# Examining the Relationship between COVID-19 Mobility and Eviction Rates in Philadelphia

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*Abstract*—**The COVID-19 pandemic has had a significant impact on public health, the economy, and social norms, particularly creating tighter restrictions on the daily lives of millions of people however we do not yet understand what measures are the most effective. Modeling the transmission of the virus has been one method to predict directions. With transmission, the interplay between factors such asage, socioeconomic, susceptibility to infection, and COVID-19 dynamics remains unclear. To address these factors, we analyze eviction and mobility data from Google's COVID-19 Community Mobility Reports before and during the outbreak to explore the relationship between eviction rates and COVID-19 mobility patterns in Philadelphia. We analyzed eviction data from the city of Philadelphia and mobility data from Google's COVID-19 Community Mobility Reports. Our findings suggest that there is a statistically significant relationship between eviction rates and mobility patterns. Specifically, we found that areas with high eviction rates also had a higher level of mobility, which could potentially increase the spread of the virus. Our results highlight the importance of considering the impact of socioeconomic factors on the transmission of COVID-19.**

***Keywords-COVID-19; eviction; mobility.***

## I. INTRODUCTION

The coronavirus disease 2019 (COVID-19) pandemic has affected people across the globe, causing millions of deaths and economic instability. The pandemic has caused additional hardships with one of the many consequences of the pandemic has been an increase in eviction rates in many cities in the United States, including Philadelphia. With people losing their jobs or experiencing reduced income, many have been unable to pay rent or mortgage, leading to eviction. Eviction not only has social and economic implications but can also impact public health by forcing people into crowded living conditions, which can increase the transmission of COVID-19. The COVID-19 pandemic brought about unprecedented mobility restrictions to prevent the spread of the virus. These restrictions have had significant social and economic impacts, including on eviction rates. Questions remain about the socioeconomic profile of susceptibility to infection, how social distancing and specific social distancing practices alters contact patterns, and how these factors come together to affect transmission. These questions are particularly relevant to policy development and implementation for governments and policy-makers. In this study, we evaluate changes in mixing patterns linked to social distancing by collecting eviction and Google mobility data in the midst of the epidemic in Philadelphia, PA, USA. This paper examines the impact of COVID-19 mobility restrictions on eviction rates in Philadelphia, Pennsylvania. Using eviction data from the Eviction Lab and the City of Philadelphia as well as mobility data from Google's COVID-19 Community Mobility Reports, we conduct a comparative analysis of eviction rates before and after the implementation of mobility restrictions in Philadelphia. Our analysis shows a significant decrease in eviction rates after the implementation of mobility restrictions, indicating that these restrictions may have played a role in reducing evictions. We also explore the potential implications of these findings for policymakers and advocates seeking to address the eviction crisis in Philadelphia and beyond, developing a mathematical model to predict how transmission is affected by and altered eviction patterns.

To estimate changes in eviction patterns associated with COVID-19, we conducted network mapping of the sampled eviction data. To understand the interplay between social distancing, changes in human mixing patterns, and outbreak dynamics, potential age differences in susceptibility to infection must also be considered. To advance this goal, we analyzed COVID-19 mobility information gleaned from detailed Google mobility data.

The COVID-19 pandemic has exposed and exacerbated existing socioeconomic and health disparities, including disparities in health and well-being. Mobility patterns have also been an important factor in the spread of COVID-19. Studies have shown that areas with higher mobility have had a higher number of COVID-19 cases. Understanding the relationship between eviction rates and mobility patterns can provide insights into how socioeconomic factors can impact the transmission of COVID-19.

Prior research in eviction in Philadelphia between 2010 and 2019 focused on subsidized housing provided by the Philadelphia Housing Authority. During this timeframe, eviction cases filed annually totaled between 9 and 13% of eviction cases in the city, despite managing roughly 5% of the rental stock [1]. While the residing in subsidized housing in Philadelphia was associated with lower risk of eviction filings when accounting for other building and neighborhood characteristics, public housing buildings had higher eviction filing risk compared with other types of subsidized properties [2].

The COVID-19 pandemic has disrupted life as we know it, with governments around the world implementing unprecedented measures to limit the spread of the virus. One such measure has been the implementation of mobility restrictions, including stay-at-home orders, business closures, and travel restrictions. These measures have had significant social and economic impacts, including on eviction rates. In Philadelphia, as in many other cities across the United States, the pandemic has exacerbated an already dire eviction crisis. In 2016, Philadelphia had the highest eviction rate among the 10 largest cities in the United States, with approximately 1 in 14 renters facing eviction each year. Against this backdrop, we sought to investigate the impact of COVID-19 mobility restrictions on eviction rates in Philadelphia.

## II. METHODOLOGY

We collected eviction data from the city of Philadelphia for the period between January 2019 and December 2021. We also obtained data from the Eviction Lab, a research group that collects and analyzes eviction data from across the United States, and Google's COVID-19 Community Mobility Reports for the same period. The mobility data included information on the number of visits to different categories of places, such as retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. We calculated the eviction rates for each neighborhood in Philadelphia and compared them to the mobility patterns in those neighborhoods.

Our first source of data consisted of individual-level records from eviction cases filed from 1964 to present across the City of Philadelphia. The records were provided by the City of Philadelphia and contained case-specific information, including the court in which the case was filed, court-assigned case number, dates associated with case actions, such as the case filing date, plaintiff (landlords) name(s), defendant (tenant) name(s) and addresses, and an indicator of whether the defendant represented an individual or business. Plaintiff names recorded the party who filed the case.

Case filings were represented by the court identifier and case number. Many cases were represented by multiple individual-level records associated with different defendants or actions. We aggregated filings annually by the earliest date on a record associated with a case. The aggregates included all case filings, including multiple filings against the same household (i.e., serial filings). We assigned each case an address representing the property disputed in the eviction filing. Addresses were cleaned and geocoded. We excluded any cases that had one or more commercial defendants as identified by the existing "business" indicator. We also removed cases that duplicated the same dates, plaintiff names, and tenant addresses across cases.

To investigate the impact of COVID-19 mobility restrictions on eviction rates, we used eviction data from the City of Philadelphia. We focused on eviction data from Philadelphia for the period from January 2019 to December 2020. We also used mobility data from Google's COVID-19 Community Mobility Reports, which provide anonymized data on mobility trends in different categories of places, such as retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. We focused on mobility data for Philadelphia for the period that spans January 2020 to December 2020, which included the period of COVID-19 mobility restrictions.

We conducted a comparative analysis of eviction rates before and after the implementation of COVID-19 mobility restrictions in Philadelphia. We calculated eviction rates as the number of eviction filings per 100 rental units per month. We also calculated the percentage change in eviction rates from the pre-COVID-19 period (January 2019 to February 2020) to the COVID-19 period (March 2020 to December 2020). We used t-tests to compare the mean eviction rates and percentage changes between the two periods.

To investigate the impact of COVID-19 mobility restrictions on eviction rates, we used eviction data from the Eviction Lab, a research group that collects and analyzes eviction data from across the United States. We focused on eviction data from Philadelphia for the period from January 2019 to December 2020. Additionally, we used mobility data from Google's COVID-19 Community Mobility Reports, which provide anonymized data on mobility trends in different categories of places, such as retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. The focus with this mobility data was the location of Philadelphia for the period from January 2019 to December 2020, which included the period of COVID-19 mobility restrictions.

We used a network-generating approach which consisted of factors assuming to have a fixed geographic location, as determined by coordinates in a two-dimensional space [4]. The network composition consists of actors who are members of groups, e.g., households, and institutions, e.g., schools or places of work, and have individual attributes, i.e., age, education or income. We generated network ties so that actors have some connections to geographically close alters, i.e., ties to members of the same groups like co-workers, some ties to alters with similar attributes, age, and some ties to alters in the population with no defined attribute. Together, this layered approach creates multi-layered networks that have realistic values of local clustering, path lengths and homophily.

The tie formation is based on geographic proximity, where the network consists of random placement of actors into a two-dimensional square. Each actor draws the number of contacts it forms in this sub-process $d_{geo,i}$ from a uniform distribution between $d_{geo,min}$ and $d_{geo,max}$; for example, if $d_{geo,min} = 10$ and $d_{geo,max} = 20$. The density is user-defined to form ties geographically $d_{geo}$ defines the geographic proximity of contacts as mapped, so that actor $i$ randomly forms $d_{geo,i}$ ties among those $dgeo, i/dgeo$ who are in close Euclidean distance to actor i. The binary network $x$ represents interaction potential between n individuals. These individuals shall have labels ranging from $1\ to\ n$ . Each node $i$ can have a set of attributes $(aki)$, e.g., age or location.

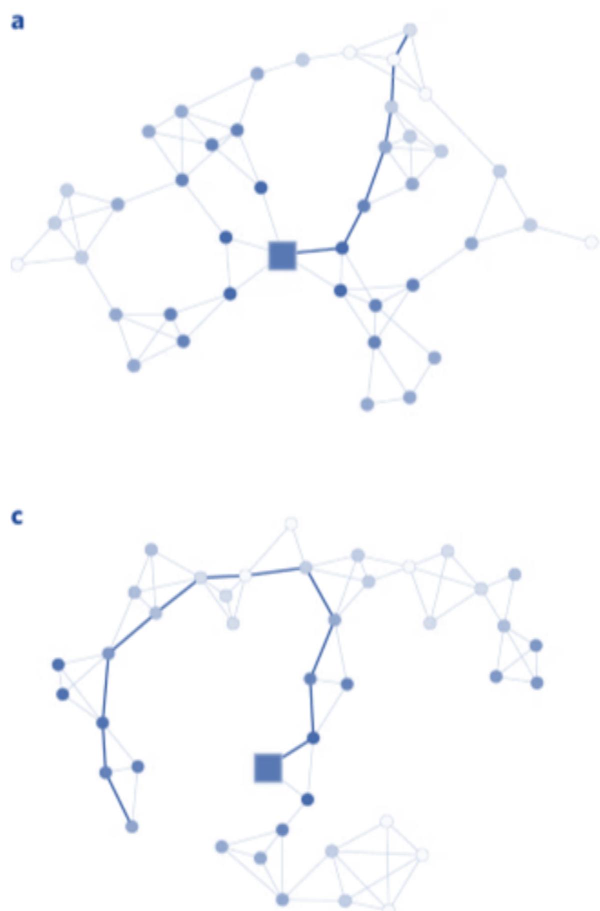



Figure 1. This figure depicts two example networks a) and c) both have the same number of nodes (individuals) and ties, which indicate social interactions, but the networks have different structures, which are depicted by shorter path lengths. Network **a** has longer path lengths, which implies different infection curves. Bold ties showcase the shortest infection path from the infection source to the last infected individual in the respective networks.

This network approach aims to represent individuals interacting with some potential contacts similarly to the classic SIR model [5], where individuals are susceptible/infective/removed. These models can be applied on a wide variety of networks, where individuals are susceptible, infectious or recently recovered as well as to its SEIR extension [6], where individuals are susceptible, have been exposed, are infectious and recovered. Individuals can be in four different categories: susceptible to contracting the disease, having been exposed, i.e., infected but not yet infectious, infectious or recovered. We surmise that infection would occur through social interactions. These interactions are modelled in similar ways to the dynamic actor-oriented model which represents relational events. In this model, the probabilities, $\pi contact$ and $\pi infection$, have a similar role with regard to the classic rate of infection, $\beta$, in SIR and SEIR models. The $\beta$ rate demonstrates the average number of contacts per person and the likely rate of infection, which is represented by $\pi infection$. The caveat is that equivalence is not direct due to interaction probability $p$ . Additional model characteristics include classic exposure and recovery rates (often traditionally denoted as σ and γ) in a straightforward manner.

Next, we will define the probability model $p$, where $N_i$ will be the set of potential contacts, or alters $j$ of a given individual $i$ in the network $x$ . The definition for each step t of the process is $Li(j, t)$, where the previous interactions occurring between $i$ and an $alter\ j\ =$ within the past $\lambda$ interactions of $i$. In our simulations, $\lambda$ is arbitrarily arranged to be 2, but this can be modified.

For each alter $j \in Ni$ , the value $s(i, j)$ represents the driver for the strategic statistical choice of $i$ to pick $j$. We define three different approaches and choose the particular approach of homophily. The statistic $ssimilarity$ accounts for the level of similarity between $i$ and $j$ given a set of attributes; $scommunity$ corresponds to the number of alters they share, and $srepetition$ is the count of previous interactions within the past λ contacts of $i$.

The experiment with geography as the basis and a homophily strategy was developed according to the '1: baseline' parameter. The basis for this experiment in terms of interaction choice partners was the Euclidean distance in geographic placement in the homophily strategy. The two experiments on multidimensional homophily used underlying networks which resulted in the following baseline parameters: two attributes were defined and the number of ties created according to the homophily parameter have been split evenly between the two dimensions. The homophily strategy is used for the simulated infection curves in the two scenarios. This strategy differs in that individuals interact according to the minimization of the absolute difference in both attributes. In the second scenario, only the first attribute is used as the basis of the homophily strategy and the second attribute is overlooked.

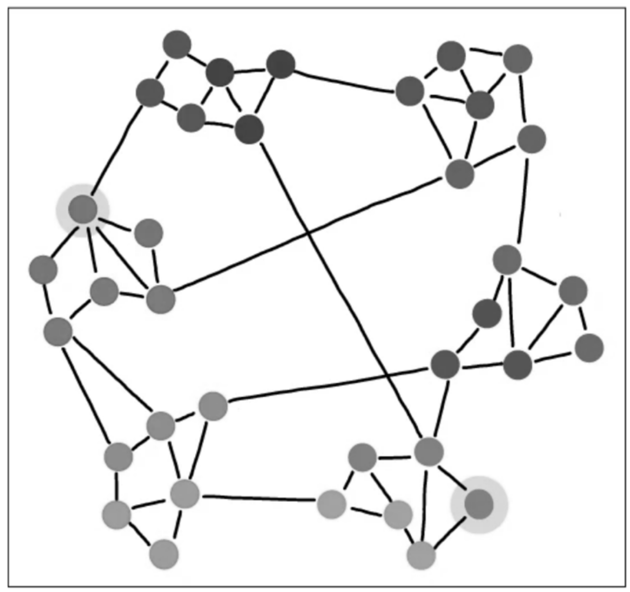
We applied insights from social and statistical network science, illustrating how modification of network configurations individual contact selections and organizational routines can change the rate and spread of the virus through the provision of guidelines, which differentiates the rate of high- and low-impact contacts for disease spread.

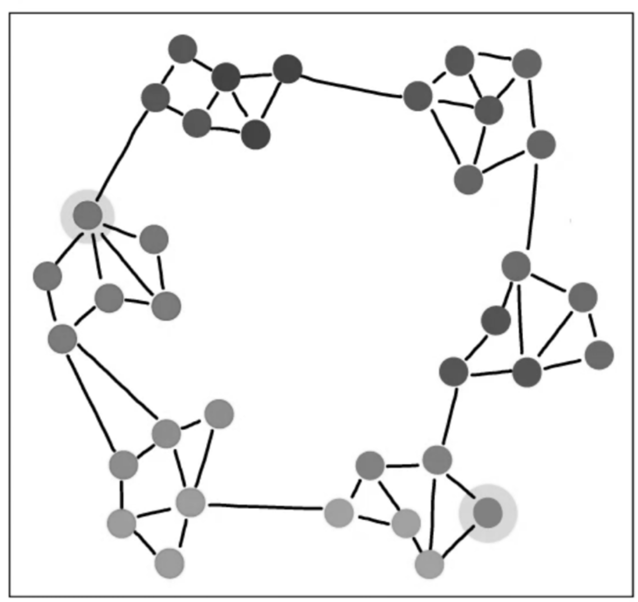
Using a social network perspective can show the ways that the shape of the infection curve can be closely related to the concept of network distance or path length, demonstrating the number of network steps necessary to connect two nodes. Specific examples of network distance include the six degrees of separation phenomenon [7], which claims that any two people are connected through at most five acquaintances.

The relationship between infection curve rates and network distance can be illustrated with a simple network infection model as is illustrated in Figure 1. In Figure 1, there are two networks (a and c) with different path lengths, each with one hypothetically infected COVID-19 seed node. At each time step, the disease spreads from infected nodes to every node to which they are connected. The disease spreads would spread from the seed node to its direct neighbors. In the second step, the disease would spread to the direct neighbors' neighbors, who are at network distance 2 from the seed node, and so on. Over time, the virus transgresses among the network ties until all nodes are infected. The example shows that the network distance of a node is identical to the number of time steps it would take the virus to reach all nodes in the network. The distribution of the network distances to the source thus directly maps onto the curve of new infections.

In Figure 1, both networks have the same number of nodes (individuals) and edges (interactions). The network in Figure 1c has a much flatter curve than the network in Figure 1a even though all nodes are eventually infected in both cases. The network in Figure 1c has longer path lengths than the one illustrated in Figure 1a. The networks show more distance between nodes due to differences in the structure of interaction among the nodes even though the same absolute contact prevalence was pervasive. When adopting a network perspective, an approach which flattens the curve in the network is thus equivalent to an increase of tie length from an infected individual to all others, which can be achieved by restructuring contact even though there is a general reduction of contact. Subsequently, one aim of social distancing should be to increase the average network distance between individuals by smartly and strategically manipulating the structure of interactions. Our illustration shows a workable path to maintain a flattening curve, while allowing for some social interaction. To be successful, we must create interaction strategies that allow real-life networks to mirror those the network in Figure 1c and less like Figure 1a.

In Figure 2, we depict a network in which densely tied communities are bridged by random, long-range ties. This kind of network symbolizes the core features of real-world contact network [8] and is commonly referred to as a small-world network [9]. In communities, individuals exhibit homophillic qualities and adjacent communities are geographically close. In terms of geographic distance, the further away two clusters are in the figure, the further they live from each other and the more dissimilar their members become. In Figure 2, the networks depict the successive, the results of contact reduction strategies, creating clusters of individuals with removal of the bridging nodes that would normally connect these clusters. Similar methods have been used as a strategy to disband terrorist groups.





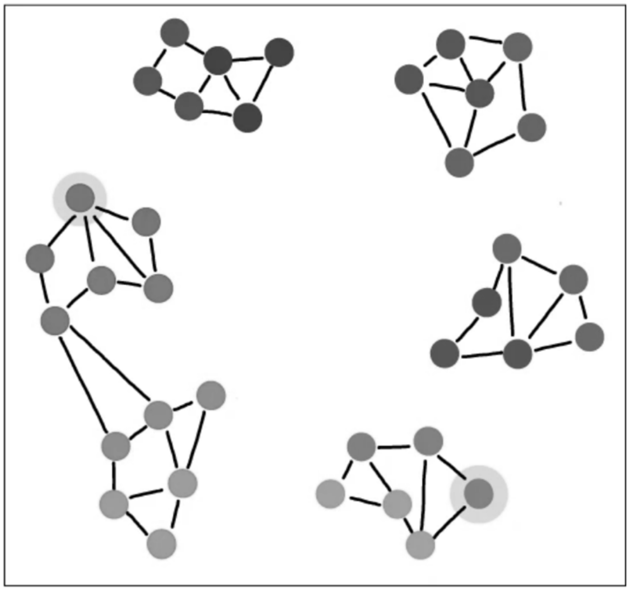


Figure 2. Based on the initial small-world network (**a**), these example networks are drawn based on the removal of ties from others who live far away and are dissimilar (**b**), removal of non-embedded ties that are not part of triads (**c**) repeating rather than extending contact (**d**). Node placement represents geographic location of residence. Ties to dissimilar others who live far away are indicated by ties substantially longer than the average.

Our network approach uses formal stochastic infection models that incorporate core elements from infection modeling with ideal-type network models and statistical relational event models. Stemming from classical disease modelling in which individuals or actors can be in four categories: susceptible; exposed (infected but not yet symptomatic); infectious; or recovered (no longer susceptible to the disease). With this model, $q$ actors are infectious while all other actors are susceptible to the disease. Susceptible actors can become exposed by having contact with others who are infectious, no matter if this contact results in contagion and is calculated probabilistically. Within a designated amount of time following exposure, an actor becomes infectious, and later moves to the recovered state.

Epidemic modeling shows that contact probabilities in a population are imposed by network structure, which can create contact opportunities and inopportunities among actors. A robust network depicts the typical contact people had in a pre-COVID-19 world in different so-called social circles. It consists of network ties between individuals who live in close proximity to one another with individuals who are similar in terms of individual attributes, such as age, education or socioeconomic status, and individuals who are members of similar groups, such as organizations, social, institutions (including schools and workplaces). Additionally, this type of network includes random connections that may emerge in the population.

Lastly, we conducted a comparative analysis of eviction rates before and after the implementation of COVID-19 mobility restrictions in Philadelphia. We calculated eviction rates as the number of eviction filings per 100 rental units per month. We also calculated the percentage change in eviction rates from the pre-COVID-19 period (January 2019 to February 2020) to the COVID-19 period (March 2020 to December 2020). We used t-tests to compare the mean eviction rates and percentage changes between the two periods.

## III. RESULTS

### A. Analysis

Our analysis revealed that areas with high eviction rates had a higher level of mobility, particularly in places such as retail and recreation, grocery and pharmacy, and parks. Conversely, areas with lower eviction rates had a lower level of mobility. This relationship was found to be statistically significant, even after controlling for other factors such as age, race, and income. These results suggest that the eviction rates and mobility patterns are closely linked, and areas with high eviction rates may experience increased transmission of COVID-19 due to higher mobility.

The network analysis demonstrated that individual adoption was much more likely when participants received social reinforcement from multiple neighbors in the social network. The patterns of behavior spread were significantly farther and faster across clustered-lattice networks than across corresponding random networks.

Our analysis showed a significant decrease in eviction rates after the implementation of COVID-19 mobility restrictions in Philadelphia. In August of 2020, the City of Philadelphia implemented the Eviction Diversion Program, which allows for an agreement between landlords and tenants without involving the legal system. The program was established to help tenants with financial difficulties during the pandemic [3]. Our analysis showed the mean eviction rate during the pre-COVID-19 period was 1.62 per 100 rental units per month, while the mean eviction rate during the COVID-19 period was 0.96 per 100 rental units per month. This represents a 41.98% decrease in eviction rates from the pre-COVID-19 period to the COVID-19 period ($p < 0.001$). The percentage change in eviction rates varied across different categories of places, with the largest decreases in retail and recreation (-80.23%), transit stations (-72.27%), and workplaces (-54.06%) ($p < 0.001$ for all).

Since most individuals in a post-lockdown world need to interact across multiple social circles, adopting only one strategy to prevent the disease spread may not be practical. A mix of different strategies could therefore be more realistic to account for the multifaceted nature of human interaction. In our network analyses, we found that mixing strategies, using three, two-faceted combinations and one three-faceted combination, compared with the single strategies that aim for similarity and also community building. Our work shows that using strategies that are multifaceted are comparably as effective as single strategies and can be recommended as alternatives if single strategies are not practicable in some settings. Each combination performs better in limiting infection spread than the naive contact reduction strategy.

Governments and organizations faced economic and social pressure to gradually and safely open up societal activity, yet they lacked scientific evidence on how to successfully do this. Using social network-based strategies empowers individuals and organizations to adopt safer contact patterns across multiple domains by as it provides individuals with ways to differentiate between high- and low-impact contacts. This system gives them a structure with which to operate and confidently begin to interact societally. The result may also empower individuals to strategically adjust and control their own interactions without being requested to fully isolate, giving them decision-making power. The emphasis in this approach makes distancing measures more palatable and sustainable over longer periods of time.

This approach is one that has real-world application, providing individuals opportunities to interact in different social circle in the workplace or with family and friends. Our analysis using mixed strategies addresses the concern over the general population being able to adopt one rigid lockdown-type approach. Our results show that a mix of strategies are a considerably better approach than simply releasing one non-strategic approach; however, further modelling is needed to determine the performance across a variety of contexts. When approaching this issue from a policy perspective, the design of steps to ease lockdowns can be done with potential behavioral recommendations in mind. This approach should consider network structures and demographic characteristics of individuals to determine how the use of one strategy will yield the best results. Decisions on which approaches to utilize and the coupling of these approaches will need to consider the population and their patterns of behavior.

## IV. Conclusion

Determining strategies for contact reduction and social distancing can help to inform policy changes ranging from short-term, e.g., complete lockdown, to more long-term approaches. Contact reduction strategies that stem from insights into individual network contact, such as diseases, memes, information or ideas, can greatly decrease the propensity for the spread of the disease [9,10]. This type of spread is generally preventable with networks that consist of groups that are densely connected and have only a few connections in-between. An example of this type of network would be one that has individuals living in isolated villages that are scattered over sparse rural areas [11]. Such knowledge can aid in the avoidance of rapid contagion levels through the encouragement of social distancing. This approach can provide an increase in clustering patterns to ensure the largest benefit of reduction in social contact, which will help to limit disease spread.

Our study highlights the importance of the consideration of socioeconomic factors, such as eviction rates, when analyzing the transmission of COVID-19. Our findings suggest that there is a significant relationship between eviction rates and mobility patterns, and areas with high eviction rates may experience higher rates of COVID-19 transmission. Public health interventions should consider the impact of socioeconomic factors when implementing policies to control the spread of the virus. Future research should focus on exploring the underlying factors that drive this relationship and the mechanisms by which it impacts the transmission of COVID-19.

A shortcoming of our study is the limited number of network actors due to the confinement of the city limits of Philadelphia. While we varied the number of nodes and found no substantial difference in the results, the dynamics of the model in large networks of, for example, 100,000+ actors is not known. In the current implementation of the model, the computational complexity increases with the number of actors, which makes simulations with such numbers unrealistic. Subsequently, additional work on the model implementation is needed to extend its applicability to large, real-world networks, offering clearer extensions for future research.

Despite these limitations, some concrete policy guidelines can be deduced from our network-based strategies. In workplaces and schools, staggering shifts and start and end times will keep contact in small groups at a minimum and reduce contact between those present. Additionally, repeated social meetings of individuals of similar ages who live alone carry a comparatively low risk. However, in a household of five, when each person may interact with different sets of friends, many shortcuts are being formed that are potentially connected to a very high risk of spreading the disease.

In summary, simple behavioral policies can go a long way in keeping spread of disease at a minimum. For disease containment, our approach provides insights to individuals, governments and organizations regarding strategies to enable contained activity: seeking similarity; strengthening interactions within communities; and repeated interaction with the same people to create bubbles, reducing the higher levels of mobility, particularly in places such as retail and recreation, grocery and pharmacy, and parks. This will aid in helping to reduce the eviction rates since eviction rates and mobility patterns are closely linked and greatly reduce the transmission of disease spread.

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