SPATIO-TEMPORAL ANALYSIS OF URBAN ECONOMIC RESILIENCE DURING COVID-19 WITH MULTILAYER COMPLEX NETWORKS

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ABSTRACT:

The COVID-19 pandemic has impacted the economic growth of almost every country, with many industries facing operational difficulties, and the failures of a large number of restaurants, in particular, have extensively tested the resilience of urban economies. The gastronomy business is one of the most decentralized and location-based consumer business in urban, which is highly related to the economic attributes of cities. However, there are few studies on quantitative analysis of urban economic resilience through the opening and closing of restaurants. Understanding and planning for the aftermath of the COVID-19 may not only minimize detrimental effects but also provide insights into the economic recovery policies. This study analyzes the phenomenon of restaurant failures after the pandemic in Shenzhen, China via percolation in multilayer complex networks. We identify the closed restaurants through data mining, and construct the human mobility network through mobile phone location data, aggregating origin and destination points into grids. We then embedded the restaurants' Points of Interest (POIs) into the grids, creating an additional restaurant network layer. By considering spatial interactions between restaurants, we constructed a geographical proximity network for restaurants in each grid. Finally, Using these multilayered nested networks, we analyzed the pandemic's impact and the occurrence of critical phenomena related to restaurant closures under lockdown policies through percolation in multilayer complex networks. As a result, this study found that the severity of the pandemic significantly increased the probability of restaurant failures, with cascade and critical phenomena. However, implementing precise lockdown measures can effectively lower the probability of restaurant closures. These results highlight the effectiveness of accurate lockdown policies in striking a balance between epidemic prevention and economic development, contingent upon the correct identification of high-risk areas. This finding suggests that policy makers and public health departments need to balance policy effectiveness with interventions in economic activities in order to increase the resilience of urban economies during the pandemic.

1. INTRODUCTION

The COVID-19 pandemic, which began in late 2019, has profoundly shocked various sectors of society, most notably urban economies, leading to the deepest global recession since the Great Depression (Bank, 2020, Guerriero et al., 2020). Non-pharmaceutical (NPI) interventions such as government-mandated lockdowns and stay-at-home policies have significantly curtailed human mobility (Schlosser et al., 2020, Lai et al., 2020). Concurrently, public fear and anxiety surrounding the virus (Goolsbee and Syverson, 2021, Palacios et al., 2022) led to a self-imposed reduction in travel frequency (Wang and Noland, 2021), which further decreased visits to social venues such as restaurants, shopping centers, and entertainment sites (Chang et al., 2021). This shift posed significant challenges to urban economies (Spelta and Pagnottoni, 2021, Wang et al., 2022), particularly industries dependent on in-person interactions. For instance, the gastronomy business, predominantly restaurants and catering services, has experienced unprecedented impacts (Felix et al., 2020, Gursoy and Chi, 2020). By August 1, 2022, the annual growth rate of global restaurant patrons sat at a mere 0.81% (Lock, 2020), reflecting the enduring and profound influence of COVID-19 on the global restaurant industry. This situation underscores not only the overall economic consequences of the pandemic, but also the urgent need to address economic resilience and develop strategies for urban planning and economic recovery (Bartik et al., 2020, Palacios et al., 2022, Wang et al., 2022).

Numerous studies have employed high-resolution mobility data to probe the effects of the COVID-19 pandemic and corresponding intervention strategies on urban mobility (Lutu et al., 2020, Schlosser et al., 2020, Deng et al., 2021, Chang et al., 2021). However, research scrutinizing the ramifications on urban economies from a microscopic perspective of population movement during the COVID-19 pandemic remains limited (Spelta and Pagnottoni, 2021, Long and Ren, 2022). Critically, only a handful of studies explore the resilience of urban economies in the face of pandemic shocks and the effectiveness of intervention policies (Bartik et al., 2020, Wang et al., 2022, Ma et al., 2023). The concept of urban resilience pertains to a city's ability to recover and adapt when confronting adversity, encompassing economic, social, cultural, and infrastructural dimensions (Evans, 2011, Hernantes et al., 2019, Shi et al., 2021). With urban resilience taking on escalating significance in policy dialogues, it's crucial to devise quantitative metrics to enhance our comprehension and promotion of this concept (Bruneau et al., 2003, Zhao et al., 2015). Such tools and metrics can guide policy decisions during crises, boosting a city's ability to withstand shocks and adapt and evolve post-crisis.

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As a highly decentralized, location-specific sector of urban commerce, the gastronomy business is pivotal in urban economies (Glaeser et al., 2017, Dong et al., 2019). Preceding studies have unveiled that restaurants can foresee various socioeconomic attributes within urban communities with remarkable accuracy, fluctuating between 90%-95% (Dong et al., 2019). Consequently, we propose that the success or downfall of restaurants can act as a metric for urban economic health and resilience during crises, notably, the COVID-19 pandemic. Studying restaurant closures throughout this global health emergency can furnish critical insights into urban economic durability, thus guiding recovery initiatives. However, such analyses are few, underscoring a pronounced knowledge void in interpreting and tackling urban economic resilience amidst pandemics.

Our research endeavors to fill this gap by examining the closures of restaurants in Shenzhen, a vibrant urban hub in China, following the COVID-19 outbreak and devising a multilayer complex network percolation method for simulation. This approach aims to quantify the pandemic's destructive toll on the urban economy and gauge the efficacy of governmental preventative measures. The gastronomy business, a vital cog in Shenzhen's economic machinery, was profoundly impacted by the pandemic's onslaught in early 2020. Our data discloses a record-high closure rate (Death_Ratio) for restaurants in 2020, accompanied by the lowest survival rate (Remaining_Ratio) in recorded history (Fig. 1. A).

Cities epitomize complex adaptive systems, capably modeling the interconnected non-linear interactions among various subsystems such as human mobility network, virus transmission network, and economic interaction network through the lens of multilayer networks (Aleta et al., 2017, Alves et al., 2019, Chang et al., 2021). Concurrently, the percolation theory in multilayer networks offers a robust framework for appraising the resilience of this complex system (Liu et al., 2018, Li et al., 2021). Therefore, percolation theory have been utilized in resilience assessment across a diverse range of complex systems, from power grids to transportation networks (Gao et al., 2016, Ambühl et al., 2023).

We aggregated three months of mobile phone location data into a mobility network, representing potential transmission paths for the virus among the population. The origin and destination points of the mobility network are a Geohash6 (1.2KM*0.6KM) grid. Simultaneously, we embed restaurants Points of Interest (POIs) into these grids, constituting a corresponding additional layer of the network (Fig. 1.C). Each grid can be regarded as a community, and thus we construct a geographical proximity network (Delaunay graph) of the restaurants within the communities as we observe the clustering nature of restaurant closures (Fig. 1.B). This network captures the spatial correlation between the states of different restaurants well. By simulating percolation in multilayer networks, we aim to identify critical phenomena that influence restaurants' survival and recovery capacity. We hope our research method can serve as a valuable tool for stakeholders to assess urban economic resilience in the backdrop of a pandemic. The findings could help policymakers understand the interplay between policy effectiveness and economic activity. Especially in pandemic control, balancing the effects of policies with economic activity interventions can enhance the elasticity of urban economies (Ash et al., 2022).

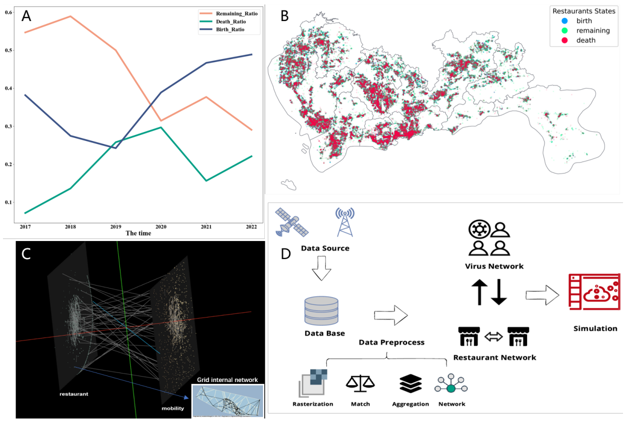

Figure 1. Resilience assessment of urban restaurants based on multilayer networks. A, the status of restaurant POIs is assessed according to their locations over the years. The status in a given year is compared to the preceding year's. If a restaurant is found in the same location, it is classified as 'remaining'. A restaurant that appears in a new location is marked as 'birth', whereas a restaurant no longer present is considered to have gone out of business, referred to as 'death'. For further details on the methodology, please refer to (Wu et al., 2021). B, spatial visualization of the state of restaurants in 2020, with closed restaurants showing spatial clustering. C, Sample visualization of a multilayer network of restaurants and human mobility (10,000 edges), where each node of the network is a Geohash6 (1.2KM*0.6KM) grid, and geographic proximity networks (Delaunay graph) are constructed inside each grid, and in the lower-right corner is a visualization of a network of restaurant proximity inside a grid, so that this is in fact a three-layer network. D, data processing flow.

2. MATERIALS AND METHODS

In this study, we apply percolation theory to analyze the impact of the COVID-19 pandemic on the local restaurants in Shenzhen. Percolation theory studies the connectivity and stability of complex networks, which can predict the phase transition phenomenon that occurs when the network is disturbed (Wang et al., 2019). Specifically, when the disturbance reaches a critical value, the network will suddenly break or malfunction. We regard the urban system as a complex network consisting of multiple subnetworks with interactions between them. Accordingly, we design two subnetworks: a virus transmission network based on human mobility and an economic activity network with restaurants as nodes. We simulate the transmission process of COVID-19 on the network and the impact of government lockdown measures on restaurants. To evaluate the robustness of the network, we use percolation theory to make some restaurant nodes malfunction and calculate the proportion of the largest connected component on the network. This proportion can reflect the ability of the urban system to maintain regular operation during the pandemic or the urban system's ability to resist the pandemic's damage (Cao et al., 2020, Duccio Piovani1, 2020).

2.1 Data Source

We collected mobile location data for residents of Shenzhen from mobile location data service providers, covering the period from September 1 to December 31, 2019. Using the location report data sorted by the time series throughout the day, we constructed user travel chains. By combining this with foundational information such as WIFI, we identified the stop-over points during travel. The origin (O) and destination (D) of each trip were determined based on the time at each stop-over point. Lastly, through data mining, we constructed a human mobility network using these OD points, which represents a relatively consistent daily travel pattern of urban residents in Shenzhen. The annual Points of Interest (POI) data for restaurants in Shenzhen from 2015 to 2022 were collected from the Gaode Map platform (https://lbs.amap.com/) at the end of each year.

For the initial values of the model, we will use empirical data on restaurant survival, death, and birth on specific geographical grids in the restaurant network and infection control zone data on specific geographical grids in the mobility network. Specifically, we will first divide Shenzhen city into 2609 grids, then aggregate the POI of each restaurant into the grid areas we divided, thus obtaining the number of restaurant survival, death, and birth in each grid.

2.2 Network and Node Status Settings

Firstly, we assume that all network edges are undirected. In the mobility network, the nodes are individuals' residences and workplaces (represented by geographical grids), and there will be edges between these locations. The edge weight is the average population flow between these locations. We use Y_{jh} to represent the mobility network.

Further, we use the Delaunay graph to construct the geographic proximity network and then use the virus infection data calculated on the mobile network, which represents which geographic grid region will be closed(Sun et al., 2010). We can simulate the survival status of specific restaurant nodes on the Restaurant-r network.

Each node can be functional at any moment ($x_i = 1$, $y_j = 1$) or non-functional ($x_i = 0$, $y_j = 0$). A non-functional node can cause secondary damage by isolating its neighbours from the rest of the network or via cascading mechanisms. Though a single node or link failure can render other parts of the network non-functional, once the initial failure is repaired, the secondary failures will typically return to functionality. For example, the failure of a node on the mobility network represents confirmed cases in the area that will be sealed off. For the restaurant network of the coupled network, the seal-off will lead to the loss of its resources, reduce its recovery rate, and increase its death rate.

Because of a coupling relationship between the two networks, there will be edges between nodes in different networks, forming a third matrix, generally located on the non-diagonal of the super adjacency matrix. We use $Z_{i,j}$ to represent it, where i is a node in the restaurant network, and j is a node in the mobility network. The specific method is as follows: firstly, we calculate the centroid of each grid on the mobile network, then arrange and combine the centroids on mobile network with restaurant node. And then we calculate the distance between the them. We add edges between nodes within a certain distance. That is, if $d_{i,j} < \kappa$, then $Z_{i,j} = 1$, otherwise it is 0. We assume $\kappa = 5km$.

2.3 Percolation Process of the Early Pandemic

For the mobility network, a node's failure is due to a pandemic infection in the area, so it needs to be sealed off. I want to use a percolation model on the mobile network to simulate the virus transmission process. It is assumed that each node on the mobility network Y has two states, one is infected, and the other is recovered (still susceptible to infection). For the method of updating node status, I choose the bond percolation method.

As mentioned earlier, the edge weight between nodes in the mobility network is the population flow. Firstly, we normalize these edge weights. We first construct the commute probability matrix p_{hj} by normalizing the outgoing flows for each source district j, with has the destination. Both h and j are located on the mobility network Y.

$$p_{hj} = \frac{F_{hj}}{\Sigma_j F_{hj}} \tag{1}$$

where $\Sigma_j p_{hj} = 1$

For an already infected node u, for each neighbour node v, there will be a pair u, v, and we randomly sample each pair edge according to the commute probability $p_{u,v}$. Then select nodes v with sample results > 0, and we update their status to be infected. Moreover, already infected nodes have a certain probability γ to recover. If it is a non-infected node u, it will come into contact with surrounding nodes. If it contacts susceptible nodes, it will be infected.

Summarized as the following algorithm: At each time step t (from t = 0 to t = T), we repeat:

For each node j in network Y:

1. If y_j is 0, node j can recover with probability γ;every edge connecting node j with its neighbour nodes will get a random number sampled from the commute probability distribution; if the number > 0, that neighbour node can also be non-functional. A random number determines the order of these two processes
2. If y_j is 1, node j will contact each infected neighbour node and will get infected.

2.4 Percolation Process of the Precision Control Stage

Compared with the rapid spread of the virus with population mobility in the early stage, precise control will isolate some areas according to the real-time outbreak situation of the virus, cutting off the transmission route of the virus from the source. The specific algorithm is as follows:

At each time step t (from t = 0 to t = T), we repeat:

1. Identify the infected nodes in the network, extract a proportion ζ of the infected nodes into the quarantine set for isolation and control
2. Update Y_{jh} and P_{hj} matrices
3. For each node j in mobility network, if y_j is 0:
   (a) If node j is in quarantine set, node j can recover with probability γ

(b) If node j is not in quarantine set, for every edge connecting node j with its neighbour nodes, it will get a random number sampled from the commute probability distribution. If the number ¿ 0, that neighbour node can also be non-functional. Besides, it can also recover.

4. If y_j is 1, node j will contact each infected neighbour node and get infected.

2.5 Percolation Process of the Restaurant Network

We know that the operation of restaurants requires a sufficient number of customers, and the pandemic will directly lead to a decrease in customers. In addition, it will also lead to a sharp decline in social and economic activities in an area, thereby affecting the survival of restaurants. Therefore, the percolation process of restaurant survival and death needs to consider the state of the nodes in the connected mobility network. To model the observed dependency, we allow the repair rate $\eta_{x,i}^r$ of the primary network X (restaurant network) at node i to depend on the state of the support network Y (mobility network) at the exact location obtaining(Danziger and Barabási, 2022).

$$\begin{aligned} \eta_{x,i}^r &= \phi\left(\langle y\rangle_i\right) \\ &= \phi(1) - \phi'(1)\left(1-\langle y\rangle_i\right) + o\left(\left(1-\langle y\rangle_i\right)^2\right) \end{aligned} \tag{2}$$

Where $\phi(x)$ is a function that represents the functional dependence of the repair rate of the system X on the state of network Y around site i, which we assess with the network average

$$\langle y\rangle_i = \frac{1}{k+1}\sum_j Y_{ij} y_j \tag{3}$$

To capture that repair resources are drawn from the neighbourhood of the failure and are affected by the networks which supply them. Here, $Y_{i,j}$ represents the adjacency matrix on the mobility network. Using it, we can count the failure situation around the nodes in the mobility network connected to a specific restaurant node, thereby measuring the number of resources the restaurant node can obtain. $y_j(t)$ represents the state of node j on the mobility network, with a value of 1 being functional and a value of 0 being non-functional. k represents the number of mobile nodes connected to the restaurant node i.

Thus $\langle y\rangle_i$ may represent the dynamically evolving customer accessibility. In 3, the variable $\langle y\rangle_i$ captures the temporally evolving local state of network Y, which may itself co-evolve with the state of the nodes in network X if dependencies exist between the two systems. Denoting with $\eta_x^{r,0} = \phi(1)$ the elastic repair rate and with $\alpha = \frac{\phi'(1)}{\phi(1)}$, we obtain

$$\eta_{x,i}^r = \eta_x^{r,0}\left(1-\alpha\left(1-\langle y\rangle_i\right)\right) \tag{4}$$

enabling us to describe the expected behavior of $\phi(x)$ to first order with the assumption that $\alpha \in (0,1)$. Specifically, we assume that damage in Y will not improve repair in X $(\phi'(1) \geq 0 \rightarrow \alpha \geq 0)$and that the repair rate must remain positive $(|\phi'(1)| \leq |\phi(1)| \rightarrow \alpha \leq 1)$.

Therefore, each of our restaurant nodes i has a recovery rate, $\eta_{x,i}^r(t)$, which means that node i has a probability of surviving according to $\eta_{x,i}^r(t)$ in the percolation process. For the percolation damage of restaurant nodes, we set a fixed damage rate η_x^d for being damaged. Each restaurant node i is likely to be damaged according to η_x^d. We use R_i to represent the number of surviving restaurants in node i, D_i to represent the number of dead restaurants in node i.

$$\begin{aligned} \dot{R}_i &= -\eta_x^d R_i + \eta_{x,i}^r D_i + B_i \\ \dot{D}_i &= \eta_x^d R_i - \eta_{x,i}^b D_i \end{aligned} \tag{5}$$

We traverse all the restaurant nodes at each time step and update the number of surviving, dead restaurants. From the above differential equations, we can see that the parameters η_x^d and $\eta_{x,i}^r$ have a significant impact on the survival status of restaurants, and the parameters η_x^d and $\eta_{x,i}^r$ will change with the severity of virus transmission. Moreover, different stages of the pandemic will affect the rate of virus transmission, ultimately profoundly impacting restaurants' survival status.

2.6 Percolation Process of the Restaurant-Inner Network

First, we use the Delaunay graph to construct the proximity network within each restaurant grid and then use the virus infection data calculated on the mobile network, which represents which geographic grid region will be closed(Sun et al., 2010). At the same time, we have calculated the R_i, D_i and B_i data on each restaurant grid, which indicates the probability of death, survival and regeneration of restaurants in grid i. We can simulate the survival status of specific restaurant nodes on the Restaurant-Inner network. The specific algorithm is as follows:

At each time step t (from $t = 0$ to $t = 100$), we repeat:

1. Update the elements in the regional state $X_{\text{adj\_new}}$ based on the value of $y_{\text{states}}[t]$, indicating the lockdown status of each region.

2. Normalize each row in $X_{\text{adj\_new}}$, and obtain the population flow matrix p_{hj}^x.

3. Normalize each row in $x_{\text{states}}[t]$, and derive the death rate and birth rate of each region node.

4. Iterate over each region:

   (a) If the region is locked down, eliminate all nodes and edges of the region from new_network, and append all nodes of the region to the death dictionary dead_nodes.

   (b) If the region is not locked down, randomly eliminate or add nodes according to the death rate and birth rate of the region, and update new_network.

   (c) If the next time point exists, and the region is not locked down at the next time point, recover the dead nodes of the region from the death dictionary dead_nodes, and update new_network.

5. Add new_network to the networks list.

6. Compute the number of nodes in the largest connected subgraph in new_network, and designate it as p_{largest}, and insert it to the p_largests list.

3. RESULTS

3.1 Effect of Lockdown on Disease Spreading Process and Economic Resilience

To measure the impact of the disease on the susceptible population, we first focus on the infection rate as a critical metric. Moreover, for each pandemic scenario, we calculate and record the following outcomes related to economic resilience: 1) the Remaining rate, which is the fraction of restaurants that survive; 2) the Death rate, which is the proportion of restaurants that go bankrupt; 3) the Birth rate, which is the ratio of new restaurants that enter the market.

Figure 2 shows that the infection rate in the population decreases as the ζ value increases, indicating that targeted control policies can effectively limit the scale of virus transmission. This finding agrees with the existing results (Schlosser et al., 2020), who analyzed Germany's lockdown policy and found that containment measures induced significant and lasting structural changes in the mobility network. These changes affected the transmission process of the epidemic by flattening the infection curve and reducing the likelihood of long-distance virus spread.

In addition to the infection rate, we examine some variables that reflect economic resilience. We observe that the remaining rate and birth rate, which represent the economic vitality of the restaurant industry, increase with the increase of the ζ value. Conversely, the death rate of restaurants decreases with the increase of the ζ value. This suggests that when epidemic prevention policies have a more local and precise impact on communities and virus transmission sources, service industries like restaurants that heavily rely on commuting labor in cities show stronger economic resilience. Some studies have also reported that urban economic resilience was affected in the initial stages of the outbreak, but timely and precise lockdown mitigated these impacts (Wang et al., 2022).

In addition to the different stages of the pandemic, we also examine how different values of ζ affect the pandemic process and economic resilience. As shown in Figure 2, we find similar patterns across different values of ζ. Figure 3 shows the infection rate of the population and the economic resilience indicators as functions of ζ. Recall that ζ is the parameter that measures the fraction of infected nodes isolated on the Y network, which influences the infection rate of the population. Figure 3A shows the case where $\zeta = 0$ means no containment measures are in place. In this scenario, the virus spreads quickly and reaches an infection rate of nearly 0.8.

As a result, the death rate of restaurants increases as more nodes on the mobile network become non-functional. Conversely, restaurants' remaining rate and birth rate decrease and the death rate is much higher than the remaining rate and birth rate. This indicates a strong coupling relationship between the mobile and restaurant networks. On the other hand, as ζ increases, the scale of virus transmission decreases, and the final infection rate drops to around 0.6 when $\zeta = 0.8$ and $\gamma = 1/9$ (Wölfel et al., 2020, ?). Fig. 3. B, C, and D show that the gap between the death rate and the remaining rate of restaurants becomes smaller, which implies that when the epidemic is effectively controlled, the city's economic resilience will recover. These results are in line with the simulations (Danziger and Barabási, 2022). They studied the recovery coupling and found that recovery will be slowed if the support networks are not functional.

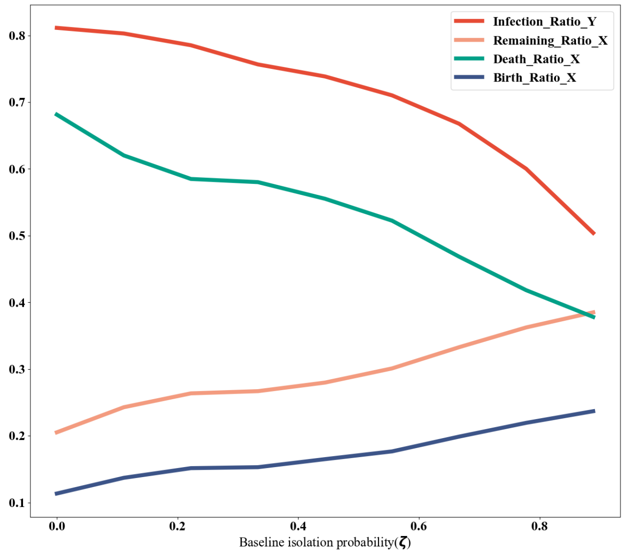

Figure 2. Lockdown effects on infection wave and economic resilience. The red line shows the percentage of infected individuals in the total population, while the green line indicates the mortality rate of restaurants due to the pandemic. The orange line reflects the resilience of restaurants that survived the pandemic shock, and the purple line denotes the emergence of new restaurants in the market. Other parameters(Table 1): η_X^d=0.5, $\eta_X^{r,0}$=0.5, $\eta_X^{b,0}$=0.5, α=1, ζ=0.9, $R0$=6, γ=$\frac{1}{9}$

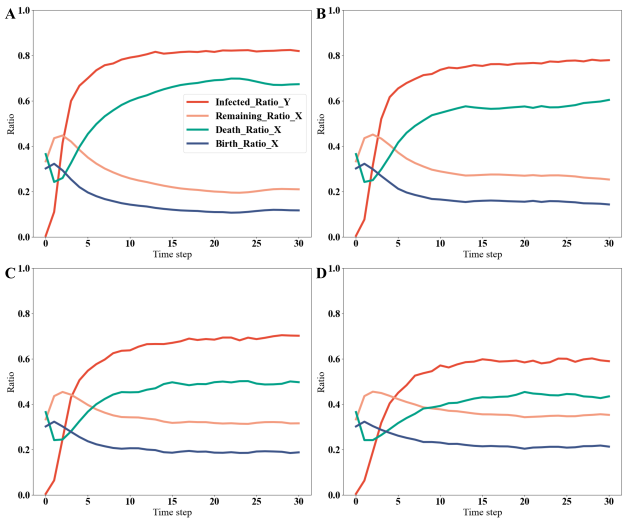

Figure 3. The dynamics of the pandemic and its effects on the restaurant industry under different ζ. The four figures (A)-(D) represent the dynamical behavior of the system under different ζ values: 0, 0.3, 0.6, and 0.8. The ζ value indicates the fraction of nodes in the Y network that are disconnected from the rest of the network due to isolation. And eventually affects its stability and oscillation. Other parameters(Table 1): η_X^d=0.5, $\eta_X^{r,0}$=0.5, $\eta_X^{b,0}$=0.5, α=1, $R0$=6, γ=$\frac{1}{9}$

3.2 A Further Look at the Critical Transition: Infections and Economic Resilience

In this study, we investigate how infections and economic resilience evolve under different stages of the pandemic. We use a day as a cut-off point to separate the early phase of the pandemic from the lockdown phase. In the early phase, the government did not adopt targeted containment strategies, whereas, in the lockdown phase, the government enforced strict lockdowns on areas and workplaces with high infection rates. Fig. 4 shows the critical transition that occurs around the cut-off point. According to our simulation results, the infection curve flattened after 20-time steps, corresponding to our cut-off point. As the infection rate declines, the pandemic's adverse effects on social and economic activities are alleviated. This leads to a decrease in the restaurant mortality rate and an increase in the restaurant survival rate and birth rate, as shown in Fig. 4. Our model's results are consistent with the existing literature. For example, some scholars suggest that precise identification and effective containment of the virus transmission sources can lower the need for extensive lockdowns and reduce economic losses (Rahman et al., 2020).

4. CONCLUSION

In this study, we empirically employ percolation theory to analyze the impact of the COVID-19 pandemic on the local restaurants and other socio-economic systems in Shenzhen. Percolation theory studies the connectivity and stability of complex networks, which can predict the phase transition phenomenon that occurs when the network is disturbed (Wang et al., 2019). Specifically, when the disturbance reaches a critical value, the network will suddenly break or malfunction. We regard the urban system as a complex network consisting of various networks that interact with each other. Accordingly, we design two networks: a virus transmission network based on population mobility and an economic activity network with restaurants as nodes. We simulate the transmission process of COVID-19 on the network and the impact of government lockdown measures on restaurants. To evaluate the robustness of the network, we use percolation theory, causing some restaurant nodes to malfunction and calculate the proportion of the largest connected component on the network. This proportion can reflect the ability of the urban system to maintain regular operation during the pandemic or the urban system's ability to resist the pandemic's damage (Cao et al., 2020).

Fig. 4 shows that in the pre-lockdown stage, both the virus transmission and the restaurant mortality rates increase significantly, while the survival and birth rates decrease rapidly. In contrast, in the lockdown stage, both the virus transmission and restaurant mortality rates start to decline, while the restaurant survival and birth rates stabilize and increase. This indicates that the precise lockdown policy can effectively control the widespread transmission of the virus, which mainly depends on identifying which areas are high-risk sources of infection(Qiu et al., 2020).

Moreover, we have also simulated the percolation process of the restaurant network under the influence of virus transmission. We have observed a clear phase transition phenomenon in different stages of the pandemic (see Fig. 5). In the pre-lockdown stage, the fraction of nodes in the largest connected component of the restaurant network drops sharply, then fluctuates and rises near the lockdown point, and finally approaches 0.7. This suggests that a small local disturbance may lead to a large-scale systematic malfunction of the entire restaurant network at a critical point, which reflects the resilience of the urban system(van de Leemput et al., 2018).

Our study not only provides an efficient method to quantify urban resilience with multi-source data, but also deepens the understanding of urban systems and sheds some light on multilayer complex network simulation in geographical fields(Sugiki et al., 2021). Our study also suggested that precise lockdown policy is an effective way to balance epidemic prevention and economic development, which depends on accurate identification of high-risk regions. Our study can provide some references for urban planners and policymakers to cope with future pandemics or other disasters.

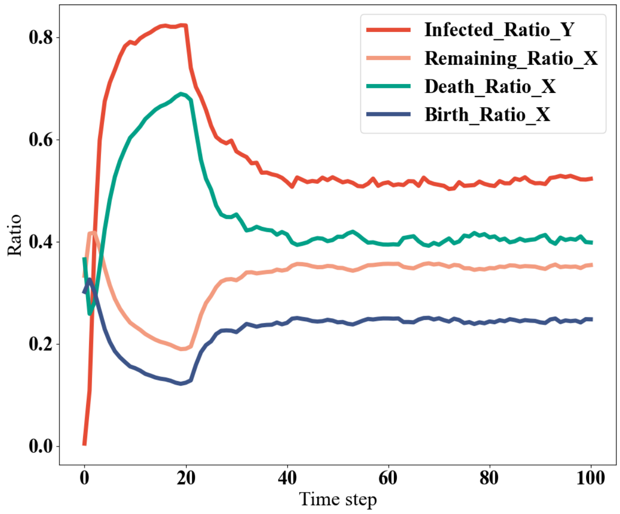

Figure 4. Comparison of the pre-lockdown recover coupling and the lockdown recover coupling corresponding to days 20. Other parameters(Table 1): η_X^d=0.5, $\eta_X^{r,0}$=0.5, $\eta_X^{b,0}$=0.5, α=1, ζ=0.9, $R0$=6, γ=$\frac{1}{9}$

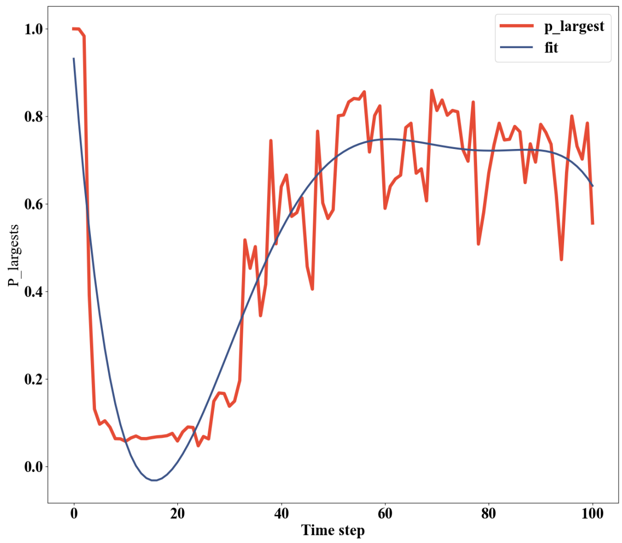

Figure 5. The fraction of nodes in giant connected component ($P_{largest}$) as a function of time.

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APPENDIX

Parameter variable	Meaning and details
η_X^d	Destruction rate
$\eta_X^{r,0}$	Initial retention rate
$\eta_X^{b,0}$	Initial birth rate
α	Coupling coefficient between networks
ζ	Proportion of isolation
R0	Basic reproduction number
γ	Recovery rate
κ	Distance threshold

Table 1. Model parameter table