

Pandemic Control in ECON-EPI Networks*

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Abstract

We develop an ECON-EPI network model to evaluate policies designed to improve health and economic outcomes during a pandemic. Relative to the standard epidemiological SIR set-up, we explicitly model social contacts among individuals and allow for heterogeneity in their number and stability. In addition, we embed the network in a structural economic model describing how contacts generate economic activity. We calibrate it to the New York metro area during the 2020 COVID-19 crisis and show three main results. First, the ECON-EPI network implies patterns of infections that better match the data compared to the standard SIR. The switching during the early phase of the pandemic from unstable to stable contacts is crucial for this result. Second, the model suggests the design of smart policies that reduce infections and at the same time boost economic activity. Third, the model shows that re-opening sectors characterized by numerous and unstable contacts (such as large events or schools) too early leads to fast growth of infections.

Keywords: Complex Networks, COVID-19, Epidemiology, Social Distance, SIR

JEL Classification: D85, E23, E65, I18

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1 Introduction

The COVID-19 pandemic of 2020 presented a formidable challenge to policymakers: for the first time in decades they faced a trade-off between epidemiological costs (lives) and economic costs (livelihoods). The key question that motivates this paper is how to design *smart* policies which are effective in reducing the spread of the disease while at the same time minimizing economic costs.

Our point of departure is that the spread of infections and economic activity happen through the same network of human interactions. We develop an ECON-EPI network model of a city, characterized by three components. The first one is the network of human interactions that specifies contacts among individuals through different network layers. The second one is the ECON component, which describes how economic activity is created on the network. The last one is the EPI component, specifying how the disease spreads through individuals across the city.

When a pandemic hits, several links of the network are severed, either as a consequence of mitigation policies or because individuals change their behavior as a response. Our key insight is that the dynamic consequences, both in terms of infections and economic outcomes, strongly depend on the type of links that are severed. Cutting certain types of links has a large impact on infections and a relatively small economic cost, while cutting other types has only a marginal impact on the infection levels but large economic costs. We find that the ECON-EPI network constitutes a useful framework to understand and measure the epidemiological and economic costs of limiting different types of social interaction, and therefore it provides guidance in designing effective policies to control the pandemic while preserving economic activity.

We start by describing a multilayered network model, of the type commonly used in the epidemiological literature. Individuals in the network differ in several dimensions (such as age, family structure and work characteristics) and interact with each other through different network layers. These layers capture the main contexts of interaction among individuals in a city, such as homes, neighborhoods, schools, public transportation, stores, entertainment venues, and workplaces. These different social contexts are also often the target of actual mitigation policies aimed at limiting the extent of interaction allowed (such as the closure of schools, the limits on large gatherings, or the shut down of non-essential businesses). Some layers (such as family and neighborhood) feature frequent and repeated interactions among a small set of individuals. Other layers (such as public transportation or shopping venues) feature less frequent and more randomized contacts among a larger set of individuals. These

differences play a critical role in the speed of diffusion of the disease throughout the city, more numerous and random contacts leading to faster spreading.

Next we introduce the EPI component, which describes the dynamics of the disease. We model the progression of the disease as in the standard Susceptible-Infected-Recovered (SIR) model, while allowing for heterogeneity among infected individuals in the manifestation of symptoms and in the transmissibility upon contact. If we interpret the individuals in the economy as nodes in the network, we can express the key difference between the standard SIR set-up and our network model in terms of the infection probability of susceptible nodes. In the SIR set-up, this probability is the same for all nodes and depends on the average number of infected nodes in the system. In the network set-up, it differs across nodes, and for each node it depends on its own fraction of infected connections. This difference is crucial to understand why the SIR and the network model generate very different infection dynamics.

The last component of the network model is the ECON one, which specifies the details of production and the links between workers and shoppers. In the economy, a homogenous final good is produced in establishments by a stable team of workers and by capital. Each establishment belongs to one of two sectors: High-contact and Low-contact (H- and L-henceforth). These two sectors are a parsimonious way of classifying actual sectors into two groups depending on the strength of the link between production and spreading of the disease. In order to identify these sectors, we use information from the Occupation Information Network (ONET) database to construct measures of physical proximity and frequent interaction between workers and customers in each 2 digit NAICS sector. We then classify the actual sectors that score above the average in both measures as belonging to the H-sector. Examples of these sectors are retail, food, accommodation, and health. Production in the H-sector is likely to cause fast spreading in a pandemic for two reasons. First, H-workers cannot produce from home and thus are more exposed to the disease. Second, as they have numerous and randomly selected daily contacts with customers, they are more likely to spread the disease. The remaining sectors are classified as belonging to the L-sector. In the L-sector, production involves minimal physical proximity and/or interaction with customers. These features imply that production in the L-sector has less impact on infection spreading for two reasons. First, workers in the L-sector have fewer and more stable contacts as they only interact with other workers in their team. Second, a significant fraction of them has the ability to work from home. In addition to the difference in spreading potential, we allow the H and L sector to differ in terms of the marginal product of each worker, so that we can evaluate more accurately the effect on output of shut-down policies

that target different sectors.

One important feature of the ECON component is that we explicitly model the productive role of customers by assuming that production in the H-sector requires both workers and customers. While workers in the H-sector are only a subset of the population, customers are drawn from the entire population, as every individual in the city shops. This implies that when a pandemic hits and most people severely limit their interactions (either because of shut-down policies, quarantine, or fear) there are two effects on production. The first one is the direct supply effect that reduces production because workers cannot work. The second one is the indirect demand effect, that reduces output because customers do not show up at H-sector establishments where they are an essential factor of production.

We next define a pre-pandemic city equilibrium where heterogeneous workers are allocated efficiently across different establishments and where the shopping capacity of the H-sector satisfies the demand of shopping trips by the population. Using restrictions from the pre-pandemic equilibrium together with sector level data from the New York-Newark-Jersey City (NY-NJ-PA) metro area, we can pick values for the parameters that fully characterize the ECON-component. Before we can use our set-up to conduct policy experiments, we need to pin down two additional set of parameters. The first is the number of contacts between different types of nodes before and during the pandemic. The second is the set of parameters that governs disease progression and transmission (the EPI component). We use the seminal work of Mossong et al. (2008) to pin down the amount of contacts in the pre-pandemic equilibrium, and data from Google Mobility reports to capture the reduction in contacts during the pandemic. Regarding the EPI component, we calibrate its parameters using both evidence from epidemiological studies and by matching key moments of the infection’s early phase in the NY-NJ-PA metro area.

Finally, we use the fully calibrated model to perform a number of experiments. The first experiment compares the dynamics of infection in our set-up with the standard SIR set-up, where meetings among individuals are randomly drawn across the whole population (as in, for example, Atkeson (2020) or Eichenbaum et al. (2021)). We put the two models on equal footing by choosing parameters in both models to match the dynamics during the early phase (March 8th - April 3rd 2020) of the pandemic in the NY-NJ-PA metro area. We then compare their predictions for the second phase of the pandemic (April 3rd - April 26th 2020) with the data. The main result is that the standard SIR model implies a counterfactually fast spreading of the infection, while the network set-up predicts a plateau of infections, as observed in the data. The reason for this difference is that in the SIR set-up new infections

depend on the average fraction of infected nodes in the system so, once total infections reach a critical level (as they did in New York), it progresses rapidly until herd immunity is reached. In the network model, however, infections depend on the number of local contacts. Therefore, it is possible that some areas of the network remain untouched by the infection, while at the same time the disease dies out in other areas due to herd immunity at a “local” level.

Our second experiment uses the ECON-component of the model more intensively to study “smart” mitigation policies that can achieve better outcomes during the lock-down phase. These policies can be valuable during a possible second wave of COVID-19, or in future pandemics. We find that policies that reduce the workers shutdown in the L-sector, while at same time increase the workers shutdown in the H-sector can, under some circumstances, achieve a double gain; that is, reduce the spreading of the disease and simultaneously reduce the output loss. It is immediate to see that such policies slow down the spread of the infection. The outcome for output depends on the relative marginal product of labor in the two sectors, which in turn is a function of the amount of capital and of the intensity of the shutdown in each sector. We show that in our NY-NJ-PA metro area case study, for the observed level of shutdown and for the calibrated level of capital in the two sectors, a policy involving a substantial double gain (reduction in infection cases equal to 2% of the population and 2% increase in output) could have been implemented.

Our third and final set of experiments concerns the reopening of the business sectors and schools, once the pandemic has passed its peak. We find that the timing and extent of the reopening are crucial. A broad reopening, which includes the H sector or the schools, at a time when the level of infections is still significant in the city inevitably leads to a large second wave. Our set-up suggests two reopening strategies that could avoid a second wave. The first one is to prolong a wide-spread shut down and then reopening only when the level of infections is minimal. The second one is to start the reopening early, but only in the L-sector, which can achieve substantial output gains with little infection growth.

There are three important lessons that we learn from ECON-EPI networks. First, the micro structure of the network is essential to understand and predict aggregate infection and economic dynamics in response to a pandemic shock (or any other shock that severs interactions). When connections are random and unstable across the network (like in the standard SIR model), an infectious disease spreads and dies out fast. The ECON-EPI connection thus implies that the economic impact of a pandemic will be large but short lived. When connections are instead clustered and repeated, the same disease stays local,

spreads slowly but also takes a long time to die out. This implies that the economic impact of a pandemic will be long lasting. Layers in our ECON-EPI network lie in between these two extremes, with some layers (the H-sector) being random and unstable and some others (like the family) being more clustered and stable. The dynamics of infection and of economic activity in a city depends on the relative importance of these layers, and on their connections and policies geared to contain infections are most effective when they can target different layers separately.

Second, in order to assess the economic cost of policies aimed at containing the infection it is important to specify the micro structure of production. The cost of shutting down a worker is its marginal product. In an undistorted equilibrium, marginal product is captured by the wage; however, during widespread shutdowns like those observed during the COVID-19 pandemic, marginal product can be different (and higher) than the wage, and thus the cost of alternative shutdown policies can be assessed only by specifying the details of production.

Finally, our set-up suggests that there are important complementarities between various types of mitigation policies. For example, we find that reopening schools is only viable if it is preceded by a strict lock-down of many economic activities, which brings infections to a minimal level. Also, we find that when people adopt practices that reduce the transmissibility of the disease (e.g. wearing face-masks), policies that reduce contacts are more effective. A key insight is that the use of a structural model of interaction is necessary to understand and quantify the extent of these complementarities.

The paper is structured as follows. Section 2 summarizes the related literature. Sections 3 and 4 describe the ECON-EPI network and our calibration strategy. Section 5 shows how the network model can help explain the data. Section 6 discusses the policy experiments and Section 7 concludes.

2 Connection to existing literature

The COVID-19 pandemic has spurred a new and fast growing literature at the interface between epidemiology and economics, studying the effects, both on infection and economic outcomes, of different policies geared to containing the spreading of the disease.

A first generation of papers has modeled the epidemiological component using versions of the standard SIR random mixing model by Kermack and McKendrick (1927). Examples of these works include Acemoglu et al. (2021), Alvarez et al. (2021), Atkeson (2020), Eichenbaum et al. (2021), Favero et al. (2020), Glover et al. (2021), Piguillem and Shi (2022) and

Jones et al. (2021).

Modern research in epidemiology has moved beyond this classical framework to explicitly model the patterns of interaction among agents, using “agent-based models.” A second generation of papers in economics explored the role of heterogeneity across sectors and across workers in the spreading of the infection and in designing efficient containment policies. Here, see Kaplan et al. (2020), Leibovici et al. (2020), and Mongey et al. (2021).¹ Arnon et al. (2020), Acemoglu et al. (2020), Alfaro et al. (2020), Boppart et al. (2021), Farboodi et al. (2021), Hur (2021), Engle et al. (2021) and Toxvaerd (2020) go one step further and endogenize the intensity of interactions. By choosing their level of work, leisure, and consumption, agents with different characteristics can affect their level of exposure to the disease. We are related to these models in that agents have individual-specific infection rates resulting from their specific roles in production and consumption. The main difference, however, is that we model social interaction within a network framework.

There is strand of research in epidemiology that makes extensive use of network theory to predict the pattern of infections in a city or in a country.² One of the main contributions of our paper is to integrate the network modeling of infection from epidemiology in an economic model of a city, where the network plays an explicit role both in the transmission of infection and in the creation of economic value. We now briefly discuss how our paper is different from other recent and excellent works that also use network theory to study the COVID-19 pandemic. Karaivanov (2020) analyzes the diffusion of COVID-19 in an abstract network and makes the point that transmission is different from the one in the standard SIR model. However he restricts his attention to the epidemiological component. Akbarpour et al. (2020a), Baqaee et al. (2020), Fajgelbaum et al. (2020) and Akbarpour et al. (2020b) also use a network framework to analyze the economic and epidemiological effects of containment and re-opening policies. Baqaee et al. (2020) focus on aggregate (US) outcomes, while Akbarpour et al. (2020b), Fajgelbaum et al. (2020), and Akbarpour et al. (2020a) focus, as we do, on metro-level outcomes. There are two important differences that distinguish our work from theirs. The first is that we model the network differently. In their works the main heterogeneity across nodes rests on the number of contacts. Nodes in our network, in addition to being heterogenous in terms of number of contacts, are also heterogenous in terms of the pool from which they draw their daily contacts.³ This feature of the contacts,

¹Dingel and Neiman (2020) and Benzell et al. (2020) take a more empirical approach to analyze the effects of heterogeneity.

²See Keeling and Eames (2005) and Jackson (2010) for excellent surveys of the literature on networks in epidemiology.

³This heterogeneity has been explored in Acemoglu et al. (2013), Acemoglu et al. (2010) and Azzimonti

which we refer to as “stability”, not only is empirically relevant, as it captures the different degree of randomness of daily contacts in different occupations, but is also quantitatively important to explain infection dynamics.⁴ The second difference is in the modeling of the production structure. Both papers assume labor is the only factor of production, while we use an establishment production function that, in addition to labor, uses capital and (for retail establishments) customers as inputs. This production function allows to evaluate the output costs of workers’ shutdown more accurately, as well as the impact on output of the reduction in shopping contacts (i.e. demand effects).

3 The ECON-EPI network

We now describe the details of the ECON-EPI network, a model designed to capture human and economic interaction in a typical US metropolitan area. We first present the network structure, i.e. the links that connect individuals in their different activities. We then proceed to specify the EPI component, i.e. how infections progress and spread through the network. Finally, we describe the ECON component, i.e. how interactions in the network produce output. In this part, we first specify a pre-pandemic steady state equilibrium, which describes the normal state of economic affairs before the pandemic. We then discuss how the arrival of a disease and the adoption of containment measures affect economic activity during the pandemic period.

3.1 A multilayered network

We construct a multilayered network where individuals of different characteristics (age, employment status, public transportation usage, etc.) interact with each other. The set-up is necessarily stylized. Nevertheless, it has enough richness to capture key aspects of the social distancing policies that have been implemented during the 2020 COVID-19 pandemic. Time is discrete and the network is generically represented by a $M \times M$, time varying, adjacency matrix \mathbf{G}_t , where each node represents an individual. Individuals are heterogeneous in several dimensions. In terms of age, there are adults and kids. Kids are a fraction ν_K

and Fernandes (2021) in information networks. In Fajgelbaum et al. (2020), the pool of contacts depends on the commuting behavior of individuals but not on their economic activity, as it does in our paper.

⁴Bisin and Moro (2022), while not explicitly using a network model, incorporate a spatial dimension which generates local herd immunity. Their focus, however, is in the evolution of infections and completely abstracts from the productive process. An important innovation of our work is to link the social network of human contacts with the economic network determining production

of total population and go to schools. In terms of employment characteristics, adults may work in different sectors or be out of the workforce. Additionally, individuals differ in the size of their household, their number of neighbors, and their use of public transportation. We now proceed to describe the various layers connecting individuals. These layers affect the probability for each individual of contracting and spreading the disease throughout the network.

Households and Neighbors: Households can be composed by two adult members or by 2 adults and a kid. Members of the same household are fully connected through intra-household links. These links form the first layer of our network, contained in the adjacency matrix \mathbf{G}^H . The left panel of Figure 1 shows an example of household links in a city with 10 households, where the circles represent adult members and the stars represent kids. Households are placed next to each other on a ring (as in Watts and Strogatz 1998), and each type of household member (adult or kid) is connected to all the same member type of N neighboring households on the left and on the right. The neighborhood links form the second layer of our network and are recorded in the adjacency matrix \mathbf{G}^N . Household and neighborhood links are ‘short-stable links,’ meaning that they are active at every point in time, and connect individuals who are close to each other.

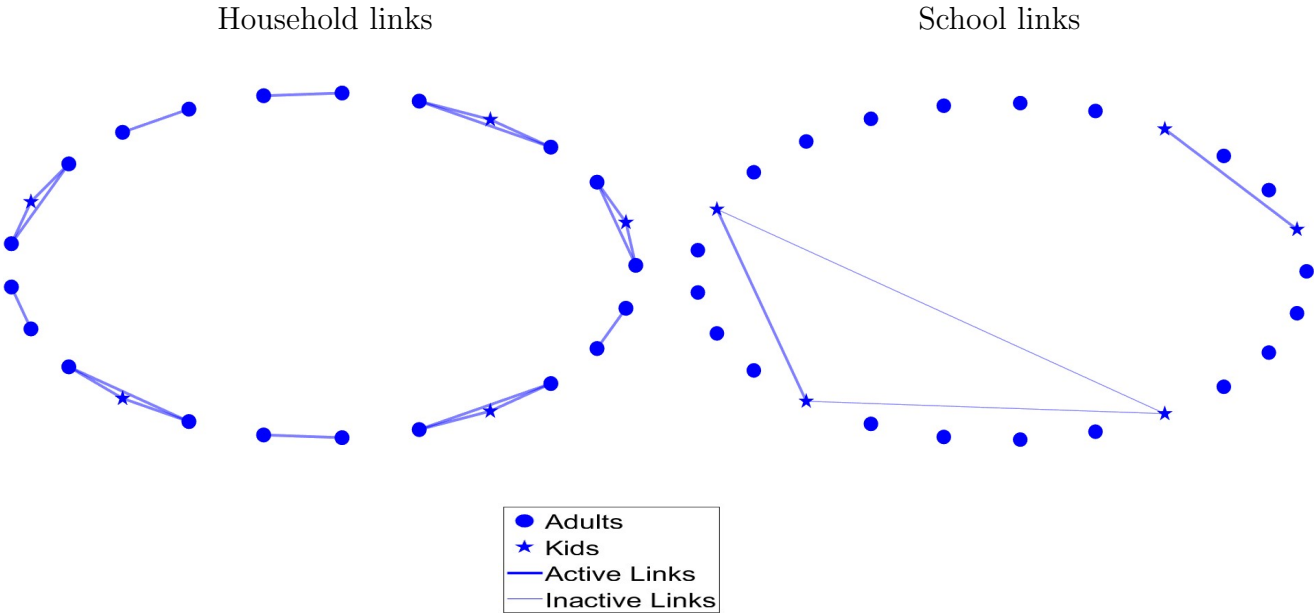


Figure 1: Households and Schools

Schools: Our third layer involves a school system where each day every kid interacts with a subset of other kids in her school. Each school draws kids which live close to each other, and the school size Q determines the pool of potential interactions of each kid. We refer to these links as “potential” school links and their associated adjacency matrix is denoted by \mathbf{G}^S . Note that we refer to school links as “potential” because, in contrast to the links in the first two layers, they are not always active: each kid has active links only with a subset, which is randomly drawn every period, of her schoolmates. The right panel of Figure 1 shows the active and inactive links for two schools (one of size 3 and one of size 2) for the same example network in the left panel of the figure. We define school links as ‘short-unstable’ meaning that they connect individuals who are geographically close to each other, and that they change their status (from active to inactive) over time. The reason for introducing this layer is to later evaluate the effect of school closures and reopenings on the spreading of the infection.

Public Transportation The next layer of the network specifies interactions through public transportation. A fraction ϕ of individuals uses public transportation. Each public transportation vehicle has a capacity of seating P individuals, and we assume that agents living close to each other use the same public transportation vehicle. This implies that each individual using public transportation is potentially connected to locally close individuals who also use public transportation. Potential public transportation links are summarized in the adjacency matrix \mathbf{G}^P . During each public transportation trip, each individual interacts with a random subset of the vehicle occupants. Therefore, individuals who use public transportation will be more exposed to the disease than those who use private means of transportation.⁵ Like school links, public transportation links are short and unstable. The difference between the two is that school links involve only kids, while public transportation connects adults as well as kids.

Workplaces A fraction of adults in the network work. The workplace layer describes how working adults interact with each other and with the rest of society. The city features two distinct workplaces, which we label L (for Low-contact) and H (for High-contact). In the L-workplace (which is meant to capture sectors like manufacturing) there are stable teams of L-workers. In the H workplace (which is meant to capture sectors like retail or entertainment)

⁵See Harris 2020 for a study on the role of public transportation in spreading the COVID-19 pandemic in New York City

there are similar teams of workers, but these workers are also connected with a time-varying subset of customers. We now describe in more detail the two workplaces.

L-Workplace L-Workers are a share ν_L of adults. Some of them (e.g. software developers) have the opportunity of working from home, which they will use in different intensity before and after the pandemic. The remaining members (e.g. assembly line workers) cannot work from home, and they are all connected to each other when working. The lightly colored nodes in panel (a) of Figure 2 are a team of L-workers. Note that two of them are connected to each other, while one (labeled home worker) is not connected. For production purposes the home worker is part of the team, but it can perform work without contact (and hence without risk of contagion) with the other team members.

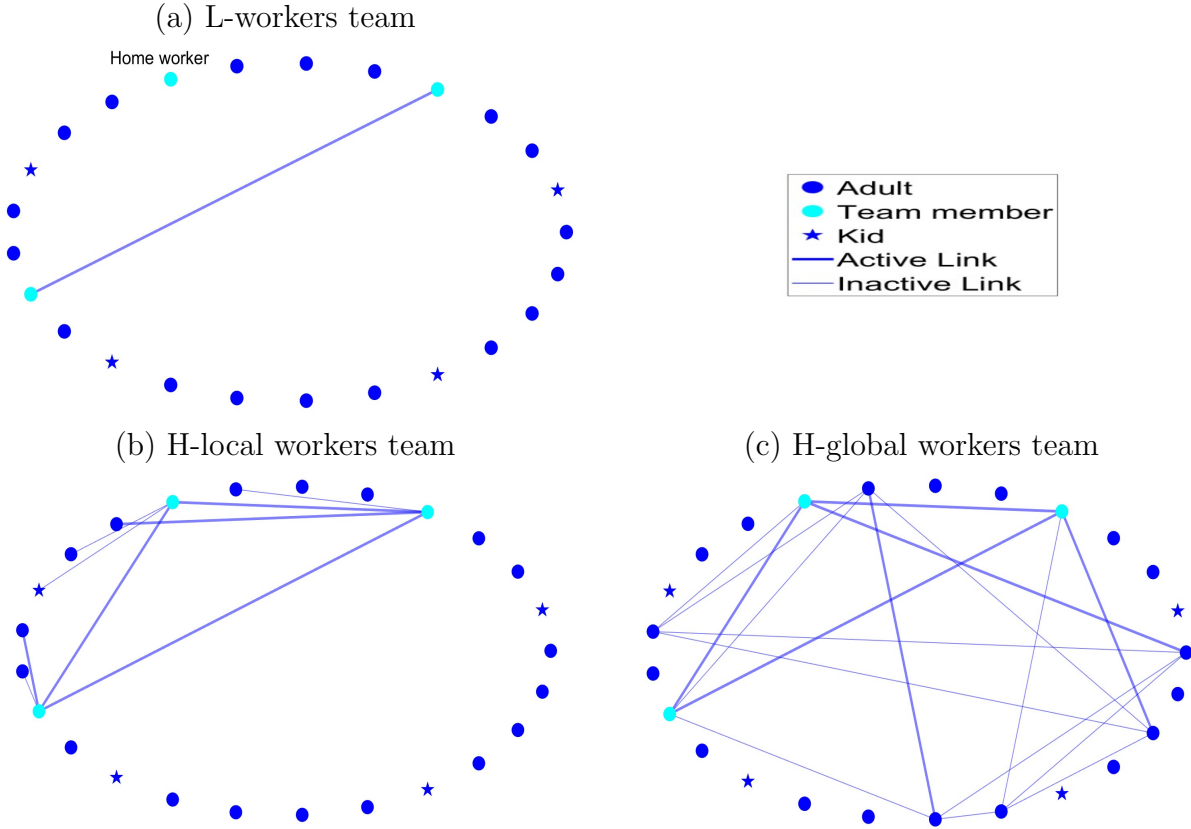


Figure 2: Workplaces

H-Workplace H-Workers are a share ν_H of adults and they work in establishments that, for the purpose of production, involve stable contacts with co-workers (just like the L-workers) as well as unstable contacts with external customers. During the 2020 COVID

pandemic, mitigation policies have not been uniform across establishment that involve contact with customers. Activities in some of them, such as retail establishments, have only been lightly restricted, while in some others, like sports event, they have been severely curtailed. For this reason we distinguish between two types of H-workplaces, which we label H-local and H-global. Panel (b) of Figure 2 illustrates a team of H-local workers. The lightly colored nodes represent the members of the team. Note that each worker in the team has potential links with other nodes in the network (potential customers, connected to the workers by the thin lines), and in each period some of these links become active (actual customers, connected to the workers by the thick lines). Note that customers are not connected to each other. This captures the fact that individuals from certain professions (i.e. shop clerks) may come into contact with several clients during a day, but sequentially, so their visits do not overlap. Note also that the customers of the H-local establishments are all located in the same area of the network. With this we want to capture the fact that many of these establishments have a local customer base. Panel (c) of Figure 2 illustrates a team of H-global workers. There are two differences between H-local and H-global. The first is that customers in H-global are (potentially) connected to each other. The second is that customers in H-global are located all over the network. These two features of the H-global are meant to capture activities like a concert or a sports event where customers come from all over the city and, by the nature of the event, have prolonged interactions with other customers. Finally observe that due to the nature of their work, H-workers do not have the opportunity of working from home. Visually Figure 2 illustrates that the same team of 3 workers has few connections in a L-workplace, more connections in a H-local workplace, and even more and widespread connections in a H-global workplace.

Worker links are, thus, intrinsically different from school links or public transportation links for two reasons. First, they include long links, connecting individuals in the network who are not necessarily in the same geographic area. Second, the number of connections of each individual worker can be different, with L-workers having only stable links, and H-workers having stable and unstable links. For convenience, we record worker links in two adjacency matrices: \mathbf{G}^W , which records all co-worker links (stable) in the H and L sector, and \mathbf{G}^C which records worker to worker to customer links in the H-sector (unstable) and customer to customer links in the H-global sector (unstable).

Network Clocks An important network feature, for the purpose of disease spreading, is the presence of unstable links between nodes. Connections in the household layer, the

neighborhood layer, and among teams of workers—in the workplace layer—are stable, as individuals are linked with the same set of people every period (e.g. their network links are always active). On the other hand, interactions in the school layer, the public transportation layer, and between shoppers and workers—in the workplace layer—are inherently unstable (e.g. only a subset of potential links are active every period). To model this, we incorporate a *clock* in the spirit of Acemoglu et al. (2010) and Acemoglu et al. (2013). More specifically, for all $t \geq 1$, we associate a *clock* to every link of the form (i,j) in the original adjacency matrix \mathbf{G}^i (where $i = S, P, C$) to determine whether the link is activated or not at time t . The ticking of all clocks at any time is dictated by i.i.d. samples from a Bernoulli Distribution with fixed parameter $\rho_i \in (0, 1]$, meaning that if the (i,j) -clock ticks at time t (realization 1 in the Bernoulli draw), the connection between agents i and j is active at time t . This is meant to capture two kids in the same school having lunch together on a given day, two persons sitting next to each other in the subway, or a customer and a cashier interacting over a transaction. The Bernoulli draws are represented by the $M \times M$ matrix of zeros and ones c_t^i . Thus, the adjacency matrices for school, public transportation and worker-customers networks evolve stochastically across time according to

$$\mathbf{G}_t^i = \mathbf{G}^i \circ c_t^i \quad (1)$$

where $i = S, P, C$

City Network: Finally, we superimpose the layers described so far to construct a meta network which corresponds to our synthetic city. The adjacency matrix capturing all links within a city, \mathbf{G}_t , is constructed as a weighted sum of the different layers. The weights correspond to the relative importance of each layer, capturing that individuals spend different amounts of time interacting with others in different social spheres. In particular, we have that

$$\mathbf{G}_t = \omega^H \mathbf{G}^H + \omega^N \mathbf{G}^N + \omega^W \mathbf{G}^W + \omega^S \mathbf{G}_t^S + \omega^P \mathbf{G}_t^P + \omega^C \mathbf{G}_t^C. \quad (2)$$

Each element in \mathbf{G}_t , denoted by $g_{i,j,t}$, summarizes the link between two individuals i and j at time t , weighted by the strength of their relationship.

3.2 The EPI component

The spread of the disease within our multilayered network is the result of two types of events: the person-to-person transmission of the disease (which depends on the network)

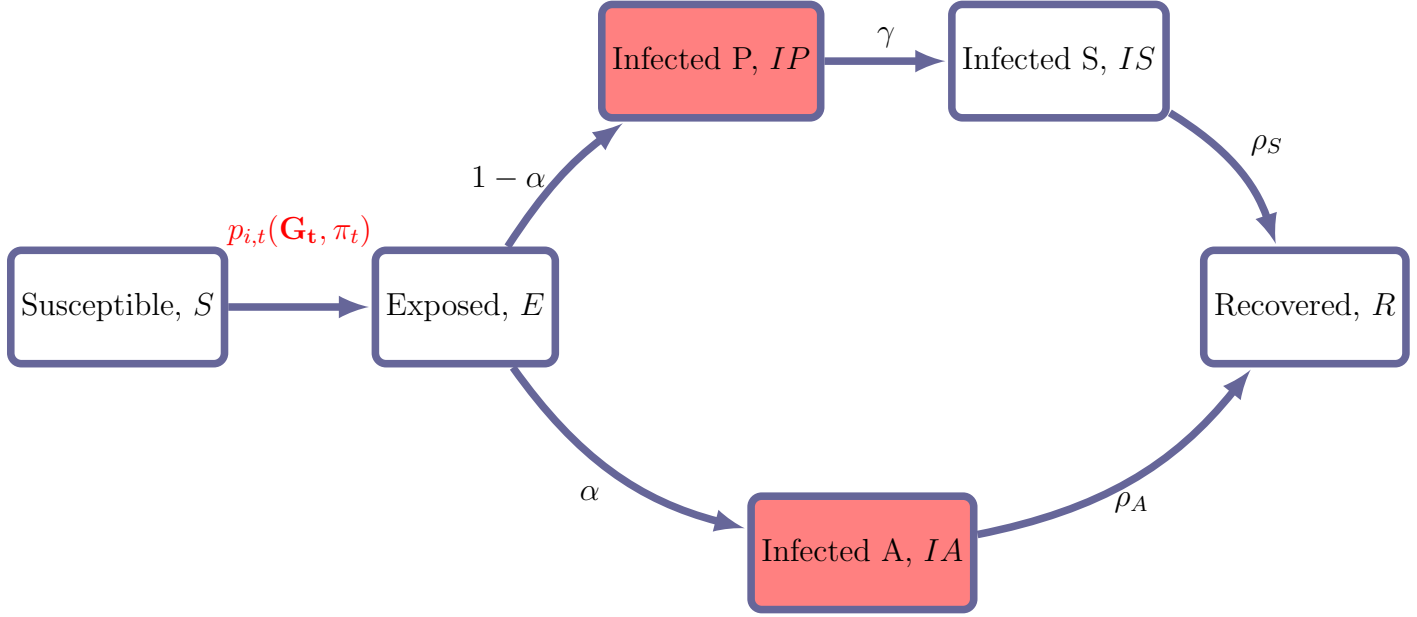


Figure 3: Transition between health states

and the progression of the disease for a given infected person, which is independent from the network structure. Our modeling of the disease progression closely follows a SEIR structure, a variant of the SIR model that is common in the epidemiological literature, where we added the possibility of an “asymptomatic” branch. This assumption is motivated by the fact that, during the COVID-19 pandemic, many infection cases went undetected, either because symptoms were mild, or because testing was not available. These cases were never officially recorded as infected, and transited directly to the recovered stage. However, according to several studies, they significantly contributed to the spread of the disease.⁶

Each individual node can be, at each point in time, in one of six health states: **S**usceptible, **E**xposed, **I**nfected-**A**symptomatic, **I**nfected-**P**re-symptomatic, **I**nfected-**S**ymptomatic, and **R**ecovered.

- (1) Susceptible (S): a node which has not been exposed to the disease, but may contract it in the future.
- (2) Exposed (E): a node which has been in contact with an infected node and has contracted the disease. Exposed nodes are not infectious and continue to perform normal activities. However they will transit with certainty to one of the infectious states the day following the exposure.

⁶See, for example, Li et al. 2020.

- (3) Infected Pre-symptomatic (IP): a node which is infected and will show symptoms in the future. Nodes at this stage do not know they are infected, so they continue to perform normal activities. They transmit the disease with probability π_t .
- (4) Infected Symptomatic (IS): a node which is infected and shows symptoms. IS nodes are removed from all layers of the network, with the exception of the household layer. They transmit the disease with probability π_t .
- (5) Infected Asymptomatic (IA): a node which is infected, but does not and will not show severe symptoms. These nodes do not know they are infected, so they continue to perform normal activities. IA nodes, when in contact with an S node, transmit the disease with probability $\eta\pi_t$, with $0 \leq \eta \leq 1$.
- (6) Recovered (R): a node which is no longer infected. Recovered nodes are immune to the disease and can resume normal activities.

Note that all nodes in an infected state can transmit the disease to susceptible nodes, although the infected asymptomatic are less likely to transmit. The transition between states is illustrated in Figure 3. A susceptible node i contracts the disease at time t with probability $p_{i,t}$ and if it does so, moves to the exposed state. An exposed node transitions to the asymptomatic stage with probability α and to the pre-symptomatic stage with probability $1 - \alpha$. A pre-symptomatic node moves to the symptomatic stage in each period with probability γ and a symptomatic node moves to the recovered stage with probability ρ_S . An asymptomatic node, on the other hand, has a probability ρ_A in each period of moving directly to the recovered stage. Finally, recovery is an absorbing state. The key object of our analysis is $p_{i,t}$, the probability that a susceptible node i contracts the disease in period t . The probability $p_{i,t}$ is a function of the active contacts of node i at time t (encoded in \mathbf{G}_t), of their health status and on the odds of contracting the disease conditional on meeting an infected node (governed by the parameters π_t and η). In particular we can write

$$p_{i,t}(\mathbf{G}_t, \pi, \eta) = 1 - \prod_{j=1}^M (1 - \pi\eta^{A(j,t)})^{g_{i,j,t}I(j,t)}. \quad (3)$$

where $g_{i,j,t}$ is the i th, j th element of \mathbf{G}_t , $I(j,t)$ is an indicator function that equals 1 when node j is infected (either pre-symptomatic, a-symptomatic or symptomatic) at time t , and zero otherwise, and $A(j,t)$ is a similar indicator function for the infected-asymptomatic status. This equation makes it clear that the spreading of the disease in the economy depends

not only on the disease prevalence (captured by $I(j, t)$ and $A(j, t)$) and on the biological transmissibility (captured by π_t and η), but also on the network structure summarized by \mathbf{G}_t . Note finally that we allow the transmission probability upon a meeting, π_t , to be time varying to allow for seasonal variation in transmission (see Atkeson et al. 2021) and for changes in the availability of personal protective equipment.

3.3 The ECON Component

Individual nodes, together with the network structure, produce, at each point in time, new infections and economic output. This section describes how output gets produced over the network and how it is affected by social distance policies and by behavioral changes that result from the progression of the infection. The two workplaces described in Section 3.1 map into two sectors where output is produced. Both sectors produce the same homogenous good (which is also the numeraire) and production is organized in establishments. In the L-sector there are Q_L ex-ante identical establishments, each endowed with the same amount of fixed capital K_L . These establishments employ teams of L-workers. In the H-sector there are also establishments which hire teams of H-workers, and we allow capital to be potentially different across establishments. As we think of these two sectors as having a substantially different occupational mix, we assume that workers cannot move across sectors.⁷ In the L-sector, production requires L-workers and capital, while in the H-sector, production requires H-workers, capital, and customers. We first describe a pre-pandemic steady state equilibrium, where there are no infected nodes and the level of economic activity is stable over time, and then move on to describe how economic activity evolves as the disease hits the city and containment measures are adopted.

3.3.1 Pre-pandemic equilibrium

L-Sector Recall that establishments in this sector are homogenous. Each establishment produces y_L units of output according to

$$y_L = K_L^\theta n_L^{1-\theta}$$

where n_L denotes units of labor. Notice that n_L is labor input which is not necessarily the same as employment, as not all L-workers supply the same amount of labor input.

⁷The details about mapping actual sectors of the economy into these two stylized sectors are discussed in Section 4.

In particular, consistently with recent empirical work by Dingel and Neiman (2020) and Leibovici et al. (2020), we assume that a fraction ω of L-workers can work from home, and the labor input (or productivity) of these workers is $\delta_\omega\%$ higher than the labor input of those that cannot work from home. Given the wage rate per unit of L-work w_L , the establishment manager chooses labor input to maximize profits, which are given by $y_L - n_L w_L$. This implies that per establishment labor demand is given by

$$n_L = K_L \left(\frac{1 - \theta}{w_L} \right)^{\frac{1}{\theta}}. \quad (4)$$

Labor supply of the L-workers is inelastic and is simply given by the total numbers of L-workers times their average labor input. A pre-pandemic equilibrium is then a wage rate w_L and quantity of L-labor per plant n_L such that, i) given wages, n_L is chosen optimally by the plant manager and ii) labor market for L-workers clear. Equation 5 summarizes these two conditions

$$\underbrace{Q_L n_L}_{\text{Labor Demand}} = Q_L K_L \left(\frac{1 - \theta}{w_L} \right)^{\frac{1}{\theta}} = \underbrace{\left[\omega(1 + \delta_\omega) + (1 - \omega) \right] \nu_L (1 - \nu_K) M}_{\text{Labor Supply}}, \quad (5)$$

where ν_L denotes the share of adults which work in the L-sector and $(1 - \nu_K)$ the share of adults in the population, implying that $\nu_L(1 - \nu_K)M$ is the total number of individuals who work in the sector, while $\omega(1 + \delta_\omega) + (1 - \omega)$ is their average effective labor.

H-Sector The locking down of high contact establishments has been at the centerpiece of the policy discussion during the 2020 COVID-19 pandemic. Although it has been widely acknowledged that larger high contact establishments (such as sports venues) lead to fast spreading of the disease, there has been much less emphasis on the fact that these establishments have more capital (see, for example, Foster et al. 2006), and thus shutting down all the workers in those establishment might be more costly, as more capital will remain idle. In order to capture this trade-off we introduce heterogeneity in H-establishments. As we already discussed in section 3.1 above we consider two types of establishments: H-local and H-global, indexed by $j = 1, 2$. There are Q_{H1} H-local establishments (small and medium retail stores) which have less capital, and have customer bases drawn from individuals in a geographically close area. There are Q_{H2} large establishments (e.g. large shopping malls, concert venues, and stadiums) which have more capital and have customer bases drawn from the entire network. Each establishment of type j in the H-sector produces y_{Hj} units of output

according to

$$y_{Hj} = K_{Hj}^\theta \left(\min \left\{ \frac{K_{Hj}d}{\mu}, n_{Hj} \right\} \right)^{1-\theta},$$

where K_{Hj} denotes the capital of establishment of type j ($K_{H1} < K_{H2}$), n_{Hj} denotes the number of workers (which in this sector are homogenous) employed by establishment of type j , μ is the number of customers that a H-worker can attend to and d represents the number of customers (per unit of capital) which shows up at establishment i . This assumption captures that in the H-sector customers and workers are complement in production: if a customer does not go to the establishment, a sale does not materialize and output is not produced. In addition, if there are too few workers, they may not be able to serve all the customers that come to the establishment. The establishment manager takes as given the wage rate w_H and the demand d and hires workers to maximize profits, which are given by $y_{Hj} - n_{Hj}w_H$. This implies that labor demand in establishment of type j is given by

$$n_{Hj} = K_{Hj} \min \left\{ \left(\frac{1-\theta}{w_H} \right)^{\frac{1}{\theta}}, \frac{d}{\mu} \right\}. \quad (6)$$

Similarly to the L-sector, the labor supply of the H-workers is inelastic and is given by the total numbers of H-workers, which is equal to $M(1-\nu_K)\nu_H$. The last element that is needed to define a pre-pandemic equilibrium is the determination of d . Recall that in our model city there are M individuals, and each person makes s shopping trip every period. It follows that the total number of customers of the H-sector is Ms . The customer capacity of the H-sector is instead given by the sum of all workers employed in that sector, times the number of customers a worker can attend, μ . Since in equilibrium the sum of all workers employed in the H-sector is the labor supply in the sector, equilibrium customer capacity is given by $\mu M(1-\nu_K)\nu_H$. We then assume that in a pre-pandemic equilibrium, the number of shopping trips per person is such that total shopping trips equals customer capacity of the H-sector, that is $s = \mu(1-\nu_K)\nu_H$.

To sum-up, a pre-pandemic equilibrium in sector H is a wage rate w_H , a quantity of H-labor per type of establishment n_{Hj} and an amount of customers per capital d , such that, i) given wages and customers, n_{Hj} is chosen optimally by the establishment manager, ii) labor market for H-workers clear and iii) the total number of shopping trips equals the customer capacity of the H sector.⁸ Note that our concept of equilibrium guarantees that in every pre-

⁸For simplicity, we do not develop an explicit theory of the individual choice of shopping trips. A possible way of doing so, that would be consistent with our equilibrium restriction, would be to have the individual benefit of shopping trips to be decreasing in the tightness of the shopping market, i.e. in the ratio between

pandemic period every shopper in each of her/his shopping trip is assigned to an H-worker that can serve her. Note that the maximization of profit at the establishment level, plus the heterogeneity in capital imply that type 2 establishments (H-global) will employ more labor, make more sales and have higher output.

3.3.2 Production during the pandemic

In the pre-pandemic equilibrium output is equal across establishments of the same type and is constant over time. During the pandemic, however, output can change over time, and it can be different across establishments of the same type. As discussed in Section 3.2 nodes that are infected and show symptoms are prevented from working and shopping. Moreover, as the disease spreads, policies are introduced that may prevent also a fraction of healthy workers from working at their establishment. We denote by n_{Lit} the number of L-workers that show up at work in establishment i in period t , by n_{Hjit} the number for H-workers that show up at work in H-establishment i of type j (local or global) in period t , and finally by d_{it} the number of customers (per unit of capital) that will show up to shop at H-establishment i in period t . By assumption, in the short run establishments can not replace workers, therefore when the number of workers falls, establishment output will also fall. Moreover, when a customer assigned to an H-establishment is sick and does not show up to shop, the output of that establishment also is reduced. We can now define Y_t , i.e. the total production of the city in period t as

$$\begin{aligned}
 Y_t = & \underbrace{\sum_{i=1}^{Q_{H1}} \left[K_{H1}^\theta \left(\min \left\{ \frac{d_{it}K_{H1}}{\mu}, n_{H1it} \right\} \right)^{1-\theta} \right]}_{\text{Output of H-local establishments}} + \underbrace{\sum_{i=Q_{H1}+1}^{Q_{H1}+Q_{H2}} \left[K_{H2}^\theta \left(\min \left\{ \frac{d_{it}K_{H2}}{\mu}, n_{H2it} \right\} \right)^{1-\theta} \right]}_{\text{Output of H-global establishments}} \\
 & + \underbrace{\sum_{i=1}^{Q_L} K_L^\theta n_{Lit}^{1-\theta}}_{\text{Output of L establishments}}
 \end{aligned}$$

The time series for Y_t during the pandemic is a key object of interest in our policy experiments below, as it summarizes the economic impact of the pandemic and of the various measures of pandemic control.

shoppers and customer capacity

4 Calibration

In this section we describe how we set the values for the parameters of the ECON-EPI network, in order to numerically assess the impact of the pandemic and the effects of several policies.

4.1 Demographics and Public Transportation

We calibrate our model to a 5% synthetic version of the New York-Newark-Jersey City (NY-NJ-PA) metro area, which in 2019 had a population of approximately 20 million. The percentage of kids in the population ν_K is set to 17% so that the synthetic city has 40% of households with kids, which matches the percentage of households with at least one child under 17 in the metro area from the 2014-2018 American Community Survey (ACS). The percentage of non working adults ν_N is set to 37%, to match the employment to population ratio for persons over 18 in the metro in 2019.⁹ The share of agents using public transportation, ϕ , is set to 32% in order to match the percentage of individuals who report commuting to work using public transportation in the NY-NJ-PA metro area from the 2014-2018 ACS.

Table 1: Demographics and Public Transportation

Parameter Name	Symbol	Value	Source
<i>Demographics</i>			
Total Population	M	1,000,000	Census Data: ACS 2018
Share of Kids	ν_K	17%	American Community Survey
Share of Non-working Adults	ν_N	37%	American Community Survey
<i>Public Transportation</i>			
Share using Public Transportation	ϕ	32%	American Community Survey

4.2 Workplace

An important aspect of the calibration is to map workers in the data to workers in the two sectors of the model: the H and L sectors. In order to do so, we first work with occupations.

⁹Employment figures are from the BLS and population figures are from the Census.

Recall that there are two key features that characterize the H-sector: one is the physical proximity with other people (so that infection can be transmitted) and the second is the instability of the contact with customers (which also speeds up the spread of the disease). To capture these two features in an occupation, we use two questions in the ONET database. The first one asks about physical proximity to other people on the job, while the second one asks about the importance of interactions with external customers.¹⁰

The answers to these questions can be used to construct two indexes, both ranging from 0 to 100, that give, for each 6-digit occupation, measures of physical proximity and external interactions. Next, using a standard crosswalk, we compute similar indices for all the private sectors at the 2-Digits NAICS level, where the index for sector i is the average of the indices of each occupation j in that sector, weighted by the national employment share of occupation j in sector i . This procedure yields indices of physical proximity and external interactions for all the 2-digits NAICS sector. Figure 4 shows these (standardized) indices for all the NAICS 2 digits private sectors.

The shaded northwest quadrant highlights the 5 sectors which have both indices above the mean; we thus construct the H-sector by aggregating them, and the L-sector by aggregating all the others.

In Table 2, we report key characteristics of workers in the two sectors using employment figures from the Census Statistics of US Business (SUSB) for the NY-NJ-PA metro area in 2016. The L-sector employs more workers (54% v/s 46%), and workers in that sector have higher average yearly wages (94k v/s 40k). In the last two columns we compute the fraction of workers in each sector that work from home and a measure of their wage premium (relative to those who do not work from home). Note that in the L sector there are many more workers that work from home and that the annual wage of the home L-workers is roughly 16% higher than the wage of the non home workers in the same sector.¹¹

In the next section, we use these numbers to pin down the labor supply and the technological differences across the two sectors.

¹⁰Specifically the first question (ONET question 21) is “How physically close to other people are you when you perform your current job?” and the second question (ONET question 8) is “In your current job, how important are interactions that require you to deal with external customers (as in retail sales) or the public in general (as in police work)?”

¹¹To measure the share of workers that work from home we first use ACS data to compute the share of home workers in each 2-digits NAICS sector and then take a weighted average of these percentages, where the weights are the employment shares of each NAICS sector in our 2 macro sectors. Similarly to compute wages of home workers we take a weighted average of the wages in each sector, where the weights are the shares of home workers in each NAICS sector.

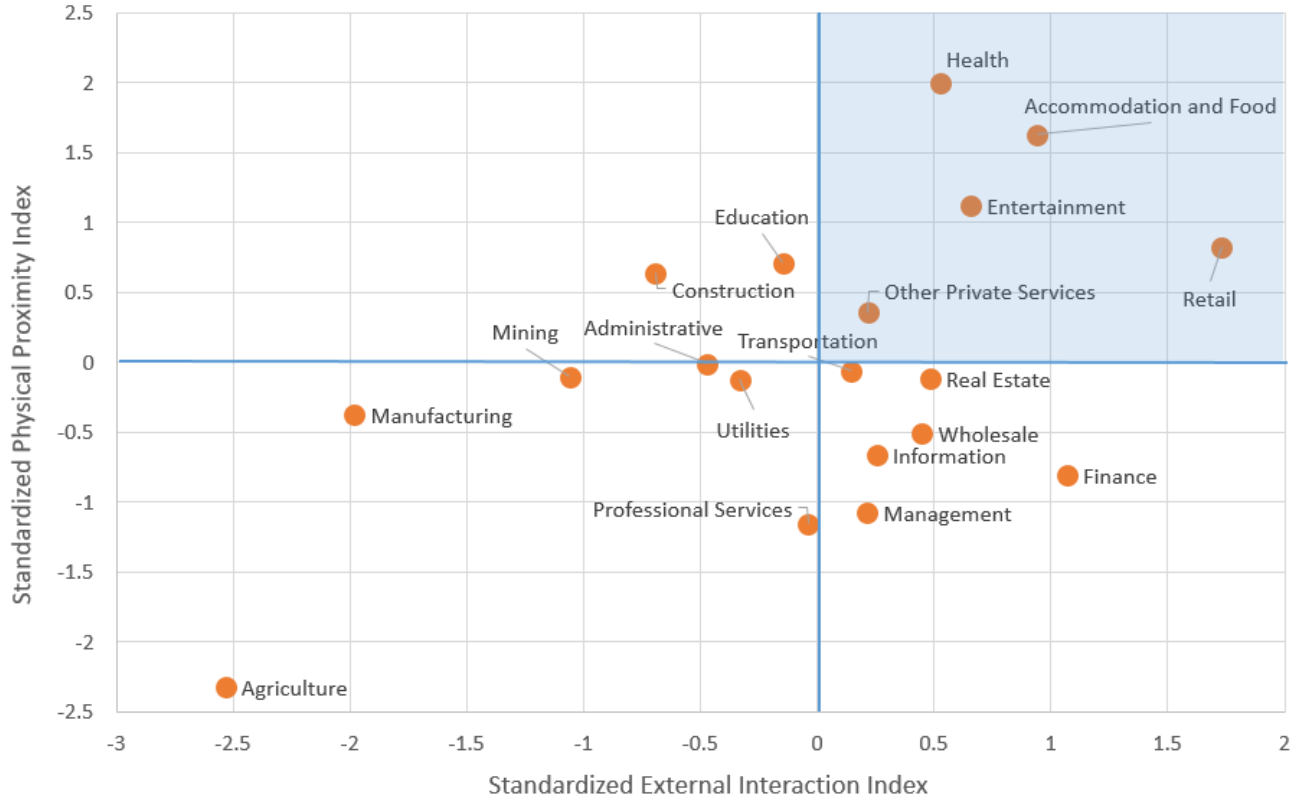


Figure 4: Identifying high contact sectors

Table 2: Characteristics of workers in H and L Sectors

	Share	Avg. yearly wages (\$)	Share Home workers	Home wage premium
L-sector	54%	94k	7%	16%
H-sector	46%	40k	3%	6%

4.3 Labor and Technology

The general logic of this section is that restrictions from the pre-pandemic equilibrium (see Section 3.3.1), plus data from firms and workers as described above, pin down the parameters that characterize the labor supply and the technology in the L and H sectors. All the parameters are reported in Table 3 below.

We first use statistics on home workers and on their wages reported in Table 2 to pin down the parameters ω and δ_ω , which determine: (i) the fraction of L-workers that can work from home and (ii) the ratio of their wage relative to the wage of those who cannot work from home in the L-sector.¹² In order to determine the fraction of L-workers who can work from home in

¹²Recall that, since few workers in the H-sector work from home, we assume that the percentage of H-workers that work from home is 0, both before and during the pandemic.

our series of experiments, we use two types of information. In Table 2, we report that in the L-sector 7% of workers already work from home before the pandemic hits. However, this is a lower bound for the fraction of workers that can actually start tele-commuting once the level of infections starts to increase and social-distance and lockdown measures are implemented. Dingel and Neiman (2020) estimate the fraction of workers that can potentially work from home in each occupation based on occupational characteristics. We compute their measure for each sector and, aggregating by sector, we find that the fraction of L-workers that can in principle tele-commute is 49.7%. We view this number as an upper bound as, in the short run, it is unlikely that such a large percentage of workers can switch to tele-commuting. For this reason, we set the fraction of workers who can actually work from home once the pandemic hits, ω , to 28% (which is the mid-point between the lower and upper bound).

In summary, we consider a pre-pandemic equilibrium with $\omega = 7\%$ and increase the number of L-workers working from home to $\omega = 28\%$ during the pandemic. We assume that non-home workers supply 1 unit of labor input and home workers supply $1 + \delta_\omega = 1.16$ units, in order to match the wage differences between the two groups in the L-sector. We then use demographic statistics from Table 1, plus worker statistics from Table 2, to pin down the parameters ν_L and ν_H , which denote the share of adults working in the L and H sectors, respectively. All these parameters determine the total labor supply (in units of labor input) in both sectors.

Both sectors share constant returns to scale production functions, where capital share is common and given by θ . We estimate θ using the standard methodology outlined in Cooley and Prescott (1995), using 2018 data for the New York Metro Area.¹³

Given θ we can normalize the wage of a unit of labor (which is equivalent to the wage of a non-home worker) in the L-sector to 1 and use the establishment labor demand (Equation 4) to pin down the labor demand per unit of capital. We then use the labor market clearing (Equation 5) to pin down the total capital in the sector $Q_L K_L$. Note that in the pre-pandemic equilibrium the number of establishments Q_L is not determined separately from the capital per establishment K_L , so we simply pick Q_L so that the number of workers per establishment in the model is 14, which matches the number of workers per establishment in the NAICS sectors that compose our L-sector.¹⁴

¹³The estimate is the ratio between capital income (consumption of fixed capital plus rent, interest and dividend income) and the sum of capital income plus labor income (compensation of employees). Data for rent, interest and dividend income, and for compensation of employees is available from BEA regional tables. Consumption of fixed capital is computed by first taking the ratio of consumption of fixed capital to GDP on national data for 2018 (the ratio is 16%) and then multiplying it by the metro area GDP.

¹⁴In the model, the number of workers per establishment is smaller than the quantity of effective labor

Table 3: Labor and Technology Parameters

Parameter Name	Symbol	Value
Share of Capital Income	θ	33%
<i>L-Sector</i>		
Share of adults working in L	ν_L	34%
Share of L-workers that can work from home	ω	28%
Home premium	δ_ω	16%
Number of establishments (14 wkrs)	Q_L	18,400
Capital per unit of labor	$\frac{K_L}{n_L}$	3.4
<i>H-sector</i>		
Share of adults working in H	ν_H	29%
Number of H-local establishments (14 wkrs)	Q_{H1}	12,500
Number of H-global establishments (56 wkrs)	Q_{H2}	500
Number of customers per H-worker	μ	4
Capital per unit of labor	$\frac{K_H}{n_H}$	0.26

Now moving to the H-sector, we use, as we did in the L-sector, the establishment labor demand (Equation 6) to pin down the labor demand per unit of capital. We then use the labor market clearing to pin down the total capital in the sector $Q_{H1}K_{H1} + Q_{H2}K_{H2}$. The next step is to identify in the data H-local and H-global establishments. Our strategy is to classify as H-global all non-health establishments with more than 40 employees in the H-sector of the NY-NJ-PA metro.¹⁵ This classification results in a share of H-workers working in H-global establishment of approximately 13.4%. We denote this share as ν_{H2} . We then pick Q_{H1} and Q_{H2} to match average establishment size in the H-local and H-global sector. In particular, we match an average establishment in the H-local sector of 14 employees and an average establishment size in the H-global sector of 56 employees. The values of Q_{H1} and Q_{H2} are reported in Table 3.

as the average worker, due to higher productivity of home workers, supplies more than one unit of effective labor.

¹⁵The reason for excluding the health sector from the H-global, despite the presence of some large establishments in that sector (large hospitals) is that these large establishments are essential and were never shut down

The remaining parameter to be determined in the H sector is μ , that is the number of customers that a worker can attend to in a day. Recall that, in a pre-pandemic equilibrium, in the H-sector the number of customers is equal to the total customer capacity. In the next section, we calibrate the equilibrium shopping trips (s) to be 1 per person, so that the total number of customers in a day is M . This implies, given the share of H-workers in the population, that the parameter μ is approximately 4; that is, an H-sector worker serves an average of 4 customers per day. One final important statistic reported in Table 3 is the capital per unit of labor, which is higher in the L-sector (3.4) than in the H-sector (0.26). The magnitude of this gap is identified from data on the wage differential (see Table 2) between workers in the two sectors. The reason why a unit of labor used in the production of the final good in the L-sector receives a higher compensation than a unit of labor used in the production of the final good in the H-sector, is that labor in the L-sector works with more capital.¹⁶

4.4 Network Contacts and Weights

The number of contacts each person has on each layer, and the weights of different layers play an important role in the spreading of the disease through the network. Our main reference for setting these in the model is the work by Mossong et al. (2008), which, using a common paper-diary methodology, has collected data on various characteristics of daily face-to-face interactions for a sample of over 7000 persons in 8 European countries.

The number of contacts of various individuals in different layers in the model and the targets from Mossong et al. (2008) are reported in the first two columns of Table 4.

Mossong et al. (2008) reports that on average each individual has 5.2 contacts in the household and during leisure activities. We map these contacts with model's contacts that take place within the household and neighborhood layers. Since the average household size in the model is 2.4, we impose that each household has on average 2 neighbors, so that each adult has an average of 5.4 household/neighbor contacts (1.4 coming from the household and 4 coming from other adults in the 2 neighbors) and each kid has an average of 2.8 contacts (2 from the households and 0.8 from the other kids in the 2 neighbors). These numbers result in an average across adults and kids of 5 contacts which is close to the 5.2 reported by Mossong et al. (2008). Mossong et al. (2008) also reports that, on average, each individual experiences

¹⁶In our set-up, we have abstracted from differences in human capital among the workers in the two sectors, and attributed all the differences in wages to differences in physical capital. Since in the short run physical capital is fixed, the results concerning output losses from shutting down workers in the two sectors are independent on whether we attribute wage differences to physical or human capital.

2 contacts during shopping and 0.4 while traveling. We set the number of shopping trips per person and the number of meetings while using public transportation in the model to match these two figures.¹⁷

Moving now to the differences between kids and adults, Mossong et al. (2008) reports that kids between the ages of 0 and 19 have on average 15.3 contacts, and adults have on average 12.4 contacts. In the model, we set the number of school contacts (which are specific to kids) to match total kids contacts. For adults, the number of contacts is more heterogenous. A fraction of adults (the non-workers) have no contacts resulting from work. Another fraction (the L-workers) have contacts resulting from meeting their team (of size T) of co-workers, where the team of workers is meant to capture the set of co-workers with which a worker interacts more closely. Finally, the H-workers have contacts resulting from the team of co-workers (of sizes T) and from meeting with customers (μ). Since we do not have much hard evidence on the size of workers teams, we simply set the size of the team $T = 7$ to match the total number of adult contacts.¹⁸ Notice also that this choice for the size of teams together with the data on establishment sizes in Table 3 implies that an L-establishment employs 2 teams, a H-global establishment employs 8 teams and a H-local establishment employs 2 teams.

Mossong et al. (2008) also reports information on the average duration of contacts, by contact type (daily, weekly and first time). We identify contacts in the household, work and school layers as daily, with an associated average duration of 3 hours. We identify shopping and neighborhood with weekly contacts, with an associated average duration of 1.4 hours and finally we think of contacts during travel as first time contacts, with an average duration of 0.5 hours. These figures results in weights of each layer (normalized to sum to 1) which are reported in the third column of Table 4. These weights are then used to identify the parameters used in equation 2 that capture the weight of each layer $\omega^H = \omega^W = \omega^S = 22\%$, $\omega^P = 4\%$ and $\omega^C = \omega^N = 10\%$.

The final column of Table 4 reports the potential pool of contacts for those layers where the actual contacts are drawn randomly every day. This information is not available in Mossong et al. (2008), however it is an important determinant of the spread of infection, and therefore we pin it down using the network structure, as well as additional information.

¹⁷The number of contacts during a shopping trip depends on where the shopping is done. Shopping in H-local establishment result in only 1 contact (the sales person). Shopping in a H-global establishment results in $V + 1$ contacts where V is the number of other customers the shopper comes into contact with. Setting set $V = 8$ results in 2 contacts for the average shopping trip

¹⁸A team size of 7 will result in 6 co-worker contacts for the H-worker, and only 5.6 contacts for the L-worker because a fraction of the workers work from home.

Table 4: Network Contacts and Weights

Person type	Layer	Actual Contacts		Weight	Contact Pool
		Model	Mossong		
<i>All:</i>	Home and Neighbor	5	5.2	[22%, 10%]	-
	Shopping overall	2	2	10%	
	H-local	$1 - v_{H2}$			14
	H-global	$9v_{H2}$			M
	Public Transport	0.3	0.4	4%	54
<i>Kids:</i>	Total	15.3	15.3		
	School	10		22%	26
<i>Adults:</i>	Total	12.4	12.4		
	Work				
	H-local (co-workers)	6		22%	-
	H-local (customers)	4		22%	M/Q_{H1}
	H-global (co-workers)	6		22%	-
	H global (customers)	4		22%	M
	L (co-workers)	5.6		22%	-

For the shopping links, every person does (on average) v_{H1} and $(1 - v_{H1})$ shopping trips to H-local and H-global establishments, respectively. When shopping at H-local, the pool of potential sales people that a shopper meets is given by 14 (the employment size of the H-local establishment). When visiting a H-global establishment, the pool of potential contacts is given M (the entire population), because the H-global draws customers from the entire network and each customer meets other customers when visiting the H-global establishment. For adults working in H-local establishment, the pool of potential customers is given by the local customer base which is equal to the size of the population divided by the number of H-local establishments Q_{H1} . Workers in H-global establishments draw their potential customers from the whole city, so their pool of contacts is the city population M .

For public transportation, we choose the number of potential contacts equal to 54 to match the seating capacity of the R160 New York City subway car. Finally, for schools, we proxy the pool of potential contacts with the class, so we set the size of the pool to 26 to match average class size (across grades) in New York City public schools for 2018-19. The ratio between the actual contacts and the contact pool for the unstable layers (shopping, public transportation, school and H-work place) is then used to set the Bernoulli parameter ρ_i in the network clocks described in Equation 1.

4.5 Disease Transmission

The final parameters to be determined are those regulating the diffusion of the disease, described in Sub-Section 3.2. We set some parameters based on epidemiological studies on COVID-19, and set the remaining, for which there is less evidence, to match the early stages of infection diffusion in the New York metro. Parameters are reported in Table 5.

Starting on the symptomatic branch, we set γ to 0.25 and ρ_S to 0.071, in order to match a duration of the pre-symptomatic and symptomatic stages of the disease to 4 and 10 days respectively (see, among others, Guan et al. 2020). Going now to the asymptomatic branch, we follow the CDC's best estimates for their Covid-19 Pandemic Planning Scenarios and set η to 0.75 and α to 0.3.¹⁹ This captures the finding that asymptomatic cases are three-quarters as infectious as the patients showing symptoms and account for 30% of cases. We assume that the duration of the disease is the same for symptomatic and asymptomatic infections and set ρ_A to match a duration of 14 days.

The literature has highlighted the importance of seasonality when modeling the spread of COVID-19. As such, we allow for seasonality in the transmission rate following the approach proposed in Atkeson (2021). Specifically, the transmission rate evolves according to

$$\pi_t = \pi \exp(\phi(t))$$

where π is a parameter to be calibrated and $\phi(t)$ is given by

$$\phi(t) = \frac{\gamma_s}{2} \left(\cos \left((t + \gamma_p) \frac{2\pi}{365} \right) - 1 \right)$$

The parameter γ_s controls the size of the difference between the peak and trough of the transmission rate and the parameter γ_p controls when transmission rates peak. We use calibrated parameters reported by the author for the United States version of their5 model. The last remaining parameters is π , the infectiousness of the symptomatic cases. Our strategy is to pick this parameters so that the infection curve in the model exactly matches the data in the initial period of the infection. In the next section we explain in more detail this choice.

¹⁹See <https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html>

Table 5: Disease Transmission Parameters

Parameter Name	Symbol	Value
Infection Probability	π	0.174
Relative Infectiousness of IA	η	0.75
Prob. of transition from E to IA	α	0.3
Initial Ratio of Asy. to Sym.	r_{as}	0.3
Prob. of transition from IP to IS	γ	0.25
Prob. of transition from IS to R	ρ_S	0.1
Prob. of transition from IA to R	ρ_A	0.071
Seasonality magnitude	γ_s	0.35
Seasonality location	γ_p	20

5 Results

This section first describes how we use mobility data to discipline changes in the network contacts during the pandemic. It then shows how the calibrated ECON-EPI network performs in explaining the infection dynamics, and contrasts it with another popular model of infection spreading, i.e. the standard random mixing SIR model. Lastly it discusses the contribution of the different layers of the network to the progression of the disease.

5.1 Changes in network structure during the pandemic

We focus on the period from March 8th, 2020, where the first 160 cases were reported in the New York metro area, until May 25th, 2020. The progress of the infection in the model does not only depend on initial conditions and epidemiological parameters, but also on the network structure which, as the pandemic spreads, evolves. In order to capture this evolution we use both information on actual regulatory changes and data on mobility, as reported by Google.²⁰ In particular Google reports four mobility series. The first three track visits of individuals at workplaces, retail and public transport hubs, while the fourth tracks length of stay of individuals at their residences. These series have a natural mapping into our model: workplace mobility maps into presence of L-workers at their establishments, retail mobility maps into presence of workers and shoppers at H-establishments and public transport mobility maps into number of individuals using public transportation. Finally residential mobility tracks the amount of time individuals spend at home, which in our model

²⁰See appendix A for a timeline of the pandemic related policies in New York.

is captured by the network weights. These four measures for New York City are reported in the top panel of Figure 5. The panel shows that initially retail, workplace and transportation mobility measures sharply fall, then they stay constant at a depressed level and partially recover towards the end of the period. Residential mobility displays the opposite pattern. This evolution is most likely the result of both changes in policy and in behavior.

Our strategy is to match this evolution by furloughing a time varying fraction of both L and H workers. In particular in each period we match the observed decline in workplace mobility in two ways. In the first days of the pandemic we match the decline in workplace mobility by having all L-workers that can work from home starting to do so. As time progresses and workplace mobility continues to decline we match the further decline by furloughing a fraction of L-workers each day. We also furlough a fraction of H-workers each day so to match the decline in retail mobility. We assume that global and local workers are shutdown at the same rate. When a worker is furloughed, her time is reallocated to their home network. Note that when we furlough H-workers we also cut a number of shopping links, as shoppers assigned to furloughed workers are not able to shop. We also cut the number of public transportation links in our network to match the decline in transportation mobility. Finally we close schools in the model on March 14th, which is the date in which K-12 schools are shut-down statewide.²¹

We use the residential mobility data to adjust the network weights to reflect the increased time individuals spent at home during the pandemic. Unlike the workplace and retail mobility figures, which count the change in individuals going to a location, residential mobility reflects the change in duration that people spent at home. Our strategy is to increase the home network weight to account for the increased time individuals spent at home. To properly apply the residential mobility data, we first construct a baseline duration that individuals spend at home. To do this we first assume that people spend a third of their day at home asleep. The remaining two-thirds of their day is allocated based on their network weights. We then calculate the implied increase in average time spent at home caused by the furloughing of workers and calculate the difference from the residential mobility time series. We then increase the home network share by this difference, removing the remaining time from the other activities in proportion to their weights.

The mobility patterns suggest a division of our period in three subperiods. The first (labeled “closing”, from March 8th to April 3rd) is the period in which mobility sharply declines, the second (labeled “lock-down”, from April 3rd to April 26th) is the period in

²¹Schools were announced to be closed on March 16th, a Monday, so we shut down schools effectively on Friday 14th.

which mobility stays low, and the last (labeled “re-opening”, from April 26th to May 25th) when mobility picks up.

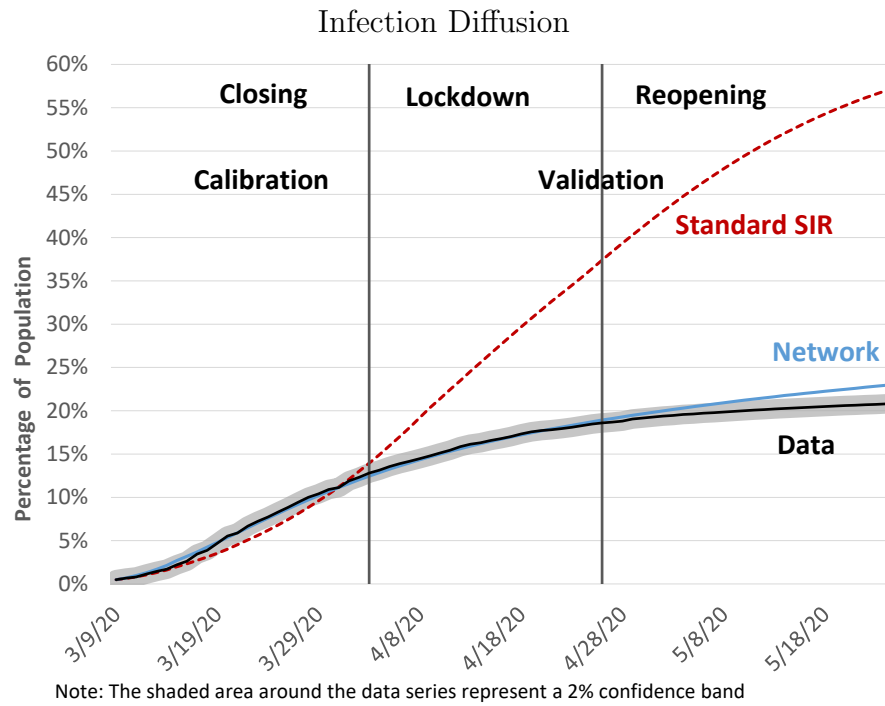
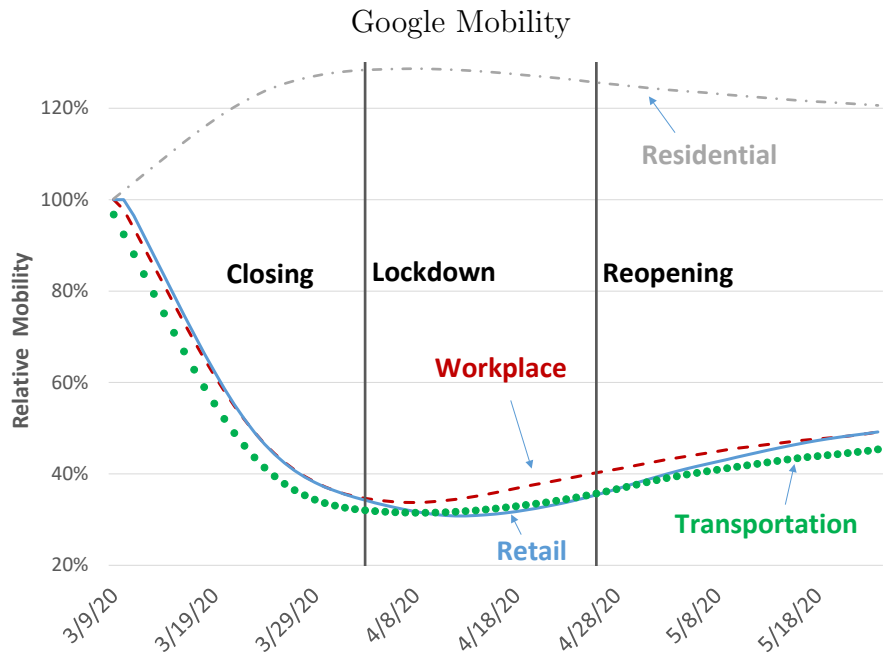


Figure 5: Network v/s SIR

5.2 Network v/s Standard SIR

The bottom panel of Figure 5 shows the cumulative infection curve generated by the network model against the data.²² Since our calibration strategy is to pick the epidemiological parameters π_t , α , and r_{as} to match the infection curve in the first sub period, the network model and the data lie on top of each other by construction until April 3rd. The periods after April 3rd, however, constitute a validation of the model. The network model is close to the empirical epidemiological curve all throughout the lock-down phase, and only shows slightly faster growth in infection (relative to the data) as the city starts to re-open. For comparison purposes, we also report the infection curve predicted by a standard SIR model, where each individual has the same number of contacts as in the network, but the contacts are randomly drawn across the entire population.²³ We calibrate the epidemiological parameters in the standard SIR in order to match the data infection curve in the first sub-period (exactly as we did for the network model), and we change the number of random contacts in the SIR so to match the average change in Google mobility. Possibly the most important message of Figure 5 is that even when the two models (Network and standard SIR) are put on equal footing, as they generate the same initial surge of infection and have similar containment measures, they have sharply different predictions for the evolution of the pandemic. In the network model, the infection naturally slows down, as the reduction in the number of contacts is enough to keep the infection local and prevent the disease from reaching the entire population. The SIR model, however, predicts that despite the reduction in contacts, the infection takes off in an exponential fashion. This is due to the random nature of contacts: in the SIR model, an individual is equally likely to meet any other individual in the city, whereas in the network model contacts are more clustered and less random. Before we move on to policy experiments, we use our calibrated model to quantify the contribution of several layers to the infection.

²²The epidemiological literature has established that reported COVID cases during the first wave were severely underreported. For this reason we construct a series of imputed cases, using information on COVID deaths. See appendix B for details on how we constructed the series.

²³We do not directly use the classic SIR model, but an equivalent network formulation. Rather than have multiple network layers, each individual has a single layer which connects them to all other nodes. The transition between health states is regulated by the same parameters as in the network model, and described in Figure 3. The probability of infection is therefore determined by the epidemiological parameters π_t and η and the per-period number of contacts. The pre-pandemic number of contacts is set to the average number of contacts across children and adults reported in Mossong et al. (2008), and each period this number is adjusted to match the average change in the Google mobility reports.

5.3 Infection Decomposition and Complementarities

In this section, we study the effect of shutting down different layers of the network, and how this shutdown interacts with the transmissibility of the disease. In order to do so, we sequentially set to 0 the weights of each layer of the network, and assess the impact of shutting down one single layer on the evolution of the infection. An important issue in assessing the impact of a given layer is the presence of mitigation policies (for example school closures) or endogenous reduction of contacts (as captured by Google mobility). If contacts in a layer are already substantially reduced, we might find that shutting down that layer completely does not have much impact on infection; this, obviously, does not reflect the importance of the layer, but rather the fact that the layer was already almost closed. For this reason, we conduct this experiment in the fully open (pre-pandemic) network.

Figure 6 shows the evolution of the disease (percentage of active cases in each day) under different scenarios. In both panels, we show epidemic curves for the network with all layers open (benchmark), with the L-establishments shut down, with the H-local shut down and finally the H-global shut down. The numbers under each label report the percentage of workers that are shut down as the result of that policy.²⁴ The panel on the left uses the infection probability parameter π from our benchmark calibration, while the right panel plots the same curves with a lower infection probability parameter, which we use later in our re-opening experiments.

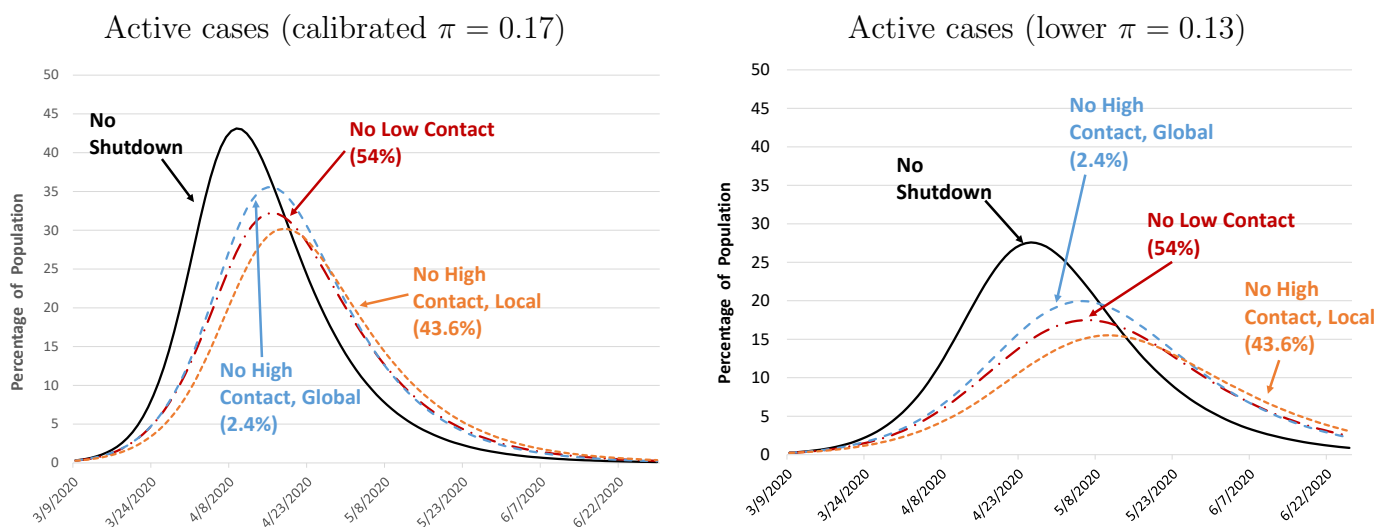


Figure 6: Infection Decomposition

²⁴We do not plot curves for schools as we will analyze the impact of school closure in the next section

Focus first on the left panel. The first finding we highlight is that closing down the H-global establishment achieves a substantial reduction of infection and delay in the peak despite involving only a small reduction in employment. This is because the workers in the H-global establishments have many contacts which are unstable and far reaching. These properties of the H-global sector makes this layer very close to a random mixing set-up, and thus very conducive to a rapid spread of the disease. The same logic applies when you compare the effect of closing down H-local v/s L-establishment. Despite involving a smaller reduction of workers (43.6% v/s 54%) shutting down the H-local achieves a larger reduction in infection and a later peak, due to the fact that the H-local involve more contacts of more unstable nature.

Next we find it interesting to compare the right and the left panel of Figure 6. The curves in the right panel are drawn from a simulation with a smaller infection probability parameter and thus, not surprisingly, are lower, as there is less infection spreading. Note however that with a smaller π the impact of shutting down high contact layers gets magnified. For example, shutting down the H-global layer in a high π environment achieves a reduction of average number of active cases over the first two months of 3.2% while the reduction is 4.9% in the low π environment. To see why this the case, consider the infection probability of a susceptible node with many infected contacts. If π is close to 1, the infection probability is close to 1 and not very sensitive to a marginal reduction of contacts. In this case, shutting down a layer (and thus reducing the number of contacts) does not affect much infection dynamics, which is always very fast. On the other hand, when π is lower (but sufficiently far from 0), Equation 3 implies that a marginal reduction of contacts can significantly reduce the infection probability. Therefore, in this case infection dynamics are more sensitive to the network structure, and mitigation policies that reduce the number of contacts are more effective. This highlights an important point, namely the *complementarity* between mitigation policies that reduce the transmission of the disease (e.g. face masks) and mitigation policies that reduce the number of contacts (i.e. shutting down malls). If the transmissibility of the disease is high (π close to 1), then a moderate reduction in contacts is not very effective in reducing infections. Similarly, if individuals have a large number of contacts, a moderate reduction in transmissibility is not effective. However, if the transmissibility is lower, then the same reduction of contacts can have a large impact on the spread of the disease, and similarly if the number of contacts is lower, the same reduction in the transmissibility of the disease can have a large impact on infection levels. We will return to these considerations later when we

analyze re-opening strategies.

Having established that the network model constitutes a good benchmark to study the evolution of the pandemic, and having analyzed the importance of various layers, we now use the model to conduct two types of policy experiments. The first set, in Section 6.1, studies how counterfactual policies would have affected ECON-EPI outcomes at the outbreak of the COVID-19 pandemic in New York City. These experiments are also helpful to evaluate different options, should a second wave of infections hit. The second set of experiments, in Section 6.2, studies different strategies for reopening the city, as the infection subsides.

6 Policy Experiments

6.1 Lock-down strategies

As Figure 5 shows, after the draconian lockdown of March and April, infections in the New York metro area stopped increasing by mid May. The question that is often asked is whether the lock-down was too strict. To answer this question, we perform a series of experiments that relax lock-down restrictions in the first four weeks of the pandemic (e.g., between March 8th and April 5th). With the lessons drawn from these experiments, we design a counterfactual *smart* mitigation policy that targets sectors with higher risk of spreading. We show that this policy could have reduced infections and increased output relative to the benchmark case.

We start from our benchmark case and compare it with three counterfactuals in which we gradually bring back the same number of shutdown workers in each sector (L, H-local, and H-global).²⁵ We then compare the epidemiological and economic outcomes to our benchmark case. Starting with the epidemiological outcomes (the top panel), we see that increasing workers in the H-global sector has a very large impact on cumulated infections (over 5% of the population). Extra workers in the H-local and L-sector have instead a more moderate impact (around 1% of population). The large increase in infections brought about by the additional H-global workers is not surprising; as discussed earlier, these workers have a lot of random contacts, thus they function as spreaders.

Moving now to the economic outcomes (the bottom panel), we first observe that the output gains are fairly similar (around 2% of GDP) across experiments. Notice however that the largest increase in output is obtained in L-sector, as this the sector where workers have the highest marginal product.

²⁵The increase in the amount of workers in each sector is around 1% of the pre-pandemic total employment.

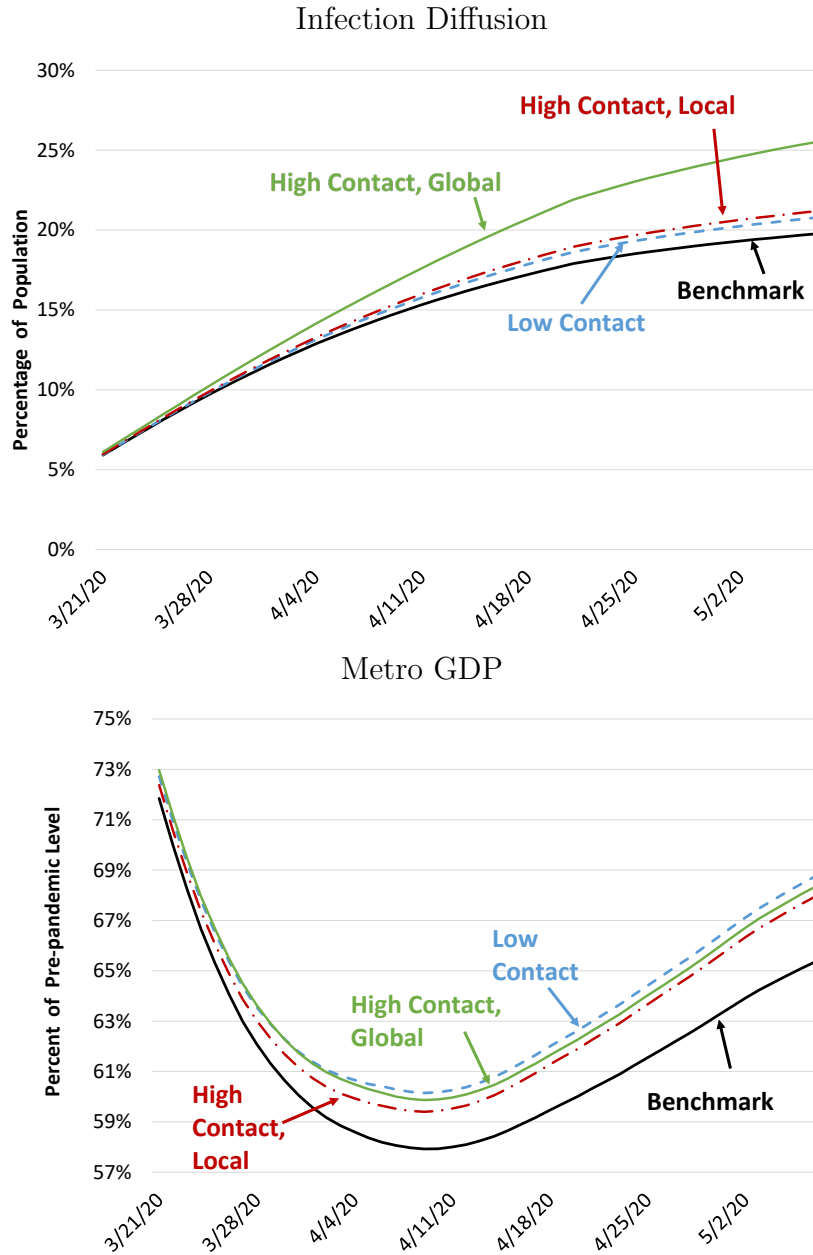


Figure 7: Policy counterfactual

The results in figure 7 suggest that tightening the shutdown in the H-sector while relaxing it in the L-sector might achieve a reduction in infection *and* an increase in output, relative to the benchmark. In Figure 8, we consider the effect of such a policy, which we label smart mitigation. More specifically, we impose stricter lock-down measures in the H-sector (both in the H-local and H-global sector) while relaxing those in the L-sector. We impose that

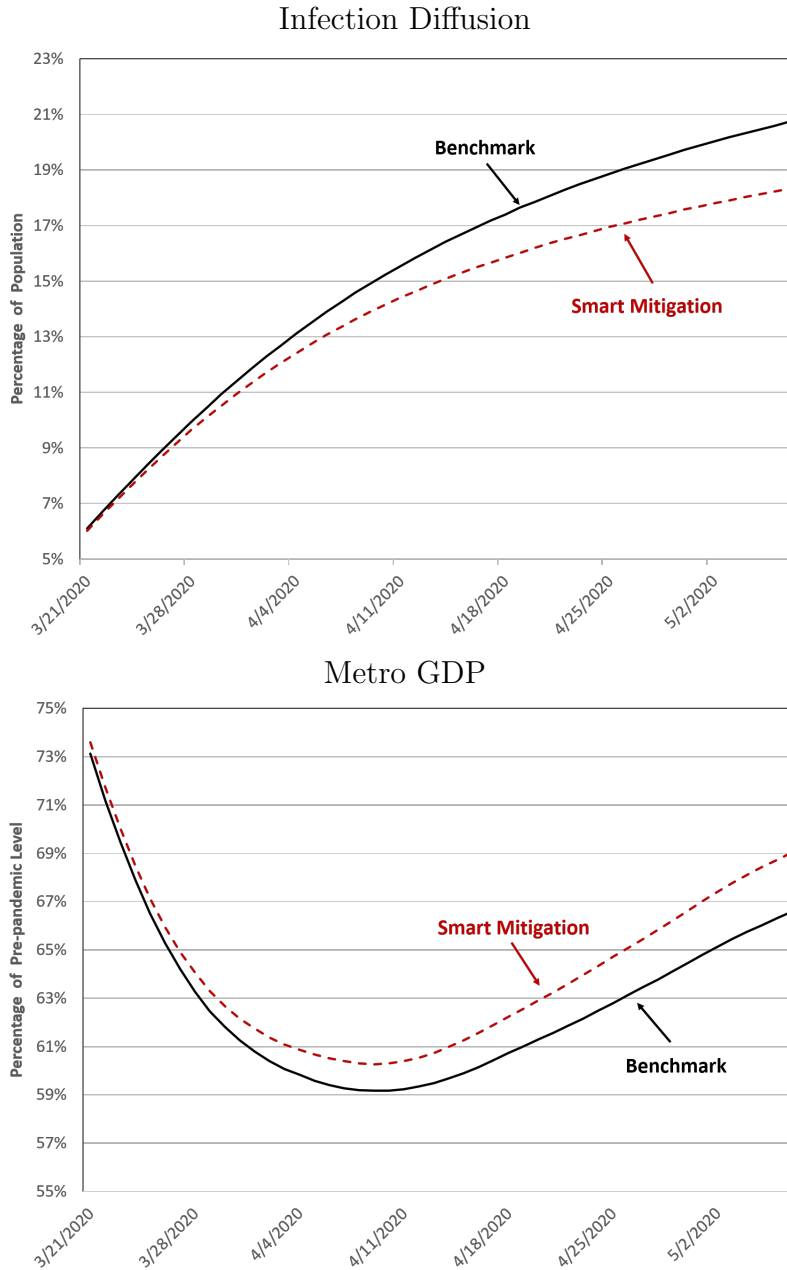


Figure 8: Smart Mitigation

the total number of individuals going to work is the same as the benchmark and that the amount of workers in each sector affected by the policy is around 1% of the pre-pandemic employment level (the same amount considered in the experiments in Figure 7). A concrete example of such a policy would be to allow more workers in manufacturing plants to go to work, while furloughing an equal number of shopping mall workers that are allowed to go to work in the benchmark. The figure shows that the smart mitigation achieves a substantial

double-gain. The top panel shows that it reduces the number of infections by 2% of the population of the metro area (400 thousands fewer cases) and the bottom panel shows that at the same time it increases output, relative to the benchmark, by an average of 2%.

6.2 Re-opening strategies

Results in Section 5 suggest that the network model captures well infection dynamics in the lock-down period. However, as the city starts to reopen in the month of May, the model predicts a level of infection that is higher than the data. One possible reason for this discrepancy is that we keep the epidemiological parameters constant throughout our period, while the much broader availability of PPE and of testing, together with social distancing (e.g. requiring individuals to be 6 feet apart from each other) has reduced the transmissibility of the disease. As this issue is critical to analyze reopening scenarios, we incorporate changes in transmissibility by assuming that in the post lock down period (after April 26th) there is a one-time decline in the parameter π . We calibrate this decline (from 0.17 to 0.13,) so that the infection curve in the reopening period (April 26th through May 25th) matches the data. The result of this procedure is illustrated in Figure 9. The figure suggests that the network model with the recalibrated π can be a good starting point to study reopening strategies, that is to predict the evolution of infection and output under different assumptions for the evolution of mobility.

In Figure 10 we consider four alternative scenarios for the reopening of New York. The figure plots the cumulated rate of infection for each scenario. The first (labeled broad reopen) is the one in which all workplaces and school fully reopen. The second is the other extreme, and is one in which network links remain severed, so economic activity is significantly limited and schools remain closed. The epidemiological outcomes in this scenarios are polar opposite. In the first the majority of the city population gets infected, and the loss of lives is very large. This suggests that in a re-opening phase policy makers face a binding tradeoff between school and workplaces. In the no-reopening scenario infection completely stops and gets eradicated. However the cost of this achievement is an output which remains 30% below its pre-pandemic level for the whole period. The third and fourth scenario consider re-opening only workplaces or only schools. The model suggests that in both these cases infection remains well below the case of broad re-opening, but in both cases is significantly above what we observe in the data. This suggest that a policy of partial closure both in the schools and in the workplace is most effective in limiting the progress of the disease through the network.

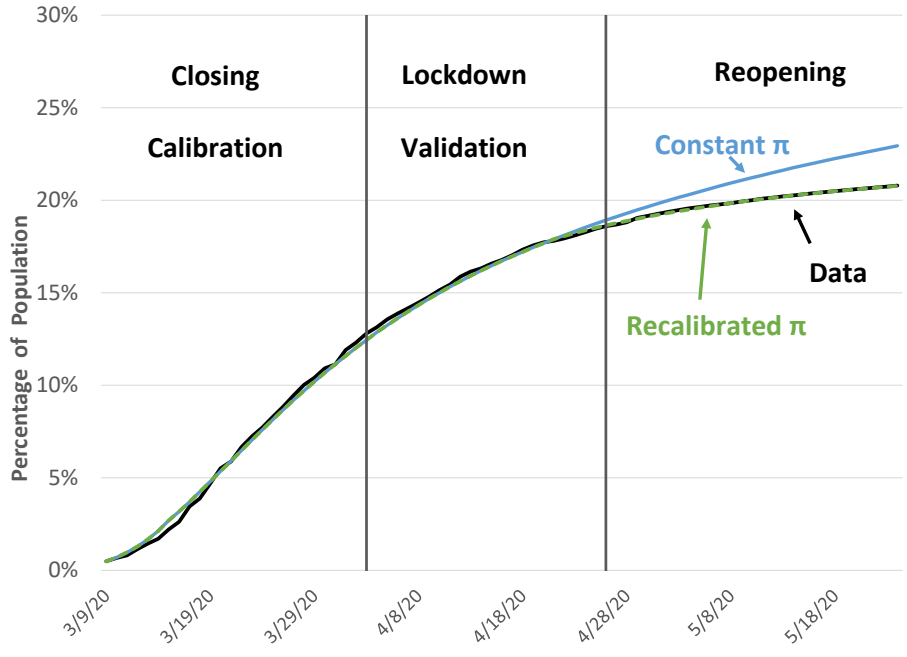


Figure 9: The impact of lower π

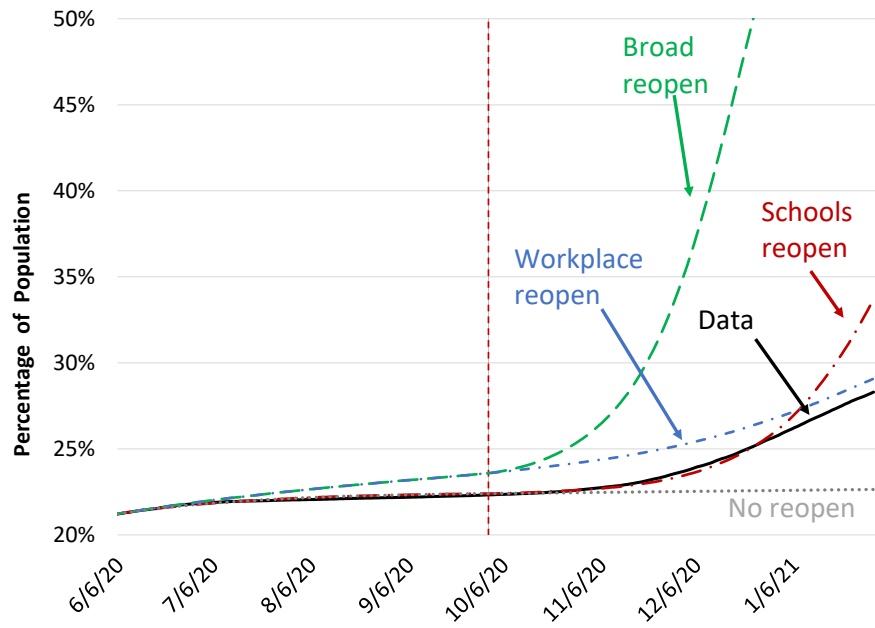


Figure 10: Reopening scenarios

7 Conclusion

We develop an ECON-EPI network model to study the impact of the COVID-19 pandemic on a large US metro area, and to evaluate policies that limit the human as well as the economic damage. We build on the traditional SIR model by using network theory to put

structure on the patterns of human interactions. We find that this structure is useful to understand observed epidemiological curves, featuring a large initial surge and a plateau at a relatively low level of infections. Moreover we use our set-up to quantify how layers of interactions contribute both to infection levels and economic activity. Network layers that feature numerous and unstable contacts (such as large gatherings or schools) work as ignition rods for the infection. Smart lock-down policies shut down these layers early, and smart reopenings keep them closed for longer. Opening sectors where workers interact with each other in stable teams (such as manufacturing) is the best strategy to minimize output losses, while at the same time keeping the spread of the disease under control.

There are several directions in which we could expand the study of pandemic control on ECON-EPI networks. In our framework interactions are, for the most part, exogenously determined. One direction for further research would be to study how the ECON-EPI pattern of contacts can change endogenously, both in the short run, in response to fear, and in the long run, in response to increased risk of a new pandemic.²⁶

Our network analysis can also prove useful to think about how to efficiently allocate limited testing/vaccination resources, which in the early phase of a pandemic are going to be typically scarce. The same principles we used to design “smart” lockdown and reopening policies, can be used to design “smart” testing or vaccination. We conjecture that it would be efficient to allocate testing/vaccination to layers of the network which have more numerous and more unstable contacts, and our framework could be used to quantify the effects of such a policy.²⁷ Another extension of our analysis would be to introduce more group level heterogeneity, such as different communities/neighborhoods in the city. Such an extension would help to understand how much of the observed large differences in disease outcomes across groups can be explained by differences in their social structure.²⁸ It could also help to design social policies that protect the more exposed communities and, at the same time, reduce average spread. Finally, a related application of our analysis would be to analyze how much of the differences in epidemiological and economic outcomes across metro areas and across countries can be explained by differences in the network of interactions.²⁹

²⁶See the recent literature on the COVID-19 pandemic studying behavioral responses to the infection, such as Alfaro et al. (2020), Farboodi et al. (2021), Krueger et al. (2020) and Toxvaerd (2020). See Fogli and Veldkamp (2021) for a study of the endogenous evolution of network of interaction in societies with difference prevalence of diseases.

²⁷For some early works on efficient testing using the standard SIR set-up see Berger et al. (2020) and Chari et al. (2021).

²⁸For evidence of local differences in disease outcomes in the New York metro see Almagro and Orane-Hutchinson (2020).

²⁹See Fogli and Pastorino (2021) for a study on the importance of network interactions to explain the

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A Changes in regulation in the New York Metro

The sequence of measures imposed by the NY government, aimed at slowing down the spread of the disease, is summarized in Figure 11. Increasingly stricter mitigation policies reducing gatherings, retail and production activities were implemented in a short span of time.

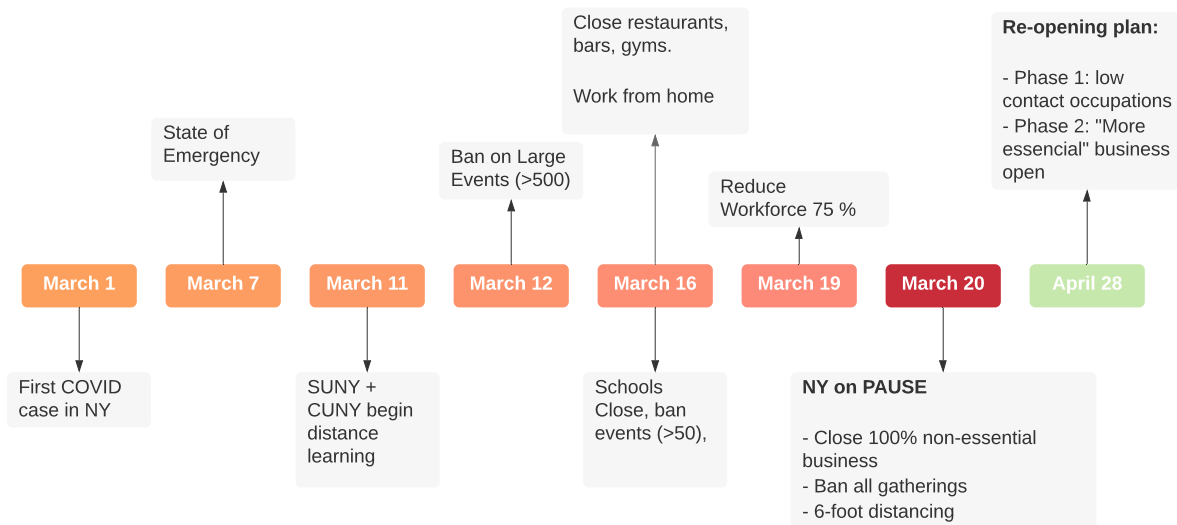


Figure 11: Timeline of lock-down Policies

B Imputation of COVID cases in New York City

B.1 Infection Fatality Ratio

The *Infection Fatality Ratio (IFR)* represents the number of individuals who die of COVID-19 among all infected individuals (symptomatic and asymptomatic). This parameter is not necessarily equivalent to the number of reported deaths per reported case because many cases and deaths are never confirmed to be COVID-19, and there is a lag in time between when people are infected and when they die. This parameter also reflects the existing standard of care, which may vary by location and may be affected by the introduction of new therapeutics. The IFR satisfies

$$IFR = \frac{\text{Deaths}}{\text{TI}},$$

where TI denotes the total number of true infections. Letting IA denote the number of asymptomatic and IS the number of symptomatic individuals,

$$\text{TI} = IS + IA.$$

Using data on the number of deaths and estimates of the IFR, it is possible to back out TI , the number of total infections, using the equation above. Because the IFR and the number of deaths vary significantly with age, we use age-specific estimates.

B.2 Data on Number of Deaths

There is no official reporting of deaths by age over time for the NYC metro area. The City³⁰, a project led by Choi, Velasquez and Welch, aggregates information from the New York City Department of Health and Mental Hygiene, the New York State Department of Health, Governor Andrew Cuomo’s office, the Center for Systems Science and Engineering at Johns Hopkins University, the U.S. Department of Health and Human Services and the Centers for Disease Control and Prevention. The number of deaths per age bin is reported in their GitHub repository³¹ for New York City between March 22, 2020 and May 16, 2020. They consider five bins: 0-17 years, 18-44 years, 45-64 years, 65-74 years and 75+ years. There is no other source that we are aware of reporting deaths by age for NYC after that period. With this data, we can compute the proportion of all COVID deaths associated to each age bin. The resulting series are shown in Figure 12

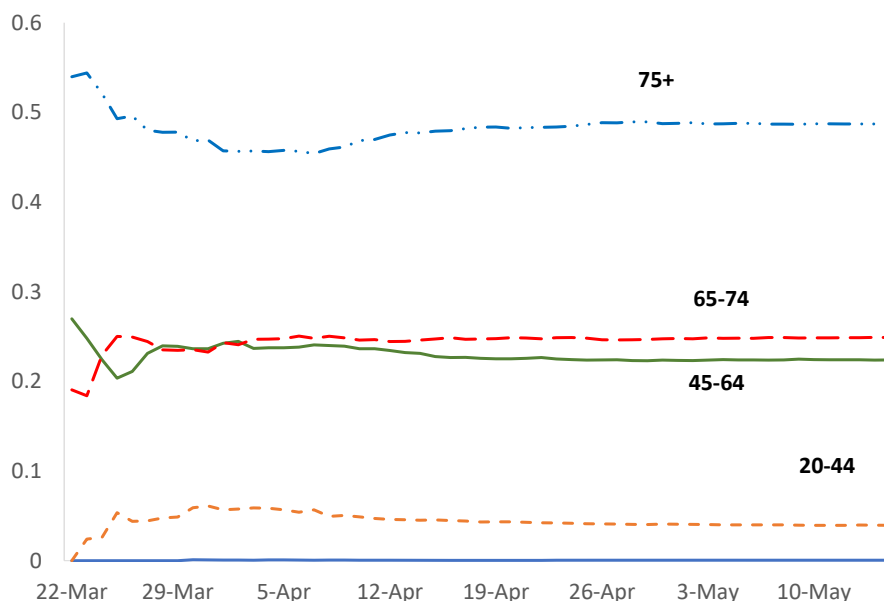


Figure 12: Fraction of COVID Deaths by Age group in NYC

While there are some fluctuations early on in the sample, the proportions converge to near-constant values by the end of April. The lowest percentage is observed in the 0-17 age-bin, which accounts for less than 0.5% of all deaths. It is followed by the 18-44 age-bin, where around 4% of all deaths are observed. The 45-64 age-bin accounts for 22.4% of all deaths, whereas the 65-74 age-bin represents 24.8% of them. By far the largest percentage corresponds to the 75+ age group, accounting for 48.7% of all deaths in the sample.³²

³⁰See https://projects.thecity.nyc/2020_03_covid-19-tracker

³¹See <https://github.com/thecityny/covid-19-nyc-data>

³²These numbers correspond to the average proportions by age bin between May 1st and May 16th 2021.

Because we are interested in a time-series for the NY metro area (not just for NY City) that would extend beyond May 16th, we need to combine this information with data on the total number of deaths over time in our area of interest. The latter can be calculated by aggregating the total number of deaths per day by county for all counties in the NY-NJ-CT Metro Area. These series are reported in the New York Times repository³³.

In order to compute the number of deaths by age group, denoted in the NY metro area, we multiply the observed proportion of deaths per group (shown in the plot) by the total number of deaths from the NY Times between March 22th and May 16th. Assuming that the percentage of deaths by age-bin remains constant thereafter, we use the average proportions by bin (computed between May 1st and May 16th). This gives us the number of deaths by age bin i on day t , denoted $Deaths_{i,t}$ in what follows.

B.3 IFR Data

The IFRs by age bin for New York are obtained from Brazeau et al. (2020) meta analysis.³⁴ The authors apply Verity et al. (2020) methodology, which relies on Seroprevalence data, to the New York metro area. The resulting IFR's per age-bins are reported in Table 6

Name	Values
Infection Fatality Ratio	0-17 years: 0.0000 18-44 years: 0.00077 45-64 years: 0.00623 65-74 years: 0.02205 75+ years: 0.05977
Median # days from IA to death	0-17 years: 10 (4, 31) days 18-49 years old: 17 (10, 30) days 50-64 years old: 19 (11, 30) days ≥ 65 years old: 16 (9, 25) days

Table 6: IFR parameters

In the table, we also report the median number of days between infection and death, as reported by the CDC.

³³See <https://github.com/nytimes/covid-19-data> and an explanation on how they smooth the series here:<https://github.com/nytimes/covid-19-data/commit/09af37ab4bd5155b6b4a455b945c92fef4ae737e>

³⁴The IFRs are reported in their Supplementary Appendix, page 25, for New York.

B.4 Imputation Procedure

Denote the age-bins as: $a = 0 - 17$, $b = 18 - 44$, $c = 45 - 64$, $d = 65 - 74$ and $e = 75+$. Under the assumption that reported deaths correspond to the true number of deaths, we can compute³⁵

$$TI_t = \frac{\text{Deaths}_{a,t-10}}{IFR_a} + \frac{\text{Deaths}_{b,t-17}}{IFR_b} + \frac{\text{Deaths}_{c,t-19}}{IFR_c} + \sum_{i=\{d,e\}} \frac{\text{Deaths}_{i,t-16}}{IFR_i},$$

where t indicates the date of the observation and i the age-bin. Note that the formula takes into consideration that a death observed in period t corresponds to an infection 10, 17, 19, or 16 days prior, as summarized in Table 6. Because some observations are lost, this restricts our first imputed total case count to March 9th, 2020. Figure 13 shows our final series of imputed Total Infections (dashed blue line, left axis) together with the total number of infections as reported by the New York Times for the NY-NJ-CT metro area (solid red line, right axis).

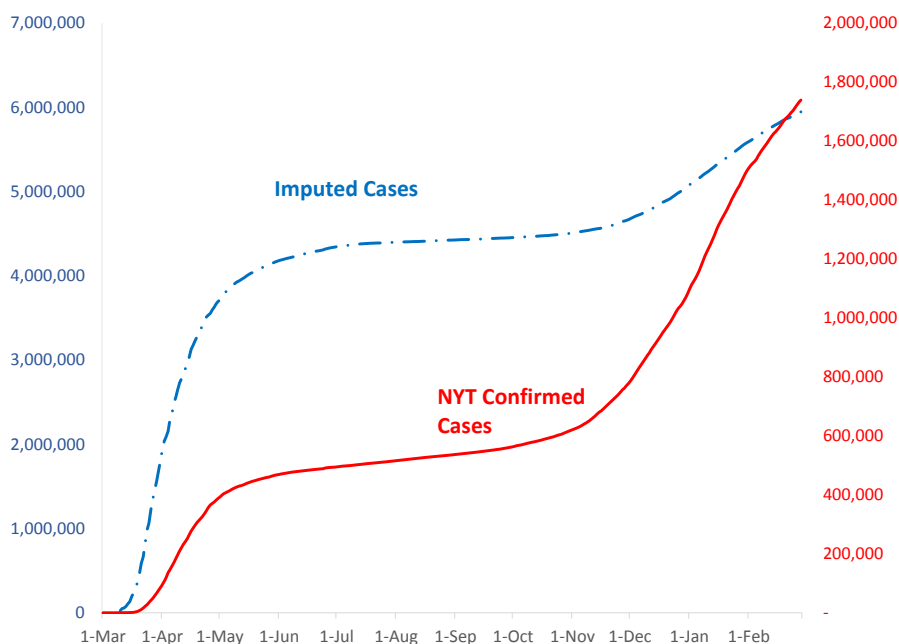


Figure 13: Imputed Total Infections

A few observations are in place. First, cases start to increase earlier in time when imputed from deaths. This is probably due to the fact that there was scarcity of testing in the NY area at the outset of the pandemic, so many asymptomatic cases went on undetected. Second, the number of imputed infections is about 10 times larger than what has been accounted for in most of the sample. During mid-April it was 12 times larger, consistent with Havers et al. (2020) study of sero-prevalence for NY. The prevalence for our imputed data during

³⁵While the IFR for the first age bin is basically zero, we do observe some deaths in that group. In such case, we simply used observed deaths as estimates of cases.

August is about 22%, consistent with the CDC seroprevalence COVID Data Tracker³⁶ for New York of 22.5% for the same period. Near the end of the sample (by late October), the ratio between imputed infections and reported infections is reduced to 6. Finally, we wanted to note that using data from the [Johns Hopkins Dashboard](#) for imputing deaths results in very similar patterns.

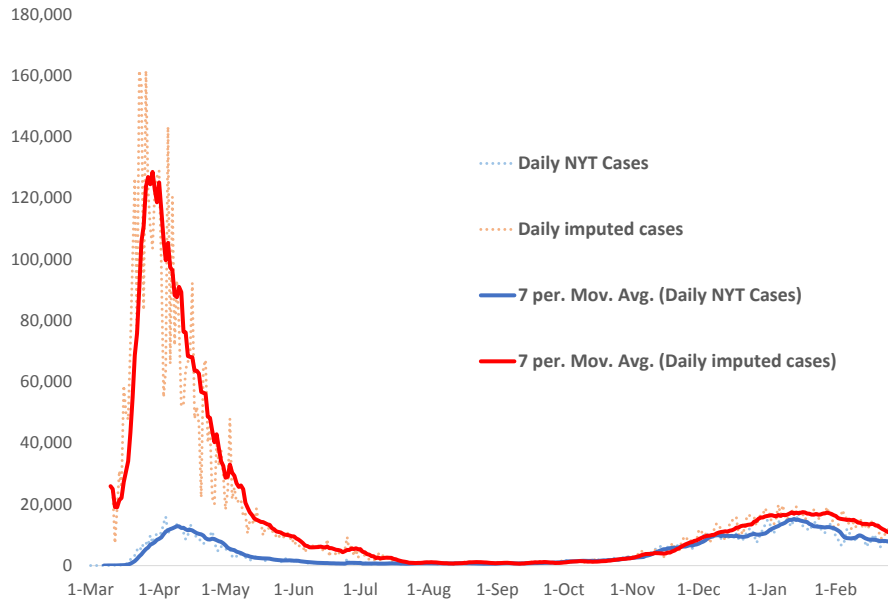


Figure 14: Reported v/s imputed cases

Daily cases (imputed and reported) are displayed in Figure 14. The dotted line is the actual data, and the solid lines represent a 7-day moving average. The number of new cases as reported by the New York Times converges to our imputed values in early August, and the two series track each other well during the second wave (see Figure 15). Between August 1st and February 28th, about 88% of our imputed cases are reported. During April 2020, only 20% of imputed cases were reported.

³⁶See <https://covid.cdc.gov/covid-data-tracker/#national-lab>.

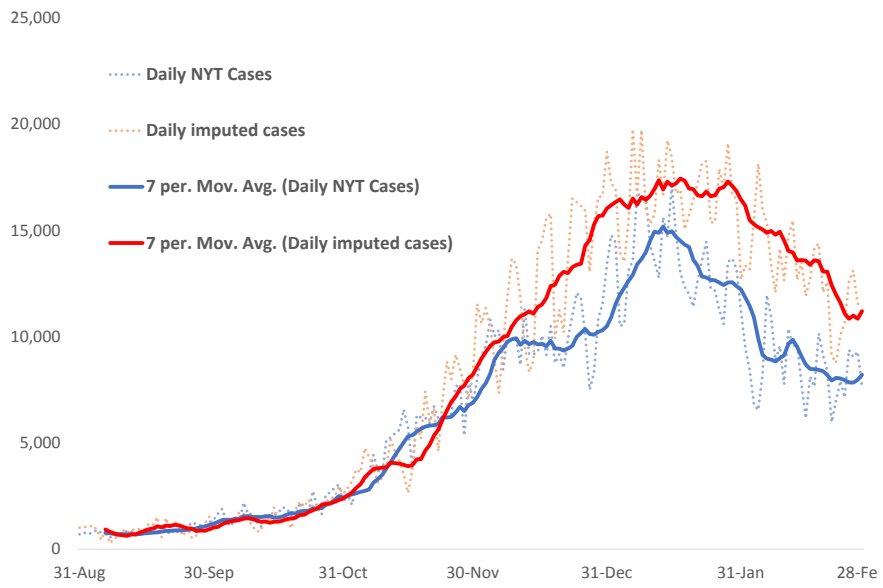


Figure 15: Reported v/s imputed cases in the second wave