Network Hazard and Superspreaders

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Abstract

Higher availability and efficacy of protective measures against infectious diseases, such as vaccines, increases individuals' propensity to socialize. Consequently, the number of visits to central points of interest (e.g., schools, gyms, grocery stores) and the rate of interactions with the agents employed therein (e.g., teachers, trainers, cashiers) increase. This opens more channels for the virus to transmit *through* the central agent or location. This leads to a manifestation of network hazard (Erol 2019). The infection rates can increase as protective measures become more effective and more available. Testable predictions of the theory are confirmed by the foot traffic data from 2019-2022 and historical COVID-19 vaccination and community transmission rates.

1 Introduction

The outbreak of COVID-19 has had a significant impact on global health and economy. The virus, caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was first identified in Wuhan, China in December 2019 and quickly spread to become a pandemic. The World Health Organization (WHO) declared COVID-19 a Public Health Emergency of International Concern in January 2020 and a pandemic in March 2020. As of 2022, the virus has infected over 600 million people and caused over 6 million deaths worldwide.[1] The rapid spread of COVID-19 and mixed public reactions to advised protective measures highlighted a need for better preparedness for and control of epidemics and pandemics. In particular, behavioral factors are not widely understood in the spread of coronavirus, and may play a greater role in efforts to control epidemic and pandemic levels (Gupta et al. (2022)).[2]

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[1] See https://covid19.who.int/ for WHO Coronavirus (COVID-19) Dashboard.

[2] Some examples of behavioral factors include how individuals interpret and respond to public health messages, how social norms and cultural practices shape behavior, or how economic and political factors influence the implementation of control measures (Berg and Lin (2020)).

Within this context, our theory describes a precautionary scenario on how the unregulated levels of social activity respond to high availability and efficacy of preventative measures. While vaccines are an important tool in controlling the spread of COVID-19, it is essential to recognize that they do not eliminate the risk of transmission entirely (Polack et al. (2020)). As more individuals become vaccinated, they may feel more comfortable interacting with others in high-risk settings, such as restaurants, schools, gyms, and grocery stores, or attending family gatherings (Usherwood et al. (2021)). The increased number of visitors and rates of activity can potentially push the viral load in closed spaces above threshold levels conducive to infections (Henriques et al. (2021)). Additionally, agents employed in these central locations, such as waiters, teachers, trainers, or cashiers can get infected and spread the virus during their asymptomatic period to many visitors. We consider a central location or agent as a central node in a network, and allow other agents to choose to form connections with the center to obtain certain benefits. Although largely available and more effective vaccines have the direct effect of reducing aggregate infections, the indirect effect via increased contact with centers and infections *through* the center can potentially offset the direct positive effect, in aggregate. We show that the increased interaction with connectors leads to a manifestation of network hazard (Erol (2019)), as the network becomes more concentrated for the virus to spread *through* the centers. On top of increasing aggregate infection rates, the correlated nature of infections by virtue of being transmitted by the center causes disproportionately large number of simultaneous infections. Such *superspreader* events are particularly important to understand in face of limited hospital capacity and ventilators.

We use monthly time-series data of visits to various types of businesses such as grocery stores, restaurants, coffee shops, etc. over the period of 2019-2022 from the geospatial data company SafeGraph. This monthly foot traffic data is combined with the publicly available COVID-19 vaccination rate and community transmission rate datasets by Centers for Disease Control and Prevention (CDC) for the same time period and geographical areas. We find that the testable predictions our model are observed in the data. As vaccination rates increase, there are more visits to the points of interest as well as higher rates of infections.

Related Literature The spread of COVID-19 in closed environments, such as households and workplaces, and the effectiveness of preventative measures, such as mask use, social distancing and ventilation, in controlling its transmission has been studied in epidemiology, mathematics, and physics.[3] Abo and

[3] See Buonanno et al. (2020), Bazant et al. (2021), Bazant and Bush (2021), Henriques et al. (2021), Ooi et al. (2021), Salmenjoki et al. (2021), Shang et al. (2022). These works emphasize the importance of limiting cumulative exposure time which is the product of the number of occupants and their time in an enclosed space. This quantity depends on the type

Smith (2020) compare the efficacy of various protective measures including physical distancing and vaccination. This literature does not factor in the society's endogenous behavior. We utilize this literature in specifying functional forms.

The effect COVID-19 on retail operations, supply chain management, and public health policy design has been studied in operations research. Delasay et al. (2022) and Shumsky et al. (2021) study the impact of social distancing and other measures on consumer behavior and foot traffic.[4] Additionally, research has played an important role in shaping public health policy by developing models to help with designing infection control policies (Kaplan (2020)), forecasting local outbreaks (Chang and Kaplan (2023)), and evaluating transmission risks in service facilities (Kang et al. (2022)).

While the early literature on COVID-19 explored the mechanics of transmissions, the urgent need for incorporating human behaviors and social processes into mathematical epidemiological models gave rise to a growing literature. El Ouardighi et al. (2022) investigate the role of popular discontent and growing social fatigue in policymaker's non-therapeutic interventions (e.g., mobility restrictions, securing social interactions) during a pandemic. Wu (2021) model an individual's decision of whether to engage in social distancing as a social dilemma game played against his/her population. Usherwood et al. (2021) predict COVID-19 trends in the United States accounting for population's level of caution and sense of safety, which increases as more individuals take the vaccination (Liu and Wu (2022)). In economics, Kaplan et al. (2020), Acemoglu et al. (2021), Fernández-Villaverde and Jones (2022) incorporate policy analysis into detailed SIR models using expected arrival time of a vaccine. Our work contributes to this literature on two dimensions. First, we factor in agents that choose socialization rates in response to vaccine availability and efficacy in our theoretical and empirical analysis. Second, we bring the novel notion of network hazard, that is originally introduced in the context of financial networks, to the literature on epidemics to shed some light on to superspreaders.

We use foot traffic data from cell phone records provided by SafeGraph. Cronin and Evans (2020) examine the role of state and local restrictions on foot traffic in different essential (e.g., retail) and nonessential (e.g., entertainment) industries. Goolsbee and Syverson (2021) measure how much of the decrease in economic activity resulted from government-imposed restrictions versus people voluntarily stay home to avoid infection. Our primary episode of focus is the recovery of foot traffic starting with the

of respiratory activity (e.g., singing, talking, etc.) and the infectiousness of the respiratory aerosols, and it increases as the rate of ventilation, air filtration, size of the room and face mask use increase. Kapoor et al. (2022) estimate the transmission probability of COVID-19 in enclosed spaces using an artificial neural network with real-time collected data.

[4] On the supply chain front, Han et al. (2022) investigate the impact of the pandemic on e-commerce operations, Khan et al. (2021) discuss its impact on medical supply chains, Mak et al. (2022) model and analyze two-dose vaccine distribution, Nikolopoulos et al. (2021) provide predictive analytics tools for forecasting and planning during a pandemic.

availability of vaccines.

The rest of the paper is organized as follows. In Section 2, we present our network model and analysis. We describe our data and empirical results in Section 3 and conclude in Section 4.

2 Theory

There is a unit mass of *agents* and one *center*. Each agent can choose to *connect* with the center to obtain some benefits. Agents who connect with the center are called *connected* agents. The center accepts all connections. The center can be a person or a group of people either with high value from connections or with a commitment to meet all demand from the connections. Examples are teachers in schools, doctors in hospitals, cashiers in grocery stores, trainers in gyms, etc. The center can also be the physical space where people gather such as schools, hospitals, grocery stores, gyms, bars and restaurants, etc.

There is an infectious *disease*. Agents can *contact* the disease and get *infected*. The contacts can happen exogenously, called *external contact*, at a given rate. The corresponding infections are called external infections. Agents who have not contacted the disease externally can still contact the disease if they are connected and some internally infected agents are also connected. Such contact is called internal contact and the corresponding infections are internal infections.[5] When the center is a person, infected connected agents infect the center, who can then create contact to other connected agents. When the center is a physical space, the mass of infected connected agents determine the viral density in the air at the center, which determines the contact probability of other connected agents (Henriques et al. (2021)). Overall, the mass of connected infected agents increase the internal contact probability. There is also a protective measure against infections, such as a vaccine, which we simply call *protection*.[6] Using protection decreases the infection probability by a factor. We call an agent *protected* if the agent uses protection.

Formally, connecting to the center grants value $v < 1$ to each connected agent. If an agent is infected, it incurs cost 1. Each agent has an exogenous contact probability κ. Denoting χ the (endogenous) mass of connected infected agents, a connected agent who has not been contacted exogenously has probability

[5]Note that agents who contacted the disease externally but did not get infected is assumed to not get infected internally. For example, an agent who contacted the virus exogenously but did not get infected builds immunity and does not get infected out of endogenous contact either. Alternatively, all interactions happen repeatedly in a short timespan wherein infected agents are asymptomatic and agents' infection statuses are determined nearly simultaneously with their contact statuses. Since such agents do not get infected internally, we assume without loss of generality that they do not contact the disease externally either.

[6]The model can be generalized to include masks in case of airborne diseases. In case of STIs protection can also be condoms.

$\Phi(\chi)$ of contacting the virus endogenously, where Φ is an increasing function. An agent who contacts the virus gets infected with probability ι, which is scaled down by $e < 1$ if the agent is protected, down to $e\iota$. We call e^{-1} is the *efficacy* of protection. For simplicity we take $\iota = 1$.

We denote p the mass of protected agents. Using protection can be a choice or it can be mandated depending on the specific case at hand. We take p to be exogenous and assume that each agent has p probability of being protected. This way, we aim to capture the gradual availability of vaccines in the US during the COVID-19 pandemic. Agents know their protection status when making their connection choice, but contact and infections are unobservable. This is, the interactions happen during the asymptomatic interval of the disease.

Equilibrium Agents, when making their connection decisions, compare the value of the connection to the center with the internal contact probability and the cost of associated potential infection. In particular, a protected agent compares v and $e(1-\kappa)\Phi(\chi)$ whereas an unprotected agent compares v and $(1-\kappa)\Phi(\chi)$. This implies that protected agents have higher expected value from connecting. Then, infection probabilities are given by the following table.

	not connected	connected
protected	$e\kappa$	$e\left(\kappa + (1-\kappa)\Phi(\chi)\right)$
not protected	κ	$\kappa + (1-\kappa)\Phi(\chi)$

The mass of agents who get infected through external contact is $\theta \equiv (pe + 1 - p)\,\kappa$. Denote $\mu_p \leq p$ the endogenous mass of connected protected agents and $\mu_u \leq 1-p$ the endogenous mass of connected unprotected agents. The following cases characterize equilibria.

1. No agent is connected: $\mu_p = \mu_u = 0$. This case is characterized by $\chi = 0$, $e(1-\kappa)\Phi(\chi) \geq v$. This is, even the protected agents prefer not to connect even if no other agent is connected. In this case, the mass of internal infections is zero as there are no connections.

2. Some protected agents are connected, no unprotected agents are connected: $\mu_p \in (0, p)$, $\mu_u = 0$. This case is characterized by $\chi = \mu_p e\kappa$, $e(1-\kappa)\Phi(\chi) = v$. This is, protected agents connect to the center up to the point of being indifferent, at which point unprotected agents prefer not to connect. In this case, the mass of endogenously infected agents is $\mu_p(1-\kappa)e\Phi(\chi)$. Denoting $\Psi(x) \equiv x\Phi(x)$, which is strictly increasing, the mass is given by $\mu_p(1-\kappa)e\Phi(\chi) = \frac{1-\kappa}{\kappa}\Psi(\chi) = \frac{1-\kappa}{\kappa}\Psi(\Phi^{-1}(\frac{v}{e(1-\kappa)}))$. The mass of internal infections is constant in p, as the marginal connected agent has fixed internal infection probability. More importantly, internal infections are *increasing* in e^{-1}. This is, for more

effective protection, there is more internal infections. This is an instance of network hazard. Agents do not internalize the infection probability and comfortably connect more when protection is better. In equilibrium, total infections increase.

3. All protected agents are connected, no unprotected agents are connected: $\mu_p = p$, $\mu_u = 0$. This case is characterized by $\chi = e\kappa p$, $(1-\kappa)\Phi(\chi) \geq v \geq e(1-\kappa)\Phi(\chi)$. This is, protected agents connect to the center up to the point of being indifferent, at which point unprotected agents prefer not to connect. In this case, the mass of endogenously infected agents is $p(1-\kappa)e\Phi(\chi) = \frac{1-\kappa}{\kappa}\Psi(\chi) = \frac{1-\kappa}{\kappa}\Psi\left(ep\kappa\right)$. The mass of internal infections is decreasing in e^{-1}, but, importantly, *increasing* in p. This is, for more widespread protection, there is more internal infections. This is also an instance of network hazard. When protection is good enough that protected agents prefer to connect, if protection gets more widespread, the mass of connected agents increase, increasing the mass of internal infections.

4. All protected agents are connected, some unprotected agents are connected: $\mu_p = p$, $\mu_u \in (0, 1-p)$. This case is characterized by $\chi = e\kappa p + \kappa\mu_c$, $v = (1-\kappa)\Phi(\chi)$. This is, unprotected agents connect to the center up to the point of being indifferent, at which point protected agents prefer to connect. In this case, the mass of endogenously infected agents is $p(1-\kappa)e\Phi(\chi) + \mu_c(1-\kappa)\Phi(\chi) = \frac{1-\kappa}{\kappa}\Psi(\chi) = \frac{1-\kappa}{\kappa}\Psi(\Phi^{-1}(\frac{v}{1-\kappa}))$.
   This is constant in both p and e^{-1}. The marginal connected agent is unprotected; hence, neither the extent of protection in the society, p, nor the efficacy of protection, e, matters for the infection probability of the marginal agents.

5. All agents are connected: $\mu_p = p$, $\mu_u = 1-p$. This case is characterized by $\chi = pe\kappa + (1-p)\kappa = \theta$, $v \geq (1-\kappa)\Phi(\chi)$. This is, even the unprotected agents prefer to connect despite all agents being connected. In this case, the mass of endogenously infected agents is $p(1-\kappa)e\Phi(\chi) + (1-p)(1-\kappa)\Phi(\chi) = \frac{1-\kappa}{\kappa}\Psi\left(\chi\right) = \frac{1-\kappa}{\kappa}\Psi\left(\theta\right)$.
   As θ is is decreasing in both p and e^{-1}, so is the mass of internally infected agents .

Note that internal infections are given by $\frac{1-\kappa}{\kappa}\Psi\left(\chi\right)$ which is isomorphic to χ. We summarize these cases in the following table of connected external infections χ.

Case	Parametric case	Connected external inf. χ	Network hazard
1	$e(1-\kappa)\Phi(0) \geq v$	0	
2	$e(1-\kappa)\Phi(e\kappa p) > v > e(1-\kappa)\Phi(0)$	$\Phi^{-1}\left(\frac{v}{e(1-\kappa)}\right)$	Increasing in e^{-1}
3	$(1-\kappa)\Phi(e\kappa p) \geq v \geq e(1-\kappa)\Phi(e\kappa p)$	$pe\kappa$	Increasing in p
4	$(1-\kappa)\Phi(\kappa(ep+1-p)) > v > (1-\kappa)\Phi(e\kappa p)$	$\Phi^{-1}\left(\frac{v}{1-\kappa}\right)$	
5	$v \geq (1-\kappa)\Phi(\kappa(ep+1-p))$	$\kappa(ep+1-p)$	

These cases are parametrically exhaustive hence characterize the equilibrium. For a fixed p, starting with $e = 1$, meaning a completely ineffective protection, and gradually increasing the efficacy e^{-1}, we see that internal infections start increasing after the cutoff $e^{-1} = \frac{(1-\kappa)\Phi(0)}{v}$ between case 1 and case 2. During the phase of case 2, more protected agents connect as a function of the efficacy of protection. At the cutoff $e^{-1} = \kappa p \Psi^{-1}(\frac{v\kappa p}{1-\kappa})^{-1}$ between case 2 and case 3, all protected agents are connected and further improvements in efficacy decreases internal infections. This is portrayed in Figure 1a.

Notice the dilemma here. As long as protected agents are not fully connected (case 2), the efficacy of protection increases internal infections. This is network hazard. Only after all protected agents are connected, the efficacy of protection starts reducing internal infections (case 3). However, when all protected agents and some unprotected agents are connected (case 4), the efficacy of protection does not affect internal infections. Therefore, network hazard hurts connected protected agents (case 2) but not the connected unprotected agents (case 4) although, in some sense, better protection is supposed to benefit protected agents compared to unprotected agents.

Next, consider a fixed e^{-1}. As we start with $p = 0$ meaning no availability of protection, and gradually increase p, we see that internal infections start increasing after the cutoff $p = \frac{1}{e\kappa}\Phi^{-1}(\frac{v}{e(1-\kappa)})$ between case 2 and case 3. During the phase of case 3, all protected agents choose to be connected and no unprotected agents do so. In some sense, a protected population who are all exposed to each other through their connection to the center is being scaled up, and so the internal infections increase. At the cutoff $p = \frac{1}{e\kappa}\Phi^{-1}(\frac{v}{1-\kappa})$ between case 3 and case 4, some unprotected agents finally find it optimal to connect, and the mass of unprotected agents further increases in protection availability. The marginal unprotected agent has constant probability of internal infection so the internal infections are constant after this point. This is portrayed in Figure 2a.

A similar dilemma appears here. Whenever there is non-trivial rates of internal infection across protected agents, larger availability of protection increases the mass of internal infections. Only after protection rate is big enough that it becomes optimal for all protected agents to connect and unprotected

Figure 1: Internal and Total Infections in Efficacy of Protection

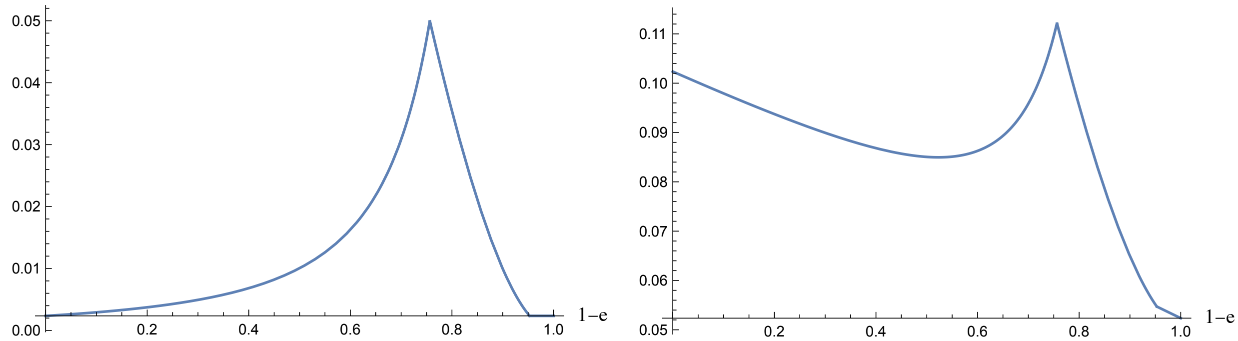


Figure 1a: Internal Infections

Figure 1b: Total Infections

Notes. The parameter values are $v = 0.1$, $\kappa = 0.1$, $\alpha = 50$, $p = 0.5$.

agents start connecting, the internal infection rate stops increasing. Therefore, larger availability of protection hurts the protected population due to externalities, which is another instance of network hazard.

Finally, note the complementarity between e^{-1} and p. The network hazard region for e^{-1}, i.e., case 2, is between $\frac{(1-\kappa)\Phi(0)}{v}$ and $\kappa p \Psi^{-1}(\frac{v\kappa p}{1-\kappa})^{-1}$ which is wider for larger p. This is, if protection is more widespread, the adverse consequences of a more effective protection is more prevalent. Similarly, the network hazard region for p, i.e., case 3, is between $\frac{1}{e\kappa}\Phi^{-1}(\frac{v}{e(1-\kappa)})$ and $\frac{1}{e\kappa}\Phi^{-1}(\frac{v}{1-\kappa})$. If the protection is more effective, the adverse consequences of more widespread protection manifests during higher availability.

The total mass of infections, $\tau \equiv \theta + \frac{1-\kappa}{\kappa}\Psi(\chi)$, is of interest as well. After all, higher efficacy e^{-1} and more availability p reduces external infections θ. Comparative statics in this case requires specifying a form for the transmission function Φ to pin down tradeoffs between internal and external infections. Referring to Henriques et al. (2021), Φ is described by $\Phi(\chi) = 1 - \mathbf{e}^{-\alpha\chi}$ where $\alpha > 0$ is a constant that depends on a host of exogenous factors.

The adverse consequences of increased p and e^{-1} on internal infections appear for e^{-1} in case 2 and for p in case 3. In the other cases, internal infections are decreasing in e^{-1} and p, so the total infections also decrease. Therefore, we focus on e^{-1} in case 2 and p in case 3 to study total infections. Case 2 is given by $e\kappa p > \chi = -\alpha^{-1}\ln\left(1 - \frac{v}{e(1-\kappa)}\right)$ and some algebra yields

$$\frac{\mathrm{d}\tau}{\mathrm{d}e^{-1}} = -\kappa p e^2 + \frac{v}{\alpha\kappa}\left(\frac{v}{e(1-\kappa)-v} + \chi\alpha\right)$$

Notice that p can be as small as $\frac{\chi}{e\kappa}$ under case 2 so $\frac{\mathrm{d}\tau}{de^{-1}}$ can be as large as $\chi\left(\frac{v}{\alpha} - e\right) + \frac{v^2}{\alpha\kappa(e(1-\kappa)-v)}$. Thus,

Figure 2: Internal and Total Infections in Availability of Protection

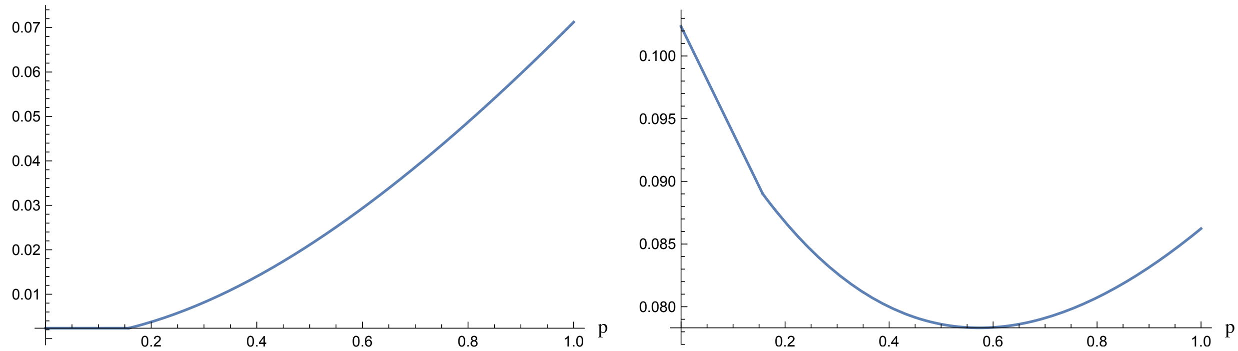


Figure 2a: Internal Infections

Figure 2b: Total Infections

Notes. The parameter values are $v = 0.1$, $\kappa = 0.1$, $\alpha = 50$, $1 - e = 0.85$.

for relatively large e^{-1}, in particular $v > \alpha e$,[7] we have $\frac{\mathrm{d}\tau}{de^{-1}} > 0$. This is, the total infections can increase as protection efficacy e^{-1} increases, particularly if protection is not too widespread and but it is highly effective. This is portrayed in Figure 1b.

Next, consider p in case 3. Case 3 is given by $\frac{v}{e(1-\kappa)} > \Phi(\chi) = \Phi(e\kappa p) > \frac{v}{1-\kappa}$, and some algebra yields

$$\frac{\mathrm{d}\tau}{\mathrm{d}p} = (1-\kappa)e\Phi(e\kappa p) - \kappa(1-e) + (1-\kappa)\kappa e^2 p\Phi'(e\kappa p)$$

Similarly, p can be chosen to make $\Phi(e\kappa p)$ arbitrarily close to $\frac{v}{e(1-\kappa)}$, in which case v can be chosen arbitrarily large. In this case, $\frac{\mathrm{d}\tau}{\mathrm{d}p} > v - \kappa(1-e)$ which is positive. Hence, the total infections can increase as protection availability p increases, particularly when protection is already widespread and value of connections is large. This case is particularly relevant to our empirical analysis as we discuss in the next section. This is portrayed in Figure 2b.

In summary, our analysis indicates that there are two cases of network hazard. First, when some protected individuals are connected but unprotected individuals are not connected with the center, the efficacy of protection increases the endogenous infection probability in the network because more protected individuals decide to form connections with the center. This increases the number of internal infections through the center due to negative externalities. The total number of infections, including both internal and external, might increase when the protection is highly effective but not widespread. Second, when all protected individuals are connected but unprotected individuals are not connected, the efficacy of protection decreases the infection probability expectedly. However, the availability of protective measures increases the infection probability because more protected individuals prefer to connect when the

[7] This does not contradict parametric specification of case 2.

protection is good enough, which in turn, increases the internal infections. Similarly, the total number of infections might increase when protection is already widespread which we observe in our empirical analysis. Only after the efficacy and the availability of protection are sufficiently large that all protected individuals connect, the internal infections decrease because the marginal connected agents' infection probability does not depend protection efficacy.

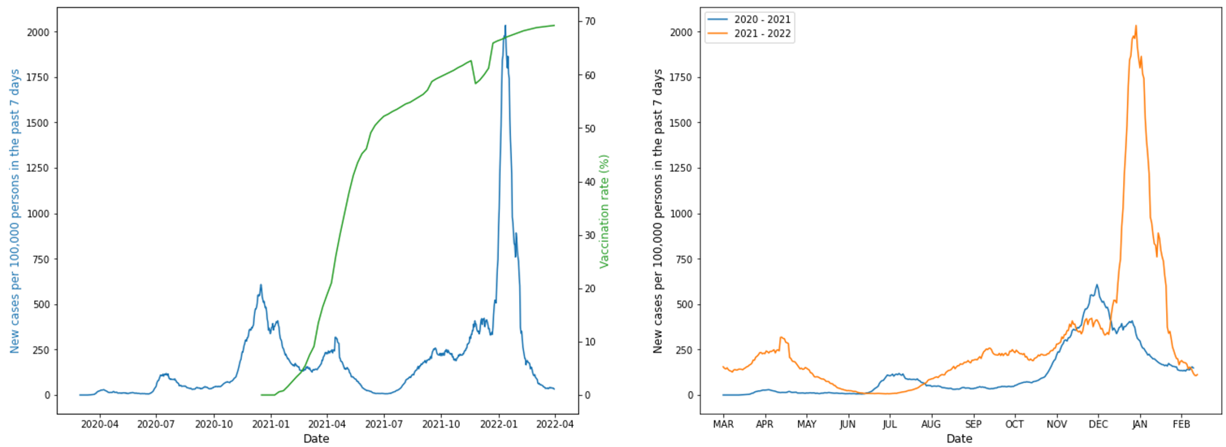
3 Data and Empirical Analysis

We first present the historical changes in the COVID-19 community transmission rate and the vaccination rate in Allegheny County in Figure 3. After the first cases were recorded in March/April 2020, the first serious community transmission in Allegheny County occurred in December 2020/January 2021. With the increasing rate of vaccinations and the ability to socialize in outdoor settings, the number of cases decreased significantly in June/July 2021 to start increasing again in September 2021. The most dramatic increase in the number of cases for the complete pandemic timeline occurred in December 2021/January 2022 when the vaccination rate almost reached to 70% in the county. Compared to the same time period previous year when the vaccinations had just started, the number of new cases per 100,000 people quadrupled during this time. This is a manifestation of network hazard where individuals forgo social distancing and engage in high-risk activities more with the comfort of being vaccinated, which in turn results in a significantly higher number of cases in the county.

The other testable prediction of our theory is the rate of social activities. As more doses of the vaccine become available, number of visits to various central points of interest should increase as individuals are less concerned with infection. To test this, we construct a monthly, county-level time series data of visits to various types of businesses using cell phone location data from the geospatial data company SafeGraph. Couture et al. (2022) show that smartphone data cover a significant fraction of the US population and are broadly representative of the general population in terms of residential characteristics and movement patterns. Our data ranges from March 2019 to February 2022, divided into three year-long episodes which allows us to net out seasonal effects. The *pre-pandemic* episode is the one-year episode from March 2019 to February 2020 serving as our benchmark. March 2020 is when the first cases of COVID-19 in the US were observed and WHO declared COVID-19 to be a pandemic. The *pre-vaccine* episode is the one-year period from March 2020 to February 2021.[8] The *post-vaccine* episode is the one-year period from March 2021 to February 2022 covering the gradually increasing availability of vaccines up to the point of the

[8]The first administration of a vaccine in PA was in December 2020. The vaccination rate in March 2021 was around %15.

Figure 3: Infection Transmission Level vs. Vaccination Rate in Allegheny County



Notes. **New cases per 100,000 persons in the past 7 days** is calculated by adding the number of new cases in the last 7 days divided by the population in Allegheny county and multiplying by 100,000. **Vaccination Rate (%)** represents the percent of people who have completed a primary series (have second dose of a two-dose vaccine or one dose of a single-dose vaccine) in Allegheny County.
Vaccination rates are by definition increasing over time. The drop at the end of 2021 is likely a glitch in data collection.

Russian invasion of Ukraine. From March 2022 onwards there has been major macroeconomic changes and we observe significant declines in number of visits to points of interest from March 2022 to December 2022, likely unrelated to COVID-19.

The points of interest we consider are restaurants, gas stations, big retailer stores, grocery stores, coffee shops, gyms, and airports.[9] We first present annual visits to the points of interests in Table 1. According to our theory, the visits to points of interests should decline from pre-pandemic episode to pre-vaccine episode, and increase from pre-vaccine episode to post-vaccine episode. This holds for restaurants, gas stations, coffee shops, gyms, and airports. These points of interest provide services or experiences that can not be completely replicated at home. In particular, visits to restaurants and gas stations come back to pre-pandemic levels. Visits to coffee shops, gyms, and airports increase but do not reach their pre-pandemic levels. This can be related to various factors that has altered consumption habits during the pandemic such as moving to suburbs or buying exercise equipment. The number of visit to big retailers and grocery stores keep declining from pre-vaccine episode to post-vaccine episode. This could be attributed a shift towards online shopping after most companies adjusted their infrastructure to accommodate deliveries during the pandemic. We believe this is beyond the scope of our paper and should be addressed in separate work. Accordingly, we focus on restaurants, gas stations, coffee shops,

[9] Restaurants: McDonald's and Wendy's. Gas stations: GetGo, Sunoco, Sheetz. Big retailer stores: Target, Walmart, Costco. Grocery stores: Giant Eagle, ALDI, Market District. Coffee shops: Starbucks. Gyms: Planet Fitness, LA Fitness, Ascend. Airports: Pittsburgh International Airport.

Table 1: Annual visits to points of interest

		2019 - 2020		2020 - 2021		2021 - 2022	
	No. of locations	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Restaurants	22	11091	865	8518	1334	10448	549
Gas Stations	39	20020	1747	15221	2396	19701	1305
Big Retailers	9	16522	2782	15210	2132	14730	2343
Grocery Stores	21	10586	1477	8671	879	8027	464
Coffee Shops	19	16347	5641	8720	2308	10809	1481
Gyms	7	2441	191	1057	393	1449	151
Airports	1	24688	2938	8235	2916	13444	3541
All Places	118	205355	27835	132596	20353	156133	11650

Notes. Visits are counted starting from March of each year to February of following year.

gyms, and airports.

Figures 4, 5, 6, 7, and 8 present the number of visits to these points of interest. Figures on the left columns overlap pre-pandemic, pre-vaccine, and post-vaccine episodes in annual plots to highlight seasonal changes in behavior. Our theory predicts an upward shift in visits from the pre-vaccine episode (orange lines) to the post-vaccine episode (green lines). Such a shift is evident in figures confirming our prediction.

Figures on the right columns display the entire time series spanning three years. Two points are marked. The black vertical dashed lines correspond to visits in January 2021. The first dose of a vaccine was administered on December 15 in Pennsylvania so it is more suitable to start analyzing the impact of vaccines on visits in the next month. Our theory predicts that visits should gradually increase starting with the black line. The red vertical dashed lines correspond to visits in January 2022. The evident spike in infection rates in Figure 3 spans the month of January 2022 from start to finish. Our theory predicts that the number of visits should increase up to January 2022. Such upward trends can be observed in the right columns of Figures 4, 5, 6, 7, and 8. Corresponding upward trend in infection rates can be seen in the right column of Figure 3 in the orange line.

In summary, our empirical analysis shows that the number of new COVID-19 cases in Allegheny County quadrupled in January 2022 when the vaccination rate reached 70% compared to January 2021 when only 2% of the population was vaccinated. This is the aforementioned network hazard in which individuals connect with the centers (e.g., restaurants, coffee shops) more with the comfort of being vaccinated, which increases the infection rate in the county. This hypothesis holds when we look at the monthly foot traffic data to the places of interest. Compared to the pre-pandemic period, the rate of social activities decreases significantly after the start of the pandemic before individuals started getting

Figure 4: Fast food restaurant visits

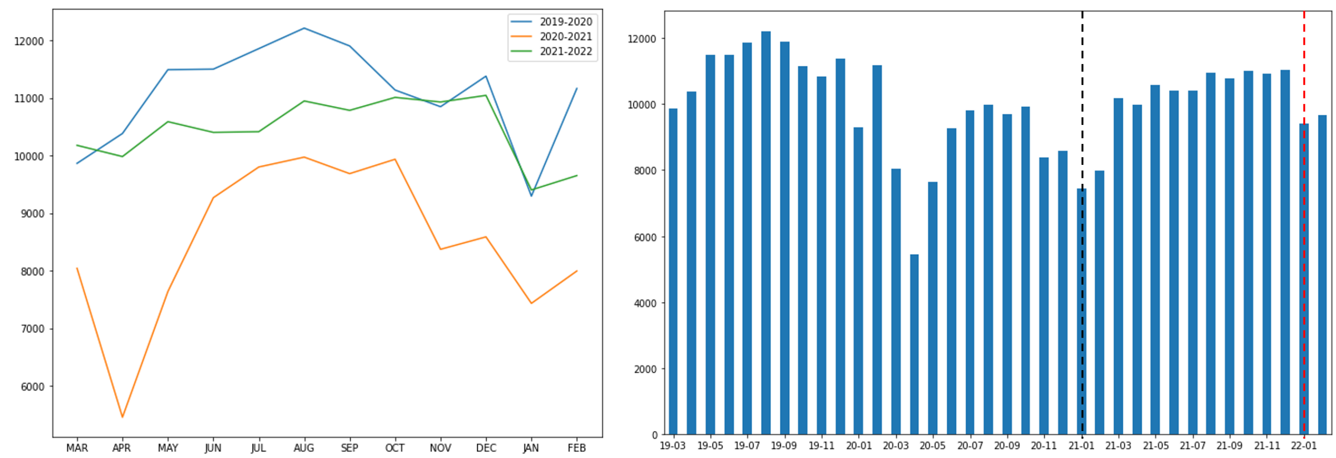
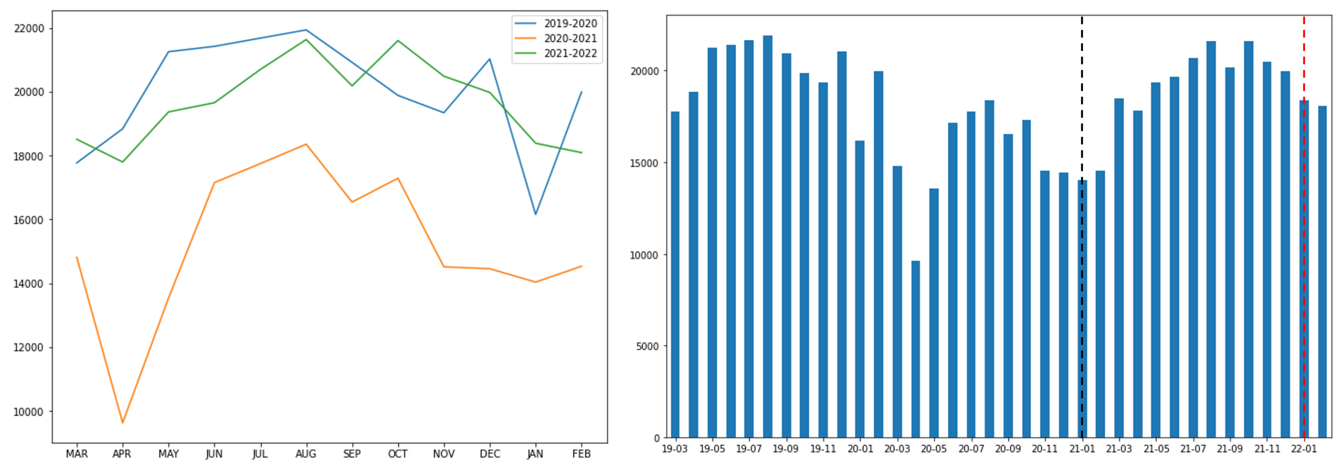


Figure 5: Gas station visits



vaccinated. With mass vaccinations, we observe an increase in social activities coupled with a sharp increase in the number of COVID-19 cases which is possible a manifestation of network hazard.

4 Conclusion

The COVID-19 pandemic revealed the importance of incorporating patterns of social interaction and the society's behavioral characteristics in building mathematical epidemiological models. Within this context, our work brings the novel idea of network hazard, originally developed to understand and analyze financial networks, to highlight the potential downside of higher efficacy and availability of protective measures in controlling the spread of the virus if contact rates are left unregulated. While protective measures reduce the risk of transmission, higher availability and efficacy of protective measures potentially make individuals more comfortable in interacting with central agents or locations, which in turn, opens more

Figure 6: Coffee shop visits

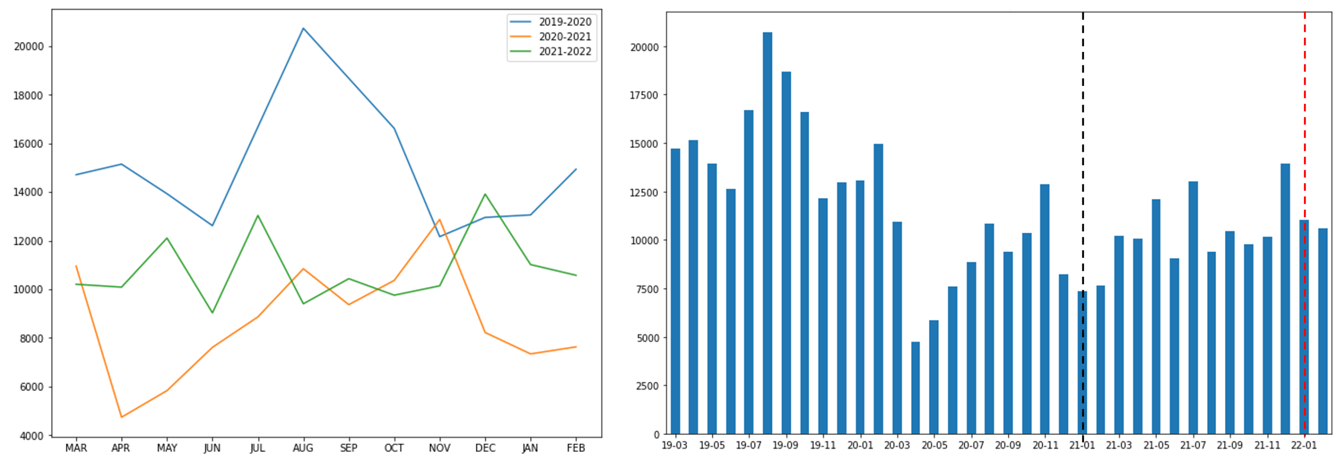
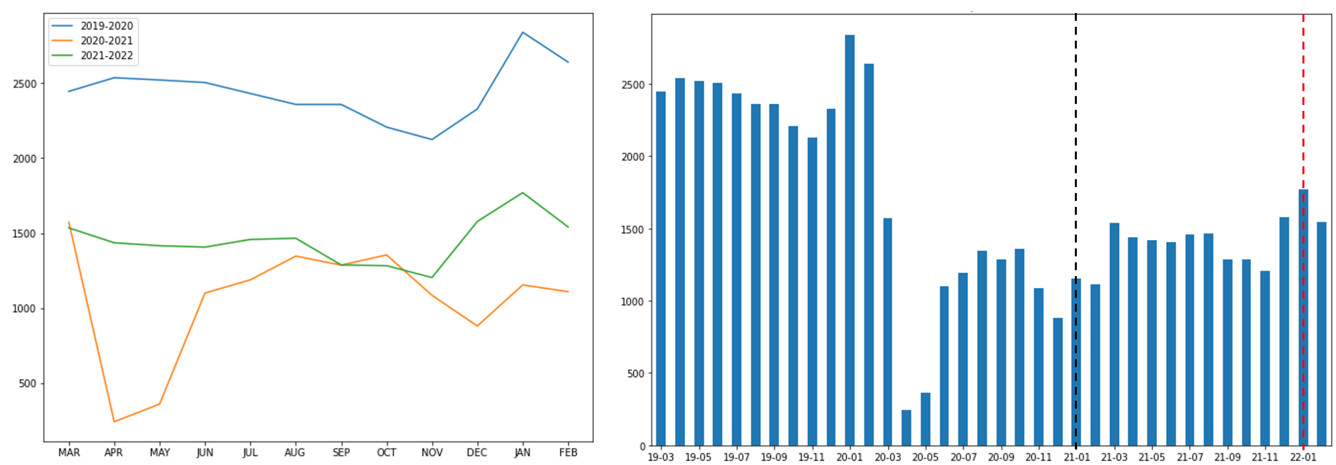


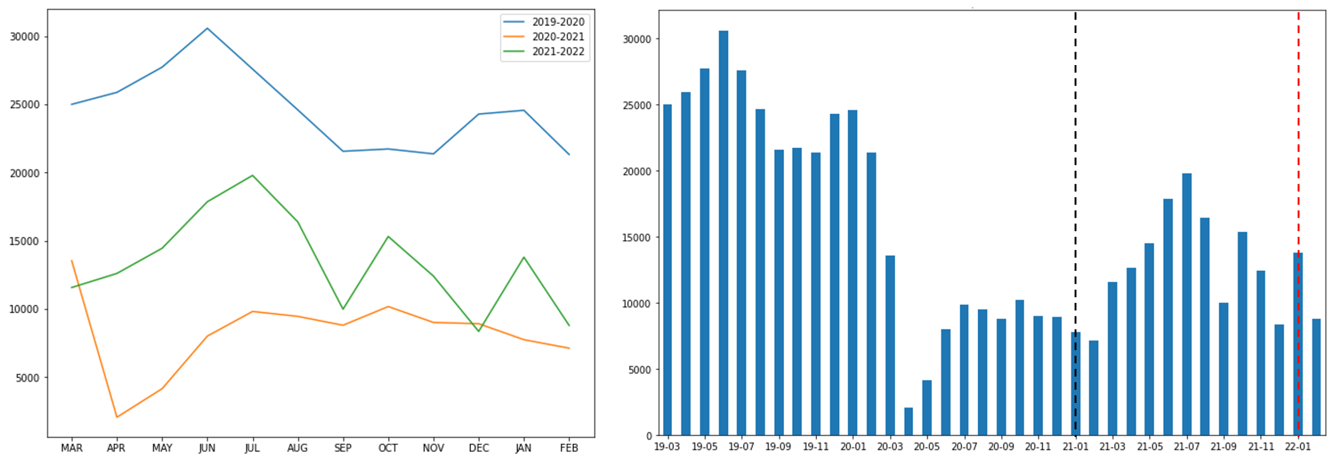
Figure 7: Gym visits



channels for transmission. As imperfect protective measures are more available and effective, the increased number of contact with central agents and location increase the risk of transmission *through* the center, which can offset the direct benefit improved protection, in aggregate. Additionally, the correlation of exposures through the central agent or location can create a fat-tailed infection distribution, causing more frequent superspreaders which constrict the healthcare system and cause high fatality. We confirm the testable predictions of our theory by using two data sets regarding Allegheny County. First, we use CDC's publicly available data on vaccination rates and infection rates. Second, we measure the changes in number of visits to central points of interest using foot traffic data covering a three-year-long episode from pre-pandemic to post-pandemic episodes.

Our work contributes to the literature on epidemiological models by incorporating a model of individuals' social behavior and shedding light on superspreaders and massive infections. Future work can

Figure 8: Airport visits



incorporate combination of protective measures and policies, such as masks and social distancing mandates. The use of protective measures is also a choice variable in various settings, which is an important avenue for future work in the light of polarized views of the public in the US. In a dynamic version of our framework, several other questions can be addressed. The evolution of the virus and its several variants would generate complex patterns of infection rates. Finally, agents would react to the news of updated infection rates which can add a robustness check to our broader theory.

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