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CAM Risk

# Complementarity, Congestion and Information Design in Epidemics with Strategic Social Behaviour*

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**Abstract**

This paper studies how private information about health states affects social distancing behaviour in epidemics. We propose a social-interaction game where agents are rational and demographically heterogeneous, and the risk of death post-infection depends on demography. Self-tests and public screening campaigns jointly determine the available information. We find that private information determines how the spatial characteristics of the social environment affect agents' strategic interplay: if private information is not available, social distancing decisions are strategic substitutes in any environment; if private information is available, complementarity arises in congestionable environments, and substitutability prevails otherwise. Policy implications ensue: if self-tests that detect illness are freely available, mass screening campaigns with tests that detect recoveries are beneficial in congestionable environments, but increase the death toll in the absence of congestion.

*JEL classification:* C72, D71, H41, I13

*Keywords:* COVID-19, Contagion, Social distancing, Collective action, Strategic complements and substitutes

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*"As for how to enter the city, Renzo had heard in a general way that there were very strict orders to admit no one without a certificate of health, but that on the other hand anyone who used his wits and seized the right moment could enter quite easily. Such was, in fact, the case..."*

— Alessandro Manzoni, *The Betrothed: XXXIV.*

*"< You can't make more stringent ones than those we have now.>*
*<No. But every person in the town must apply them to himself.>*
*Cottard stared at him in a puzzled manner, and Tarrou went on to say that there were far too many slackers, that this plague was everybody's business, and everyone should do his duty."*

— Albert Camus, *The Plague: Part II.*

# 1. Introduction

Among the many lessons to be learnt after the recent SARS-CoV-2 pandemic[1], one is of particular relevance for policy-making: to properly design social-distancing norms is an hard job, but even harder it is to enforce them. In an oft-quoted *Lancet* commentary of March 2020, Anderson et al. (2020b) warned that "*how individuals respond to advice on how best prevent transmission will be as important as government actions, if not more important*"[2]. The concern was readily echoed by many governments and public agencies[3].

The problem with social distancing in epidemics can be summarised as follows: public health is a public good, and *collective interests do not necessarily produce collective action*"[4]. In deciding whether or not to abstain from social activities, rational agents trade off the indirect cost of staying home (forgone income and social activities) with all direct infection-related costs (long-term consequences of illness, possibly death). Circular reasoning arises from the fact that the abstention rate population-wide determines the risk of infection for those who choose not to abstain: the anticipation of widespread abstention reduces the individual willingness to abstain, and *vice versa*. A paradox ensues: effective policies may be self-defeating, because they encourage too much free-riding by decreasing perceived risk.

[1] Unconfirmed early cases of COVID-19 infections date back to October 2019 – see Allam (2020) (Chapter 3) for a detailed timeline of the early stage of the pandemic. On 30 January 2020 the World Health Organisation officially declares the outbreak of COVID-19. With a subsequent PHEIC declaration (Public Health Emergency of International Concern), it raises COVID-19 to the pandemic status on 11 March 2020. The PHEIC is finally lifted on 5 May 2023.

[2] Quoted from page 934. We came across this quotation in McAdams (2020).

[3] See e.g. Maloney and Taskin (2020) (World Bank), ECDC (2020) (EU), and Rutherford et al. (2021) (Scotland).

[4] See Heckathorn (1996), page 250.

Further complications arise when private information enters the scene. Social abstention responds to actual and *perceived* risk, and the latter depends on what the agents know about their health states – their *health beliefs*, in brief[5]: the less vulnerable to contagion they expect to be, the less willing to abstain they are, and *vice versa*. Once they become aware of their states, ill and recovered agents have no incentive whatsoever to abstain from social activities, since they cease to perceive any risk in interactions.

If the provision of health-related information is centralised (e.g. via screening campaigns directly administered by the public authority), no problems arise: ill agents are detected and readily quarantined. However, if the provision of health-related information is private and decentralised (e.g. via marketed self-test), ill agents cannot be isolated, and contagion spreads quicker – as they cease to abstain from social activities throughout the entire epidemic. On this ground, concerns about a widespread use of PCR-based self-tests were indeed expressed in 2021 by the European Center for Disease Prevention and Control (see ECDC (2021a,b)).

This paper studies how private information about agents' health states shapes social-distancing behaviour in epidemics. We propose a simple but rich social-interaction game where, at every point in time, a large population of demographically heterogeneous agents decides whether or not to abstain from social activities to self-protect against contagion. Agents trade-off the direct costs of social abstention with the indirect costs that accrue to the potential exposure to the virus. Collective social behaviour determines the riskiness of interactions together with the spatial characteristics of the social environment. Agents' health beliefs are affected by several informational sources: self-tests and screening campaigns administered by the central authority.

Two are the key results of this paper – theoretical the first, policy-oriented the second.

First, we prove that private information is crucial to understand how the spatial characteristics of the social environment (namely, its *congestionability*) affect social distancing decisions. If no health-related information is privately available to the agents, individual social distancing decisions are strategic substitutes in any social environment. However, if infected agents privately know their states, social distancing decisions among their non-infected counterparties are complements if the social environment is congestionable, and substitutes otherwise. Besides its theoretical interest,

[5] The 'health belief model' is a workhorse psychological model that explains health-related threat perception in terms of *"two beliefs: perceived susceptibility to illness or health breakdown and anticipated severity of the consequences of such illness"* (Abraham and Sheeran (2015)). See Zewdie et al. (2022) for a review of its COVID-19 applications.

the complements-or-substitutes issue is relevant for policy-making. The rational anticipation of high abstention rates (policy effectiveness) has *opposite* effects, in the two strategic regimes, on the actual abstention rate – that *increases* with complementarity and *decreases* with substitutability. Thoroughly-enforced lockdowns are self-enforcing in the first case, and self-defeating in the second.

Second, we characterise the optimal response with informational instruments to the uncontrolled proliferation of self-tests. Self-tests disseminate private information about health states with little or no control by the public authority, thus giving to ill-asymptomatic agents a significant information advantage over the policy-maker. We show that the public provision of health-related information by the policy-maker (e.g. via screening campaigns) in response to such scenario may be socially beneficial or harmful depending on (*i*) the congestionabilitiy of the social environment and (*ii*) the private information that the agents already possess. We evaluate the aggregate effects of four screening regimes: *a*) no tests available – agents use the aggregates to form beliefs about their states; *b*) decentralised self-testing with assays that detect illness – infected agents privately learn their states; *c*) centralised screening with assays that detect immunity – recovered agents learn their states, privately or publicly; *d*) decentralised self-testing with both assays. Our findings are:

*i*) the dissemination of private information about illness is always suboptimal: regardless of the amount of information (if any) provided by centralised screening campaigns, the availability of self-tests increases the death toll;

*ii*) if the dissemination of private information cannot be prevented, the optimal response of the policy-maker (information design) depends on the congestionability of the social environment:

- if the social environment is congestionable, providing additional information about immunity via a centralised screening campaign with assays that detect recoveries reduces the death toll;
- the reverse is true if the social environment is not congestionable: providing no additional information reduces the death toll.

Our contribution to the literature is threefold. First, we complement the extant results on strategic complementarity in social distancing behaviour by proving that the spatial characteristics of the social environment alone can never be a source of complementarity – private information and health beliefs are key ingredients. Second, we qualify the merits of the 'test, test, test' approach to screening policies, advocated by the World Health Organisation (see e.g. WHO (2020)) and the

World Bank Group (see e.g. de Walque et al. (2020)), and endorsed by some scholarly work in the early stage of the pandemic[6]. In particular: we show that massive testing may be suboptimal if agents already possess private information about their health states, and that, in any case, screening policies must be fine-tuned to the spatial characteristics of the social environment. In so doing, we add to the literature on optimal test design. Third, by capturing in reduced-form the effects on congestion, we link the literature on endogenous social-distancing, where the spatial dimension of social interactions is bypassed via the use of aggregative (mean-field) spillover terms, with that on spatial interactions (see e.g. the spatial SIR[7] of Bisin and Moro (2022a,b)), where the 'geography' of interactions is explicitly taken into account.

This paper is structured as follows. Section 2 presents a brief literature review. Section 3 outlines the model. Section 4 presents the complementarity result and studies the role of private information. Section 5 outlines the equilibrium characterisation and further discusses the relevance of private information. Section 6 discusses information design and policy implications. Section 7 wraps up and concludes the paper. Appendix A collects all proofs and derivations. The online appendices B and C provide extensions to the baseline model and additional material.

## 2. Contribution to the Literature

In the spirit of Bisin and Moro (2022b), we deliberately overlook optimal lockdown design[8], and focus instead on the endogenous reaction of decentralised compliance behaviour to exogenous policy prescriptions. Closest to our paper are Chen (2012), Garibaldi et al. (2020a,b), Lebeau (2020), McAdams (2020), Toxvaerd (2020), Engle et al. (2021), Farboodi et al. (2021) and Phelan and Toda (2022): in a SIR epidemiological model *à la* Kermack and McKendrick (1927)[9], they endogenously determine self-protection against contagion via social distancing by a continuum of rational agents

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[6] de Walque et al. (2020) opens with a quotation from Eichenbaum et al. (2021): "The social returns to gathering [..] information and acting upon it is high: it reduces both the death toll and the size of the economic contraction". Choi and Shim (2021) prescriptions may be summarised as 'test massively, test early'.

[7] Susceptible-Infected-Recovered: a mathematical epidemiological model – see Footnote 9 for the details.

[8] Many papers have studied optimal lockdowns: see e.g. Alvarez et al. (2020, 2021), Gonzalez-Eiras and Niepelt (2020), Acemoglu et al. (2021), Eichenbaum et al. (2021), Pestieau and Ponthiere (2022) and Calvia et al. (2023).

[9] Pioneered by Kermack and McKendrick (1927), the SIR(D) framework is a workhorse epidemiological model that reproduces the dynamics of a stylised epidemic via a set of simple differential equations, that govern the transitions in time of a predetermined and fixed amount of interacting 'units' across three or four epidemiological states – Susceptible-Infected-Recovered-(Dead), SIR(D). See Avery et al. (2020) for an overview of the related literature.

that interact strategically[10]. The overall social behaviour determines the risk of contagion in interactions, thus feeding back into individual social distancing. An equilibrium is a configuration such that the individual social distancing is consistent with the risk of contagion it induces in the aggregate. A common result ensues: full self-protection is generally unattainable in equilibrium. Several explanations are put forth. Toxvaerd (2020), Engle et al. (2021) and Farboodi et al. (2021) trace the result back to the fact that social distancing decisions are *strategic substitutes* in the sense of Bulow et al. (1985) – the individual gain from social distancing decreases in the number of agents that opted for the same course of action. Lebeau (2020) and McAdams (2020) find that, if the pleasantness of social activities is taken into account, social distancing decisions can be *strategic complements* – the individual gain from social distancing increases in the number of agents that opted for the same course of action. More interactions increase the risk of contagion, but also the utility that agents derive from social activities. Dasaratha (2023) also allows for complementarity by allowing for *ad hoc* positive spillovers. Garibaldi et al. (2020a,b) consider an even richer payoff structure. Chen (2012) highlights that social distancing decisions can be both complements and substitutes depending of the matching technology that governs interactions – if the latter exhibits 'saturation' social distancing decisions are complements; otherwise, they are substitutes.

Our paper shares with these contributions a common modelling approach – it is a canonical SIR(D) model, augmented with endogenous social distancing behaviour by agents assumed rational and strategically sophisticated. However, our results differ in three significant respects.

First, we highlight that strategic complementarity can arise from the contagion mechanism itself, without appealing to warm-glow spillovers from collective social behaviour. This complements the results of Lebeau (2020) and McAdams (2020) – where complementarity arises from the fact that social activities entail psychological benefits that increase in the total mass of interactions and may offset infection-related costs at some point in time.

Second, we prove that private health-related information is crucial to understand under which conditions complementarity can indeed arise. In an early contribution, Chen (2012) already showed that social-distancing decisions can be complements if the risk of infection decreases in the number

[10] In Garibaldi et al. (2020a,b), Lebeau (2020) and Farboodi et al. (2021) self-protection amounts to a reduction in social activities – e.g. in the number social interactions per-period. In Toxvaerd (2020) and Engle et al. (2021), self-protection is the level of costly 'vigilance' an individual exerts when interacting with others – e.g. wearing a mask, avoiding handshaking –, and it is modelled as continuous choices variable that scales down the disease passing rate.

of social interactions. When this occurs, the matching technology is said to display 'saturation': additional interactions dilute the risk of contagion by 'crowding out' matchings with infected counterparties. According to Chen (2012), complementarity boils down to a physical property of the matching technology (saturation), and no explanation is provided about *why* the matching technology may exhibit such property[11]. We complement and qualify the result of Chen (2012) in two respects. First, by proving that it is private information, not the matching technology, that drives complementarity[12]. Indeed, what we find is that saturation is *not* a property of the matching technology *per se*; rather, it is a by-product of the informational state of agents: if ill agents do not privately know to be so, saturation can *never* occur regardless of the workings of the matching technology. Second, having characterised what saturation really is, we are able to determine why and under which conditions saturation can indeed occur. What we find is that if ($i$) the average physical proximity of interactions is high because the social environment is congestionable, and ($ii$) ill agents privately know to be so, saturation occurs and complementarity arises; if the social environment is congestionable, but no private information is available, saturation is absent and complementarity can never arise. The take home message is therefore: the matching technology *per se* does not generate complementarity, nor can it be its primary driver: it is private information that really makes the difference.

Third, we account for the uneven exposure to disease-related costs that stems from heterogeneity in demographic traits. Garibaldi et al. (2020a,b), Lebeau (2020), McAdams (2020), Toxvaerd (2020), Engle et al. (2021) and Farboodi et al. (2021) all consider homogeneous populations, thus overlooking that the uneven distribution of risk-taking affects the death toll. In this respect, closer in spirit to our model are Kremer (1996) and Greenwood et al. (2019), both dealing with HIV/AIDS, and Acemoglu et al. (2021) and Brotherhood et al. (2020), both dealing with SARS-CoV-2[13]. Similarly to our model, these contributions account for heterogeneity in disease-related costs. Differently from our model, they focus on environments where heterogeneity is either 'dichotomous' (young vs. old in Brotherhood et al. (2020), short- vs. far-sighted in Greenwood et al. (2019)) or 'discrete' (as in the

[11] The crowding-out effect described by Chen (2012) describes *how* saturability works, but does not explain *why* saturability may arise in the first place.

[12] Chen (2012) overlooks the role of information since he assumes *a priori* that infected agents know their states.

[13] Kaplan et al. (2020), too, consider heterogeneous agents within an economic-epidemiological model. However, in their contribution heterogeneity is postulated on economic variables (employment status), and determines the exposure of the individual to epidemic-related economic shocks.

‘multi-group’ SIR of Acemoglu et al. (2021)). In our model, disease-related costs vary continuously with demographic traits, thus potentially allowing for the analysis of targeted lockdowns where subgroups are endogenously determined – we discuss this issue in the conclusions.

Since we deal with private information and information design, our paper also relates to the recent literature on (optimal) testing. Most of the literature deals with the optimal allocation of a scarce testing capacity with imperfect enforcement of conditional quarantines, with tests directly administered by the public authority – see e.g. Troger (2020), Lipnowski and Ravid (2021),Acemoglu et al. (2023),Finster et al. (2022), Hu and Zhou (2022), Phelan and Toda (2022), Piguillem and Shi (2022), Akbarpour et al. (2024) and Bobkova et al. (2024). Our approach is different in two respects. First, we overlook the scarcity problem, and assume instead that tests are available in unrestricted supply: rationing (if any) boils down to a deliberate decision of the policy-maker to limit information provision. Second, we focus on the aggregate effects of the provision of *private* health-related information (acquired by the agents via self-tests), and study the potential problems that arise from the informational advantage they give to ill-asymptomatics. In this respect, closer in spirit to our model is Troger (2020) that, in a static mechanism-design framework, accounts for the role of private information. In Troger (2020), voluntary testing entails direct costs and benefits, and no dynamic analysis is performed. Coversely: testing is free in our framework; we simulate virus dynamics conditional to several testing strategies; we relate their evolution to the spatial characteristics of the social environment. Our model considers a two-test battery with different diagnostic targets – PCR to detect illness, antibody serology to detect immunity from recovery. In this respect, it relates to the analysis of Acemoglu et al. (2024), but with a different focus: while Acemoglu et al. (2024) consider tests with imperfect sensitivity directly administered by the central authority, we analyse perfect tests whose use is fully decentralised.

## 3. Social-Interaction Game

An infectious disease spreads in discrete time $t = 1, 2, \dots, T$ in a measure-one continuum of atomistic agents, uniformly distributed over the unit interval and indexed by $i$. Agents are risk-neutral[14] and have heterogeneous demographic traits – age, sex, general health conditions, presence of pre-

[14] The assumption is without significant loss of generality. In the online Appendix C we extend the analysis to agents with a generic risk attitude.

existing/chronic pathologies and the like. The *demographic profile*

$$x(i) := \bar{x} + \varepsilon(i)\,, \qquad \text{with } \{\varepsilon(i)\}_{i\in[0,1]} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0\,,\sigma_x^2\right), \tag{1}$$

summarises the demographic traits of agent $i$, and determines his/her resilience to the disease – the smaller $x(i)$, the younger/healthier agent $i$ is, the higher his/her resilience, and *vice versa*. Accordingly, $\bar{x} \in \mathbb{R}$ is the average demographic type population-wide, and $\sigma_x > 0$ parameterises cross-sectional demographic heterogeneity[15]. At every point in time, every agent $i$ self-protects against the disease by choosing his/her abstinence $a_t(i) \in [0,1]$ from social activities – the higher $a_t(i)$, the lower the risk of contagion, *ceteris paribus*. Individual choices are decentralised, rational and strategic.

### 3.1 Disease

At $t=0$, $\widehat{NI}_0 \in (0,1)$ agents suddenly turn infected 'out of thin air': contagion begins. Ill agents remain asymptomatic forever with probability $p \in (0,1)$, and show disease-specific symptoms otherwise. All symptomatics are recognised and quarantined immediately, so that contagion is driven only by the asymptomatics. At every point in time, ill individuals: $(i)$ die with probability

$$q^D(x) := \Phi\big(\theta + \alpha x\big), \qquad \text{with } \alpha > 0 \text{ and } \Phi(\,\cdot\,) \text{ the Normal standard CDF}\,, \tag{2}$$

that strictly increases in $x$ since older/weaker individuals are less resilient to the disease[16]; $(ii)$ recover with probability

$$q^R(x) := \gamma\big(1 - q^D(x)\big), \qquad \text{with } \gamma \in (0,1)\,, \tag{3}$$

and stay immune forever; $(iii)$ remain ill, hence infective, with probability $q^I(x) := (1-\gamma)(1-q^D(x))$. An agent that does not display symptoms is therefore either susceptible $(s)$, ill-asymptomatic $(asy)$ or recovered $(r)$. We call

$$e_t(i) \in \mathbf{e} := \{s, asy, r\} \tag{4}$$

the *individual health state* of agent $i$ at the beginning of period $t$, and

$$\langle\, S_t, ASY_t, R_t \,\rangle =: E_t \in \mathbf{E} \subset [0,1]^3 \tag{5}$$

the *aggregate state of the epidemic* at the beginning of the same period – with $S_t$, $ASY_t$ and $R_t$,

[15] Extending LLN reasoning to continua of i.i.d. random variables $\int_0^1 x(i)\,\mathrm{d}i = \int_0^1 \bar{x}\,\mathrm{d}i + \int_0^1 \varepsilon(i)\,\mathrm{d}i = \bar{x}$ holds almost surely, since $\int_0^1 \varepsilon(i)\,\mathrm{d}i = \mathbb{E}\left[\varepsilon(i)\right] = 0$ holds almost surely – see Judd (1985) and Vives (1988, 2014).

[16] The common component $\theta \in \mathbb{R}$ is a disease-specific driver of mortality that represents the fact that some diseases are more aggressive than others, *ceteris paribus*.

respectively, the total masses of susceptibles, ill-asymptomatics and recovered. The beginning-of-period total mass of ill agents (symptomatics plus asymptomatics) is $I_t$.

## 3.2 Contagion

Ill-asymptomatics spread contagion by interacting with susceptibles in a stylised 'social environment'. At every point in time, the probability of infection faced by a susceptible agent is affected by: *(i)* the intensity $1 - a_t(i) \in [0, 1]$ of his/her social life – the more intense, the higher the probability of contagion; *(ii)* the composition of the interacting population – the larger the share of ill-asymptomatics, the higher the probability of contagion; *(iii)* the spatial characteristics of the social environment – the more congestionable it is, the higher the probability of contagion. We call

$$A_t \;=\; \int_0^1 (1 - a_t(i))\,\mathrm{d}i \tag{6}$$

the average intensity of social life population-wide in period $t$, with $M(A_t)$ the total mass of social interactions generated by $A_t$. Accordingly, we define

$$G(A_t) \;:=\; \beta \underbrace{\left(\frac{\#ASY[M(A_t)]}{M(A_t)}\right)}_{:=\,\pi(A_t)} \underbrace{\Big(M(A_t)\Big)^{\phi}}_{:=\,\varphi(A_t)}, \qquad \text{with } \phi > 0\,, \tag{7}$$

the average risk of contagion, with $\#ASY[M(A_t)]$ the mass of interactions among the $M(A_t)$ that involve ill-asymptomatics, $\beta \in (0, 1)$ the disease-specific contagiousness, and $\pi(A_t)$ and $\varphi(A_t)$, respectively, the *intensive and extensive margin of contagion.* $G(A_t)$ can be interpreted as a matching function, that collapses the tangle of pairwise social interactions into a single mean-field term – that represents, in reduced form, all feedbacks from collective social behaviour. In particular:

*i)* the intensive margin $\pi(A_t)$ is the disease prevalence in the interacting population, and therefore proxies the probability to interact with an ill-asymptomatic counterparty;

*ii)* the extensive margin $\varphi(A_t)$ scales how quickly the probability of contagion increases in the total mass $M(A_t)$ of interactions: given $\pi(A_t)$, it increases quickly if the environment is congestionable ($\phi \in (0, 1)$: $\varphi(A_t)$ is concave), and slowly otherwise ($\phi > 1$: $\varphi(A_t)$ is convex).

The extensive margin $\varphi(A_t)$ captures the importance of physical proximity in determining how fast contagion spreads. The intuition is the following: if the social environment is congestionable, the average physical proximity of interactions is high(er): droplets, aerosols and airborne particles increase the probability of contagion for all interacting individuals, even if they are not directly facing an infected counterparty[17] – aerosols and droplets had indeed been crucial in the spread of SARS-CoV-2, see e.g. Anderson et al. (2020a). To sum up: the extensive margin of contagion captures the idea that, for any given pattern of interactions, the spatial characteristics of the social environment speed up or slow down contagion, hence virus dynamics.

### 3.3 Essential Activities

As in Alvarez et al. (2020, 2021) and Calvia et al. (2023), we assume that a share $(1 - L) \in [0, 1]$ of agents is employed in activities deemed 'essential', whose operations must be ensured *"even in a disaster scenario"*[18] – production of food and energy, provision of healthcare services, public security and transportation among others. $a_t(i) = 0$ holds by assumption for all these agents in all periods, since they must interact with others to carry out their professional duties. For simplicity, we further assume that the demographic composition of the essential cluster $1 - L$ is identical to that of the overall population.

### 3.4 Dynamics

Every period $t$ has an internal sequential structure that governs how events unfold:

| | |
|---|---|
| beginning-of-period: | the initial state of the epidemic in period $t$, $E_t$, is determined by the evolution of the aggregates in the previous period $t - 1$. |
| belief updating: | all agents form health beliefs using the available information $\mathcal{I}_t^i$, and assess the risk of contagion in social interactions at state $E_t$ by rationally anticipating the social behaviour of all other agents. |
| social interactions: | all agents choose optimally their levels of social abstention $a_t(i)$, thus determining the total mass of interactions $M(A_t)$. |
| variations in the aggregates: | social interactions determine the mass of new infections $NI_t$ via the matching function $G(A_t)$; agents that got infected in previous periods die (new deaths $= ND_t$) and recover (new recoveries $= NR_t$). |

[17] To fix ideas: a congestionable environment is a closed, overcrowded, poorly ventilated space (e.g. public transportation), while its non-congestionable counterpart is open and airy (e.g. streets and parks). In the online Appendix C we provide a spatial-interaction model that microfounds the extensive margin $\varphi(A_t)$.

[18] Quoted from Alvarez et al. (2020), page 5.

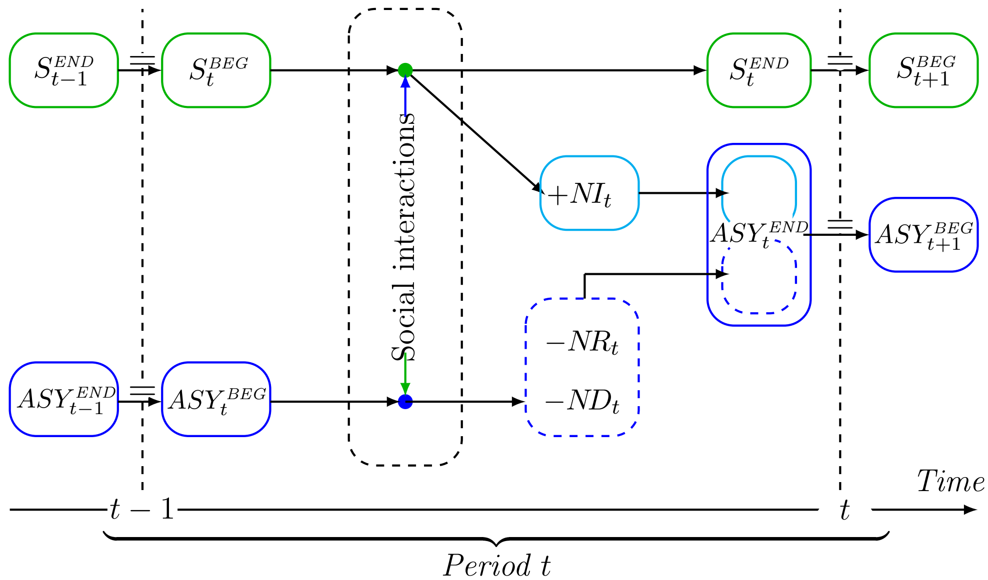


**Figure 1.** Within-period sequential structure of events.

The state $E_t$, net of all within-period variations, determines the initial state of the subsequent period $t+1$ – Figure 1 fixes ideas. The mass of new infections $NI_t$ is given by

$$NI_t \;=\; S_t(1-A_tL)G(A_t)\,. \tag{8}$$

For consistency, we assume that newly-infected in period $t$ begin to die and recover from $t+1$ on.

A key strength of our model is that, at every point in time, mortality rates are both endogenous and *cohort-specific*: not only do they vary with social behaviour, they also reflect the demographic composition of new infections. In equilibrium, the exposure to contagion varies across agents, since the less resilient agents self-protect more, *ceteris paribus*, than the most resilient ones. The demographic composition of each cohort of newly-infected varies accordingly – if the share of resilient agents is relatively high, the cohort-specific mortality rate is relatively low, and *vice versa*. We keep track of this dynamics by defining the average mortality rate of any new cohort $NI_t$ as

$$\bar{Q}^D(A_t) \;=\; \left(\frac{1-L}{1-A_tL}\right)\bar{q}^D + \left(\frac{L(1-A_t)}{1-A_tL}\right)\int_{-\infty}^{+\infty}\Big[\,q^D(x)\big(1-a_t(x)\big)\Big]\,\phi\left(\frac{x-\bar{x}}{\sigma_x}\right)\mathrm{d}x\,, \tag{9}$$

with

$$\bar{q}^D \;=\; \Phi\left(\frac{\theta+\alpha\,\bar{x}}{\sqrt{1+\alpha^2\sigma^2}}\right)$$

the average mortality rate population-wide[19], and where $\phi(\,\cdot\,)$ indicates the Normal standard PDF. Recovery rates are defined accordingly via (3).

[19] Via Corollary 1 in Ellison (1964) (page 93) we know that, for any random variable $Z$ with $Z\sim\mathcal{N}(\mu_Z,\sigma_Z^2)$, $\mathbb{E}[\Phi\,(Z)] \;=\; \Phi(\mu_Z/\sqrt{1+\sigma_Z^2})$ holds almost surely. See also Owen (1980).

### 3.5 Payoffs

Death entails a private cost $D \gg 0$ identical for all agents, that have common time preferences summarised by the discount factor $\lambda \in (0,1)$. The *discounted cost of death* faced by a newly-infected in period $t$ with demographic profile $x$ is therefore[20]

$$\widetilde{D}^i(x) \;=\; \lambda D \left[ \frac{q^D(x)}{1-\lambda\,(1-\gamma)\,\big(1-q^D(x)\big)} \right]. \tag{10}$$

As it is often assumed in the literature, agents are myopic: they know via (10) that infection entails a stream of future costs, but fail to anticipate that current behaviour affects future decision-making. Indicating with $v_t^i(\bar{e}) = \Pr(e(i)=\bar{e}\,|\,\mathcal{I}_t^i)$ the probability of being in health state $\bar{e} \in \{s, asy, r\}$ at the beginning of period $t$, estimated by agent $i$ conditioning on information $\mathcal{I}_t^i$, we define the individual expected utility $u(a_t(i)\,|\,\mathcal{I}_t^i; x(i), A_t, E_t) \;\equiv\; U_t^i$ as

$$U_t^i \;:=\; -\frac{c}{\delta}a_t(i)^\delta + \omega(i)a_t(i) - v_t^i(s)\left[\left(1-\frac{a_t(i)}{K(\delta)}\right)\widetilde{D}^i(x)G(A_t)\right] - v_t^i(asy)\Big[q^D(x)D + \widetilde{D}^i(x)\Big], \tag{11}$$

with $c > 0$ and $\delta \geq 1$, and where $-a_t(i)^2 c/\delta$ is the private cost of social abstention, $K(\delta) \geq 1$ is a normalising constant that rules out corner solutions for $\delta > 1$[21], and

$$\omega(i) \;:=\; \bar{\omega} + \eta(i)\,, \quad \text{with } \{\eta(i)\}_{i\in[0,1]} \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0\,,\sigma_\omega^2\right) \text{ for all } i\,, \tag{12}$$

is an idiosyncratic 'moral' component, that captures the fact that agents may be willing to abstain from social activities even if they know not to be vulnerable to contagion – e.g. out of sense of duty. We allow $x$ and $\omega$ to be correlated, with $\rho \in [-1,+1]$ their Pearson correlation coefficient. The moral components $\omega$ add some realism to the model but are inessential for its results.

Note that the coefficient $\delta$, that scales the private cost of abstention, can be interpreted as a proxy for lockdown design: $\delta = 1$ entails a binary choice between extremes ($a_t^*(i) \in \{0,1\}$), while $\delta > 1$ allows for internal solutions ($a_t^*(i) \in (0,1)$). The former case proxies a strict lockdown policy, where agents are required to stay home, and every deviation, however small, amounts to non-compliance. The latter case proxies a milder social-distancing policy, where agents face a menu of alternatives – stay home, go out but wear a mask, go out but avoid overcrowded places, and the like.

[20] See the online Appendix B1 for its derivation.

[21] And with the convention that $K(1) = 1$ without any loss of generality.

# 4. Complementarity, Congestion and Private Information

In a rational-choice environment as that outlined in Section 3, virus dynamics depend on the strategic interplay between agents' decision-making. Social distancing decisions are strategic substitutes in the sense of Bulow et al. (1985) if the marginal benefit of social abstention decreases in the aggregate abstention population-wide. Otherwise, they are strategic complements. Negative feedbacks arise in the former case: any increase in aggregate social abstention decreases the individual willingness to abstain, and *vice versa*. Positive feedbacks arise in the latter case: any increase in aggregate social abstention increases the individual willingness to abstain.

Besides its theoretical interest, the complements-or-substitutes issue is relevant for policy-making. If substitutability prevails, lockdowns can be self-defeating: the rational anticipation of widespread abstention reduces the willingness to abstain in the first place, thus fostering, in equilibrium, lower self-protection and higher risk of contagion. Conversely, if complementarity prevails, lockdowns can be self-fulfilling: the rational anticipation of widespread abstention further encourages individual abstention, thus fostering, in equilibrium, higher self-protection and lower risk. Instability is the other side of the coin of complementarity: the same positive feedbacks that sustain social abstention suddenly drive it down when the tide changes – i.e. when agents lose confidence in others' willingness to abstain. Overall, social distancing behaviour is relatively stable with substitutability, and highly volatile with complementarity.

In this section we characterise necessary and sufficient conditions for strategic complementarity that are valid both in- and out-of-equilibrium. In so doing, we prove that, together with the spatial characteristics of the social environment, private information about health states is crucial to determine the complements-or-substitutes nature of the strategic interplay.

## 4.1 Sufficient Conditions for Complementarity

Recall that, at every point in time, $\delta = 1$ entails a dichotomous choice between zero and full abstention, while $\delta > 1$ brings about internal solutions $a_t^* \in (0, 1)$ and smooth responses to changes in the state of the epidemic. When the action space is binary, individual actions are strategic complements if the net utility gain/loss experienced by agent $i$ in switching from zero to full abstention (his/her *payoff differential*) increases in the mass of individuals that opted for the full abstention. Via (11), we define

$$\Delta U_t^i(1,0) \,=\, v_t^i(s)\widetilde{D}^i(x)G(A_t) + \omega(i) - c \tag{13}$$

the payoff differential of agent $i$. When the action space is continuous, individual actions are strategic complements if the cross-derivative $\partial^2 U_t^i/\partial a_t(i)\partial A_t$ increases in the aggregate level of social abstention $A_t$. Via (11) and (13), it is immediate to check that

$$\frac{\partial^2}{\partial a_t(i)\partial A_t} U_t^i \,\propto\, \frac{\partial}{\partial A_t}\Delta U_t^i(1,0) \,=\, v_t^i(s)\widetilde{D}^i(x)\frac{\partial}{\partial A_t}G(A_t) \tag{14}$$

holds for all agents $i$ at all states $E_t$. Therefore, individual social distancing decisions are strategic complements if $\partial G(A_t)/\partial A_t \geq 0$, and strategic substitutes otherwise. Note that $\partial G(A_t)/\partial A_t \geq 0$ implies that the risk of contagion *increases* in the average level of social abstention: in the parlance of Heesterbeek and Metz (1993) and Chen (2012), this amounts to saying that the matching function $G(A_t)$ exhibits 'saturation'. Via (7) and expression (14), the following result can be proved.

**PROPOSITION 1.**

*Let $\delta \geq 1$ hold. Moreover, let disease prevalence be strictly positive, so that $\#ASY_t[M(A_t)] > 0$ holds. Then, if all ill-asymptomatics privately know to be invulnerable to contagion, the social distancing decisions of all other agents are:*

*i) strategic complements if $\phi \in (0,1)$ – i.e. if the social environment is congestionable;*

*ii) strategic substitutes if $\phi > 1$ – i.e. if the social environment is not congestionable.*

*Formally: if $v_t^i(s \,|\, e_t(i) = asy) = 0$ holds for all agents $i$ with $e_t(i) = asy$, then $\phi \in (0,1)$ is a sufficient condition for $\partial G(A_t)/\partial A_t > 0$ to hold.*

*Proof.* See Appendix A.1. □

In words: Proposition 1 states that congestionability ($\phi \in (0,1)$) is a sufficient condition for strategic complementarity if all ill-asymptomatics know to be invulnerable to contagion. The intuition is the following. Individual agents care about collective social behaviour just because the latter determines the riskiness of social interactions – hence, the marginal private value of social abstention. Direct consequence is that a rational agent ceases to behave strategically once he/she becomes aware to be invulnerable to contagion: his/her social abstention, if any, is solely driven by the idiosyncratic moral concerns summarised by the utility component $\omega(i)$. Ill-asymptomatics face no risk of contagion by definition, since they are already ill. Therefore, once the awareness of being invulnerable severs the strategic link between their social behaviour and that of all other agents, the mass of social interactions that involve ill-asymptomatics becomes *fixed*[22]. When this is the case, any increase in the aggregate social abstention amounts by construction to an increase in the relative mass of interactions involving ill-asymptomatic parties, hence to an increase in the *ex ante* probability to interact with an ill-asymptomatic – *vice versa* for a decrease in the aggregate abstention. Social distancing turns into a coordination game: the anticipation of high(er) social abstention increases in the first place the willingness to abstain of susceptibles and recovered, since the anticipated risk of contagion becomes high(er).

Proposition 1 identifies a sufficient condition for complementarity that does not hinge on equilibrium behaviour. Nothing more can be said about the complements-or-substitutes issue out-of-equilibrium. The following corollary highlights the result.

**COROLLARY 1.**

*If the ill-asymptomatics do not know to be invulnerable, nothing can be said a priori about the strategic nature of social distancing decisions out-of-equilibrium: they can be both complements or substitutes.*

*Proof.* See Appendix A.2. □

In Section 5 we prove that, in equilibrium, the indeterminacy highlighted by Corollary 1 is resolved by private information, that turns congestionability into a *necessary* condition for complementarity.

### 4.2 The Importance of Private Information

Taken together, Proposition 1 and Corollary 1 prove that the spatial characteristics of the social environment are relevant to predict if strategic complementarity can *potentially* arise in epidemics, but it is agents' private information that actually determines whether or not such potential is ever to be realised. If the social environment is congestionable, social distancing decisions *may* be complements under generic information structures, but they are complements *for sure* if ill-asymptomatics privately know to be invulnerable. These are robust results, since they do not hinge on the consistency imposed by equilibrium behaviour: they are true in every state, at every point in time, for every arbitrary social behaviour and regardless of how agents form their health beliefs.

[22] Formally, the element $\#ASY[M(A_t)]$ in the matching function $G(A_t)$ becomes a parameter – see definition (7).

# 5. Equilibrium Characterisation

Health beliefs play at best an ancillary role in the extant literature on endogenous social distancing. The neglect seems to be warranted by the observation that similar results can often be derived under opposite assumptions about what the agents know. Toxvaerd (2020), Engle et al. (2021) and Farboodi et al. (2021), for instance, all find that equilibrium social distancing decisions are strategic substitutes: but the agents of Toxvaerd (2020) privately know their true health states, whereas those of Engle et al. (2021) and Farboodi et al. (2021) use the observed aggregates to form common health beliefs. Similarly, McAdams (2020) and Lebeau (2020) both have complementarity results: but the agents of Lebeau (2020) privately know their true health states, whereas those of McAdams (2020) have common health beliefs driven by the observed aggregates.

We already showed in Section 4 that health beliefs actually shape the strategic environment when congestionability is taken into account. We also highlighted that, in this respect, it is what agents *privately* know that really matters: complementarity is only a potential if the social environment is congestionable, but becomes a reality if ill-asymptomatics privately know to be invulnerable. We now complete the analysis by proving that, in equilibrium, private information is even more crucial to the strategic interplay: if ill-asymptomatics do not know to be invulnerable, social distancing decisions can *never* be complements in equilibrium, even if the social environment is congestionable. If congestion is present but ill-asymptomatics do not know to be invulnerable, social distancing decisions are strategic substitutes as they would be in a non-congestionable environment. We then compare our complementarity result with those already established by the literature.

## 5.1 Belief Updating and Characterisation

As it is commonplace in the literature, we focus on two extreme cases. At every point in time, agents either $(i)$ do not possess any information about their health states ($\mathcal{I}_t^i = \{\varnothing\}$), or $(ii)$ they perfectly know them ($\mathcal{I}_t^i = \{e_t(i)\}$)[23]. In the former case, agents use the observed aggregates to form *common* health beliefs, whereby

$$v_t^i(s\,|\varnothing\,) \;=\; \frac{S_t}{S_t + ASY_t + pR_t} \qquad \text{for all } i \text{ at every } t \geq 1\,. \tag{15}$$

[23] Less extreme cases will be studied in Section 6. In the online Appendix C we also explore the possibility that health belief depend on the entire history of past social behaviour.

In words: at every $t$, the subjective probability of being susceptible (the *expected vulnerability*) coincides with the share of susceptible agents among those that never showed symptoms in the past – note indeed that the $(1-p)R_t$ recovered from symptomatic illness know for sure to be immune. In the latter case, it holds that

$$v_t^i(s \mid e_t(i)) \;=\; \begin{cases} 1 & \text{if } e_t(i) = s\,, \\ 0 & \text{otherwise}\,, \end{cases} \qquad \text{for all } i \text{ at every } t \geq 1\,. \tag{16}$$

For the moment, these two information structures are taken as exogenous scenarios. We will show in Section 6 that both scenarios can be obtained as the byproduct of optimal information design by a benevolent policy-maker that administers mass-screening campaigns to reduce the death toll. The following proposition outlines the equilibrium characterisation in the two informational scenarios.

**PROPOSITION 2.**

*Let $\mathcal{I}_t^i \in \{\{\varnothing\}, \{e_t(i)\}\}$ hold. Then, in every period $t$:*

*i) for $\delta = 1$, the social-interaction game has a monotone pure-strategy equilibrium with*

$$a_t^*(i) \;=\; \begin{cases} 1 & \text{for all agents } i \text{ with } \omega(i) \geq \omega_t^*(x, A_t^*), \\ 0 & \text{for all agents } i \text{ with } \omega(i) < \omega_t^*(x, A_t^*), \end{cases}$$

*where the critical values $\omega_t^*(x, A_t^*)$ are defined by*

$$\omega_t^*(x, A_t^*) \;=\; c - v_t^i(s \mid \mathcal{I}_t^i)\widetilde{D}(x)G(A_t^*)\,,$$

*and the fixed-point condition*

$$A_t^* = \int_{x\,\in\,\mathbb{R}} \Phi\left(\frac{\bar{\omega} + \rho\,\sigma_\omega\sigma_x^{-1}(x-\bar{x}) - \omega_t^*(x, A_t^*)}{\sigma_\omega\sqrt{1-\rho^2}}\right)\phi\left(\frac{x-\bar{x}}{\sigma_x}\right)dx\,, \tag{17}$$

*identifies the aggregate social abstention among those with $v_t^i(s \mid \mathcal{I}_t^i) > 0$.*

*ii) for $\delta > 1$, the social interaction game has a pure-strategy equilibrium with*

$$a_t^*(i) \;=\; \Big[\big(\omega(i) + v_t^i(s \mid \mathcal{I}_t^i)\widetilde{D}^i(x)G(A_t^*)\big)/K(\delta)c\Big]^{\frac{1}{\delta-1}} \in [0,1]\,,$$

*for all agennts $i$, where the fixed-point condition*

$$A_t^* \;=\; \int_{x\,\in\,\mathbb{R}}\int_{\omega\,\in\,\mathbb{R}} \Big[\big(\omega + v_t^i(s \mid \mathcal{I}_t^i)\widetilde{D}(x)G(A_t^*)\big)/K(\delta)c\Big]^{\frac{1}{\delta-1}} \phi\left(\frac{x-\bar{x}}{\sigma_x}\right)\phi\left(\frac{\omega - \bar{\omega}|x}{\sigma_\omega\sqrt{1-\rho^2}}\right)dx\,d\omega\,,$$

*with* $\bar{\omega}|x = \mathbb{E}[\omega|x] = \bar{\omega} + \rho\sigma_\omega\sigma_x^{-1}(x - \bar{x})$*, identifies the aggregate social abstention among those with* $v_t^i(s \,|\, \mathcal{I}_t^i) > 0$*.*

*If the social environment is not congestionable* ($\phi > 1$)*, social distancing decisions are strategic substitutes regardless of what agents know. If the social environment is consegionable* ($\phi \in (0,1)$)*, social distancing decisions are strategic substitutes if* $v_t^i(s) > 0$ *for all agents, and strategic complements otherwise. When substitutabiltiy prevails, the equilibrium is globally unique. When complementarity prevails, a discrete, finite number of equilibria can possibly exist at some state of the epidemic* $E_t$*.*

*Proof.* See Appendix A.3. □

In the presence of strategic complementarity equilibrium uniqueness cannot be proved analytically in some regions of the state space $\mathbf{E}$. However, numerical simulations show that complementarity equilibria are generally unique. The following remark highlights the claim.

**REMARK 1.**

*For* $\phi \in (0,1)$*, the equilibria of Proposition 2 are generally unique at every state of the epidemic* $E_t$*.*

For $\delta > 1$, agents choose intermediate levels of abstention $a(i) \in (0,1)$, and smoothly adjust their self-protection as the epidemic evolve – they gradually increase $a(i)$ as disease-prevalence increases, and gradually decrease $a(i)$ after peak-prevalence. Aggregate abstention smoothly adjusts accordingly. For $\delta = 1$, agents constantly oscillate between zero and full abstention, and aggregate abstention may change dramatically as the epidemic evolves. This is particularly true when social distancing decisions are strategic complements. Borrowing the definition from Angeletos and Pavan (2004), we say that strategic interactions are 'weak' in the former case, and 'strong' in the latter. Accordingly, we say that there is *strong complementarity* when $\delta = 1$, and *weak complementarity* when $\delta > 1$. In a strategic environment governed by strong complementarity agents may be trapped in highly risky equilibria where no agent self-protects believing that all other agents will do the same. Since we interpreted $\delta$ as a proxy for lockdown design[24], this amounts to saying that the policy-maker affects the intensity of strategic interaction with policy design. As we will show in Section 6, this has a bearing on optimal information design.

[24] Recall: $\delta = 1$ corresponds to a strict lockdown where agents either stay home or go out; $\delta > 1$ corresponds to a milder social distancing policies where agents choose among a menu of alternatives.

## 5.2 Necessary Conditions for Complementarity

Proposition 2 implies that, in the absence of private information about health states, all agents adopt the same type-contingent equilibrium strategies. Therefore, at the aggregate level $\mathcal{I}_t^i = \{\varnothing\}$ entails that

$$\begin{aligned} M(A_t)\,\big|\,\{\varnothing\} \;&=\; (S_t + ASY_t + pR_t)(1 - A_tL) + (1-p)R_t\,\Phi(\sigma_\omega^{-1}(\bar{\omega} - c))\,, \\ \#ASY[M(A_t)]\,\big|\,\{\varnothing\} \;&=\; ASY_t(1 - A_tL)\,, \end{aligned} \tag{18}$$

since ill-asymptomatics do not know to be invulnerable to contagion and strategically respond to the endogenous risk, whereas $\mathcal{I}_t^i = \{e_t(i)\}$ entails that

$$\begin{aligned} M(A_t)\,\big|\,\{e_t(i)\} \;&=\; S_t(1 - A_tL) + (ASY_t + R_t)\,\Phi(\sigma_\omega^{-1}(\bar{\omega} - c))\,, \\ \#ASY[M(A_t)]\,\big|\,\{e_t(i)\} \;&=\; ASY_t\,\Phi(\sigma_\omega^{-1}(\bar{\omega} - c))\,, \end{aligned} \tag{19}$$

since all recovered and ill-asymptomatics know to be invulnerable and their abstention is solely driven by moral concerns. The intermediate case where ill-asymptomatics are aware of being invulnerable while recovered are not can be easily accommodated by the characterisation of Proposition 2: in that case $v_t^i(s\,|\,\{e_t(i) \neq asy\}) = S_t/(S_t + pR_t)$ via Bayes rule, whereby

$$\begin{aligned} M(A_t)\,\big|\,\{e_t(i) \neq asy\} \;&=\; (S_t + pR_t)(1 - A_tL) + (ASY_t + (1-p)R_t)\,\Phi(\sigma_\omega^{-1}(\bar{\omega} - c))\,, \\ \#ASY[M(A_t)]\,\big|\,\{e_t(i) \neq asy\} \;&=\; ASY_t\,\Phi(\sigma_\omega^{-1}(\bar{\omega} - c))\,. \end{aligned} \tag{20}$$

Via expressions (18) to (20) the following result can easily be proved.

**COROLLARY 2.**

*Let all conditions of Proposition 1 hold. Then, if all ill-asymptomatics privately know to be invulnerable to contagion, the congestionability of the social environment ($\phi \in (0,1)$) is a necessary condition for strategic complementarity.*

*Proof.* See Appendix A.4. □

Corollary 2 resolves the indeterminacy result of Corollary 1, and complements the analysis of Proposition 1 by proving that, in equilibrium, environmental congestionability and private awareness of invulnerability by ill-asymptomatics are jointly *necessary and sufficient* conditions for strategic complementarity. If the ill-asymptomatics are aware of being invulnerable, the social distancing decisions of all other agents are necessarily strategic complements if the social environment is congestionable, and necessarily strategic substitutes otherwise. If the ill-asymptomatics are not aware

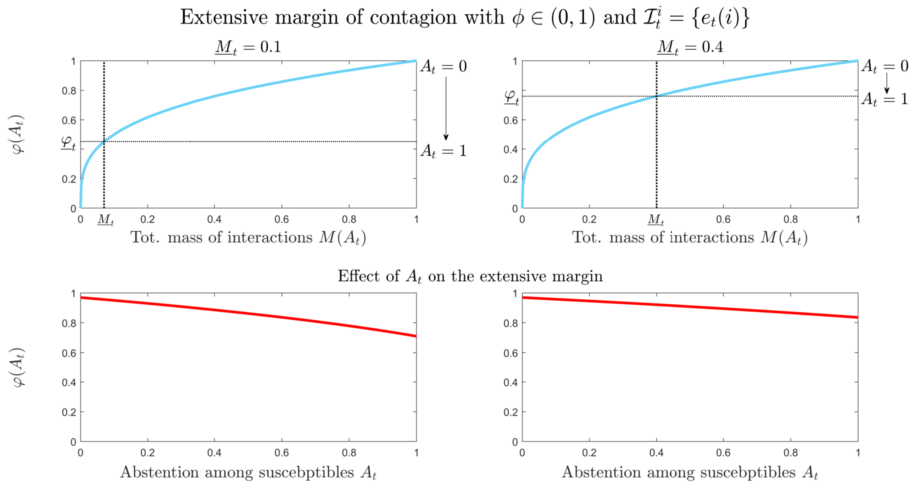


**Figure 2.** Extensive margin of contagion ($\varphi(A_t)$) in a congestionable social environment ($\phi \in (0, 1)$) where ill-asymptomatics and recovered know to be invulnerable to contagion ($\mathcal{I}_t^i = \{e_t(i)\}$). The extensive margin is plotted as a function of the total mass of interactions $M_t(A_t)$ – upper panels — and of the abstention among susceptibles $A_t$ – lower panels.

of being invulnerable, social distancing decisions are necessarily strategic substitutes, regardless of congestionability.

### 5.3 The Role of Congestion

The overall risk of contagion $G(A_t)$ is determined by the overlapping of two margins: the extensive margin $\varphi(A_t)$, that always increases in the mass of interactions $M(A_t)$ since it is congestion-driven; the intensive margin $\pi(A_t)$, that increases or decreases depending on how social distancing decisions coordinate. Formally, complementarity arises when the two margins are decoupled, and the intensive margin more-than-offsets the extensive counterpart. Figure 2 provides a graphical intuition for why this can happen in a congestionable environment.

The social environment is congestionable for every $\phi \in (0, 1)$. When this is the case, the extensive margin of contagion is strictly concave in $M(A_t)$. When $\mathcal{I}_t^i = \{e_t(i)\}$, the social abstention of ill-asymptomatics and recovered is exogenously determined by moral concerns. This imposes a fixed lower bound

$$\underline{M}_t \,\big|\, \{e_t(i)\} \;=\; M(A_t\!=\!1) \,\big|\, \{e_t(i)\} \;=\; (ASY_t + R_t)\, \Phi(\sigma_\omega^{-1}(\bar{\omega} - c))$$

on the total mass of interactions, hence on the extensive margin $\underline{\varphi}_t = (\underline{M}_t)^\phi$. Since the environment is congestionable, the fixed mass $\underline{M}_t$ quickly exhausts the extensive margin: the larger $\underline{M}_t$, the smaller the impact of the social behaviour of susceptibles. Conversely, when $\mathcal{I}_t^i = \{e_t(i)\}$ the intensive margin $\pi(A_t)$ is highly sensitive to the social behaviour of susceptibles: the more they abstain, the larger the reduction in the intensive margin, the lower the risk of contagion. Overall, the intensive-margin effect dominates its extensive counterpart, and the risk of contagion $G(A_t)$ strictly decreases in $A_t$.

### 5.4 Complementarity in Epidemics: Compare and Contrast

Complementarity results are rare but not entirely new in economic epidemiology. Chen (2012), McAdams (2020), Lebeau (2020) and Dasaratha (2023) all consider the possibility that social distancing decisions be strategic complements. Lebeau (2020) and Dasaratha (2023), however, impose complementarity *a priori* by introducing *ad hoc* positive spillovers from social activities. McAdams (2020) adopts a similar modelling strategy[25]. In this respect, we show that the contagion mechanism itself can be a source of complementarity, even in the absence of positive warm-glow benefits from social interactions that countervail the increased risk of contagion.

In an early contribution, Chen (2012) already showed that complementarity may arise directly from the contagion mechanism. However, he traced the result back to a specific property of the matching function: its saturability. Building on Heesterbeek and Metz (1993), Chen (2012) defines 'saturable' any matching function that generates a risk of infection that strictly decreases in the number of interactions. The mechanics of saturability are broadly explained by the crowding-out effect we discussed in Subsection 4.1 – if susceptibles and recovered abstain less, the number of interactions involving non-infective agents increases, thus decreasing, on average, the probability to interact with an infective counterparty. No explanation is provided about *why* the matching function may behave like this. Besides filling this gap by providing a rationale for saturability, our analysis shows that saturability is not a property of the matching function *per se*: rather, it is jointly determined by the spatial characteristics of the social environment *and* by the private information that agents possess. Note indeed that, in our framework, *congestionability does not coincide with saturability.* If ill-asymptomatics are privately unaware of being invulnerable, the matching function is *not* saturable even if the social environment is congestionble. Consequently, we prove that saturability is not a physical property, but the byproduct of an epistemic state.

[25] For the sake of rigour, the modelling strategy of McAdams (2020) is subtler: social distancing decisions are complements if positive spillovers (more interactions overall increase the pleasantness of social activities) more-than-offset negative ones (more interactions overall increase the risk of contagion); they are substitutes otherwise.

# 6. Information Management in Epidemics

## 6.1 Screening and Diagnostic Tests

As discussed in Section 4, complementarity renders social distancing decisions volatile and prone to self-fulfilling prophecies: aggregate abstention suddenly plummets as the riskiness of social interactions decreases, self-sustained by the common belief that all susceptible agents will indeed abstain less. In equilibrium, this negatively affects the death toll.

The key theoretical result of our paper is that complementarity is primarily driven by private information about health states: in the presence of congestion, it arises when ill-asymptomatics privately know to be invulnerable to contagion; it is absent otherwise. Direct consequence is that the policy-maker can dampen the adverse effects of complementarity via information design – it can hide or disclose information about health state by forbidding self-tests and/or by implementing massive screening campaigns.

In this section we study the aggregate effects of centralised information design via screening policies. Following de Walque et al. (2020), we focus on a battery of two binary assays (whose outcome is 'positive' or 'negative') with perfect sensitivity and specificity to their diagnostic targets (true positive rate = true negative rate = 1):

*i*) a PCR-based test (nasal swab, $\tau_{swab}$), that identifies the ill-asymptomatics – its outcome is positive with probability one if the agent is ill, and negative with probability one otherwise[26];

*ii*) an antibody test (blood test, $\tau_{blood}$), that identifies the recovered – its outcome is positive with probability one if the agent is recovered, and negative with probability one otherwise.

The implications of mandatory screening campaigns with the tests we are considering are reasonably straightforward. Consider PCR-based swab tests – those that detect ill-asymptomatics. If directly administered by the public authority, mandatory screening with these tests is clearly beneficial: ill-asymptomatics are detected and quarantined, and contagion stops or slows down. Trade-offs can only arise if (*i*) tests are imperfect (they give false positives and false negatives with

[26] This is an utter simplification. In reality, PCR-based tests have severe diagnostic limitations. In this respect, see the remarks in Acemoglu et al. (2024) and the references therein.

nonzero probabilities), and/or (*ii*) testing/quarantine capacities are limited[27]. A wide host of theoretical contributions already studied these trade-offs in-depth. For this reason, we focus instead on *voluntary* screening, and study how the policy-maker can optimally respond with informational instruments to a contingency in which agents can privately acquire an informational advantage via *private* self-testing.

We proceed as follows. First, we characterise a simplified equilibrium where moral concerns are absent. Then, we analyse the aggregate effects of several exogenous informational scenarios, each corresponding to a screening policy perfectly enforced by the central authority. Finally, we check under which conditions such scenarios are consistent with agents' optimal decentralised decision-making, and draw some policy implications.

### 6.2 Belief Updating

Formally, a test $\tau \in \{\tau_{swab}, \tau_{blood}\}$ is the joint distribution of the state space $\boldsymbol{e} = \{s, asy, r\}$ and a binary outcome space $\boldsymbol{m}(\tau) = \{pos, neg\}$. Since both tests have perfect sensitivity and specificity, they can be represented as a partition $h \in \mathcal{P}(\boldsymbol{e})$ of the state space: the swab test $\tau_{swab}$ corresponds to the partition $h = \big\{\{asy\}, \{s, r\}\big\}$, since it perfectly identifies ill-asymptomatics but cannot tell susceptibles and recovered apart; the blood test $\tau_{blood}$ corresponds to the partition $h = \big\{\{r\}, \{s, asy\}\big\}$, since it perfectly identifies recovered but cannot distinguish between susceptibles and ill-asymptomatics. In the absence of tests, agents do not possess any private information ($\mathcal{I}^i_t = \varnothing$), and the expected vulnerability to contagion is $v^i_t(s \,|\, \varnothing) = S_t/(S_t + ASY_t + pR_t)$ as in (15). If a single test is available, we have

$$v^i_t(s \,|\, m(\tau)) \;=\; \begin{cases} 0 & \text{if } \tau = \tau_{swab} \text{ and } m = pos\,, \\[2ex] S_t/(S_t + pR_t) & \text{if } \tau = \tau_{swab} \text{ and } m = neg\,, \\[2ex] 0 & \text{if } \tau = \tau_{blood} \text{ and } m = pos\,, \\[2ex] S_t/(S_t + ASY_t) & \text{if } \tau = \tau_{blood} \text{ and } m = neg\,. \end{cases} \tag{21}$$

via Bayes rule. If both tests are available, every agent perfectly learns his/her health state as in (16) – since the two-test battery corresponds to the exhaustive partition $h = \big\{\{s\}, \{asy\}, \{r\}\big\}$.

[27] As it is the case e.g. in Phelan and Toda (2022), where the policy-maker faces a limited screening rate $\sigma \in (0, 1)$, and the $1 - \sigma$ undiagnosed infected continue to spread contagion.

## 6.3 Simplified Equilibrium

To isolate the pure effects of information design, we focus on a simplified model specifcation without moral concerns $\omega$, where agents are purely self-interested, and ill-asymptomatics massively cease to abstain once they become aware to be invulnerable. Appendix C1 surveys some empirical evidence about the social behaviour of ill-asymptomatics during the recent SARS-CoV-2 pandemic, and confirms that, albeit extreme, this behavioural prescription stands the proof of facts. The equilibrium characterisation becomes as follows.

**PROPOSITION 3.**

*Let $\bar{\omega} = 0$ and $\sigma_\omega \longrightarrow 0$, so that moral concerns $\omega$ are sterilised. Moreover, let the available private information be $\mathcal{I}_t^i \in \big\{\{\varnothing\}, \{m(\tau_{swab})\}, \{m(\tau_{blood})\}, \{m(\tau_{swab}), m(\tau_{blood})\}\big\}$. Then, in every period $t$:*

*a) for $\delta = 1$, the social-interaction game has a two strategic regimes, unambiguously identified by the state of the epidemic $E_t$:*

- *an 'anarchy regime', where $a_t^*(i) = 0$ for all agents $i$;*
- *a 'discipline regime', where*

$$a_t^*(i) \;=\; \begin{cases} 1 & \text{for all agents } i \text{ with } v_t^i(s\,|\,\mathcal{I}_t^i) > 0 \text{ and } x(i) \geq x_t^*(A_t^*)\,, \\ 0 & \text{for all agents } i \text{ with } v_t^i(s\,|\,\mathcal{I}_t^i) > 0 \text{ and } x(i) < x_t^*(A_t^*)\,, \\ 0 & \text{for all agents } i \text{ with } v_t^i(s\,|\,\mathcal{I}_t^i) = 0\,, \end{cases}$$

*with the critical values $x_t^*$ unambiguously identified by the indifference condition*

$$v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}^i(x_t^*)G(A_t^*) \;=\; c\,,$$

*and where the fixed-point condition*

$$A_t^* \;=\; \Phi(\sigma_x^{-1}(\bar{x} - x_t^*(A_t^*)))$$

*identifies the aggregate social abstention $A_t^*$ among the agents with $v(s\,|\,\mathcal{I}_t^i) > 0$.*

*b) for $\delta > 1$, the social-interaction game has a pure-strategy equilibrium with*

$$a_t^*(i) \;=\; \begin{cases} \Big[\, v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}^i(x)G(A_t^*)\,/K(\delta)c\,\Big]^{\frac{1}{\delta-1}} & \text{for all agents } i \text{ with } v_t^i(s\,|\,\mathcal{I}_t^i) > 0\,, \\ 0 & \text{for all agents } i \text{ with } v_t^i(s\,|\,\mathcal{I}_t^i) = 0\,, \end{cases} \tag{22}$$

*where the fixed-point condition*

$$A_t^* \;=\; \int_{x\,\in\,\mathbb{R}} \Big[\big(v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}(x)G(A_t^*)\big)/K(\delta)c\Big]^{\frac{1}{\delta-1}}\phi\left(\frac{x-\bar{x}}{\sigma_x}\right)dx\,.$$

*identifies the aggregate social abstention among $A_t^*$ among the agents with $v_t^i(s\,|\,\mathcal{I}_t^i) > 0$.*

*If the social environment is not congestionable ($\phi > 1$), social distancing decisions are strategic substitutes regardless of what the agents know. If the social environment is consegionable ($\phi \in (0,1)$), social distancing decisions are strategic substitutes if $v_t^i(s) > 0$ for all agents, and strategic complements otherwise. When substitutability prevails, the equilibrium is unique. When complementarity prevails, a discrete, finite number of equilibria can possibly exist at some states of the epidemic $E_t$.*

*Proof.* See the online Appendix B3. □

In the presence of strategic complementarity equilibrium uniqueness cannot be proved analytically in some regions of the state space $\mathbf{E}$. However, as it was the case for Proposition 2, numerical simulations show that complementarity equilibria are generally unique.

**REMARK 2.**

*For $\phi \in (0,1)$, the equilibria of Proposition 3 are generally unique at every state of the epidemic $E_t$. Moreover, zero-abstention equilibria may exist for $\delta = 1$ even in the discipline regime.*

## 6.4 Informational Scenarios: Analysis and Policy Implications

Building on the simplified characterisation of Proposition 3, we simulate virus dynamics in four informational scenarios:

| | |
|---|---|
| maximum opacity: | no test is administered, whereby $\mathcal{I}_t^i = \varnothing$ at every $t$. |
| swab-test only: | swab tests $\tau_{swab}$ are massively administered, whereby $\mathcal{I}_t^i = m(\tau_{swab})$ at every $t$ and all ill-asymptomatic learn to be invulnerable. |
| blood-test only: | blood tests $\tau_{blood}$ are massively administered, whereby $\mathcal{I}_t^i = m(\tau_{blood})$ at every $t$ and all recovered learn to be invulnerable. |
| maximum transparency: | both tests $\tau_{swab}$ and $\tau_{blood}$ are massively administered, whereby $\mathcal{I}_t^i = \{m(\tau_{swab}),m(\tau_{blood})\}$ at every $t$ and both ill-infected and recovered learn to be invulnerable. |

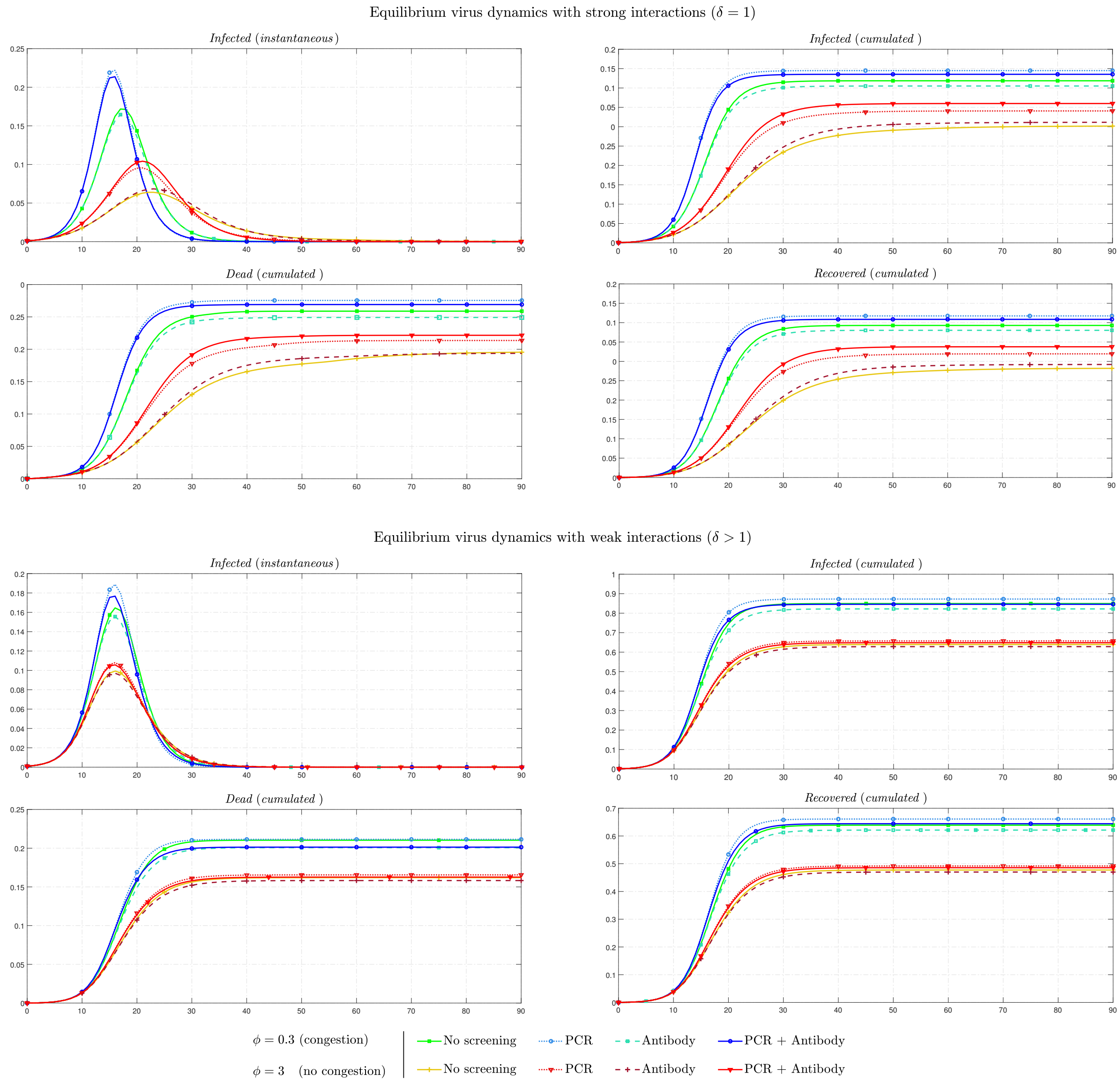


**Figure 3.** Equilibrium virus dynamics in the four informational scenarios under strong ($\delta = 1$) and weak ($\delta > 1$) strategic interactions. The essential cluster $(1 - L)$ is 0.3. Congestion is simulated with $\phi = 0.3$, no-congestion with $\phi = 3$. See the online Appendix B4 for further details.

Figure 3 collects the simulations. Direct inspection suggest that the availability of self-tests that detect illness negatively affects the death toll. In the recent SARS-CoV-2 pandemic, public authorities indeed expressed concerns with the uncontrolled proliferation of self-tests, since they disseminate private information about health states with little or no control by the public authority (see ECDC (2021a,b)). In this respect, our simulations suggests that these concerns are warranted: banning self-tests, or at least containing their proliferation, is socially beneficial.

More counterintuitive policy implications can be drawn from our scenario analysis. Recall from

Section 5 that $\delta = 1$ corresponds to a strategic environment where interactions are strong in the sense of Angeletos and Pavan (2004), whereas $\delta > 1$ corresponds to an environment where they are weak. Recall further that, in a broad sense, $\delta$ can be interpreted as a proxy for lockdown design – $\delta = 1$ corresponds to a strict lockdown, $\delta > 1$ to a milder social distancing policy. In this light, Figure 3 therefore suggests that:

*i*) if interactions are weak because the lockdown is mild ($\delta > 1$), congestionability does not affect the optimal response of the policy-maker to the proliferation of self-tests: providing additional information via mass screening campaigns that detect immunity from recovery (antibody blood tests) always reduces the death toll;

*ii*) if interactions are strong because the lockdown is strict ($\delta = 1$), optimal information design in response to a widespread use of self-tests depends on congestion:

  - if the social environment is congestionable, providing additional information via centralised screening campaigns that identify recovered agents unambiguously reduces the death toll;
  - the reverse is true if the social environment is not congestionable: providing no additional information is the best available alternative.

Differences between strict and mild lockdowns in the simulated virus dynamics of Figure 3 boil down to the different intensity of strategic interactions in the two regimes. For $\delta > 1$, interactions are weak: agents choose intermediate levels of abstention $a(i) \in (0, 1)$ and smoothly adjust their self-protection as the epidemic evolves. For $\delta = 1$, interactions are strong: agents switch relentlessly from zero to full abstention, and may be trapped into risky zero-abstention equilibria self-sustained by the common belief that all agents will indeed choose zero abstention.

For $\delta = 1$, observed differences between congestionable and non-congestionable environments accrue to the mechanics of contagion and the interplay between its margins:

- in a congestionable environment, few social interactions quickly exhaust the extensive margin, that soon becomes insensitive to the social behaviour of agents. In this case, the intensive margin is the main driver of contagion.

– in a non-congestionable environment, the extensive margin is highly sensitive to the social behaviour of agents: if the mass of interactions exceeds a critical threshold, the risk of contagion begins to increase exponentially. In this case, it is the extensive margin that drives contagion.

When the intensive margin drives contagion, the policy-maker can slow down new infections by detecting recovered (immune) agents with antibody tests $\tau_{blood}$ and leveraging on strong complementarities. Once they learn to be invulnerable with testing, recovered agents massively switch to zero abstention and, in so doing, they significantly dilute disease prevalence in the interacting subpopulation. The decrease in risk triggered by such dilution further encourages the most resilient susceptibles to switch to zero abstention, and this encourages slightly weaker agents to follow suit. The cascade continues until the process settles. As a result, new infections plummet in equilibrium. When the extensive margin drives contagion, the opposite holds true.

### 6.5 Voluntary Screening and Further Policy Implications

Those analysed in Subsection 6.4 were exogenous informational scenarios. We now prove such scenarios are actually consistent with optimal decentralised behaviour (voluntary testing). The proposition that follows outlines the results.

**PROPOSITION 4.**
*Let $\delta \geq 1$ and $\mathcal{I}_t^i = \{\varnothing\}$ hold. Moreover, let self-tests $\tau_{swab}$ that perfectly detect illness be privately available to agents in unrestricted supply. Then, it is always optimal for every agent to privately take the test at every state $E_t$ of the epidemic.*

*Proof.* See Appendix A.5. □

In words: starting from an epistemic state of complete ignorance ($\mathcal{I}_t^i = \{\varnothing\}$), privately self-testing for illness is individually optimal at every state of the epidemic $E_t$. Accordingly, the scenario analysis performed in Subsection 6.4 extends one-to-one to a strategic environment where informational states are determined by decentralised, optimal voluntary testing. Optimal information design therefore entails that:

– forbidding self-tests is the best alternative;

– if self-test cannot be banned, optimal information design depends on the intensity of strategic interactions ($\delta$) and the spatial characteristics of the social environment ($\phi$):

  – if interactions are weak ($\delta > 1$), providing additional information about immunity from past illness is always the best response;

  – if interactions are strong ($\delta = 1$), the best response depends on congestion: if the social environment is congestionable, it is optimal to provide additional information via mandatory screening with antibody tests; if the social environment is not congestionable, it is optimal not provide any additional information.

## 7. Conclusions

We studied how private information about health states interacts with the spatial characteristics of the social environment in shaping social behaviour in epidemics. To this end, we proposed a stylised social-interaction game where demographically heterogeneous agents choose rationally and strategically how much to abstain from social activities to self-protect against contagion. Demography affects the risk of death post-infection, that increases in the physical proximity of interactions – hence, in the congestionability of the social environment.

Our key theoretical result is that congestionability is necessary but not sufficient for social distancing decisions to be strategic complements: it is private information about health states that really makes the difference. In congestion is absent, social distancing decisions are strategic substitutes regardless of private information. If there is congestion, social distancing decisions are strategic complements if ill-asymptomatics know to be invulnerable to contagion (e.g. because PCR-based self-tests are freely available), and strategic substitutes otherwise.

Complementarity negatively affects the death toll by rendering social distancing more volatile: self-protection drops abruptly when perceived risk decreases. Since complementarity is information-driven, the policy-maker can dampen its adverse effects via a proper information design. Policy implications ensue. Forbidding the unregulated use of PCR-based self-tests is always optimal for the policy-maker. However, if the proliferation of self-tests cannot be stopped, the optimal information design depends on two factors: the toughness of the lockdown and the congestionability of the social environment. If the lockdown is tough and there is congestion, it is optimal for the policy-maker to provide additional information to the citizenry via mass screening campaign with antibody tests – that detect recovered agents. If the lockdown is tough but there is no congestion, it is optimal for the policy-maker not to provide any additional information. Finally, if the lockdown is mild, congestion no longer matter: it is always optimal for the policy-maker to provide additional information via publicly-administered antibody tests.

For future research, our analysis can be extended in several ways. First, the individual history of past social behaviour can be included as a source of private information. Many contributions in economic epidemiology have forward-looking social behaviour but, to the best of our knowledge, none has attempted to study perfect recall. The task is analytically challenging and computationally intensive. Second, our continuous specification of demographic heterogeneity may allow for the study of targeted lockdowns with endogenous clustering. To the best of our knowledge, the extant literature has considered discrete demographic groups of pre-determined size: the problem of the policy-maker is how to optimally enforce lockdowns within each of the exogenously-given clusters. With continuous demographic types, it may be possible for the policy-maker to endogenously partition the citizenry into optimally-designed demographic clusters, and then to enforce targeted lockdowns. Preliminary analyses in this direction highlight a trade-off between size and demographic composition: if the citizenry is evenly distributed among clusters, enforcing the lockdown only in the least resilient ones reduces the death toll; however, if some clusters are significantly larger in size, enforcing lockdowns only in those clusters reduces the death toll regardless of demography.

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# Appendix A

# PROOFS

## A.1 PROOF OF PROPOSITION 1

Differentiating the matching function $G(A_t)$ as defined by (7) with respect to the aggregate social abstention $A_t$ we obtain

$$\frac{\partial}{\partial A_t} G(A_t) \;=\; \beta M(A_t)^{\phi-1}\left[\frac{\partial}{\partial A_t}\#ASY[M(A_t)] + \#ASY[M(A_t)]^{-1}(\phi-1)\frac{\partial}{\partial A_t}M(A_t)\right]. \tag{A.1}$$

Note that $M(A_t)^z > 0$ for every $z \in \mathbb{R}$, since $M(A_t) > 0$ by definition. Therefore, expression (A.1) is strictly positive if

$$\frac{\partial}{\partial A_t}\#ASY[M(A_t)] + \#ASY[M(A_t)]^{-1}(\phi-1)\frac{\partial}{\partial A_t}M(A_t) \;>\; 0\,. \tag{A.2}$$

Note further that $\partial M(A_t)/\partial A_t < 0$, since the total mass of interactions decreases by construction in the aggregate social abstention $A_t$. Via the expected utility (11), note finally that

$$\#ASY[M(A_t)] \;=\; \begin{cases} ASY_t\,\Phi\left(\sigma_\omega^{-1}\left(\bar{\omega}-c\right)\right) & \text{for } \delta = 1\,, \\[2ex] ASY_t\displaystyle\int_{-\infty}^{+\infty}(\omega/c)^{\frac{1}{\delta-1}}\,\phi\left(\sigma_\omega^{-1}(\bar{\omega}-\omega)\right)\mathrm{d}\omega & \text{for } \delta > 1\,. \end{cases}$$

holds at every state $E_t$ if $v_t^i(s) = 0$ holds for all ill-asymptomatics. In words: if all ill-asymptoamtics know to be invulnerable to contagion, the total mass $\#ASY[M(A_t)]$ of interactions involving asymptomatic parties no longer responds to $A_t$ – it is solely determined by the idiosyncratic moral components $\omega(i)$. When this is the case

$$\frac{\partial}{\partial A_t}\#ASY[M(A_t)] \;=\; 0 \tag{A.3}$$

holds by construction at every $E_t$. Then, if $\#ASY[M(A_t)] > 0$ (i.e. if the disease prevalence is positive),

$$\begin{aligned} \#ASY[M(A_t)](\phi-1)\frac{\partial}{\partial A_t}M(A_t) \;&<\; 0 \qquad \text{if } \phi > 1\,, \\ \#ASY[M(A_t)](\phi-1)\frac{\partial}{\partial A_t}M(A_t) \;&=\; 0 \qquad \text{if } \phi = 1\,, \\ \#ASY[M(A_t)](\phi-1)\frac{\partial}{\partial A_t}M(A_t) \;&>\; 0 \qquad \text{if } \phi < 1\,, \end{aligned}$$

necessarily holds. Therefore, via (A.2) and (A.3), the assumptions $\#ASY[M(A_t)] > 0$ and $v_t^i(s\,|\,e_t(i) = asy)$ for all $i$ with $e_t(i) = asy$ imply that the sign of the derivative (A.1) is unambiguously determined by the magnitude of $\phi$: (*i*) $\phi > 1$ entails $\partial G(A_t)/\partial A_t < 0$ – social distancing decisions are strategic substitutes; (*ii*) $\phi = 1$ entails $\partial G(A_t)/\partial A_t = 0$ – social distancing decisions are independent; (*iii*) $\phi \in (0,1)$ entails $\partial G(A_t)/\partial A_t > 0$ – social distancing decisions are strategic complements. *QED*

## A.2 PROOF OF COROLLARY 1

The condition $\#ASY[M(A_t)] \geq 0$ implies that the derivative (A.1) is positive if expression (A.2) is positive, and negative if expression (A.2) is negative. If the ill-asymptomatics do not know to be invulnerable to contagion, it is impossible to determine *a priori* the sign of $\partial \#ASY[M(A_t)]/\partial A_t$, hence of expression (A.2). Consequently, complementarity and substitutability are both possible *a priori*. $QED$

## A.3 PROOF OF PROPOSITION 2

### *A.3.1. Characterisation for $\delta = 1$*

Substituting for $\delta = 1$ into the expected utility (11) we have

$$U_t^i \,|\, \mathcal{I}_t^i \;=\; a_t(i)\left[v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}^i(x)G(A_t) + \omega(i) - c\right] - v_t^i(asy\,|\,\mathcal{I}_t^i)\left[q^D(x)D + \widetilde{D}^i(x)\right] \tag{A.4}$$

for every $\mathcal{I}_t^i \in \big\{\{\varnothing\}, \{e_t(i)\}\big\}$. The expected utility (A.4) is linear in $a_t(i)$, whereby $a_t^*(i) \in \{0, 1\}$ must hold for all agents $i$ at every state $E_t$. Since $\omega \in \mathbb{R}$ by definition, for every arbitrary $A_t \in [0, 1]$ and every $x \in \mathbb{R}$ at every state $E_t$ there always exists a finite critical value

$$\omega_t^*(x, A_t) \;=\; c - v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}(x)G(A_t) \tag{A.5}$$

such that $a_t^*(i) = 1$ if $\omega(i) \geq \omega_t^*(a, A_t)$ and $a_t^*(i) = 0$ otherwise. Since $x$ and $\omega$ are *a priori* correlated via $\rho := Cov(x, \omega)(\sigma_x\sigma_\omega)^{-1} \in [-1, +1]$, and both have Normal marginal distributions, we can write their prior joint distribution as

$$\begin{bmatrix}\omega \\ x\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}\bar{\omega} \\ \bar{x}\end{bmatrix}, \begin{bmatrix}\sigma_\omega^2 & \rho\,\sigma_x\sigma_\omega \\ \rho\,\sigma_x\sigma_\omega & \sigma_x^2\end{bmatrix}\right), \tag{A.6}$$

whereby

$$\omega\,|\,x \;\sim\; \mathcal{N}\left(\bar{\omega} + \rho\left(\frac{\sigma_\omega}{\sigma_x}\right)(x - \bar{x})\;,\; \sigma_\omega^2(\,1 - \rho^2)\right) \tag{A.7}$$

for every $x \in \mathbb{R}$. Conditioning on $x$, the moral components $\omega$ are i.i.d. in the cross-section of agents. Consequently, via the law of large numbers applied to continua of i.i.d. random variables (see e.g. Judd (1985)) the share of agents with demography $x(i) = x$ and abstention $a_t^*(i) = 1$ is

$$\begin{aligned} A_t^*(A_t\,|\,x) \;&=\; \Pr\big(\omega \geq \omega^*(x, A_t)\,\big|\,x\,\big) \quad \text{almost surely}\,, \\ &=\; \Phi\left(\frac{\bar{\omega} + \rho\,\sigma_\omega\sigma_x^{-1}(x - \bar{x}) - \omega^*(x, A_t)}{\sigma_\omega\sqrt{1 - \rho^2}}\right) \quad \text{almost surely}\,, \end{aligned} \tag{A.8}$$

for every arbitrary $A_t$ at every state $E_t$ – with $\Phi\,(z) = \int_{-\infty}^{z} \phi\,(t)\,\mathrm{d}t$, $z \in \mathbb{R} \cup \{\pm\infty\}$, the CDF of the Normal standard distribution. Since, for every pair of realisations $\langle x, \omega\rangle \in \mathbb{R}^2$ we can write $\Pr(x, \omega) = \Pr(\omega\,|\,x)\Pr(x)$, integrating (A.8) over $x$ with the marginal distribution of $x$ we obtain the aggregate law

$$A_t^*(A_t) \;=\; \int_{x\,\in\,\mathbb{R}} \Pr\big(\,\omega \geq \omega^*(x,A_t)\,\big|\,x\,;\,A_t\,\big)\Pr(x)\,\mathrm{d}x\,, \\ =\; \int_{x\,\in\,\mathbb{R}} \Phi\left(\frac{\bar{\omega}+\rho\,\sigma_\omega\sigma_x^{-1}(x-\bar{x})-\omega^*(x,A_t)}{\sigma_\omega\sqrt{1-\rho^2}}\right)\phi\Big(\frac{x-\bar{x}}{\sigma_x}\Big)\,\mathrm{d}x\,, \tag{A.9}$$

with $\phi\,(z) = (2\pi)^{-1/2}\exp\{-z^2/2\},\ z,t\in\mathbb{R}\cup\{\pm\infty\}$ the PDF of the Normal standard distribution. The equilibrium aggregate abstention rate $A_t^*$ of the agents with $v_t^i(s\,|\,\mathcal{I}_t^i)>0$ is identified by the fixed-point condition

$$A_t^*(A_t^*) \;=\; A_t^*, \tag{A.10}$$

provided it is non-empty. To identify the fixed points of (A.10), we have to differentiate (A.9) with respect to $A_t$. To do so, we have to prove first that the regularity conditions that permit to extend the Leibniz integral rule to improper integrals are indeed met for (A.9) – namely: $(i)$ existence of the improper integrals with respect to the integrand function and its first derivative, and $(ii)$ uniform convergence of such proper integrals to their improper counterparts. The proof is lengthy: not to weigh down the exposition, we postpone it to the online Appendix B2. Differentiating (A.9) with respect to $A_t$ via the Leibniz integral rule we obtain

$$\frac{\partial}{\partial A_t}A_t^*(A_t) = -\frac{1}{\sigma_\omega\sqrt{1-\rho^2}}\int_{x\,\in\,\mathbb{R}}\phi\left(\frac{\bar{\omega}+\rho\,\sigma_\omega\sigma_x^{-1}(x-\bar{x})-\omega^*(x,A_t)}{\sigma_\omega\sqrt{1-\rho^2}}\right)\phi\left(\frac{x-\bar{x}}{\sigma_x}\right)\frac{\partial}{\partial A_t}\omega^*(x,A_t)\,\mathrm{d}x\,, \tag{A.11}$$

whose sign is unambiguously determined by the sign of $\partial\omega^*(x,A_t)/\partial A_t$, with

$$\frac{\partial}{\partial A_t}\omega^*(x,A_t) \;=\; -v_t^i(s\,|\,\mathcal{I}_t^i)\widetilde{D}(x)\frac{\partial}{\partial A_t}G(A_t) \tag{A.12}$$

via expression (A.5). Note that: $(i)$ if $\mathcal{I}_t^i=\varnothing$, then all agents are in the same informational state, and since they are atomistic, they must use the same equilibrium strategy; $(ii)$ if $\mathcal{I}_t^i=e_t(i)$, then $v_t^i(s\,|\,\mathcal{I}_t^i)=0$ for all recovered and ill-asymptomatics and $v_t^i(s\,|\,\mathcal{I}_t^i)=1$ for all susceptibles. Accordingly, the social abstention of recovered and ill-asymptomatics ceases to respond strategically to $A_t$ – it is solely driven by the moral components $\omega$, with

$$k \;:=\; \Phi\big(\sigma_\omega^{-1}(\bar{\omega}-c)\big) \tag{A.13}$$

the fixed share that opts for full abstention. In the first case ($\mathcal{I}=\varnothing$), we have

$$M(A_t)\,\big|\,\{\varnothing\} \;=\; (S_t+ASY_t+pR_t)(1-A_tL)+(1-p)R_tk\,, \\ \#ASY[M(A_t)]\,\big|\,\{\varnothing\} \;=\; ASY_t(1-A_tL)\,, \tag{A.14}$$

with $k\in(0,1)$ the fixed share (A.13), whereby

$$\frac{\partial}{\partial A_t}G(A_t)\,\big|\,\{\varnothing\} \;=\; -\beta ASY_tL\,[M(A_t)]^{\phi-2}\Big\{(1-p)R_tk+\phi(1-A_tL)(S+ASY_t+pR_t)\Big\}\,, \tag{A.15}$$

that is strictly negative for every $A_t\in[0,1]$ and every $\phi>0$. Therefore, via (A.12), the informational assumption $\mathcal{I}_t^i=\{\varnothing\}$ implies that the derivative (A.11) is strictly negative for every $A_t$ at every state $E_t$.

Accordingly, the fixed-point condition (A.10) unambiguously identifies a unique value $A^*_t$ at every state $E_t$. In the second case ($\mathcal{I}^i_t = e_t(i)$), we have

$$\begin{aligned} M(A_t)\,\big|\,\{e_t(i)\} \;&=\; S_t(1-A_tL) + (ASY_t + R_t)k\,, \\ \#ASY[M(A_t)]\,\big|\,\{e_t(i)\} \;&=\; ASY_t k\,, \end{aligned} \tag{A.16}$$

whereby

$$\frac{\partial}{\partial A_t}G(A_t)\,\big|\,\{e_t(i)\} \;=\; (1-\phi)\Big\{\beta k ASY_t S_t L\,[M(A_t)]^{\phi-2}\Big\}\,, \tag{A.17}$$

that, for every $A_t \in [0,1]$, is: $(i)$ strictly positive for $\phi \in (0,1)$; $(ii)$ null for $\phi = 1$; $(iii)$ strictly negative for $\phi > 1$. Therefore, via (A.12) the informational assumption $\mathcal{I}^i_t = \{e_t(i)\}$ implies that the derivative (A.11) is: $(i)$ strictly positive for $\phi \in (0,1)$ – complementarity; $(ii)$ null for $\phi = 1$ – independence; $(iii)$ strictly negative for $\phi > 1$ – substitutability. For $\phi \in (0,1)$ the aggregate law (A.9) increases in $A_t$. However, it is immediate to check that $A^*_t(0) > 0$ and $A^*_t(1) < 1$, therefore at least one stable fixed point exists. A uniqueness results cannot be easily established. However, $A^*_t(A_t)$ is smooth in $A_t$, and its first derivative never changes sign. Therefore, in its domain $[0,1]$ it crosses the 45-degree line at a finite number of points.

### *A.3.2. Characterisation for $\delta > 1$*

For $\delta > 1$ the expected utility (11) has a global maximum identified by the (sufficient) FOC $\partial U_t(i)/\partial a_t(i) = 0$, that yields

$$a^*_t(i)\,\big|\,A_t \;=\; \left[\Big(\omega(i) + v^i_t(s\,|\,\mathcal{I}^i_t)\widetilde{D}^i(x)G(A_t)\Big)\Big/K(\delta)c\right]^{\frac{1}{\delta-1}}, \tag{A.18}$$

with $a^*_t(i) \in [0,1]$ at every $A_t \in [0,1]$ and every $E_t$ for $c$ sufficiently large. Fix an arbitrary value $\omega = \omega' \in \mathbb{R}$ for the moral component. Then, for every $\mathcal{I}^i_t \in \big\{\{\varnothing\}, \{e_t(i)\}\big\}$ at every $A_t \in [0,1]$, the average abstention among the agents with $\omega = \omega'$ is

$$A^*(A;\omega') \;=\; \int_{x\,\in\,\mathbb{R}} \left[\Big(\omega' + v^i_t(s\,|\,\mathcal{I}^i_t)\widetilde{D}^i(x)G(A_t)\Big)\Big/K(\delta)c\right]^{\frac{1}{\delta-1}} \phi\left(\frac{x-\bar{x}}{\sigma_x}\right)\mathrm{d}x\,. \tag{A.19}$$

The probability mass at $\omega = \omega'$ when $x = x'$ is given by the conditional distribution (A.7). Integrating (A.19) over $x$ using (A.7) as a density we obtain the aggregate law

$$A^*_t \;=\; \int_{x\,\in\,\mathbb{R}}\int_{\omega\,\in\,\mathbb{R}} \Big[\big(\omega + v^i_t(s\,|\,\mathcal{I}^i_t)\widetilde{D}(x)G(A_t)\big)\big/K(\delta)c\Big]^{\frac{1}{\delta-1}} \phi\left(\frac{x-\bar{x}}{\sigma_x}\right)\phi\left(\frac{\omega-\bar{\omega}|x}{\sigma_\omega\sqrt{1-\rho^2}}\right)\mathrm{d}x\mathrm{d}\omega\,, \tag{A.20}$$

with $\bar{\omega}|x = \mathbb{E}[\omega|x] = \bar{\omega} + \rho\sigma_\omega\sigma_x^{-1}(x-\bar{x})$. The fixed-point condition (A.10) again identifies, if non-empty, the equilibrium aggregate abstention rate $A^*_t$. To identify fixed points, if any, we have to differentiate (A.20) with respect to $A_t$. It is possible to prove, as we did for the case $\delta = 1$, that (A.20) satisfies all regularity conditions that allow for the use of the Leibniz integral rule – the online Appendix B2 collects the (lengthy) proof. It is immediate to check that the Leibniz integral rule readily extends to double integrals via Fubini's theorem, since the extrema of integration do not depend on $A_t$. Differentiating (A.20) with respect to $A_t$ we obtain

$$\frac{\partial}{\partial A_t} A_t^*(A_t) \;=\; \int_{x\,\in\,\mathbb{R}} \int_{\omega\,\in\,\mathbb{R}} \left( \frac{\partial}{\partial A_t} a_t^* \,\middle|\, A_t \right) \phi\left( \frac{x-\bar{x}}{\sigma_x} \right) \phi\left( \frac{\omega - \bar{\omega}|x}{\sigma_\omega \sqrt{1-\rho^2}} \right) \mathrm{d}x \mathrm{d}\omega \,, \tag{A.21}$$

with $a_t^*|A_t$ the optimal abstention (A.18) and

$$\frac{\partial}{\partial A_t} a_t^* \,\big|\, A_t \;=\; \frac{\partial}{\partial A_t} G(A_t) \left\{ \frac{1}{\delta - 1}\, v_t^i(s\,|\,\mathcal{I}_t^i) \widetilde{D}(x) \left[ \Big( \omega(i) + v_t^i(s\,|\,\mathcal{I}_t^i) \widetilde{D}^i(x) G(A_t) \Big) / K(\delta) c \right]^{-\frac{\delta}{\delta-1}} \right\} . \tag{A.22}$$

The sign of the derivative (A.21) is unambiguously determined by the sign of $\partial G(A)/\partial A_t$. Note that, with respect to the case $\delta = 1$, nothing changes in $G(A_t)$ but for the definition of $A_t$. Therefore, the analysis of $\partial G(A)/\partial A_t$ outlined for the case $\delta = 1$ extends one-to-one to the case $\delta > 1$. For every $A_t \in [0,1]$, the derivative (A.21) is: $(i)$ strictly positive for $\phi \in (0,1)$ – complementarity; $(ii)$ null for $\phi = 1$ – independence; $(iii)$ strictly negative for $\phi > 1$ – substitutability. For $\phi \in (0,1)$ the aggregate law (A.20) increases in $A_t$. However, it is immediate to check that $A_t^*(0) > 0$ and $A_t^*(1) < 1$, therefore at least one stable fixed point exists. A uniqueness results cannot be established. However, $A_t^*(A_t)$ is smooth in $A_t$, and its first derivative never changes sign. Therefore, in its domain $[0,1]$ it crosses the 45-degree line at a finite number of points.

*QED*

## A.4 PROOF OF COROLLARY 2

Consider case $\mathcal{I}_t^i = \{\varnothing\}$. Then, we know via (A.15) that $\partial G(A_t)/\partial A_t$ is strictly negative for every $\phi > 0$. Accordingly, social distancing decisions are strategic substitutes regardless of $\phi$. In our model, being susceptible is a residual condition: diagnostic tests identify illness and/or recovery. Therefore, besides the case $\mathcal{I}_t^i = \{\varnothing\}$, the sole possible scenario in which ill-asymptomatics remain unaware of being invulnerable is one in which diagnostic tests identify immunity from recovery – in this case, an agent tested negative is either susceptible or ill-asymptomatic, hence $\mathcal{I}_t^i = \big\{\{s, asy\}, \{r\}\big\}$. We have

$$\begin{aligned} M(A_t)\,\big|\,\mathcal{I}_t^i \;&=\; (S_t + ASY_t)(1 - A_t L) + R_t k \,, \\ \#ASY[M(A_t)]\,\big|\,\{\varnothing\} \;&=\; ASY_t(1 - A_t L) \,, \end{aligned} \tag{A.23}$$

with $k \in (0,1)$ the fixed share (A.13), whereby

$$\frac{\partial}{\partial A_t} G(A_t)\,\big|\,\mathcal{I} \;=\; -\beta ASY_t L \,[M(A_t)]^{\phi-2} \Big\{ R_t k + \phi(1 - A_t L)(S + ASY_t) \Big\} \,, \tag{A.24}$$

that is strictly negative for every $A_t \in [0,1]$ and every $\phi > 0$. Accordingly, social distancing decisions are strategic substitutes regardless of $\phi$. Overall, if the ill-asymptomatics do not know to be invulnerable, strategic complementarity can never arise for any $\phi > 0$, which proves the corollary.

*QED*

## A.5 PROOF OF PROPOSITION 4

To check under which conditions voluntary self-testing with swabs is individually optimal, we compare the expected utility of the generic agent $i$ before testing with the *ex ante* evaluation of its *ex post* outcome-contingent counterpart. We begin with the case $\delta = 1$. Before testing $\mathcal{I}_t^i = \{\varnothing\}$ holds, and health beliefs are formed in accordance with (15). In this case $a_t^*(i) \in \{0, 1\}$, with

$$a_t^*(i) \,\big|\, \{\varnothing\} \;=\; \begin{cases} 1 & \text{if } v_t^i(s \,|\, \varnothing)\widetilde{D}^i(x)G(A_t^*) \;\geq\; c\,, \\ 0 & \text{otherwise}\,. \end{cases}$$

After testing $\mathcal{I}_t^i = \{m(\tau_{swab})\}$ holds. A positive result $(m(\tau_{swab}) = pos)$ entails $v_t^i(s \,|\, pos) = v_t^i(r \,|\, pos) = 0$ and $v_t^i(asy \,|\, pos) = 1$. In this case $a_t^*(i) = 0$ and

$$U_t^* \,\big|\, \{pos\} \;=\; -\left[q^D(x)D + \widetilde{D}^i(x)\right] \,. \tag{A.25}$$

A negative result $(m(\tau_{swab}) = neg)$ entails $v_t^i(s \,|\, neg) = S_t/(S_t + pR_t) > S_t/(S_t + ASY_t + pR_t) = v_t^i(s \,|\, \varnothing)$. In this case $a_t^*(i) \in \{0, 1\}$, with

$$a_t^*(i) \,\big|\, \{neg\} \;=\; \begin{cases} 1 & \text{if } v_t^i(s \,|\, neg)\widetilde{D}^i(x)G(A_t^*) \;\geq\; c\,, \\ 0 & \text{otherwise}\,. \end{cases} \tag{A.26}$$

*Ex ante*, the probabilities of positive and negative outcomes are $v_t^i(asy \,|\, \varnothing)$ and $v_t^i(s \,|\, \varnothing) + v_t^i(r \,|\, \varnothing)$, respectively. Note that $a_t^*(i)|\varnothing = 1$ implies $a_t^*(i)|neg = 1$, since the incentive to switch from $a_t(i) = 0$ to $a_t(i) = 1$ increases in $v_t^i(s)$ and $v_t^i(s \,|\, neg) > v_t^i(s \,|\, \varnothing)$ by definition. Therefore, we have to compare utilities in three possible cases: *(i)* $a_t^*(i)|\varnothing = 1$ and $a_t^*(i)|neg = 1$; *(ii)* $a_t^*(i)|\varnothing = 0$ and $a_t^*(i)|neg = 0$; *(iii)* $a_t^*(i)|\varnothing = 0$ and $a_t^*(i)|neg = 1$. In the first case, testing is optimal if

$$-v_t^i(s \,|\, \varnothing)c - v_t^i(asy \,|\, \varnothing)\left[q^D(x)D + \widetilde{D}^i(x)\right] \;>\; -c - v_t^i(asy \,|\, \varnothing)\left[q^D(x)D + \widetilde{D}^i(x)\right]\,,$$

that simplifies to $c\left(1 - v_t^i(s \,|\, \varnothing)\right) > 0$, always met by definition. In the second case, testing is optimal if

$$\begin{aligned} -v_t^i(s \,|\, \varnothing)\left[v_t^i(s \,|\, neg)\widetilde{D}^i(x)G(A_t^*)\right] - v_t^i(asy \,|\, \varnothing)\left[q^D(x)D + \widetilde{D}^i(x)\right] \;>& \\ > -v_t^i(s \,|\, \varnothing)\widetilde{D}^i(x)G(A_t^*) - v_t^i(asy \,|\, \varnothing)&\left[q^D(x)D + \widetilde{D}^i(x)\right]\,, \end{aligned}$$

that simplifies to $v_t^i(s \,|\, \varnothing)\widetilde{D}^i(x)G(A_t^*)\big(1 - v_t^i(s \,|\, neg)\big) > 0$, always met by definition. In the third case, testing is optimal if

$$\begin{aligned} -v_t^i(s \,|\, \varnothing)c - v_t^i(asy \,|\, \varnothing)\left[q^D(x)D + \widetilde{D}^i(x)\right] \;>& \\ >\; -v_t^i(s \,|\, \varnothing)\widetilde{D}^i(x)G(A_t^*) - v_t^i(asy \,|\, \varnothing)&\left[q^D(x)D + \widetilde{D}^i(x)\right]\,, \end{aligned} \tag{A.27}$$

that simplifies to $v_t^i(s \,|\, \varnothing)\big[\widetilde{D}^i(x)G(A_t^*) - c\big] > 0$. Note that $\widetilde{D}^i(x)G(A_t^*) > v_t^i(s \,|\, neg)\widetilde{D}_t^i G(A_t^*) > c$ holds via (A.26) since $a_t^*(i)|neg = 1$ by assumption, hence condition (A.27) is always met. Therefore, testing with $\tau_{swab}$ is always optimal for $\delta = 1$. We now turn to the case $\delta > 1$. Before testing

$$a_t^*(i)\,\big|\,\{\varnothing\} \;=\; \Big[\,v_t^i(s\,|\,\varnothing)\widetilde{D}(x)G(A_t^*)\,/c\,\Big]^{\frac{1}{\delta-1}} \in (0,1)$$

holds, whereby

$$\begin{aligned} U_t^*\,\big|\,\{\varnothing\} \;=\; c^{-\frac{1}{\delta-1}}\left(1-\frac{1}{\delta}\right)\Big[\,v_t^i(s\,|\,\varnothing)\widetilde{D}^i(x)G(A_t^*)\,\Big]^{\frac{\delta}{\delta-1}} + \\ -v_t^i(s\,|\,\varnothing)\widetilde{D}^i(x)G(A_t^*) - v_t^i(asy\,|\,\varnothing)\,\Big[q^D(x)D + \widetilde{D}^i(x)\Big]\;. \end{aligned} \tag{A.28}$$

After testing, a negative result entails $a_t^*(i) = 0$, hence the expected utility (A.25), while a negative result entails

$$a_t^*(i)\,\big|\,\{\varnothing\} \;=\; \Big[\,v_t^i(s\,|\,neg)\widetilde{D}(x)G(A_t^*)\,/c\,\Big]^{\frac{1}{\delta-1}} \in (0,1)\,,$$

hence

$$U_t^*\,\big|\,\{neg\} \;=\; c^{-\frac{1}{\delta-1}}\left(1-\frac{1}{\delta}\right)\Big[\,v_t^i(s\,|\,neg)\widetilde{D}^i(x)G(A_t^*)\,\Big]^{\frac{\delta}{\delta-1}} - v_t^i(s\,|\,neg)\widetilde{D}^i(x)G(A_t^*)\,. \tag{A.29}$$

Comparing (A.28) with (A.29) it is easy to check that testing with $\tau_{swab}$ is optimal if

$$v_t^i(s\,|\,neg)^\delta \;=\; [S_t/(S_t+pR_t)]^\delta \;>\; S_t/(S_t+ASY_t+pR_t) \;=\; v_t^i(s\,|\,\varnothing)\,. \tag{A.30}$$

Solving (A.30) in $ASY_t$ we obtain the condition

$$ASY_t \;>\; (S_t+pR_t)^{1-\delta}\big(S_t^{1-\delta} - (S_t+pR_t)^{1-\delta}\big)\,,$$

that is always verified, since the LHS is non-negative by definition and the RHS is strictly negative for at every $E_t$. $QED$