

Social and Economic Distancing ^{*}

Selman Erol[†] Guillermo Ordoñez[‡]

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PRELIMINARY AND INCOMPLETE

Abstract

Dealing with pandemics, such as the recent COVID-19 virus, has highlighted the critical role of social distancing to avoid contagion and deaths. New technologies that allow replacing in-person for at-distance activities have blurred the mapping between social and economic distancing. In this paper we model how individuals react to social distancing guidelines by changing their network of economic relations, affecting total output, wealth inequality and long-term growth.

^{*}The usual waiver of liability applies.

[†]Carnegie Mellon University (e-mail: erol@cmu.edu)

[‡]University of Pennsylvania and NBER (e-mail: ordonez@econ.upenn.edu)

1 Introduction

The recent COVID-19 pandemic has reminded us of the relevance and effectiveness of *social distancing* in the presence of highly contagious diseases. Social distancing practices, voluntary and mandated, prevent disease transmission by reducing contact rates between infected and susceptible individuals, minimizing the extent of the epidemic. Historical data and preliminary recent data indeed suggest that preventing large gatherings is successful in slowing down the rate of contagion. Even though COVID-19 in particular has a low fatality rate, slowing down the rate of transmission is critical to avoid overwhelming the health system, preventing deaths that can be prevented by the reaction of doctors, nurses, hospital beds and, in this particular case, ventilators.

The social distancing that is so effective in preventing contagion and deaths is however, at least in principle, insidious for economy activity, as social distancing usually implies *economic distancing*: most industries require workers to collaborate shoulder to shoulder to produce goods (assembly lines in car factories, production in bakeries, etc), while several services require close contact between clients and providers (restaurants, universities, barber shops, hotels, airlines, etc) or among clients (sport events, casinos, amusement parks, etc).

The ubiquitous link between social and economic distancing uncovers a notable void in the economic literature. Most models abstract from the role of distance in economic and social interactions. Perhaps the most notable exceptions can be found in the trade literature, in which gravity models use distance to capture transportation costs, and in the urban economics, which use distance as affecting commuting costs, an important determinant of people agglomeration and the shape of cities.

Distance, however, is an element that pervades all human and economic interactions. Yet, it is not explicitly modeled at a microeconomic level to capture macroeconomic implications. How distance among coworkers affect their productivity? What services can be provided at distance and which require close contact? These questions may have sounded moot in normal times, as performing activities face to face or at a distance just differs on commuting, infrastructure or logistic costs. Pandemics unveil

that social and economic distancing are closely related and shocks that affect the relative cost of distance may have dramatic consequences on how economic activity reorganizes, having consequences for output, wealth inequality and growth.

In this paper we propose a model that includes both social and economic distancing, and in which as a response to social distancing needs individuals reshape their economic relations, both in terms of ways to operate (in-person or at-distance) and in terms of their productive network. This model captures well the reaction of a society during a pandemic, in which economic costs are not from the disease itself (with a rather low fatality rate) but instead from social distancing practices implemented to minimize the effects of the disease.

In the model, economic activity is performed by collaboration of pairs of individuals, who can operate in-person or at-distance. Individual-pairs are heterogeneous on the relative payoffs of operating at-distance, and as such sort their activities into no collaborating at all, collaborating in-person or collaborating at-distance.

Indeed, in recent years, and as a response to large technological improvements several industries have already adapted working at-distance, or telecommuting. Estimates from the Census Bureau show that just over 5 percent of the U.S. workforce primarily worked from home in 2017 (in 2006 this figure was 3.9%). Noonan and Glass (2012), using data from NLSY and CPS, show that approximately 10% of workers telecommuted (worked regularly but not exclusively) in the mid-1990s, increasing to 17% in the early 2000s and to 24% late 2000s. Telecommuting does not seem different between young and old cohorts, but college-educated workers and those in managerial and professional occupations are significantly more likely to telecommute than the population as a whole. Finally, telecommuters are less likely to be Black or Hispanic and less likely to be married compared with those not telecommuting.

There have been some studies on the impact of teleworking on productivity, most of them focused on experiments and with mixed results. Bloom et al. (2015) present evidence from a field experiment with call centre employees in China that teleworking enhanced TFP. In contrast, Battistin et al. (2017) use a natural experiment with a public sector firm in the UK, finding that productivity is higher when teammates are in the same room and that the effect is stronger for urgent and complex tasks.

Dutcher (2012) claims that telecommuting may have a positive impact on the productivity of creative tasks but a negative impact on the productivity of dull tasks. These results show the heterogeneity among activities that we explore in this model.

Pandemics in our model arrive as a shock that increases the cost of operating in-person, as it increases the probability of acquiring the virus. Individuals react in two ways. One is individually changing the way of interacting with their partners, both at an extensive margin (cutting off activities) and at the intensive margin (replacing activities from in-person to at-distance). The other is by changing the network of relations and the identity of partners. These reactions by the way individuals collaborate and with whom they collaborate buffers the shock's economic implications.

In a recent paper, Dingel and Neiman (2020) classify the feasibility of working at home for all occupations in the U.S., and estimate that 37% of jobs could be done at home (lawyers, teachers, finance, etc), with a large heterogeneity across regions, much larger than the reported telecommuting happening in the U.S. before the pandemics.¹ Saltiel (2020) extended this computation for developing countries, where in average 13% of jobs could be done at home in ten countries composing the so called STEP survey. Again in those countries, the feasibility of working from home is positively correlated with high-paying occupations, educational attainment, formal employment status and household wealth.

In case of pandemics, however, individual reactions are not enough: contagious diseases create negative externalities (in terms of affecting both economic activity and the health of other agents). When an individual considers the cost of getting sick, he does not internalize the effect on reducing the output of the economic partner, not the probability of also transmitting the disease to the economic partner (and to the economic partners of the economic partner). As such we consider a government that restricts social interactions, by introducing social distancing mandates, prohibiting individuals to meet with a large mass of other individuals.

We solve for the reaction of individuals to the pandemics shock and the social dis-

¹This is consistent with the estimation of 40% that Matthews and Williams (2005), who were motivated by the potential positive effects of telecommuting on climate.

tancing mandates. Individuals rearrange their economic activities by moving more to in-distance operations and by cutting some operations. Further they rearrange their network such that it displays assortative matching and a polarization of economic activity. The main reason is that individuals that can operate at-distance tend to cluster their activities, leaving activities in-person to cluster among themselves.

We solve for the optimal social distancing mandates that trade-off economic and health costs. Too stringent social distancing reduces economic output and increases income inequality, while too relaxed social distancing increases contagion and death. This obvious trade-off heavily depends on the technology that drives the mapping between social and economic distancing, but more interesting middle class individuals find social distancing mandates too stringent compared to low and high income individuals. While economic output does not suffer much for low income individuals, high income individuals can easily operate at-distance.

We also discuss the effect of pandemics and social distancing mandates for long-term growth. In the presence of adjustment costs to adopt new at-distance activities, or in the presence of coordination failures to adopt new technologies, the shock induced by social distancing restrictions may speed up the adoption of superior technologies, having indeed a positive long-term effect on economic activity after the shock has passed. Indeed, a recent Gartner, Inc. survey of 317 CFOs and Finance leaders on March 30, 2020 revealed that 74% will move at least 5% of their previously on-site workforce to permanently remote positions post-COVID 19.² This survey also highlights that CFOs were more motivated to make the change once many competitors make the change.

2 In-person and at-distance activities

Activities We index activities with $a \in A$. These can be economic or social activities. Each activity a can be performed in-person (taxi, construction, surgery,...), at-distance (call service, cargo shipping,...), or both (teaching, consulting,...). We

²<https://www.gartner.com/en/newsroom/press-releases/>

assume that the in-person surplus is p_a and at-distance surplus is d_a , then $p_a = -\infty$ and $d_a = -\infty$ encompasses the activities that can not be performed in-person or at-distance, respectively.

Denote $P_0 \subset A$ and $D_0 \subset A$ the distinct set of activities that end up being performed in-person and at-distance, whereas $N_0 = A \setminus (P_0 \cup D_0)$ denotes the set of activities that are not performed at all because their surplus are negative either in-person or at-distance. Then, optimality prescribes that $P_0 = \{a : p_a > \max\{d_a, 0\}\}$, $D_0 = \{a : d_a > \max\{p_a, 0\}\}$, and $N_0 = \{a : 0 > \max\{p_a, d_a\}\}$.

We envision a shock that increases the cost of performing all activities in-person. The natural example is a pandemics, which increases the probability fo contagion of any social and economic interaction. Naturally, different activities can be subjected to this shock differently, but a pandemic has the property of increasing the relative expected cost of in-person activities across the board. Then, we model the effect of pandemics simply with a downward shift in the surplus function from p_a to $p_a - c_a$, where c_a captures the probability of getting the virus times the cost in that case (being sick, being hospitalized and in the worst case scenario, death).

Pandemics discourage in-person activities, to $P_c = \{a : p_a - c_a > \max\{d_a, 0\}\} \subset P_0$. In contrast, there is an expansion of the set of activities performed at-distance to $D_c = \{a : d_a > \max\{p_a - c_a, 0\}\} \supset D_0$, and of the set of activities not performed at all $N_c = A \setminus (P_c \cup D_c) = \{a : 0 > \max\{p_a - c_a, d_a\}\} \supset N_0$.

The set $N_c \setminus N_0$ is the set of displaced activities due to the shock, *the extensive margin effect of pandemics*. The set $D_c \setminus D_0$ is the set of replaced activities that switch from in-person to at-distance due to the shock, *the intensive margin effect of pandemics*.

Figure 1 shows an illustration of the optimal distancing that individuals endeavor in the presence of a pandemics when $A = [0, 1]$ and $c_a \equiv c > 0$ constant. Agents react both in the extensive margin (displacing activities) and on the intensive margin (replacing activities).

From activities to agents. Now we introduce a society $S = [0, 1]$ that captures the networking relations across agents and then how the cost $c(a)$ may endogenously

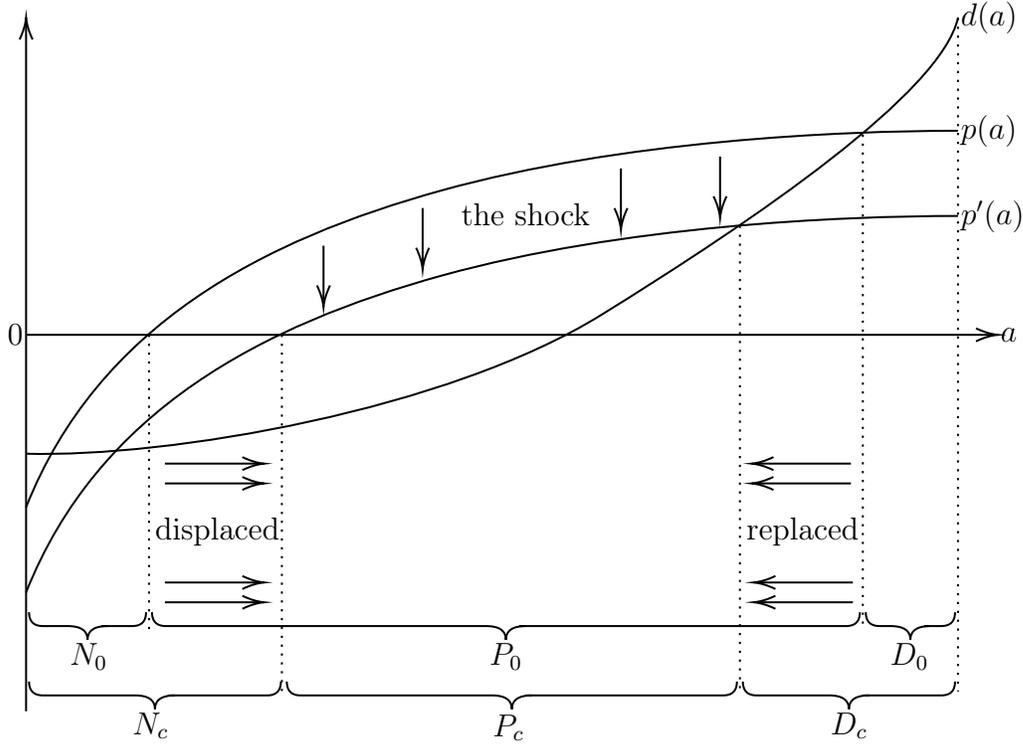


Figure 1: Activities

depend on the network, and then how the network reacts to exogenous shocks, such as pandemics.

We assume that activities are performed by pairs of agents, i and j . For example, two consumers i and j can go to a restaurant together, or a consumer i can obtain a service from producer j , or two producers i and j work together to produce goods. Every $\{i, j\}$ -pair is a potential activity, as described above.

For simplicity of notation and clarity of figures, we will use the convention that symmetric ordered pairs (this is (i, j) and (j, i)) represent the same activity. Accordingly, we assume that $A \subset S^2$ is the symmetric set of technologically feasible activities and it captures the combinations of possible economic and social networks. Now, p_{ij} and d_{ij} are i 's marginal benefits of in-person and at-distance activities/connections with j . If p and d are symmetric functions of (i, j) , then there is no conflict between agents about if or how an activity will be performed. At first we focus on the

symmetric case for simplicity: $p_{ij} = p_{ji}$ and $d_{ij} = d_{ji}$.

Given the symmetric surplus functions p_{ij} and d_{ij} we call $P_0 = \{(i, j) \in A : p_{ij} > \max\{d_{ij}, 0\}\}$ the pre-shock equilibrium in-person network and $D_0 = \{(i, j) \in A : d_{ij} > \max\{p_{ij}, 0\}\}$ the pre-shock equilibrium at-distance network. N_0 is the set of remaining unperformed activities. We denote $P_{0,i} = \{j : (i, j) \in P_0\}$ the in-person activities/connections of i , $D_{0,i} = \{j : (i, j) \in D_0\}$ is the at-distance activities/connections of i , and $N_{0,i} = S \setminus (P_{0,i} \cup D_{0,i})$ the potential but unperformed activities/connections of individual i .

The shape of these payoffs, and the consequent network of activities, can be very general. Hence, for expositional reasons we will restrict attention to the following example.

$$\begin{aligned} p_{ij} &= -m_1 + n_1 \frac{i+j}{2} \\ d_{ij} &= -m_2 + n_2 \frac{i+j}{2} \end{aligned} \tag{1}$$

This example implies that the surplus of activities increase in average “label” of individuals. The label of the individual may correspond to his/her human capital, skills, etc. If two individuals, i and j that are “highly labeled,” (this is both i and j are large numbers) get together, their average label is high, and can perform a very valuable activity.

This example displays absolute comparative advantages of an individual on all activities, and no complementarity of the pair of individuals performing the activity (this is, the surplus depends on the average label, and not on some multiplicative function).

We further assume for now, i) $m_1 > 0$ and $m_2 > 0$, this is the lowest labeled pair, with $i + j = 0$ does not perform any activity together, ii) $n_2 > n_1 > 0$, this is the surplus of at-distance activities is more elastic to labels than for in-person activities and iii) $\frac{m_2}{n_2} > \frac{m_1}{n_1}$, this is a pair that is indifferent between not performing the activity, or doing it at-distance, strictly prefers to do it in-person.

Denote $r_P = \frac{m_2 - m_1}{n_2 - n_1}$ and $r_D = \frac{m_1}{n_1} < r_P$. In equilibrium, the activity $(i, j) \in A$ is performed at-distance if $\frac{i+j}{2} > r_P$, performed in-person if $r_P > \frac{i+j}{2} > r_D$, and not performed if $r_D > \frac{i+j}{2}$. These conditions characterize P_0 and D_0 .

Giving this simple example, the activities and their equilibrium distancing for all possible pairs are illustrated in Figure 2.

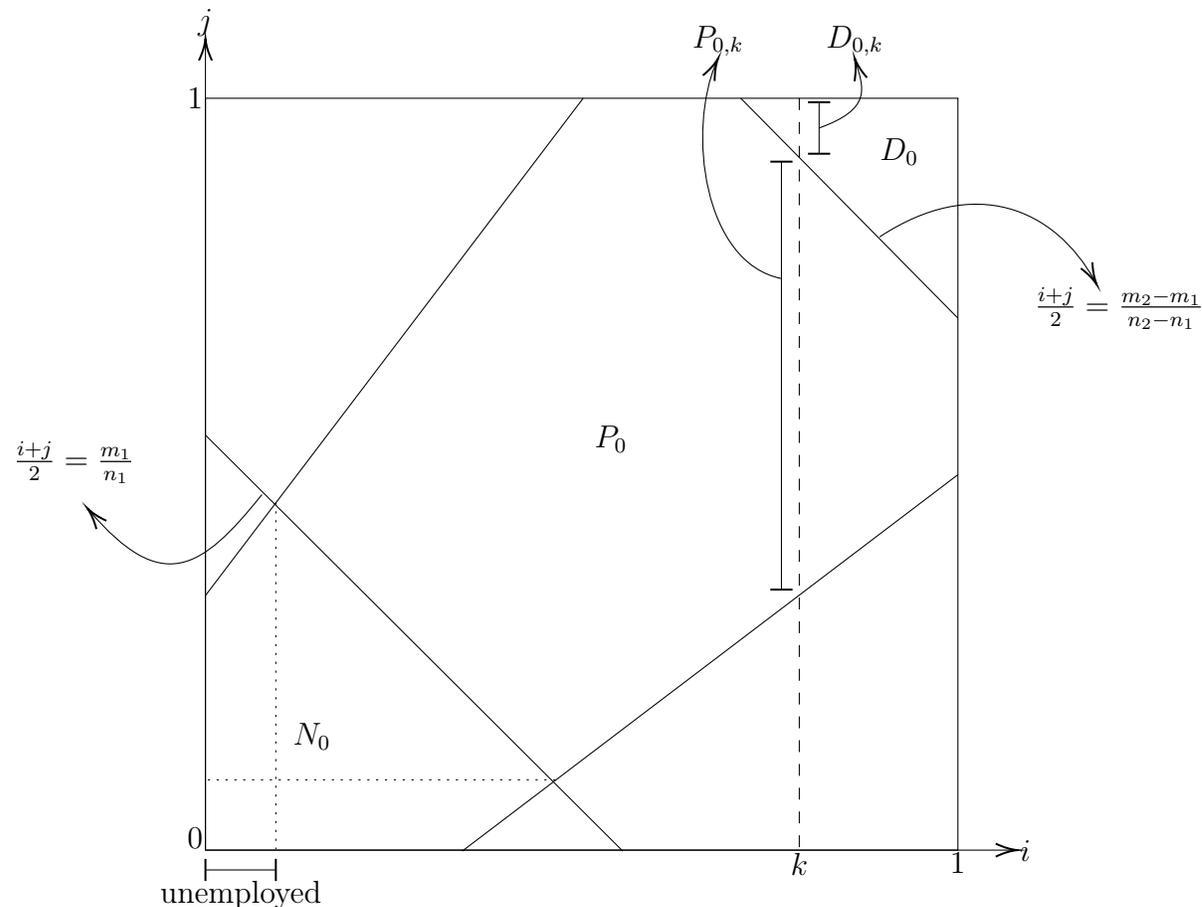


Figure 2: Agents and activities

Network reactions to shocks to in-person costs Now we will assume a shock (such as COVID-19) that reduces the surplus from all in-person activities, and will study how the at-distance network reacts to such shock.

For simplicity we assume that the shock increases the cost of each in-person activity by a constant $c > 0$. In the context of COVID-19, this can be the marginal

expected cost of being infected for risk-neutral agents.³ Then d stays the same but p shifts to $p - c$.

We call P_c the post-shock equilibrium in-person activity network and D_c the post-shock equilibrium at-distance activity network. Denote $r_{P,c} = \frac{m_2 - m_1 - c}{n_2 - n_1}$ and $r_{D,c} = \frac{m_1 + c}{n_1}$.

Now, in equilibrium, the activity $(i, j) \in A$ is performed at distance if $\frac{i+j}{2} > r_{P,c}$, performed in-person if $r_{P,c} > \frac{i+j}{2} > r_{D,c}$, and not performed if $r_{D,c} > \frac{i+j}{2}$. These conditions characterize the networks P_c and D_c . The impact the shock has on the networks is illustrated in Figure 3.

3 Social Distancing Restrictions

In the benchmark above we consider pandemics as a shock that individually increases the likelihood of catching a virus, but we did not consider the possibility that getting sick also affects the probability that another related agent gets sick. In few words we have abstracted from externalities, eliminating the need for policy. Next we introduce contagion over the network as the main source of externality. Then we discuss other potential sources of externalities. Only for this section, we simplify notation and drop the c subscript as it does not cause any confusion, as we study the ex-post effect of a shock on the network.

3.1 Health externalities - Contagion

Most pandemics are not extremely deadly, so have the externality that a sick individual may be spreading the virus while performing his activities. In the case of COVID-19, for instance, this characteristic is particularly pervasive given the large fraction of asymptomatic infected individuals that have the capacity to spread the virus. Depending on the particular virus, it may travel long distances along the

³At the background, there is a benefit $b_{ij}^{P/D}$ and cost $c_{ij}^{P/D}$ from activity (i, j) to both i and j if performed in-person/at-distance. Then $p/d \equiv b^{P/D} - c^{P/D}$. The marginal cost c^P of an in-person activity then becomes $c^P + c$ due to the shock.

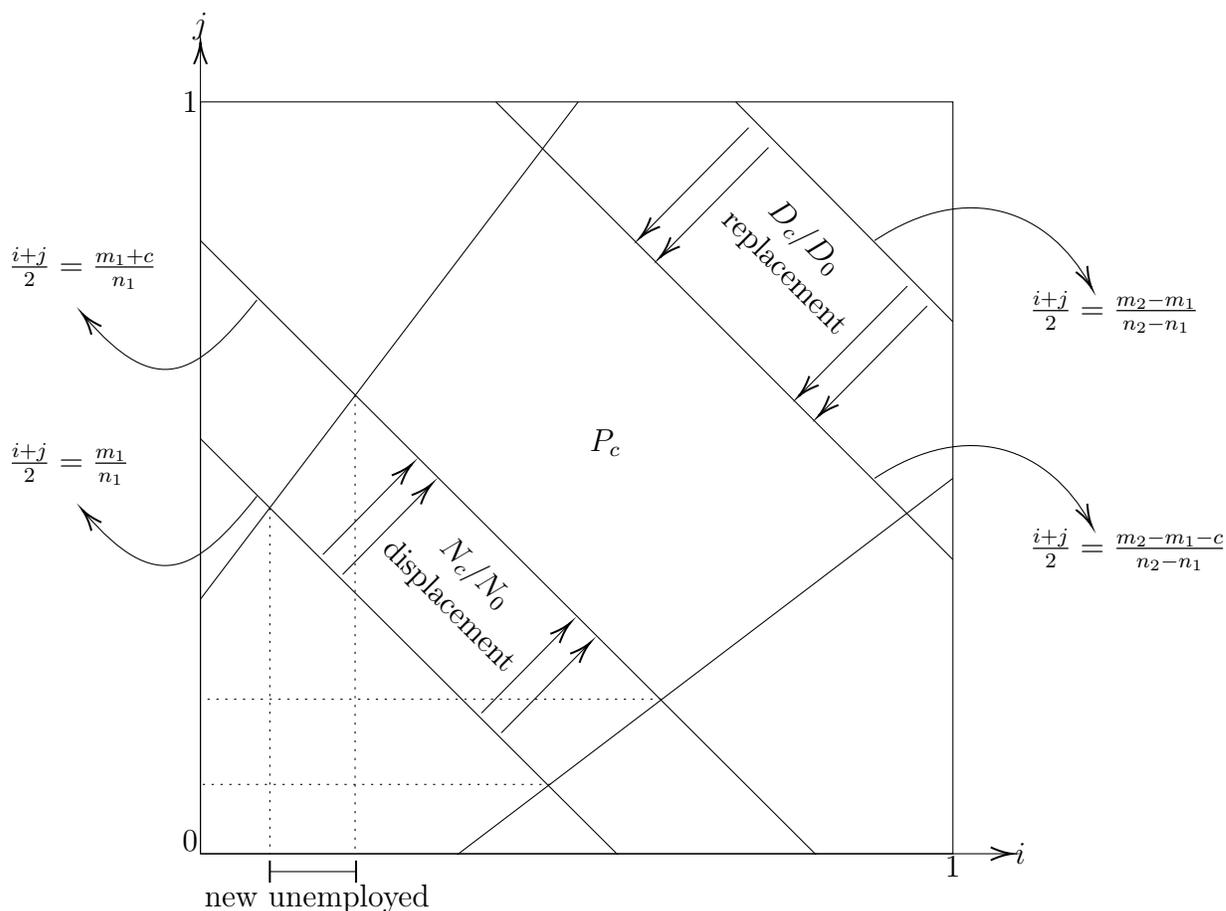


Figure 3: Network reactions to the shock

networks. In this case, the virus-related marginal cost of in-person connections will be a function that depends on the entire endogenous in-person network P .

Assume for simplicity that the virus kills the patient with very low probability (as COVID-19). Instead, upon infection, the agent incurs an expected cost c (with a low probability the agent may die and with a high probability it does not display symptoms). Define η_i the probability that agent i gets infected. Notice that our benchmark corresponds to $\eta_i = \pi_i$ where $\pi_i = |P_i|$ the mass of in-person connections of individual i .

Now we take the probability of infection to take a more general form. Suppose

that there are two rounds of infections, this is, by the third round there is a vaccine. In the first round, agents can get infected as a function of their measure of in-person connections. In the second round, they can get infected by their in-person connections who got infected in the first round. We model this simply with

$$\eta_i = \rho_1 \pi_i + \rho_2 \int_{P_i} \pi_k \mathbf{d}k$$

Here, ρ_2 captures contagion externalities. In Section A we put more structure on the infection probability η_i and study ρ coefficients in more detail. Agent i 's payoff is then

$$\int_{P_i} p_{ik} \mathbf{d}k + \int_{D_i} d_{ik} \mathbf{d}k - c\eta_i$$

In words, the individual's utility simply adds all surpluses from in-person and at-distance activities, minus the expected cost of being infected times the probability of infection. Notice that in-person and at-distance activities payoffs depend on the network position, while the probability of infection only depend on the in-person network. In a way, in-person activities become more expensive, and even more the more connected are the counterparties.

3.2 Economic externalities

Even though contagion is the main source of externality in a pandemic environment, there are additional, economic, sources fo externality. First, an infected agent reduces the payoff of counterparties that interact with the agent. Second, there are workers in activities that are particularly relevant (essential activities such as doctors and nurses, postal and delivery agents, safety workers, etc) whose infection magnify their economic impact.

Consider an agent i that, upon infection dies and immediately leaves the economy. The main externality of this individual is not health-wise (he does not spread the virus further), but economic-wise (he stops producing). This creates an externality in that an infected agent's connections do not receive any economic surplus from

their activities with the infected individual since the individual leaves the economy. Then individual i 's expected payoff from networks P and D is

$$\underbrace{(1 - \eta_i)}_{i \text{ stays}} \left(\int_{P_i} \underbrace{(1 - \eta_k)}_{k \text{ stays}} p_{ik} \mathbf{d}k + \int_{D_i} \underbrace{(1 - \eta_k)}_{k \text{ stays}} d_{ik} \mathbf{d}k \right)$$

The term $-\eta_k$ in the integrals is the externality caused by k 's in-person connections on i . These connections can take k out of the networks and reduce i 's payoff. Notice that intuitively this sort of externality implies that being sick and dying destroys pairs, creating a negative externality to partners.

While dying from the infection destroys links, this effect can be magnified upon heterogeneity in the importance of activities. This is because the destruction of links among those activities also reduce the surplus of link in other activities. Indeed, some activities are essential for well-being. For example, groceries and health care are immutable activities that can not be easily substituted. Suppose that a relatively small set of agents E provide essential services to the society and the access to activities with E are complementary to all other activities. Denote E_i the connections of individual i to essential agents. Then the payoff of i is given by

$$\min \left\{ \chi |E_i|, \int_{P_i} p_{ik} \mathbf{d}k + \int_{D_i} d_{ik} \mathbf{d}k \right\}$$

Now the conditions and connections of agents in E have externalities on the rest of the society.

When health and economic externalities are combined, the expected payoff of individual i is given by

$$(1 - \eta_i) \min \left\{ \chi |E_i|, \int_{P_i} (1 - \eta_k) p_{ik} \mathbf{d}k + \int_{D_i} (1 - \eta_k) d_{ik} \mathbf{d}k \right\} - c\eta_i$$

where for all j

$$\eta_j = \rho_1 \pi_j + \rho_2 \int_{P_j} \pi_k \mathbf{d}k$$

is the probability that j gets infected.

The combination gets to the heart of one of the key aspects of the current COVID-19 pandemic. Society prefers to have some level of connections among themselves for economic surplus. This creates risk of contagion in the society. The society would indeed have some level of distancing to tradeoff the benefits and costs. But they all need access to essential services, which puts essential workers at heightened risk of contagion. If essential workers get infected and leave the economy, this would have large welfare consequences. Individuals in the society do not internalize the risk that their normal connections can increase their risk, which then can be transmitted to essential workers, taking them off the economy, creating large welfare losses uniformly across the society.

Since essential workers provide disproportionately important tasks for the society, they can be perhaps be protected by making the rest of the society have less links among themselves than they would have wanted to. This brings us to widespread physical distancing.

These sources of externalities justify the actions of governments by mandating stay at home orders, or in several cases outright restrictions to transit and to gather in public and private spaces. As there are several and complex sources of negative externalities, the government should act in particular in certain parts of the network.

Our setting shows how individuals react to pandemics by cutting activities and moving to some of them that can be operated at-distance. However, they do not react enough.

3.3 Imposing social distancing

In response to this particular health shock, physical distancing can be an effective tool for policy. Regardless of whether it is optimal in its current form or not, physical distancing has been implemented world-wide. We model this policy with a parameter $s \geq 0$ that limits the measure of in-person connections that each agent can maintain: $|P_i| \leq s$. Next we consider the economic consequences of this policy in our benchmark, and then we discuss optimal social distancing restrictions.

In order to simplify the rest of the analysis, we take $A = S^2$ and work with the lead example in equation (1). Denote P_c^s the equilibrium in-person network and D_c^s the equilibrium at-distance network under cost c and distancing s . Here $s = 1$ corresponds to no-distancing restrictions (as all individuals perform activities with the whole population of individuals in the society). We already know that $P_c^1 = P_c = \{(i, j) : r_{D,c} > \frac{i+j}{2} > r_{P,c}\}$ and $D_c^1 = D_c = \{(i, j) : \frac{i+j}{2} > r_{D,c}\}$.

Now we study the equilibrium structure of P_c^s and D_c^s when s is small, this is there is a restriction on the mass of individuals to get in touch and perform in-person activities (for example, restaurants are closed so the interaction between the waiters and clients is eliminated altogether, soccer leagues are cancelled, so the interaction between fans in stadiums are cancelled, etc).

Notice that $D_c^s = D_c^1$ for any s because s is assumed not constraining any at-distance connections. A different application in which for some reason the government restricts access to certain digital platforms or social media would be an example of restricting s for at-distance activities.

3.3.1 Inequality effects of distancing with “only in-person” activities.

We start with an illuminating thought exercise that studies a “only in-person” activities (formally, this is $p - c > d$ for all activities $r_{D,c} > 1$). This could be achieved, for instance if m_2 is very small. Two centuries ago, for instance, no activities could be performed at-distance due to technological constraints. This means that $D_c^1 = \emptyset$.

Before the shock ($c = 0$) and without distancing ($s = 1$), agent $i \geq r_{D,0}$ performs all possible activities ranging from 0 to 1 (this is because, even if $j = 0$, an agent $i \geq r_{D,0}$ would perform the activity in person and an agent $i < r_{D,0}$ would not perform the activity). This can be seen in Figure 2. Then i 's payoff is

$$-m_1 + \frac{n_1}{2} \left(\underbrace{\int_0^1 i dj}_{\text{individual quality}} + \underbrace{\int_0^1 j dj}_{\text{connections quality}} \right)$$

$$= -m_1 + \frac{n_1}{2} \left(i + \frac{1}{2} \right) \quad (2)$$

Now suppose that the shock materializes ($c > 0$) and that physical distancing is implemented ($s < 1$). Due to the monotonicity in p , equilibrium matching is assortative. Agents $[1 - s, 1]$ connect with each other as they are the most desirable partners. Then $[1 - 2s, 1 - s]$ connect with each other as they are the most desirable partners who are still available, and so on. The equilibrium network of connections is shown in Figure 4. Then agent $i > r_{P,c}$ is connected with $[r_i, r_i + s]$ where $r_i = 1 - \lceil \frac{1-i}{s} \rceil s$. Then i 's payoff is

$$\begin{aligned} & -m_1 s + \frac{n_1}{2} \left(\underbrace{\int_{r_i}^{r_i+s} i dj}_{\text{individual quality}} + \underbrace{\int_{r_i}^{r_i+s} j dj}_{\text{connections quality}} \right) - cs \\ &= -m_1 s + \frac{n_1}{2} \left(is + \frac{s^2 + 2sr_i}{2} \right) - cs \quad (3) \\ &= \underbrace{s}_{\text{distancing multiplier}} \left(-m_1 + \frac{n_1}{2} \left(\underbrace{i}_{\text{individual quality}} + \underbrace{\frac{s + 2r_i}{2}}_{\text{average connections quality}} \right) \right) - \underbrace{c}_{\text{direct cost}} \end{aligned}$$

The distancing multiplier s and the direct cost c are exogenous effects. The equilibrium effect is the change in the connections quality due to assortativity. Low quality agents suffer large and disproportionate losses in their payoffs by the imposition of s because assortativity kicks in, which is reflected by r_i in connections quality term. In particular, for small s , the direct assortativity effect is

$$s + 2r_i \approx s + 2 \left(1 - \frac{1-i}{s} s \right) = s + 2i$$

The quality of average connections decline on the individual quality i and on the distancing restrictions s .

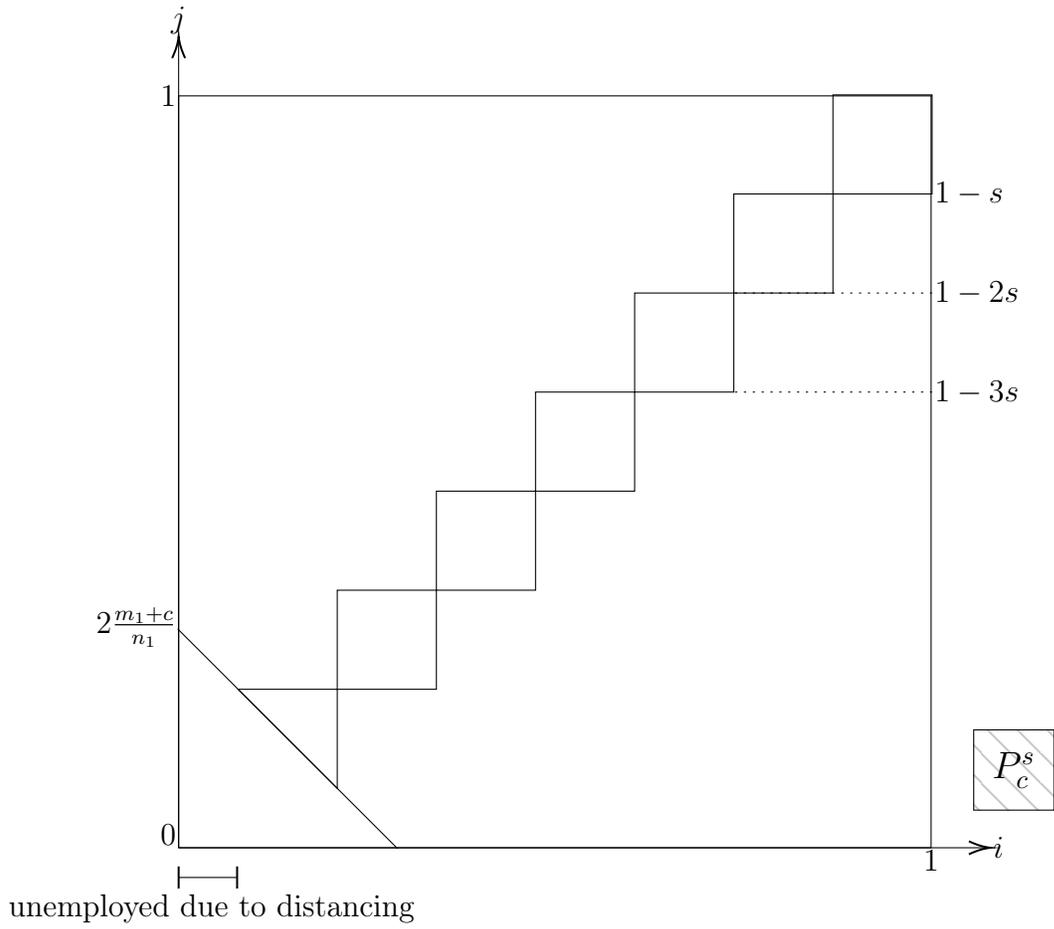


Figure 4: Direct assortative matching in the absence of at-distance activities

3.3.2 Inequality effect of distancing with both activities

The previous “only in-person” economy illuminates a direct assortativity inequality effect that distancing introduces by reshaping economic networks. In particular, distancing restrictions introduces assortative matching and makes low quality individuals suffer relatively more from an economic point of view. Here we show that, when at-distance activities are also in place, there is an additional assortativity effect that magnify the inequality effects of social distancing.

Denote $q_c := 2r_{D,c} - 1$. In equilibrium, agent 1 has at-distance connections to

$[q_c, 1]$ and so he can have in-person connections to $[q_c - s, q_c]$. All of these agents will be happy to use one of their at-distance links with agent 1 as he is the most desirable connection. The argument extends and due to assortativity, agent $i \in [q_c, 1]$ will have in-person connections with $[q_c + 1 - i - s, q_c + 1 - i]$. Agent $i \in [q_c - s, q_c]$ will have connections with $[q_c + 1 - i - s, 1] \cup [q_c - s, 2q_c - s - i]$.

The group of agents in $[q_c - s, 1]$ form connections with each other in this particular way, as shown in Figure 5. There is a “smoothing” effect on the payoffs of these agents as even the low quality agents within the group have links with high quality ones among them. For agents in $[0, q_c - s]$, the standard assortative matching applies. Agents in $[q_c - 2s, q_c - s]$ match with each other, agents in $[q_c - 3s, q_c - 2s]$ match with each other, and so on. This is also shown in Figure 5.

The existence of at-distance activities is a (roughly) Pareto improvement on the hypothetical world without such activities. The low quality agents are not hurt by the at-distance segment of the economy per se, but they do not benefit from it at all, whereas there is a form of smoothing at the higher segment of the economy. For the higher segment of the economy, the negative economic effects of distancing is dampened by the smoothing possibility introduced by operating at distance, above and beyond the direct dampening effects by the at-distance activities. Neither forms of smoothing apply for the lower segment. This is an additional force that widens the inequality gap that arose in the absence of at-distance activities, but in this case introducing a *polarization* force in the economy. In a way, the possibility of working at distance gives a buffer to workers in such position, creating a large disparity in the effect of pandemics across the population.

We formalize these effects by computing payoffs. Consider first an agent $i \in (2\frac{m_1+c}{n_1}, q_c - s)$, such that it does not get to participate in at-distance activities. Without the shock ($c = 0$), without distancing ($s = 1$), the payoff for such agent is given by

$$\int_0^1 p_{ij} dj = -m_1 + \frac{n_1}{2} \left(i + \frac{1}{2} \right)$$

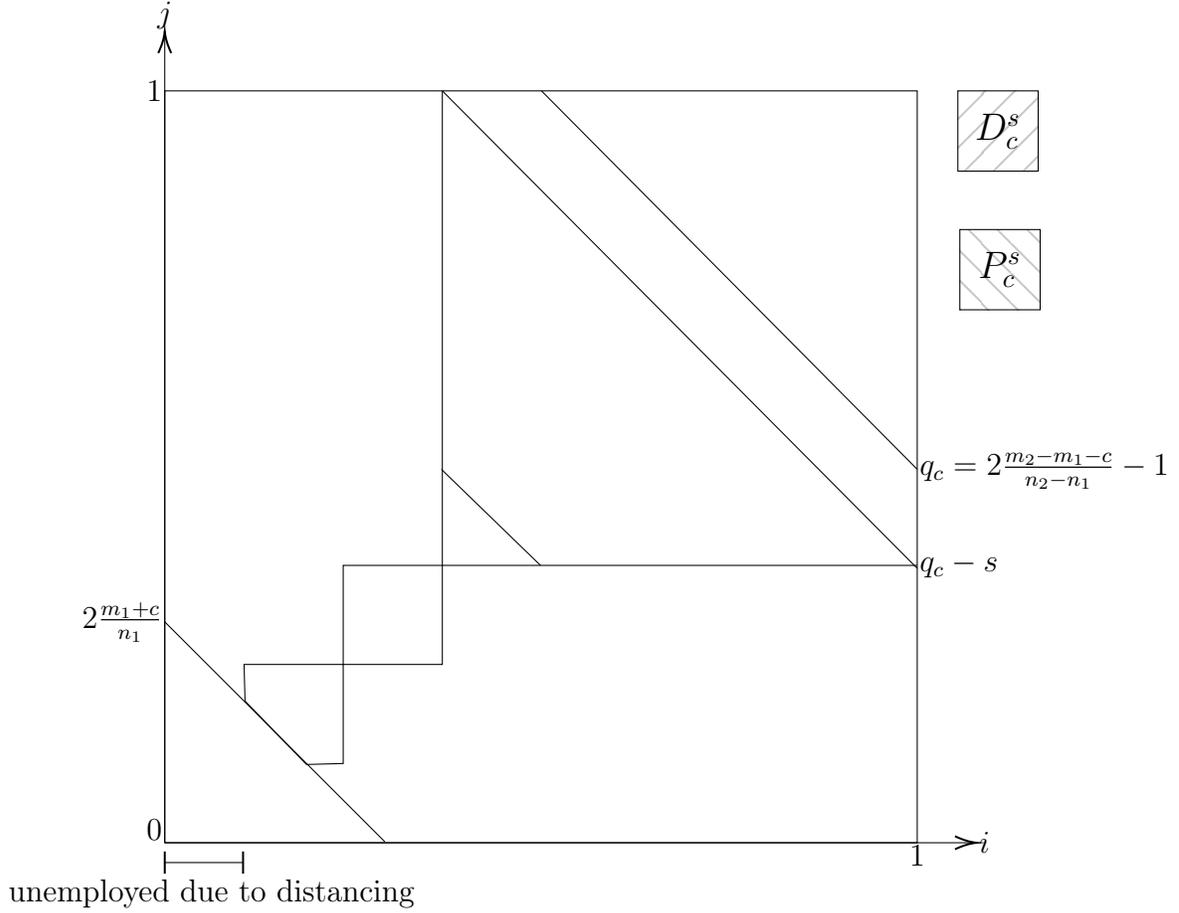


Figure 5: Assortative matching in the presence of at-distance activities

After the shock c , with distancing s , such agent i 's payoff is

$$\begin{aligned} \int_{q_c - \lceil \frac{q_c - i}{s} \rceil s}^{q_c - \lceil \frac{q_c - i}{s} \rceil s + s} p_{ij} dj - cs &\approx \int_i^{i+s} p_{ij} dj - cs \\ &= s \left(-m_1 + n_1 \left(\frac{i}{2} + \frac{s + 2i}{4} \right) - c \right) \end{aligned}$$

The effects on i 's payoff is roughly the same than the one outlined in the earlier in equations (2) and (3), which were derived under the assumption of only in-person activities. As agent i does not have any at-distance activities, his entire payoff is

scaled down by the distancing multiplier. Moreover, assortative matching is direct, and it enters the payoff of i directly proportional to the quality of i via $s + 2i$, as discussed above.

Next consider an agent $i > q_c$. Before the shock, without distancing, the payoff is

$$\begin{aligned} & \int_{q_0+1-i}^1 d_{ij} \mathbf{d}j + \int_0^{q_0+1-i} p_{ij} \mathbf{d}j \\ &= \int_{q_0+1-i}^1 d_{ij} \mathbf{d}j + (1 - i + q_0) \left(-m_1 + \frac{n_1}{2} \left(\frac{1 + i + q_0}{2} \right) \right) \end{aligned}$$

After the shock, with distancing, such at-distance agent i 's payoff is

$$\begin{aligned} & \int_{q_c+1-i}^1 d_{ij} \mathbf{d}j + \int_{q_c+1-i-s}^{q_c+1-i} p_{ij} \mathbf{d}j - cs \\ &= \int_{q_c+1-i}^1 d_{ij} \mathbf{d}j + s \left(-m_1 + \frac{n_1}{2} \left(\frac{2q_c + 2 - s}{2} \right) - c \right) \end{aligned}$$

The reduction in payoffs when at-distance activities are a possibility is dampened by various effects compared to the reduction that low quality agents suffer. First, the at-distance activity term is weakly larger (since $q_c \leq q_0$), and not affected by the distancing multiplier. The reason is simply that these activities were operated at distance before any restriction, and then are not prevented by social distancing requirements. Second, the relative effect of the distancing multiplier on the in-person activities term is $\frac{s}{1-i+q_0}$ for i , which is smaller than s . Recall that the multiplier is exactly s for low quality agents. This is because high quality agents do not rely on in-person activities as much as low quality agents do, pre-shock. Third, the average connections quality from in-person activities, modulo direct cost c increases. Notice that $2q_c + 2 - s > 1 + i + q_0$ if s and c are not too large.

This discussion shows that there are three separate equilibrium effects that dampen the losses of high quality agents. In few words, high quality agents are not affected by social distancing because they already relied on few in-person activities, they can move some of their in-person activities at-distance and the quality of the in-person

activities that remain increases.

As none of these network dampening effects of distancing restrictions apply to low quality agents, there is a polarization based on social distancing restrictions, which widens inequality above and beyond the initial equilibrium effect of direct assortative matching.

4 Optimal level of social distancing with contagion

Here we explore the optimal level of social distancing imposed when just considering health externalities, or contagion. This restriction on the nature of externalities is motivated because dealing with contagion has been the main consideration behind interventions against the COVID-19 pandemics. It is also helpful to capture the main trade-offs and to uncover the role of inequality on supporting that policy. We study the combination with economic externalities in Appendix A.

The payoff of agent i is

$$\int_{P_i} p_{ik} dk + \int_{D_i} d_{ik} dk - c \left(\rho_1 \pi_i + \rho_2 \int_{P_i} \pi_k dk \right)$$

Note that for agent i who does not have a connection with agent j , the marginal benefit of adding an in-person connection is

$$p_{ij} - c(\rho_1 + \rho_2 \pi_j)$$

Going forward, we assume that

$$- m_1 = p_{00} > c(\rho_1 + \rho_2) \tag{4}$$

Under this assumption, regardless of the shape of the network, each agent would prefer to add any in-person activity instead of not having it. For two agents i and j , not having the activity (i, j) is strictly dominated by having it in-person.

Due to strict dominance, under any s , all agents will have s mass of in-person

activities in equilibrium. Then infection probability is

$$\rho_1 s + \rho_2 s^2$$

The equilibrium network will feature assortativeness as described in Section (3). The network structure will be as given in Figures 4 and 5.

Equilibrium payoffs Notice that payoffs from at-distance activities do not depend on restrictions on social distancing, as they do not depend on s . Then, we focus on the case of only “in-person” activities economy benchmark, and then we interpret the payoff as “net of at-distance” activities.

Under s , the equilibrium payoff of agent i is

$$u_i = \int_{P_i} p_{ik} \mathbf{d}k - c(\rho_1 s + \rho_2 s^2)$$

Consider the boxes in Figure 4. Index these boxes from right to left: $X_t = [x_t - \frac{s}{2}, x_t + \frac{s}{2}]$ where $x_t = 1 - s \lceil \frac{1-i}{s} \rceil + \frac{s}{2}$.⁴ Note that for all $i \in X_t$, $P_i = X_t$. Then agent $i \in X_t$ has payoff

$$\begin{aligned} u_i &= \int_{X_t} p_{ik} \mathbf{d}k - c(\rho_1 s + \rho_2 s^2) \\ &= -m_1 s + n_1 s \frac{x_t + i}{2} - c(\rho_1 s + \rho_2 s^2) \end{aligned} \tag{5}$$

4.1 Social optimal distancing

Next we look into the optimal distancing, s^* that a benevolent social planner would introduce in this economy (again restricting attention to only “in-person” activities, which are the ones affected by the social distancing policy).

⁴Note that the agents at the last interval would have a box of size smaller than s so their x_t is also different.

The sum of payoffs of agents in X_t is

$$\begin{aligned}\int_{X_t} u_i \mathbf{d}i &= \int_{X_t} \int_{X_t} p_{ik} \mathbf{d}k - \int_{X_t} c(\rho_1 s + \rho_2 s^2) \\ &= (-m_1 + n_1 x_t) s^2 - c(\rho_1 s + \rho_2 s^2) s\end{aligned}$$

For now, assume away integer problems: $ks = 1$ for some integer k . This means that $s \in \mathcal{I} = \{1, \frac{1}{2}, \frac{1}{3}, \dots\}$. Then the sum of payoffs is

$$\begin{aligned}W_s &= \sum_{t=1}^k (-m_1 + n_1 x_t) s^2 - c(\rho_1 s + \rho_2 s^2) s \\ &= \left(-m_1 + \frac{n_1}{2}\right) s - c(\rho_1 s + \rho_2 s^2)\end{aligned}$$

Note that W_s is indeed the welfare for $s \in \mathcal{I}$. For $s \notin \mathcal{I}$, the welfare is close to W_s with some small error term. (The discreteness is problematic for obtaining analytical results.) So, for insights, we will consider $\arg \max W_s$ over $s \in [0, 1]$.

Note that

$$W'_s = \left(-m_1 + \frac{n_1}{2}\right) - c(\rho_1 + 2\rho_2 s)$$

The planner chooses s^* that maximizes this expression, then

$$s_{\text{planner}}^* = \frac{-m_1 + \frac{n_1}{2} - \rho_1 c}{2\rho_2 c} \tag{6}$$

which is interior if and only if

$$\frac{-m_1 + \frac{n_1}{2}}{\rho_1} > c > \frac{-m_1 + \frac{n_1}{2}}{(\rho_1 + 2\rho_2)}.$$

Intuitively, if c is very large it is optimal to shut down all economic activity (this is $s^* = 0$), and if c is very small, it is optimal not to intervene (this is $s^* = 1$).

4.2 Public support to social distancing

An interesting question is. What level of social distancing an agent i would support knowing the way the network will react after the announcement?

Agent i would prefer s to maximize (5). Note that the parametric assumption in (4) does not imply that the maximizer of (5) is $s = 1$. For any given network, agent i wants to have all links he can, but he does not want other agents to have all their links among themselves. Given an announcement of distancing s , if agent i would be free to choose his own degree (the links for himself) disregarding the social distancing restrictions, he would choose to connect with everyone. This is the deep source of externality, that given the rest of the network an individual would maximize his own connections, but would not if his connections are forced face the same social distancing restrictions of the rest.

If s were to be imposed on all agents, including himself, agent i would trade off between his own payoff, which is increasing in s , and externalities that are accumulated across other agents and passed on to i , which is also increasing in s .

Agent i prefers s to be

$$\arg \max_{s \in \mathcal{I}} \left(-m_1 + n_1 \frac{x_t + i}{2} \right) s - c(\rho_1 s + \rho_2 s^2)$$

Consider agent $i = 1$, for instance. Then $x_t = 1 - \frac{s}{2}$ and

$$\begin{aligned} u_1 &= -m_1 s + n_1 s \frac{1 - \frac{s}{2} + 1}{2} - c(\rho_0 + \rho_1 s + \rho_2 s^2) \\ &= -m_1 s + n_1 \left(s - \frac{s^2}{4} \right) - c(\rho_0 + \rho_1 s + \rho_2 s^2) \end{aligned}$$

Agent $i = 1$ would maximize this utility and would like to support a level of social distancing (that impacts himself but the rest too) of

$$s_{i=1}^* = \frac{-m_1 + n_1 - \rho_1 c}{(2\rho_2 + \frac{n_1}{2}) c} \quad (7)$$

Consider now the other extreme, agent $i = 0$. Then

$$u_1 - m_1 s + n_1 \left(s - \frac{s^2}{4} \right) - c(\rho_0 + \rho_1 s + \rho_2 s^2)$$

Agent $i = 0$ would maximize this utility and would like to support a level of social distancing of

$$s_{i=0}^* = \frac{-m_1 - \rho_1 c}{\left(2\rho_2 - \frac{n_1}{2}\right) c} \quad (8)$$

Therefore, although all agents strictly prefer to have any in-person activity over not having the activity, when s is imposed, agents do not necessarily want $s = 1$. This is because s reduces the externality imposed on them, and so they trade off negative externalities against

Comparing equations (6) and (7), the high end of the economy prefers to have less distancing restrictions than the planner. The reason is that the economic surplus those agents are forgoing is higher and would rather not restrict much the economy in order not to restrict themselves either. The opposite holds for low end of the economy, from comparing equations (6) and (8). The planner balances these concerns and indeed prefers an intermediate level of social distancing that balances in average the surplus cost with the contagion cost.

4.3 Non-monotonicity

The monotonicity is a nice and intuitive insight. Here we explore additional forces that can factor into this. We remain agnostic about which forces are more prevalent than others.

Sustenance Suppose that there is sustenance level of utility that must be achieved. An agent below the sustenance level incurs a large disutility. Formally, for agent i , if the economic surplus $\tilde{u}_i = \int_{P_i} p_{ik} dk$ is less than a cutoff κ , then has 0 payoff. Then the payoff is

$$u_i = \mathbf{1}_{\tilde{u}_i \geq \kappa} (\tilde{u}_i - c(\rho_1 s + \rho_2 s^2))$$

Now consider an agent i .

$$\begin{aligned}\tilde{u}_i &= m_1 s + n_1 s \frac{x_t + i}{2} \approx m_1 s + n_1 s i \\ u_i &= \mathbf{1}_{\tilde{u}_i \geq \kappa} (\tilde{u}_i - c(\rho_1 s + \rho_2 s^2)) \approx \mathbf{1}_{s \geq \frac{\kappa}{m_1 + n_1 i}} s (m_1 + n_1 i - c\rho_1 - c\rho_2 s)\end{aligned}$$

Agent i will never prefer $s \leq \frac{\kappa}{m_1 + n_1 i}$. Then the (approximate) maximizer of u_i with respect to s with the constraint $s \geq \frac{\kappa}{m_1 + n_1 i}$ is given by

$$\max \left\{ \frac{m_1 + n_1 i - c\rho_1}{2c\rho_2}, \frac{\kappa}{m_1 + n_1 i} \right\}$$

This is U shaped in i . The low segment is worried about the sustenance level. Since they are disadvantaged already in terms of their productive skills, they need s to be large to be able to maintain the sustenance level. This is less of a concern for middle segment and they prefer smaller s . For the high segment, sustenance is not a problem but their opportunity cost of distancing is high and they prefer high s .

Complementarities Now we go back and reintroduce at-distance activities. The network will be as in Figure 5. Some algebra shows that shows that the agents in $[q_c, 1]$ have exactly the same payoff from their in-person connections. This is the outcome of the smoothing we had mentioned earlier. Instead of direct assortative matching as in the higher segment, there is “band” wherein high and low types mix with each other. This means that the optimal s for agents in $[q_c, 1]$ is identical. Optimal s is increasing up to q_c , and constant thereafter.

An important reason behind this “plateau” is the fact that payoffs feature perfect substitution. The functional forms of p_{ij} and d_{ij} feature perfect substitution between i and j ’s talent because of the term $i + j$. Alternative, we can consider a form with complementarity, say ij . So consider the case with

$$\begin{aligned}p_{ij} &= -m_1 + n_1 ij \\ d_{ij} &= -m_2 + n_2 ij\end{aligned}$$

Under the appropriate parametric assumption that would ensure that in-person links dominate not having any links, we would know that all potential activities would be performed. Then under s , all agents will have s degree. So the payoffs will look identical, with ij instead of $\frac{i+j}{2}$. Now agent $i > \frac{m_2-m_1}{n_2-n_1}$ will have at-distance activities with $j > \frac{m_2-m_1}{n_2-n_1} \frac{1}{i}$ and in-person activities with $j \in \left(\frac{m_2-m_1}{n_2-n_1} \frac{1}{i} - s, \frac{m_2-m_1}{n_2-n_1} \frac{1}{i} \right)$. Then the in-person total payoff of i is

$$\int_{\frac{m_2-m_1}{n_2-n_1} \frac{1}{i} - s}^{\frac{m_2-m_1}{n_2-n_1} \frac{1}{i}} (-m_1 + n_1 ij) \, dj = s \left(-m_1 + n_1 \left(\frac{m_2 - m_1}{n_2 - n_1} - \frac{is}{2} \right) \right)$$

This is decreasing in i . Thus, when $i > \frac{m_2-m_1}{n_2-n_1}$ solves for the tradeoff between in-person benefits and contagion risk, the optimum is decreasing in i . For the high end of the economy, optimum is decreasing. For the low end, direct assortative matching applies and there is no smoothing. This the optimal s is increasing in i . So optimal s is inverse U shaped.

5 Long-terms effects of distancing

Can there be positive effects of social distancing in the long-term, given how it shapes the network? This question is relevant when discussing how to finance economic relief and expenditures required by lockdown and social distancing practices. Most likely, these expenditures have to be financed by future taxes, and those are more likely to be sustainable if accompanied by larger economic growth.

It is possible, for instance, that some activities that could have been performed at-distance more beneficially than in-person were still being performed in-person. For example, simple doctor consultations, seminars and teaching could in principle being performed online. Why were those not? Is it possible that the pandemics can improve long-term growth that makes easier to finance in the future its negative consequences?

There can be multiple reasons that might have prevented a switch in the past, even though beneficial. Agents may lack the accurate information about the surplus

associated with performing tasks at-distance without having experimented it in the past, due for instance to coordination failures or adjustment costs.

In what follows we explore these possibilities and argue that, in the presence of coordination failures or adjustment costs, pandemics in a technological world may have imbedded the keys for financing its own economic cost.

5.1 Adjustment costs

We first consider adjustment costs for adopting technologies that allow at-distance activities (virtual conferences, remote teaching technologies, telemedicine, etc).

Suppose that there are two periods. The second period captures the “long-term.” Agents have discount factor β . In the beginning, all activities start off at the status-quo of being performed in-person. The surplus from at-distance activity is d_{ij} , which can be larger than p_{ij} , but switching to at-distance costs f to both parties. For simplicity suppose that $p_{ij}, d_{ij} > c$ for all activities. Denote $\delta_{ij} = d_{ij} - p_{ij}$.

In the absence of any shock, the activity (i, j) with $(1 + \beta)\delta_{ij} > f$ switches to at-distance in the first period (and stays so in the long-run) and the rest of the activities remain in-person. Then the long run surplus is just

$$\int p_{ij} \mathbf{d}(i, j) + \int_{\frac{f}{1+\beta} < \delta_{ij}} \delta_{ij} \mathbf{d}(i, j)$$

Now suppose that the shock c hits in the first-period, but it is expected to go away in the second period. An activity switches to at-distance and stays so in the long run if $(1 + \beta)\delta_{ij} > f - c$ and $\delta_{ij} > 0$. An activity switches to at-distance and reverts back to in-person if $\delta_{ij} > f - c$ and $\delta_{ij} < 0$. An activity never switches to at-distance otherwise. Then, the long surplus is

$$\int p_{ij} \mathbf{d}(i, j) + \int_{\max\{\frac{f-c}{1+\beta}, 0\} < \delta_{ij}} \delta_{ij} \mathbf{d}(i, j)$$

Clearly, the long run surplus is higher with the shock. This is because it forces more tasks to switch to at-distance in the first period, some of which efficiently remain so

in the long-run. (Notice that the two would be identical under $f = 0$ because tasks can always switch back after the shock.)

5.2 Coordination failures

We can model coordination failures by allowing for asymmetric benefits to parties from activities in reduced form. We assume that both parties must agree to a switch if the switch is to take place. We do not allow for transfers as a way of capturing some form of lack of coordination.

Again consider two periods, the second being the “long-term.” Initially, the status-quo is that all activities are performed in-person. A pair can change their pair-specific status-quo only if both agree to do so. The outcome of the first period is the status-quo in the second period. In the second-period, the pair can change the activity from this new status-quo if they both agree to. Again we take $d_{ij}, d_{ji}, p_{ij}, p_{ji} > c$ for simplicity.

In the absence of the shock, first and second period payoffs are the same. Thus, i, j switch to at-distance if $\min\{\delta_{ij}, \delta_{ji}\} > 0$. It is possible that $\delta_{ij} + \delta_{ji} > 0$ but the switch needs the participation of both parties. The long run surplus is

$$\int p_{ij} \mathbf{d}(i, j) + \int_{\min\{\delta_{ij}, \delta_{ji}\} > 0} \frac{\delta_{ij} + \delta_{ji}}{2} \mathbf{d}(i, j)$$

Now suppose that the shock hits in the first period, which is expected to go away in the long-run. Then the pair switches to at-distance and remains at-distance if $(1 + \beta) \min\{\delta_{ij}, \delta_{ji}\} > -c$ and $\max\{\delta_{ij}, \delta_{ji}\} > 0$. The pair switches to at-distance and reverts back to in-person if $\min\{\delta_{ij}, \delta_{ji}\} > -c$ and $\max\{\delta_{ij}, \delta_{ji}\} < 0$. The other activities remain in-person throughout. Then the long-run surplus is

$$\int p_{ij} \mathbf{d}(i, j) + \int_{\substack{(1 + \beta) \min\{\delta_{ij}, \delta_{ji}\} > -c \\ \max\{\delta_{ij}, \delta_{ji}\} > 0}} \frac{\delta_{ij} + \delta_{ji}}{2} \mathbf{d}(i, j)$$

The difference is

$$\int_{\substack{0 > \delta_{ji} > -\frac{c}{1+\beta} \\ \delta_{ij} > 0}} \frac{\delta_{ij} + \delta_{ji}}{2} \mathbf{d}(i, j) + \int_{\substack{0 > \delta_{ij} > -\frac{c}{1+\beta} \\ \delta_{ji} > 0}} \frac{\delta_{ij} + \delta_{ji}}{2} \mathbf{d}(i, j) \quad (9)$$

Notice that in the symmetric case we would have $\delta_{ij} = \delta_{ji}$ and so the difference is an integral over an empty set, making 0. For the asymmetric case, the shock clearly extends the region of tasks that switch to and remain at-distance. Nevertheless, it might be inefficient that the activity stays at-distance because it is possible to have $\delta_{ij} + \delta_{ji} < 0$. If asymmetries are stark and c is large, it is perhaps possible that many tasks switch to at-distance but inefficiently stay that way due to lack of coordination.

We go back to our lead example guidance and modify it as follows. Now $p_{ij} = -m_1 + n_1 \frac{i+j}{2} + \epsilon_1(i-j)$ and $d_{ij} = -m_2 + n_2 \frac{i+j}{2} + \epsilon_2(i-j)$. This gives high quality agents slightly higher bargaining power in terms how much they get out of the total surplus. Then $\delta_{ij} = -\delta_m + \delta_n \frac{i+j}{2} + \delta_\epsilon(i-j)$, where $\delta_m = m_2 - m_1$, $\delta_n = n_2 - n_1$, and $\delta_\epsilon = \epsilon_2 - \epsilon_1$.

Note that $\frac{\delta_{ij} + \delta_{ji}}{2} = -\delta_m + \delta_n \frac{i+j}{2}$. Now, $0 > \delta_{ji} > -\frac{c}{1+\beta}$ and $\delta_{ij} > 0$ if and only if

$$\delta_\epsilon(i-j) > -\delta_m + \delta_n \frac{i+j}{2} > \max \left\{ \delta_\epsilon(j-i), \delta_\epsilon(i-j) - \frac{c}{1+\beta} \right\} \quad (10)$$

Then (10) necessitates $i > j$ if $\delta_\epsilon > 0$ and it necessitates $j > i$ if $\delta_\epsilon < 0$. Take some $x > 0$ and consider the region of all i, j with $i-j = x$ if $\delta_\epsilon > 0$ or the region $j-i = x$ if $\delta_\epsilon < 0$. For such i, j the condition (10) is

$$|\delta_\epsilon|x > \frac{\delta_{ij} + \delta_{ji}}{2} > \max \left\{ -|\delta_\epsilon|x, |\delta_\epsilon|x - \frac{c}{1+\beta} \right\}$$

Then in this region, the integral of $\frac{\delta_{ij} + \delta_{ji}}{2}$ is non-negative if and only if

$$|\delta_\epsilon|x \geq \left| \max \left\{ -|\delta_\epsilon|x, |\delta_\epsilon|x - \frac{c}{1+\beta} \right\} \right|$$

which is always true. It is strictly positive if $2|\delta_\epsilon|x > \frac{c}{1+\beta}$. Thus, the integral in (9) is also positive. That is, even if some activities inefficiently remain at-distance after the shock, the effect of activities that efficiently switch to at-distance due to the shock dominate and there is a long run benefit from the shock.

6 Conclusions

The death toll of pandemics can be curbed by strict social distancing restrictions. This has become clear as never before in history during the almost unanimous global response to the COVID-19 crises. Social distancing tended to map almost one to one to economic distancing, having large disruptions in the economy health. New technologies, however, have allowed some in-person activities to be substituted with at-distance activities. We present a model to explicitly include these decisions and to study the network reaction to social distancing guidelines.

We provide three conceptual insights. First, economic distancing and economic networking reactions to social distancing practices may have an important role on buffering their economic impact. Second, individuals not only react to social distancing guidelines by changing their way to interact (in-person vs. at-distance) but also the people they interact with. This endogenous network reaction may have important implications to magnify income inequality, even more when at-distance activities are predominant. Finally, in the presence of coordination failures or adjustment costs to the adoption of at-distance activities, pandemics can induce long-term growth and then facilitate the financing of its economic cost.

Within the realm of the model, we are also able to characterize the optimal extent to social distancing practices. Our model accommodates both health externalities (contagion) and economic externalities (sick or death individuals affect the productivity of others). It is not surprising that the optimal social distancing would balance the economic cost and health costs. What is surprising in our setting is that, given the inequality effects of pandemics, individuals relying more on at-distance activities view social distancing restrictions excessive compared to individuals who rely more on in-person activities.

Our work highlights the importance of discussing the role of telecommuting, working at home and at-distance activities more forcefully. Not only the present output (in the midst of a pandemic) depend on understanding its economic relevance, but also potentially the future output possibilities, once the pandemic has receded and the world wakes up to a new technological and production reality. The model is rich enough to accommodate heterogeneous activities and infectious patterns.

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A Externalities

Infection probability A less reduced form way to study contagion is as follows. Denote $\pi_{i,1} = |P_i|$ is the in-person degree of i and $\pi_{i,2} = \int_{(k,i) \in P} \pi_{k,1} dk$ is the sum of in-person degrees of i 's in-person neighbors. Suppose there are three periods. Let $\phi_{i,t}$ be the probability that i is not infected in period t . Denote α the original seed size. That is, each agent has α exogenous probability of getting infected. Then in period 0,

$$\phi_{i,0} = 1 - \alpha$$

Let θ be the infectiousness of the disease. In period 1,

$$\begin{aligned} \phi_{i,1} &= \phi_{i,0} \times \left(1 - \theta \int (1 - \phi_{k,0}) dk \right) \\ &= (1 - \alpha) (1 - \theta \alpha \pi_{i,1}) \end{aligned}$$

Then in period 2,

$$\begin{aligned} \phi_{i,2} &= \phi_{i,1} \times \left(1 - \theta \int (1 - \phi_{k,1}) dk \right) \\ &= (1 - \alpha) (1 - \theta \alpha \pi_{i,1}) \times \left(1 - \theta \int (1 - (1 - \alpha) (1 - \theta \alpha \pi_{k,1})) dk \right) \\ &= (1 - \alpha) (1 - \theta \alpha \pi_{i,1}) \left(1 - \theta \int (\alpha + (1 - \alpha) \theta \alpha \pi_{k,1}) dk \right) \\ &= (1 - \alpha) (1 - \theta \alpha \pi_{i,1}) (1 - \theta \alpha (\pi_{i,1} + (1 - \alpha) \theta \pi_{i,2})) \\ &= (1 - \alpha) (1 - \theta \alpha \pi_{i,1}) (1 - \theta \alpha \pi_{i,1} - (1 - \alpha) \alpha \theta^2 \pi_{i,2}) \end{aligned}$$

This is clearly hard to work with. Take a constant $\rho > 0$. Set $\theta^2 \alpha = \rho > 0$ and take $\alpha \rightarrow 0$. Then $\theta \alpha = \sqrt{\frac{\rho}{\alpha}} \alpha \rightarrow 0$ as well. Then

$$\begin{aligned} \phi_{i,0} &= 0 \\ \phi_{i,1} &= 0 \\ \phi_{i,2} &= 1 - \rho \pi_{i,2} \end{aligned}$$

After period 2, if there is a vaccine or medicine, contagion stops. If not, θ is so large that everybody gets infected and the economy ends. So we don't need to model period 3 anyways. Therefore, the probability of infection is $\eta_i = \rho \int_{k \in P_i} \pi_k dk$. The term $\pi_{i,2} = \int_{k \in P_i} \pi_{k,1} dk$ captures contagion externalities in a very simple form.

Notice that the reduced form infection probability $\eta_i = \rho_1 \pi_i + \rho_2 \int_{k \in P_i} \pi_k dk$ covers this case if we set $\rho_1 = 0$, which does not violate any of the assumptions we have made.

Combined externalities We consider the combination of contagion and leaving the economy externalities under this microfounded infection probability $\eta_i = \rho \int_{k \in P_i} \pi_k dk$. Denote $\phi_i = 1 - \eta_i$. Then

$$\begin{aligned} u_i &= \phi_i \left(\int_{P_i} \phi_k p_{ik} \mathbf{d}k + \int_{D_i} \phi_k d_{ik} \mathbf{d}k \right) - (1 - \phi_i)c \\ &= \phi_i \left(\int_{P_i} \phi_k p_{ik} \mathbf{d}k + \int_{D_i} \phi_k d_{ik} \mathbf{d}k + c \right) - c \end{aligned}$$

Equilibrium network Throughout, we will focus on in-person activities and assume $-m_1 = p_{00} > 0$. For agent i , the marginal benefit of adding a link with j is

$$\phi_i \phi_j p_{ij} - \rho \pi_j \left(\int_{P_i} \phi_k p_{ik} \mathbf{d}k + \int_{D_i} \phi_k d_{ik} \mathbf{d}k + c \right)$$

Then, for agent i , adding in-person link with j strictly dominates not having the link if

$$\frac{1}{\frac{1}{p_{ij}} + \frac{1}{\max\{p_{i1}, d_{i1}\}}} > \rho (c + \max\{p_{i1}, d_{i1}\}) \quad (11)$$

The proof of this at the end of the section.

A sufficient condition for this to hold for all i and j is given by

$$\frac{1}{\rho} - 1 > c \left(\frac{1}{p_{00}} + \frac{1}{\max\{p_{01}, d_{01}\}} \right) + \frac{\max\{p_{11}, d_{11}\}}{p_{00}} \quad (12)$$

Under this assumption, regardless of the shape of the network, each agent would prefer to add any in-person activity instead of not having it. For two agents i and j , not having the activity (i, j) is strictly dominated by having it in-person.

Due to strict dominance, under any s , all agents will have s mass of in-person activities in equilibrium. Then

$$\phi_i = \psi_s = 1 - \rho s^2$$

The matching will be assortative as described before. The network structure will be as given in Figures 4 and 5.

Under s , the payoff of i is

$$\begin{aligned} u_i &= \psi_s \left(\psi_s \int_{P_i} p_{ik} \mathbf{d}k + c \right) - c \\ &= \psi_s \left(\psi_s s \left(-m_1 + n_1 \frac{x_t + i}{2} \right) + c \right) - c \end{aligned} \quad (13)$$

Consider $i = 1$. Recall that $x_t = 1 - \frac{s}{2}$. Then the derivative of u_1 with respect to s at $s = 1$ is negative if and only if

$$\left. \frac{du_1}{ds} \right|_{s=1} < 0 \iff c > \frac{(1-\rho)^2}{2\rho} \left(\frac{n_1}{2} - m_1 \right) - 2(1-\rho) \left(\frac{3n_1}{4} - m_1 \right)$$

Note that this is consistent with (12). It is possible that the preferred s for agents is not necessarily $s = 1$ despite the fact that it is strictly dominant for all agents to have all links.

Next consider the planner. The sum of payoffs of agents in X_t is

$$\begin{aligned} \int_{X_t} u_i \mathbf{d}i &= \int_{X_t} \left(\psi_s \left(\psi_s \int_{P_i} p_{ik} \mathbf{d}k + c \right) - c \right) \mathbf{d}i \\ &= \psi_s \left(\psi_s s^2 (n_1 x_t - m_1) + cs \right) - cs \end{aligned}$$

For $s \in \mathcal{I}$, the the sum of payoffs is

$$\begin{aligned} W_s &= \sum_{t=1}^k \left(\psi_s \left(\psi_s s^2 (n_1 x_t - m_1) + cs \right) - cs \right) \\ &= \psi_s \left(\psi_s s \left(\frac{n_1}{2} - m_1 \right) + c \right) - c \end{aligned} \quad (14)$$

Note that $\frac{1}{2}W'_s|_{s=0} = \frac{n_1}{2} - m_1 > 0$. That is, the optimal s is not 0. Also

$$\begin{aligned} \frac{1}{2}W'_s|_{s=1} &= \left(\frac{n_1}{2} - m_1 \right) \left((1-\rho)^2 - 2\rho(1-\rho) \right) - \rho c < 0 \iff \\ c &> \left(\frac{n_1}{2} - m_1 \right) \left(\frac{(1-\rho)^2}{\rho} - 2(1-\rho) \right) \end{aligned}$$

Note that this is consistent with (12). This assumption ensures that optimal s is not 1. That is, the optimal s is interior.

Proof that (12) implies strict dominance Denote $X = P_i \cup P_j$ and $|X| = x$. For agent i , the marginal benefit of adding the link with j is

$$\begin{aligned}
& \phi_i \phi_j p_{ij} - \rho \pi_j \left(\int_{P_i} \phi_k p_{ik} \mathbf{d}k + \int_{D_i} \phi_k d_{ik} \mathbf{d}k + c \right) \\
& \geq \phi_i \phi_j p_{ij} - \rho \pi_j \left(\left(\int_{P_i} \phi_k \mathbf{d}k + \int_{D_i} \phi_k \mathbf{d}k \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& \geq \phi_i \phi_j p_{ij} - \rho \pi_j \left(\left(\int \phi_k \mathbf{d}k \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& = \left(1 - \rho \int_{P_i} \pi_k \mathbf{d}k \right) \left(1 - \rho \int_{P_j} \pi_k \mathbf{d}k \right) p_{ij} - \rho \pi_j \left(\left(1 - \rho \int_S \int_{P_k} \pi_{k'} \mathbf{d}k' \mathbf{d}k \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& \geq \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 p_{ij} - \rho x \left(\left(1 - \rho \int_S \int_{P_k} \pi_{k'} \mathbf{d}k' \mathbf{d}k \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& = \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 p_{ij} - \rho x \left(\left(1 - \rho \int_S \int_{P_{k'}} \pi_{k'} \mathbf{d}k \mathbf{d}k' \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& = \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 p_{ij} - \rho x \left(\left(1 - \rho \int_S \pi_{k'}^2 \mathbf{d}k' \right) \max \{p_{i1}, d_{i1}\} + c \right) \\
& = p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) + \rho^2 |X| \max \{p_{i1}, d_{i1}\} \int_S \pi_k^2 \mathbf{d}k \\
& = p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) \\
& \quad + \rho^2 x \max \{p_{i1}, d_{i1}\} \left(\int_X \pi_{kX}^2 \mathbf{d}k + \int_X \pi_{kX^c}^2 \mathbf{d}k + \int_{X^c} \pi_{kX}^2 \mathbf{d}k + \int_{X^c} \pi_{kX^c}^2 \mathbf{d}k \right) \\
& \geq p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) \\
& \quad + \rho^2 x \max \{p_{i1}, d_{i1}\} \left(\int_X \pi_{kX}^2 \mathbf{d}k + \int_X \pi_{kX^c}^2 \mathbf{d}k + \int_{X^c} \pi_{kX}^2 \mathbf{d}k \right) \\
& \geq p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) \\
& \quad + \rho^2 x \max \{p_{i1}, d_{i1}\} \left(\left(\int_X \pi_{kX} \mathbf{d}k \right)^2 + \left(\int_X \pi_{kX^c} \mathbf{d}k \right)^2 + \left(\int_{X^c} \pi_{kX} \mathbf{d}k \right)^2 \right)
\end{aligned}$$

$$\begin{aligned}
&= p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) \\
&\quad + x \max \{p_{i1}, d_{i1}\} \left(\left(\rho \int_X \pi_{kX} \mathbf{d}k \right)^2 + 2 \left(\rho \int_X \pi_{kX^c} \mathbf{d}k \right)^2 \right) \\
&\geq p_{ij} \left(1 - \rho \int_X \pi_k \mathbf{d}k \right)^2 - \rho x (c + \max \{p_{i1}, d_{i1}\}) \\
&\quad + x \max \{p_{i1}, d_{i1}\} \left(\rho \int_X \pi_k \mathbf{d}k \right)^2 \\
&\geq \frac{1}{\frac{1}{p_{ij}} + \frac{1}{x \max \{p_{i1}, d_{i1}\}}} - \rho x (c + \max \{p_{i1}, d_{i1}\}) \quad (\text{by convexity in } \rho \int_X \pi_k \mathbf{d}k) \\
&\geq \min \left\{ 0, \frac{1}{\frac{1}{p_{ij}} + \frac{1}{\max \{p_{i1}, d_{i1}\}}} - \rho (c + \max \{p_{i1}, d_{i1}\}) \right\} \quad (\text{by concavity in } x)
\end{aligned}$$

The assumption in (12) makes this last term positive, meaning that having a link in-person strictly dominates not having the link. .