balance these conflicting goals optimally determining the intensity of the policy measure over a finite time horizon, representing the duration of the epidemic management program. We calibrate the model's parameters according to Italian data related to the first epidemic wave, occurred between February to July 2020 in order to exemplify the relevance of our analysis in real world situations. We characterize how the optimal social distancing policy depends on the main environmental factors, showing that social distancing alone is not enough to reverse the growth pattern of both disease prevalence and pollution. Indeed, the optimal policy allows for a reduction of disease prevalence only at a cost of a deterioration in environmental outcomes, suggesting that placing too much emphasis on epidemic management as done in the policy arena risks to leave us with a high environmental bill which will require massive efforts in the near future to improve environmental conditions in order to achieve long-run sustainability. We also extend our baseline model to account for the role of strategic interactions between some neighbor economies in which not only pollution is transboundary but also disease prevalence is. We show that free-riding induces important efficiency losses, quantifiable in about 5% excess disease prevalence and 10% excess pollution at the end of the epidemic management program when the number of neighbor economies is two, but this loss substantially higher when the number of interacting economies increases. This suggests that policy coordination is essential in order to effectively mitigate the consequences of infectious diseases. To the best of our knowledge, ours is the first attempt to quantify how environmental conditions may depend on and affect the optimal management of the macroeconomic-epidemiological trade-off.

The paper proceeds as follows. Section 2 presents the main ingredients of our pollution-extended macroeconomic-epidemiological framework where disease prevalence determines and is affected by both economic and environmental outcomes. Section 3 characterizes the optimal solution of the epidemic management problem from a normative perspective, presenting some numerical experiments based on our Italian data calibration. Section 4 introduces strategic interactions between multiple policymakers to explore the implications of free-riding opportunities on the optimal policy and the eventual effectiveness of the epidemic management program. Section 5 presents concluding remarks and directions for future research. Appendix A and appendix B present the full description of our baseline and extended models, respectively.

2 The Model

We consider a pollution-extended macroeconomic-epidemiological framework in which the spread of an infectious disease drives output production and emissions, and social distancing which reduces output further but also decreases disease incidence and emissions is used to manage the epidemic. On the macroeconomic side disease prevalence affects output, while the epidemiological side is described by a SIS model in which disease prevalence determines emissions (through output production and behavioral changes) which in turn drive the disease-induced mortality. This gives rise to feedback effects between health and macroeconomic outcomes. A similar setting has been recently analyzed in La Torre et al. (2021b) to determine the optimal social distancing policy, abstracting completely from pollution considerations and health-environment feedback effects.

On the epidemiological side, the interactions between susceptible and infective individuals, denoted by S_t and I_t respectively, normalized by the population size N_t, determine disease incidence, $\mathcal{I}$, which is given by the following expression:

$$\mathcal{I}_t = \alpha(1-u_t)\frac{I_t}{N_t}S_t, \tag{1}$$

where $\alpha > 0$ measures the infectivity rate and $0 < u_t < 1$ the intensity of the social distancing measures (i.e., lockdowns). By determining the share of businesses allowed to remain open and the share of workers allowed to effectively work, social distancing limits the possible interactions between susceptibles and infectives reducing disease transmission and thus disease incidence. Disease incidence is thus determined by biological factors, α, public policy, u_t and social interactions between individuals (either on the workplace or for daily life activities), $\frac{I_t}{N_t}S_t$. The latter term states that the patterns of social contacts and human interactions are stable over time independently of the spread of the disease, and thus disease transmission and incidence ultimately depend on the share of the infectives, $\frac{I_t}{N_t}$, rather than the total number of infectives, I_t. Apart from the effects of public policy in reducing the spread of the diseases, single individuals take specific actions (i.e. purchasing plastic face masks and gloves) to minimize their exposure to infection, which generate some pollution (in excess to the normal pollution trend), P_t, which in turn increases the disease-induced mortality, $\bar{\mu}$, as follows:

$$\bar{\mu}_t = \mu\left(1+\frac{P_t}{N_t}\right), \tag{2}$$

where $\mu > 0$ quantifies the magnitude of such environmental effects on mortality. Disease-induced mortality depends thus on the amount of per-capita pollution $\frac{P_t}{N_t}$ which quantifies the impact at the single individual level of the environmental externality. Pollution is a stock variable which accumulates with emissions, $\mathcal{E}$, which are driven by production and behavioral patterns as follows:[2]

$$\mathcal{E}_t = \theta Y_t + \chi I_t, \tag{3}$$

[2]As a matter of simplicity, we assume that there is a single pollution stock whose accumulation is determined by the emissions generated by production and behavioral patterns and whose total stock affects disease-induced mortality. We could alternatively assume the existence of two separate pollution stocks, one driven by production activities and unrelated to mortality, and another one driven by behavioral attitudes and related to mortality. Apart from complicating the setup such an alternative specification would not lead to results substantially different from ours thus it seems convenient to present the model in its simplest possible form.

where $\theta > 0$ and $\chi > 0$ measure the dirtiness of production, Y_t, and individuals' preventive response to the infection, respectively. Pollution is driven by firms' production activities, θY_t, and by the needs of single households to reduce their disease exposure, χI_t. The importance to take precautionary measures (i.e., wearing plastic face masks) is related to the number of infectives which determines individuals' incentive to modify their behavior to reduce their probability of infection. As social distancing limits economic production it allows to reduce emissions, but only to the extent to which they do not depend on individuals' behavioral response to the epidemic.

On the macroeconomic side, the social planner decides the intensity of the social distancing policy to reduce the spread of a communicable disease in order to minimize the social cost associated with the epidemic management program. Individuals entirely consume their income, which is produced through a linear production function by the number of susceptibles but since only a certain share of the social contacts, $1 - u_t$, is allowed to regularly occur output net of social distancing is given by:

$$Y_t = (1 - u_t)S_t. \tag{4}$$

The social cost is the weighted sum of two terms: the discounted sum of the instantaneous losses associated with the epidemic management program during its duration and the discounted final damage associated with the remaining level of disease prevalence (quantified by the number of susceptibles, I_t) and pollution at the end of the epidemic management program. The instantaneous loss function is the weighted average between two terms capturing the social loss and the environmental loss associated with the epidemic management program. The social loss depends on the spread of the disease, the output lost due to social distancing, the passivity (i.e., the cost of not imposing enough social distancing in the presence of infectives) and the lives lost due to the epidemic, while the environmental loss only on the pollution stock. The relative weight of the environmental loss with respect to the social loss is captured by $\omega > 0$. The final damage function is the weighted average between two terms capturing the social damage and the environmental damage. The social damage depends on the share of infectives and the lives lost due to the epidemic, while the environmental damage only on the remaining level of pollution. The relative weight of the final damage in terms of the instantaneous losses is measured by $\phi > 0$, which represents the degree of sustainability concern.

The complete specification of our pollution-extended macroeconomic-epidemiological framework is presented in appendix A, but from our brief discission of the peculiarities of our setting due to the bidirectional relation between epidemiological and environmental outcomes it should be clear the role of social distancing on economy, health and environment. A higher policy intensity deteriorates macroeconomic conditions increasing the output loss due to the epidemic management program, but at the same time by reducing disease incidence and production it improves epidemiological and environmental outcomes decreasing infection and pollution. An optimal policy requires to carefully balance these conflicting needs, and while most papers in literature have focused on the macroeconomic-epidemiological trade off we will emphasize the role played by environmental factors and considerations. In particular, we will analyze how the optimal policy and health-economic-environmental outcomes depend on the degree of sustainability concern (ϕ), the weight attached to the environmental loss (ω), the degree of environmental inefficiency of production activities (θ) and the dirtiness of individual response to infection (χ).

3 The Optimal Policy

We now present the results of our numerical analysis based on our calibration of the model's parameters according to the daily data from the Italian COVID-19 experience during the first epidemic wave (spring 2020) – see appendix A for further details. Apart from the parameter values specifically calibrated, we arbitrarily set the degree of sustainability concern, the relative weight of the environmental loss in the social cost function, the environmental inefficiency production activities and the dirtiness of individual response to the epidemic to show how different values of these parameters may affect our results. Specifically, as a benchmark we rely on the following parametrization: $\phi = 1$, $\omega = 0.6$, $\theta = 0.07$ and $\chi = 0.01$. We also arbitrarily set the initial conditions for the pollution stock and the level of disease prevalence to show how the optimal policy changes with different initial health and environmental conditions. In our benchmark parametrization we set: $p_0 = \frac{P_0}{N_0} = 0.04$ and $i_0 = \frac{I_0}{N_0} = 0.2$. The next figures present the results of our numerical analysis.

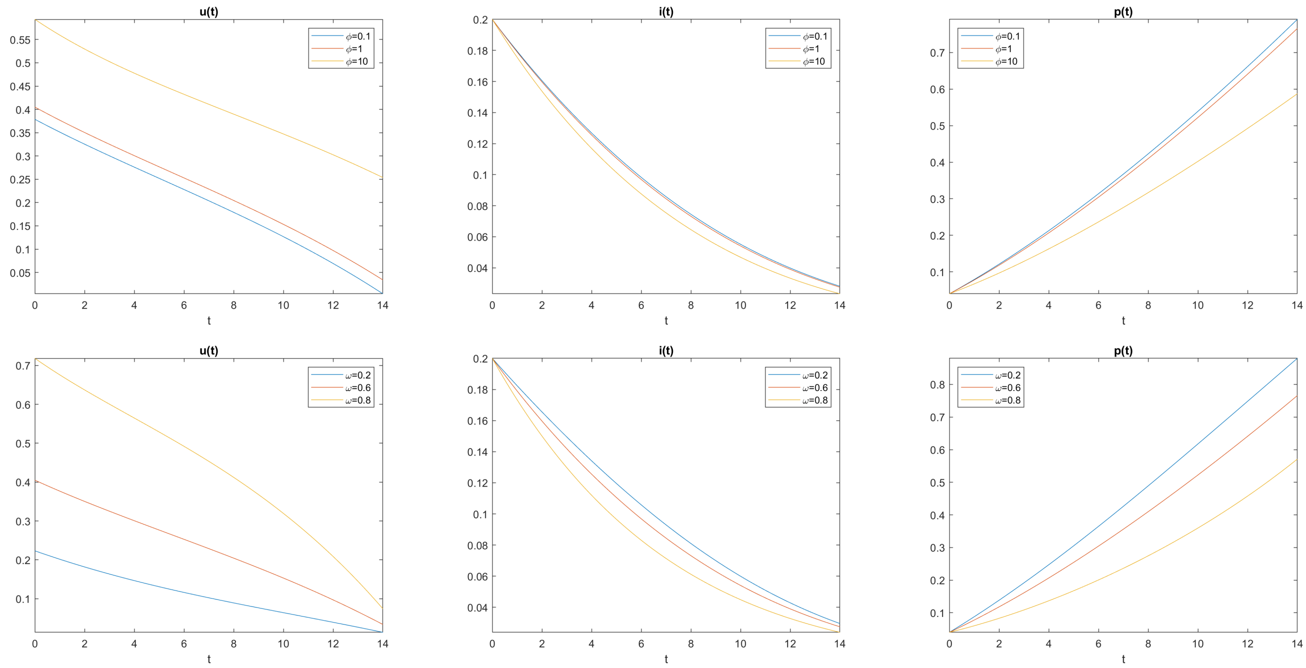

Figure 1: Evolution of social distancing (left), disease prevalence (center) and pollution (right) for different values of sustainability concerns (top) and relative weights of environmental loss (bottom).

Figure 1 shows the dynamics of the social distancing intensity (left panels), of the share of infectives (central panels) and of the pollution stock (right panels), for different values of the degree of sustainability concern (top panels) and the relative weight of the environmental loss in the social cost function (bottom panels), while similarly Figure 2 focuses on the effects of the environmental inefficiency of production activities (top panels) and the dirtiness of the individual response (bottom panels). In all scenarios the qualitative behavior of the variables is the same and in particular social distancing is initially high to then monotonically decrease over time and this generates a monotonic reduction in prevalence which however is not enough to reverse the pollution growth pattern, which instead monotonically increases over time. The effect of the different parameters are quite intuitive. A higher weight for long-run outcomes requires a stronger mitigation policy, which slows down disease incidence reducing both disease prevalence and pollution. Also a higher

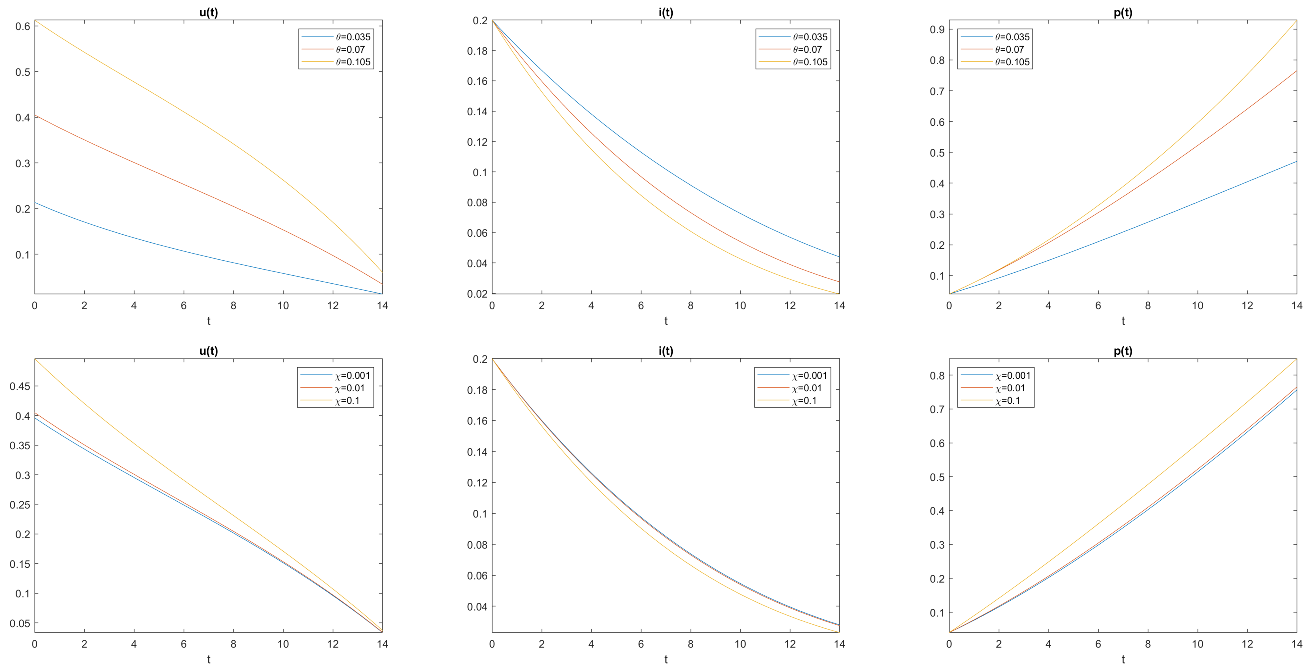

Figure 2: Evolution of social distancing (left), disease prevalence (center) and pollution (right) for different values of environmental inefficiencies of production activities (top) and dirtiness of individual response (bottom).

relative importance for environmental outcomes with respect to social ones needs for a stronger policy intervention, which thus decreases prevalence and pollution. A higher inefficiency of production activities and a higher dirtiness of individual response to the epidemic both lead to higher pollution which thus demands for a stronger mitigation policy to limit the extra deaths due to pollution; by reducing disease prevalence a more stringent social distancing policy tends to reduce pollution; however, this effect is not enough to compensate for its higher environmental inefficiency which instead tends to increase pollution; the latter effect dominates and thus pollution increases with both the degrees of inefficiency and dirtiness.

Figure 3 shows the dynamic evolution of the variables for different initial conditions for the pollution stock (top panels) and the level of disease prevalence (bottom panels). An initially higher pollution stock requires stricter social distancing, which allows for a lower prevalence; despite the lower prevalence tends to reduce pollution, this effect is not enough to compensate for its larger initial value, thus the higher the initial pollution stock the higher the environmental degradation at any moment in time. Similar are the effects of an initially higher disease prevalence. A higher stock of infectives requires stricter social distancing, which allows to decrease incidence and prevalence reducing pollution; despite the lower incidence tends to reduce prevalence, this effect is not enough to compensate for its larger initial value, thus the higher the initial prevalence level the higher disease prevalence at any moment in time.

Consistent with previous works, these figures show that over a finite time horizon it is not possible to achieve disease eradication by employing social distancing measures, even if policy intervention allows for a monotonic reduction in disease prevalence (La Torre et al., 2021b). However, different from previous works which completely abstract from environmental considerations they also suggest that social distancing cannot be used to reduce the side effects generated by the epidemic on the environment. Indeed, social distancing

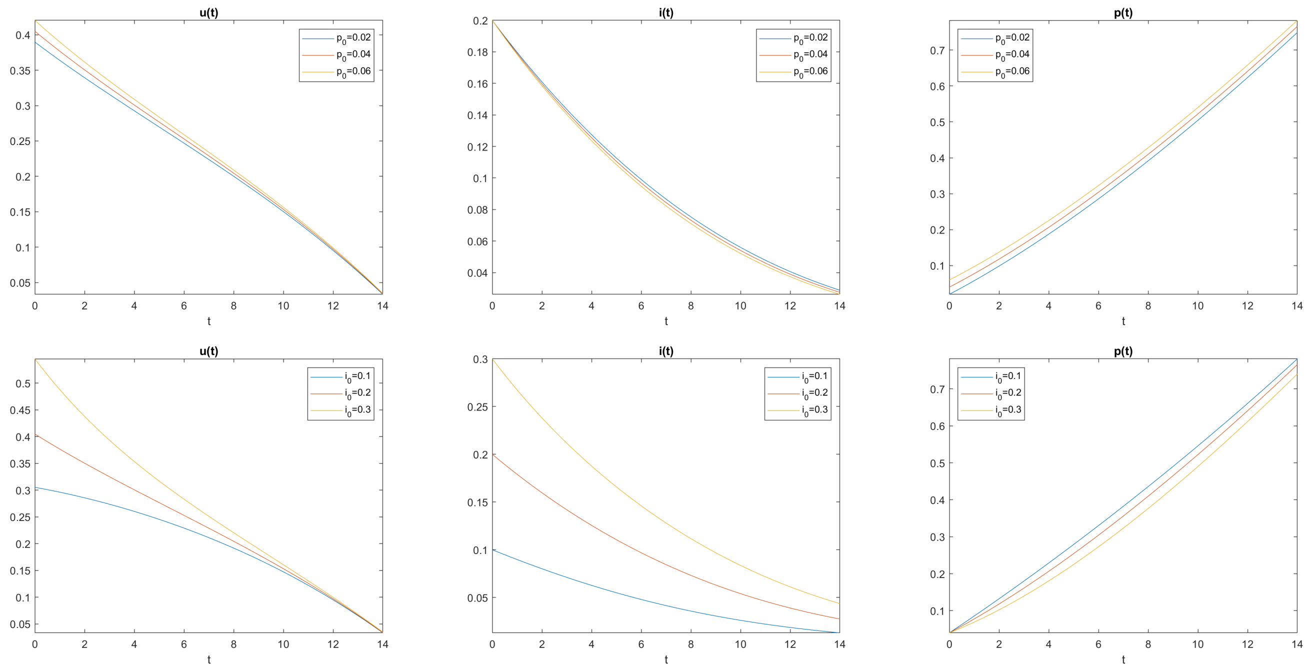

Figure 3: Evolution of social distancing (left), disease prevalence (center) and pollution (right) for different initial conditions for pollution (top), and disease prevalence (bottom).

alone is not enough to reverse the growth pattern of both disease prevalence and pollution. Despite social distancing reduces disease incidence and thus can be effectively used to improve both epidemiological and environmental outcomes, our results surprisingly suggest that it is not optimal to do so but rather it is convenient to rely on social distancing to contain the disease spread reducing its prevalence at the cost of tolerating a higher level of pollution. Therefore, in order to properly managing the pollution problem another policy instrument (i.e., taxes to finance abatement) is needed. This suggests that the strong emphasis that has been placed on epidemic management during the ongoing COVID-19 pandemic, in which environmental issues have been to a large extent neglected from policy considerations, is likely to leave us with a high environmental bill which by deteriorating environmental and climatic conditions will require massive interventions in the near future in order to promote long-run sustainability.

4 The Role of Strategic Interactions

We now extend our baseline model to allow for strategic interactions between economies in order to understand how free-riding opportunities may affect the optimal social distancing policy. Several works have analyzed the role of strategic interactions in determining the relation between the spread of COVID-19 and macroeconomic outcomes (Cui et al., 2020; Bouveret and Mandel, 2021; La Torre et al., 2021a), but none has thus far considered the role played by environmental considerations. All these works discuss how the externality generated by disease dynamics affects the choice of single players while encompassing also environmental dynamics requires to account also for the presence of a pollution externality, thus different from extant literature in our setting both disease prevalence and pollution are transboundary and we wish to characterize how such transboundary features affect the single economy's policy intensity and the joint health-economy-environment outcome.

Specifically, we consider J neighbor economies (i.e., J regions) indexed by $j = 1, 2, \dots, J$ in the absence of interregional movement restrictions, and we focus on the non-cooperative equilibrium in which each region takes its own decision regarding social distancing. Therefore, each region decides independently its social distancing intensity $0 < u_{jt} < 1$. In the absence of restrictions on interregional movements, the disease can spread freely between regions which thus share the same level of disease prevalence, along with the same pollution stock. Individual region's social distancing choice partly contributes to reduce disease incidence, which thus ultimately depends on the average of the social distancing policy between the J regions as follows:

$$\mathcal{I}_t = \alpha \left(1 - \frac{1}{J}\sum_{k=1}^{J} u_{kt}\right) \frac{I_t}{N_t} S_t \tag{5}$$

Disease incidence as in our baseline model drives prevalence and thus emissions determining thus the evolution of pollution. Consistent with the recent COVID-19 experience in which policymakers have announced which level of social distancing would be implemented for a certain short period of time (i.e., usually one or two weeks), we assume that regions determine the policy intensity at the beginning of the planning horizon and commit to such a level for the entire duration of the epidemic management program. Therefore, we characterize the open-loop equilibrium outcome in which the individual region's optimal policy depends only upon time. The complete description of our pollution-extended macroeconomic-epidemiological framework under strategic interactions is presented in appendix B.

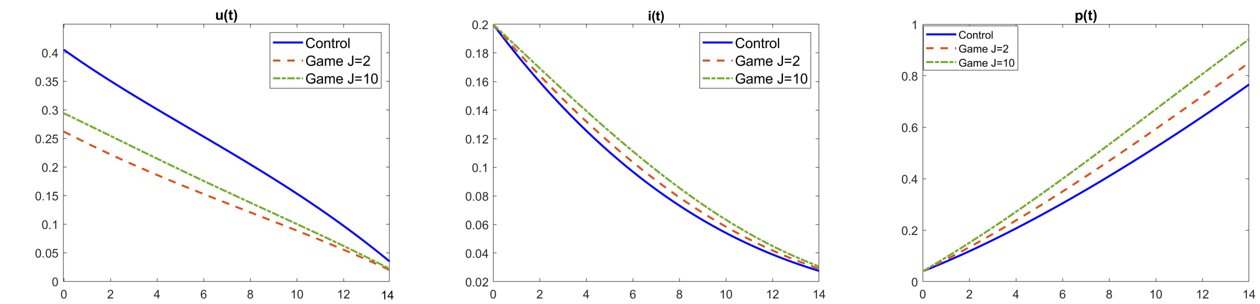

Figure 4: Evolution of social distancing (left), disease prevalence (center) and pollution (right) in the baseline (solid blue) and the strategic interactions model (dashed red, two players) and (dash-dotted green, ten players).

We proceed as before by presenting the results of our numerical analysis based on our previous Italian-data calibration. Figure 4 compares the dynamic evolution of the main variables for our baseline model with no strategic interactions (blue curve) and for the extended model with strategic interactions (red curve, two players, and green curve, ten players,) in the benchmark parameter configuration. Intuitively, because of free-riding effect social distancing is lower and thus both disease prevalence and pollution are higher in the game than in baseline framework. Increasing the number of players (from $J = 2$ to $J = 10$ in the figure) leads to an increase of social distancing, but boosts both disease prevalence and pollution. Apart from the quantitative effects induced by free-riding opportunities, in both setups the variables present the same qualitative behavior. Comparing the two models for different values of the degree of sustainability concern (ϕ), the relative weight of the environmental loss in the social cost function (ω), the environmental inefficiencies of economic production (θ) and the dirtiness of individual response to the epidemic (χ), as well as for different initial conditions for the pollution stock (p_0) and the level of disease prevalence (i_0), leads to qualitatively the same conclusions as those illustrated in Figure 4.

Table 1: Inefficiency induced by free-riding for different values of ϕ and ω. Two players case.

	$\phi = 0.1$	$\phi = 1$	$\phi = 10$	$\omega = 0.2$	$\omega = 0.6$	$\omega = 1.8$
Δu_T	-34.40	-43.07	-38.20	-44.07	-43.07	-37.83
Δi_T	4.58	5.55	11.62	2.38	5.55	10.04
Δp_T	9.56	11.05	22.99	4.69	11.05	23.08

Table 2: Inefficiency induced by free-riding for different values of θ and χ. Two players case.

	$\theta = 0.035$	$\theta = 0.07$	$\theta = 0.105$	$\chi = 0.001$	$\chi = 0.01$	$\chi = 0.1$
Δu_T	-38.43	-43.07	-40.03	-43.07	-43.07	-42.90
Δi_T	4.26	5.55	1.30	5.55	5.55	5.38
Δp_T	3.94	11.05	19.35	10.91	11.05	12.41

In order to assess the inefficiency induced by free-riding, the following tables quantify the outcome differences (in terms of social distancing intensity, disease prevalence and pollution) between our extended and baseline frameworks at the end of the weekly planning horizon measured as a percentage with respect to the baseline model. Tables 1 and 2 focus on how the results change for different parameter values, while Table 3 on the effects of different initial conditions for the two-player ($J = 2$) case.

Table 3: Inefficiency induced by free-riding for different initial conditions. Two players case.

	$i_0 = 0.1$	$i_0 = 0.2$	$i_0 = 0.4$	$p_0 = 0.02$	$p_0 = 0.04$	$p_0 = 0.06$
Δu_T	-44.61	-43.07	-40.65	-42.98	-43.07	-43.15
Δi_T	5.63	5.55	5.43	5.44	5.55	5.65
Δp_T	10.11	11.05	11.81	10.92	11.05	11.18

Overall, free-riding generates sizeable efficiency losses in term of the final prevalence and pollution levels, increasing them by about 5% and 10% respectively. The impact of different initial conditions on the size of inefficiency is particularly limited, while that of the main parameters is more sizeable especially on the final pollution level which in some cases may even exceed 20% (when either the degree of disease concern or the relative weight of environmental loss gets particularly large). These results suggest that allowing individual economies to independently determine the intensity of disease mitigation policies is not an effective approach to reduce final prevalence and pollution levels. This also confirms what stated in extant literature regarding the importance of promote coordination across different economies in order to reduce the losses induced by free-riding (Barrett, 2003; La Torre et al., 2022).

Tables 4, 5 and 6 collect the results for the ten-player ($J = 10$) case, showing the same qualitative behavior as in the two-player case. We can observe in Tables 4, 5 and 6 that although the number of players has been multiplied by five, the relative differences with respect to the baseline model have been approximately doubled. This intuitively suggests that the inefficiency induced by free riding substantially increases with the number of players.

Table 4: Inefficiency induced by free-riding for different values of ϕ and ω. Ten players case.

	$\phi = 0.1$	$\phi = 1$	$\phi = 10$	$\omega = 0.2$	$\omega = 0.6$	$\omega = 1.8$
Δu_T	-28.28	-36.84	-22.38	-41.71	-36.84	-20.61
Δi_T	9.24	11.37	27.71	4.52	11.37	24.46
Δp_T	19.60	22.97	53.84	8.99	22.97	56.64

Table 5: Inefficiency induced by free-riding for different values of θ and χ. Ten players case.

	$\theta = 0.035$	$\theta = 0.07$	$\theta = 0.105$	$\chi = 0.001$	$\chi = 0.01$	$\chi = 0.1$
Δu_T	-35.34	-36.84	-27.32	-36.94	-36.84	-35.73
Δi_T	8.20	11.37	1.76	11.37	11.37	10.98
Δp_T	7.53	22.97	44.94	22.61	22.97	26.42

Table 6: Inefficiency induced by free-riding for different initial conditions. Ten players case.

	$i_0 = 0.1$	$i_0 = 0.2$	$i_0 = 0.4$	$p_0 = 0.02$	$p_0 = 0.04$	$p_0 = 0.06$
Δu_T	-39.37	-36.84	-29.02	-36.82	-36.84	-36.85
Δi_T	11.45	11.37	11.03	11.16	11.37	11.59
Δp_T	20.40	22.97	26.72	22.66	22.97	23.26

5 Conclusion and Policy Implications

The ongoing COVID-19 pandemic has shown more clearly than ever that economy, environment and health are mutually related and that exogenous epidemic shocks may affect them all at once. Despite a growing body of the literature analyzes the nature of the trade off between epidemiological and macroeconomic outcomes involved in disease containment policies, very little has been done to explore the role of environmental factors on optimal mitigation policies. However, this is particularly important since social distancing measures favor a reduction in industrial emissions while health regulations and recommendations contribute to increase it, generating overall unclear effects on pollution, which in turn affects the probability of severe health consequences (including death) following an infection from COVID-19. We thus analyze the extent to which environmental considerations may affect the design of optimal disease containment policy, in the form of social distancing, which by reducing disease incidence allows to decrease prevalence and emissions eventually improving health and environmental outcomes. In particular, we develop a pollution-extended macroeconomic epidemiological model with bilateral health-environment feedback effects through emissions and mortality. By focusing on a calibration based on the Italian COVID-19 experience during the first epidemic wave, we characterize how the optimal social distancing policy depends on the main environmental factors, showing that social distancing alone is not enough to reverse the growth pattern of both disease prevalence and pollution. Indeed, the optimal policy allows for a reduction of disease prevalence only at a cost of a deterioration in environmental outcomes, suggesting that placing too much emphasis on epidemic management as done in the policy arena risks to leave us with a high environmental bill which will require massive efforts in the near future to improve environmental conditions in order to achieve long-run sustainability. We also extend our baseline model to account for the role of strategic interactions between some neighbor economies in which both pollution and disease prevalence are transboundary. In this context we show that free-riding induces important efficiency losses, quantifiable in about 5% excess disease prevalence and 10% excess pollution at the end of the epidemic management program when the number of neighbor economies is two, but this loss substantially higher when the number of interacting economies increases. This suggests that policy coordination is essential in order to effectively mitigate the consequences of infectious diseases.

Some remarks are needed in order to better contextualize our contribution to literature. Even if our discussion has been based on the recent COVID-19 experience, we believe that the degree of applicability of our analysis is much broader. Indeed, our model can be generalized to account for the peculiarities of any large scale socially transmittable disease generating macroeconomic consequences, thus our conclusions regarding the importance of including environmental considerations in the determination of the optimal mitigation policy may extend even to future epidemics. Since biodiversity loss and climate change increase pandemic risk such that epidemics are likely to be more frequent in the future, understanding how to effectively design and implement disease containment plans accounting also for their environmental effects is a priority even in the post COVID-19 era. Moreover, despite we have shown that our qualitative results hold true in different contexts, we wish to stress that our conclusions are driven by the specific COVID-19 parametrization employed in our numerical analysis. Given the large degree of uncertainty surrounding economic and environmental parameters and the large heterogeneity in epidemiological parameters between countries and across diseases, some caution is needed before inferring how the optimal policy might look like in the wake of a future pandemic threat. Nevertheless, we believe our paper sheds some important lights on the complex policy-induced interrelations among health, economy and environment and thus it represents a first step to design more accurate and comprehensive disease containment strategies.

To the best of our knowledge, ours is the first paper exploring how environmental factors may affect the intensity of disease containment policies, thus we have considered a simple and intuitive framework to make our arguments as clear as possible. However, this has precluded us from the possibility to consider some important aspects of the problem. Apart from its effects on mortality, by driving climate change pollution may also affect the likelihood of an epidemic outbreak which is likely to increase the relevance of environmental considerations in determining the optimal policy intensity (Brock and Xepapadeas, 2020). It would thus be interesting to extend our analysis in order to enrich the nature of the feedback health-environment effects and analyze their implications on epidemiological, environmental and macroeconomic outcomes. This is left for future research.

Competing Interests

The authors declare none.

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A The Baseline Model

Before introducing our macroeconomic-epidemiological setup, we briefly review the basic SIS model with vital dynamics, having its origin in the seminal works by Kermack and McKendrick (1927) and Busenberg and van den Driessche (1990), and extend it to account how the disease spread affects and is affected by pollution. The population, N_t, which grows because of natality at rate $b > 0$ and shrinks because of mortality at rate $d > 0$, is composed by healthy individuals who are susceptible to the disease, S_t, and the infectives who have already contracted the disease and can transmit it by getting in contact with susceptibles, I_t. Thus, at any moment in time we have that $N_t = S_t + I_t$, and the interactions between susceptibles and infectives determine the evolution of the two subpopulation groups. Infectives spontaneously recover at the rate $\delta > 0$ but suffer the excess mortality induced by the infection at rate $\bar{\mu} > 0$, and susceptibles become infective by interacting with infectives which occurs at the rate $\alpha > 0$, measuring the number of social contacts required to give rise to a new infection (i.e., the product between the number of contacts between infectives and susceptibles per unit of time and the probability that one contact leads to disease transmission). In order to control the spread of the disease policymakers implement social distancing measures (i.e., lockdowns) to limit the social contacts by a percentage $0 < u_t < 1$ reducing thus disease transmission and disease incidence.

Firms' production and individual households' activities aiming to minimize infection (i.e. purchasing plastic face masks and gloves) drive pollution accumulation, P_t, which increases the disease-induced mortality as follows: $\bar{\mu}_t = \mu(1+\frac{P_t}{N_t})$, where $\mu > 0$ measures the magnitude of such environmental effects on mortality. Pollution accumulates according to the difference between emissions and natural absorption: emissions are proportional to production Y_t at a rate $\theta > 0$ quantifying the dirtiness of economic activities and to disease prevalence at a rate $\chi > 0$ quantifying the dirtiness of individuals' preventive response to the infection, while the pollution decay rate is $\eta > 0$. This implies that the dynamics of susceptibles, infectives, population and pollution can be described through a dynamic system as follows:

$$\begin{aligned}
\dot{S}_t &= bN_t - dS_t + \delta I_t - \alpha(1-u_t)\frac{I_t}{N_t}S_t, && (6)\\
\dot{I}_t &= \alpha(1-u_t)\frac{I_t}{N_t}S_t - \delta I_t - dI_t - \mu\left(1+\frac{P_t}{N_t}\right)I_t, && (7)\\
\dot{N}_t &= (b-d)N_t - \mu\left(1+\frac{P_t}{N_t}\right)I_t, && (8)\\
\dot{P}_t &= \theta Y_t + \chi I_t - \eta P_t. && (9)
\end{aligned}$$

The above system can be recast in terms of susceptible and infective shares, $s_t = \frac{S_t}{N_t}$ and $i_t = \frac{I_t}{N_t}$ respectively, and per capita pollution, $p_t = \frac{P_t}{N_t}$, as follows:

$$\begin{aligned}
\dot{s}_t &= b(1-s_t) + \delta i_t - [\alpha(1-u_t) - \mu(1+p_t)(1-i_t)]i_t s_t, && (10)\\
+\dot{i}_t &= \alpha(1-u_t)i_t s_t - i_t[b+\delta+\mu(1+p_t)(1-i_t)], && (11)\\
\dot{p}_t &= \theta y_t + \chi i_t - [\eta + b - d - \mu(1+p_t)i_t]p_t, && (12)
\end{aligned}$$

where $y_t = \frac{Y_t}{N_t}$ is per capita production. Since $s_t = 1 - i_t$, the above system can be recast in terms of the following planar system:

$$\begin{aligned}
\dot{i}_t &= \alpha(1-u_t)(1-i_t)i_t - [b+\delta+\mu(1+p_t)(1-i_t)]i_t, && (13)\\
\dot{p}_t &= \theta y_t + \chi i_t - [\eta + b - d - \mu(1+p_t)i_t]p_t. && (14)
\end{aligned}$$

As extensively discussed in mathematical epidemiology, the long-run disease outcome depends on the relative intensity of the effective speed of disease transmission, $\alpha(1-u_t)$, and the effective speed of recovery[3], $b+\delta+\mu(1+p_t)$. Only if the latter exceeds the former it may be possible to achieve disease eradication in the long run, and since the effective speed of transmission depends on social distancing public policy may be effectively used to promote eradication. Social distancing by reducing disease incidence limiting the number of possible contacts between susceptibles and infectives allows to decrease both disease prevalence and pollution (through its effects on production activities), improving eventually both epidemiological and environmental outcomes.

After having described a pollution-extended SIS model, we now introduce our macroeconomic setup in which the public policy (i.e., social distancing) intensity is optimally determined. Specifically, we consider a short time horizon framework in which the social planner decides the policy measures to reduce the spread

[3]The relative size of these two factors determines the magnitude of the "basic reproduction number", $\mathcal{R}_0$, measuring the average number of secondary infections produced by a typical infectious individual introduced into a completely susceptible population (Hethcote, 2000; 2008).

of a communicable disease in order to minimize the social cost associated with the epidemic management program. The short time horizon suggests that saving and capital accumulation are irrelevant, thus we simply assume that individuals entirely consume their income as follows: $c_t = y_t$, where $c_t = \frac{C_t}{N_t}$ denotes per capita consumption (while C_t is aggregate consumption). Output is produced through a linear production function by the number of susceptibles as follows: $Q_t = S_t = N_t - I_t$, but since only a certain share of the social contacts, $1-u_t$, is allowed to regularly occur output net of social distancing is given by: $Y_t = (1-u_t)Q_t$, which in per capita terms reads as: $y_t = (1-u_t)(1-i_t)$. The effects of social distancing on health and environment are exactly as discussed before, and thus disease prevalence and pollution dynamics are given by (13) and (14) , respectively.

The social cost is the weighted sum of two terms: the discounted sum ($\rho > 0$ is the time discount rate) of the instantaneous losses associated with the epidemic management program during its duration and the discounted final damage associated with the remaining level of disease prevalence and pollution at the end of the epidemic management program. The instantaneous loss function is the weighted average between two terms capturing the social loss and the environmental loss associated with the epidemic management program. The social loss is assumed to depend on the spread of the disease, the output lost due to social distancing, the passivity, $\Theta = (1-u_t)i_t$, and the lives lost due to the epidemic, $\Delta_t = \mu(1+p_t)i_t$, and to take a quadratic form as follows: $\ell_1(i_t, u_t q_t, \Theta_t, \Delta_t) = \frac{i_t^2 + u_t^2 q_t^2 + (1-u_t)^2 i_t^2 + \mu^2(1+p_t)^2 i_t^2}{2}$, penalizing deviations from the disease-free status, from the no-production-loss and the passivity scenarios and from the no-lives-loss outcome. The environmental loss is assumed to be quadratic in the pollution stock: $\ell_2(p_t) = \frac{p_t^2}{2}$. The relative weight of the environmental loss with respect to the social loss is captured by $\omega > 0$. The final damage function is the weighted average between two terms capturing the social damage and the environmental damage. The social damage is assumed to depend on the share of infectives and the lives lost due to the epidemic at the end of the epidemic management program, and to take a quadratic non-separable form as follows: $\vartheta_1 = \frac{i_T^2[1+\mu^2(1+p_T)^2]}{2}$. The environmental damage is assumed to depend only on the amount of pollution at the end of the epidemic management program, and to take a quadratic form as follows: $\vartheta_2 = \frac{p_T^2}{2}$. The relative weight of the final damage in terms of the instantaneous losses is given by $\frac{\phi}{T} > 0$, which measures the concerns for long-run socio-environmental outcomes proxying sustainability concerns, and depends on the degree of sustainability concern, $\phi > 0$, and the final time period, T. This means that, independently of the degree of sustainability concern, the weight attached to long-run outcomes critically depends on today's distance from the long-run date: the longer the epidemic management program the smaller the importance of the remaining levels of disease prevalence and pollution at the end of the program itself.

Therefore, given the initial conditions $i_0 > 0$ and $p_0 > 0$, the social planner problem reads as follows:

$$
\begin{aligned}
\min_{u_t} \quad & \mathcal{C} = \int_0^T \left\{ \frac{i_t^2 + u_t^2(1-i_t)^2 + (1-u_t)^2 i_t^2 + \mu^2(1+p_t)^2 i_t^2}{2} + \omega \frac{p_t^2}{2} \right\} e^{-\rho t} dt + \phi \left\{ \frac{i_T^2[1+\mu^2(1+p_T)^2]}{2} + \omega \frac{p_T^2}{2} \right\} e^{-\rho T} \\
s.t. \quad & \dot{i}_t = \alpha(1-u_t)(1-i_t)i_t - i_t[b+\delta+\mu(1+p_t)(1-i_t)], \qquad (15) \\
& \dot{p}_t = \theta(1-u_t)(1-i_t) + \chi i_t - [\eta + b - d - \mu(1+p_t)i_t]p_t.
\end{aligned}
$$

From the problem above, it should be clear that social distancing reduces not only disease incidence ($\alpha(1-i_t)i_t$) and thus disease prevalence but also firm's emissions ($\theta(1-i_t)$) and thus pollution, allowing thus to lower disease-induced mortality. However, such beneficial effects on health and environmental outcomes are traded off against a deterioration in macroeconomic conditions which increases the social cost of the epidemic management program.

After some simple algebra, the optimality conditions can be stated as follows, where λ_{it} and λ_{pt} denote the costate variables associated with the share of infectives and the pollution stock respectively:

$$
\begin{cases}
\dot{i}_t = -i_t \left(b + \delta + \frac{\alpha(1-i_t)^2(\theta\lambda_{p_t}+\alpha i_t\lambda_{it}-(1-i_t))}{1-2(1-i_t)i_t} + \mu(1-i_t)(1+p_t) \right), \\
\dot{p}_t = p_t(d - b - \eta + \mu i_t(1+p_t)) - \frac{\theta(1-i_t)^2(\theta\lambda_{p_t}+\alpha i_t\lambda_{it}-(1-i_t))}{1-2(1-i_t)i_t} + \chi i_t, \\
\dot{\lambda}_{it} = \lambda_{it}(b+\delta+\rho-\alpha+\mu(1+p_t)) - \frac{(i_t(\alpha(1-i_t)\lambda_{it}+i_t)+\theta(1-i_t)\lambda_{p_t})((3\alpha\lambda_{it}+\theta\lambda_{p_t}+i_t(3-2i_t)(1-\alpha\lambda_{it})-2)i_t-\alpha\lambda_{it})}{(1-2(1-i_t)i_t)^2} \\
\qquad - \left(2\lambda_{it}(\mu(1+p_t)-\alpha) + \mu^2(1+p_t)^2 + 2\right) i_t + \lambda_{p_t}(\theta - \mu p_t(1+p_t) - \chi), \\
\dot{\lambda}_{p_t} = -\lambda_{p_t}(d - b - \eta - \rho + \mu(1+2p_t)i_t) - \mu^2 {i_t}^2(1+p_t) + \mu(1-i_t)i_t\lambda_{it} - \omega p_t, \\
\lambda_{iT} = \phi\left(1 + \mu^2(1+p_T)^2\right) i_T, \\
\lambda_{pT} = \phi(\mu^2(1+p_T)i_T^2 + \omega p_T), \\
i_{t=0} = i_0, \\
p_{t=0} = p_0.
\end{cases}
$$

Solving explicitly the above system is not possible due to high degree of nonlinearity involved, however it is possible to solve it numerically to visualize the behavior of the optimal policy and dynamics and to explore how they depend on some key parameters. The results shown in the main test represent the numerical solution of the above system based on the parameter values associated with our Italian-data calibration. Specifically, we consider a fortnightly planning horizon by setting $T = 14$. The birth and the death rates are determined according to demographic research as follows: $b = 0.007/365$ and $d = 0.011/365$ (World Bank, 2021). The infectivity and the recovery rates are set from Italian epidemiological studies as $\alpha = 0.1328$ and $\delta = 0.0476$, respectively (La Torre et al., 2021b). Some works show that the probability of dying from COVID-19 increases by 15% by living in areas with one extra unit of particulate matter, from which we determine $\mu = 0.15$ (Wu et al., 2020). The time preference and the pollution decay rate are set according to traditional macroeconomic and environmental economics papers, that is $\rho = 0.04/365$ and $\eta = 0.01$ (Mullingan and Sala-i-Martin, 1993; Economides and Philippopoulos, 2008). The remaining parameters (ϕ, ω ,θ and χ) and the initial conditions (p_0 and i_0) are arbitrarily set as discussed in the main text.

B The Extended Model

In our extended J neighbor economies (i.e., J regions) model in the absence of interregional movement restrictions, since disease incidence depends on the average of the social distancing policy between the J regions, the disease and pollution dynamics, common to all regions, is given by the following equations:

$$
\begin{aligned}
\dot{i}_t &= \alpha \left(1 - \frac{1}{J} \sum_{k=1}^{J} u_{kt} \right) (1-i_t)i_t - i_t[b + \delta + \mu(1+p_t)(1-i_t)], && (16) \\
\dot{p}_t &= \theta \left(1 - \frac{1}{J} \sum_{k=1}^{J} u_{kt} \right) (1-i_t) + \chi i_t - [\eta + b - d - \mu(1+p_t)i_t]p_t. && (17)
\end{aligned}
$$

Therefore, the epidemic management problem in region j can be summarized as follows:

$$
\begin{aligned}
\min_{u_{jt}} \quad & \mathcal{C} = \int_0^T \left\{ \frac{i_t^2 + u_{jt}^2(1-i_t)^2 + (1-u_{jt})^2 i_t^2 + \mu^2(1+p_t)^2 i_t^2}{2} + \omega \frac{p_t^2}{2} \right\} e^{-\rho t} dt + \phi \left\{ \frac{i_T^2[1+\mu^2(1+p_T)^2]}{2} + \omega \frac{p_T^2}{2} \right\} e^{-\rho T} \\
s.t. \quad & \dot{i}_t = \alpha \left(1 - \frac{1}{J} \sum_{k=1}^{J} u_{kt} \right) (1-i_t)i_t - i_t[b+\delta+\mu(1+p_t)(1-i_t)], \\
& \dot{p}_t = \theta \left(1 - \frac{1}{J} \sum_{k=1}^{J} u_{kt} \right) (1-i_t) + \chi i_t - [\eta + b - d - \mu(1+p_t)i_t]p_t.
\end{aligned} \tag{18}
$$

The optimality conditions in a symmetric open-loop Nash equilibrium in which $u_{jt} = u_t$, $\lambda_{ji_t} = \lambda_{it}$ and $\lambda_{jp_t} = \lambda_{p_t}$ for $j = 1, 2, \ldots, J$ read as follows:

$$
\begin{cases}
\dot{i}_t = \dot{i}_t = \alpha\,(1-u_t)\,(1-i_t)i_t - i_t[b+\delta+\mu(1+p_t)(1-i_t)], \\
\dot{p}_t = \theta\,(1-u_t)\,(1-i_t) + \chi i_t - [\eta+b-d-\mu(1+p_t)i_t]p_t, \\
\dot{\lambda}_{it} = \lambda_{it}(b+\delta+\rho+(\mu(1+p_t)-\alpha(1-u_t))(1-2i_t)) + u_t^2 - 2i_t - \mu^2(1+p_t)^2 i_t \\
\qquad\quad +\lambda_{p_t}(\theta(1-u_t) - \mu p_t(1+p_t) - \chi), \\
\dot{\lambda}_{p_t} = -\lambda_{p_t}(d-b-\eta-\rho+\mu(1+2p_t)i_t) - \mu^2 {i_t}^2(1+p_t) + \mu(1-i_t)i_t\lambda_{it} - \omega p_t, \\
u_t = \dfrac{\alpha\lambda_{it}(1-i_t)i_t + \theta\lambda_{p_t}(1-i_t) + J i_t^2}{J((1-i_t)^2 + i_t^2)}, \\
\lambda_{iT} = \phi\left(1+\mu^2(1+p_T)^2\right) i_T, \\
\lambda_{pT} = \phi(\mu^2(1+p_T)i_T^2 + \omega p_T), \\
i_{t=0} = i_0, \\
p_{t=0} = p_0.
\end{cases}
$$