Urban determinants of COVID-19 spread: A comparative study across three cities in New York State

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Urban determinants of COVID-19 spread: A comparative study across three cities in New York State

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Abstract The ongoing pandemic is laying bare dramatic differences in the spread of COVID-19 across seemingly similar urban environments. Identifying the urban determinants that underlie these differences is an open research question, which can contribute to more epidemiologically resilient cities, optimized testing and detection strategies, and effective immunization efforts. Here, we perform a computational analysis of COVID-19 spread in three cities of similar size in New York State (Colonie, New Rochelle, and Utica) aiming to isolate urban determinants of infections and deaths. We develop detailed digital representations of the cities and simulate COVID-19 spread using a complex agent-based model, taking into account differences in spatial layout, mobility, demographics, and occupational structure of the population. By critically comparing pandemic outcomes across the three cities under equivalent initial conditions, we provide compelling evidence in favor of the critical role of hospitals. Specifically, with highly efficacious testing and detection, the number and capacity of hospitals, as well as the extent of vaccination of hospital employees are key determinants of COVID-19 spread. The modulating role of these determinants is reduced at lower efficacy of testing and detection, so that the pandemic outcome becomes equivalent across the three cities.

Keywords Agent-based model · COVID-19 · Resilient cities · Urban design

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1 Introduction

World-wide urban areas remain the major targets of the ongoing COVID-19 pandemic due to their high population densities, frequent human interactions, and daily commutes [1,2]. Analyzing the spread in metropolitan areas can help alleviate the epidemiological burden, by supporting the design of policies for detection [3–5], immunization [6,7], and intervention [8,9]. Alongside with scientifically backed policy-making, research on COVID-19 spread in urban environments can support the identification of factors that reduce vulnerability to future pandemics [10] and create epidemiologically-resilient cities [11,12]. Predictably, population density has been proposed as an important determinant of the spread [13–15]. Empirical studies have also demonstrated the impact of demographics [16–19], socio-economic factors [20,21], and climate [22] on the local spread of the pandemic.

While evidence-based analysis is key to assess the current state of the pandemic and identify causal associations, computational models of COVID-19 spread have been instrumental in the simulation of several what-if scenarios that have shaped public health policies across the globe [23–27]. With a strong focus on major urban areas, these models have helped quantify the benefits of non-pharmaceutical interventions [28–30], identify optimal schemes for prioritizing and administering vaccines [31–35], understand the implications of human mobility [36–38], and devise safe reopening strategies for the economy [39–42].

Several studies have investigated the spread in urban environments, in search of characteristics that influence the spread, often towards informing data-driven models. For example, Bhowmik *et al.* [43] performed a county-level analysis of the United States and proposed a model of COVID-19 spread that is informed by demographics, socio-economic factors, and healthcare availability. Aguilar *et al.* [44] analyzed different types of urban layouts with respect to spread dynamics and effectiveness of mobility restrictions. Through simulations of an infectious disease in synthetic cities with different geographical layouts, Brizuela *et al.* [45] demonstrated that heterogeneous urban design may lead to a highly non-uniform distribution of the epidemic, potentially targeting the most vulnerable. In a study of 163 cities across the World, Hazarie *et al.* [46] discovered that COVID-19 contagion increases proportionally to human mobility in densely populated areas. Li et al. [47] proposed a series of major urban fabric contributors to the initial COVID-19 epidemic in Wuhan, including the distribution of public facilities, hospitals, roads, and subway stations.

In this work, we complement these efforts through a high-resolution computational model at the granularity of a single individual for the spread of COVID-19 in three different cities in New York State: Colonie, New Rochelle, and Utica. These cities are selected for their similar size, but also because they differ by geographic layouts, population density of their residents, demographics, socio-economic characteristics, and mobility patterns within their populations [48]. COVID-19 spread is simulated within each city using an agent-based model, which builds upon our previous work [34, 35,42]. By modeling the cities under equivalent initial conditions for the contagion, we can successfully distill urban determinants of COVID-19 spread. Unique to this study is the estimation of the extent to which different location types influence infections and deaths, by selectively excluding one of them at a time from the analysis. Likewise, we also detail the specific role of different agents in the spread in hospitals, from COVID-19 patients to staff.

Our results confirm the key role of testing and detection on the ability to shape the spread across different urban environments. As highly efficacious testing and detection is attained, our model projections suggest a crucial effect of the number and capacity of hospitals on the spread of the virus, making cities with large and concentrated sanitary hubs more effective to combat the spread than those with more scattered and smaller hospitals. Moreover, vaccination of hospital employees seems to be a further salient factor that contributes to halting the spread. The modulating role of these factors is reduced for lower testing and detection efficacy, whereby poor detection and testing lead to substantially equivalent COVID-19 spreading dynamics across the three cities. Our work highlights the importance of testing and the need for reducing the spread from the hospitals through case isolation and immunization of the personnel. Urban planning should consider the location and structure of hospitals, which may be critical in containing the pandemic.

2 Methods

Our computational framework consists of two components: a detailed database of the cities and their population, and an agent-based model of COVID-19 spread with the resolution of the single individual. The core framework is described in our earlier publications [34,35, 42], to which we point the interested reader for further details.

2.1 Database

The database of each city contains the coordinates of all the public and residential buildings along with resident demographics. With this information, we are able to recreate synthetic cities – the fabric upon which software agents mimicking individuals will live, interact, and contract the infection. The locations of schools, retirement homes, and hospitals were collected using OpenStreetMap [49] and Google Maps [50]. The number of students in each primary, middle, and high school was estimated using the data from the National Center of Education Statistics [51]. Capacities of daycares were assessed using the U.S. child care database and building sizes [52–54]. The number of students in colleges and the number of residents of retirement homes were estimated using websites of specific institutions. The number of in-patients in hospitals due to conditions other than COVID-19 in New Rochelle and Utica represented about 60% of the bed capacity recorded by New York State Department of Health [55] and the American Hospital Directory [56]. For Colonie, we hypothesized that hospitals would be able to treat COVID-19 patients, although, in practice, these hospitals were clinics that do hospitalize patients. Consistent with the premise of lack of hospitalization, we assumed that none of the virtual bed capacity of Colonie was allocated to non-COVID-19 patients.

The residents work in and outside of their city; their workplace locations were determined using the U.S. Census data [48] and SafeGraph [57]. The public transit commute patterns were gathered from Google Maps [50]. Our model also includes various non-essential businesses and locations, such as restaurants, malls, and grocery stores. Similar to workplaces, non-essential business locations were determined using SafeGraph [57]. The database also includes several major schools, retirement homes, or hospitals located in close proximity of the city but outside its administrative boundaries due to the high likelihood of residents using and frequenting those places. All the private and public modeled locations are displayed in Figure 1a).

The geographic coordinates of residential buildings were collected using ArcGIS [58], without distinguishing the number of individual units in each residential building. A proxy for the distribution of buildings with multiple units was instantiated in our model using the U.S. Census data [48]. While the local layout of such units may differ from the real one, we made sure that the real and the modeled distributions are statistically equivalent. This procedure simplifies our previous approach [34, 42], in which all the building locations and types were manually collected, toward the systematic automation of the data collection phase. Details of this approach for the collection of site locations and the verification of its validity with respect to the manual collection technique proposed in [34, 42] are described in the Supplementary Material.

To recreate city populations we used the U.S. Census data on age distribution, household and family structure, commute times and modes, and employment characteristics [48]. All the generic workplaces and agents working in them were divided into five occupational categories, as shown in Figure 1b). Such a fine categorization is an important improvement with respect to our previous work [34, 42], in which we only distinguished between schools, retirement homes, and hospital employees [34, 42].

The rationale for such a fine categorization lies in the need to capture the different employment structure of the three cities and the corresponding variation of workplace-related infection risks. In our model, we explicitly simulate COVID-19 spread in the workplaces that are in the cities. Each of these locations has an assigned occupational category and a category-specific transmission rate, contributing to the infection risk for all the agents employed therein. Contrarily, the occupational category of an agent who works outside of city is a characteristic of the agent, rather than the location. This stems from the fact that our model avoids simulations of the entire region by approximating the contagion in the out-of-city locations. The workplace-related infection risk for an agent working out-of-city corresponds to the estimated fraction of infected people in the region multiplied by occupation type transmission rate. Overall, the employment type distribution matches the U.S. Census [48] data with details on its distribution and rate computation enclosed in the Supplementary Material.

The age distributions of the cities' residents are shown in Figure 1c), while other characteristics of the cities are summarized in Table 1. The three cities differ in some characteristics, such as spatial layout, population density, fraction of residents in the 0–9 age cohort, unemployment rates, commute patterns, workplace locations, and percentage of people working in low- versus high-risk occupations. At the same time, the three cities have similar household and family structure and age distribution of older children and adults.

2.2 Agent-based model

In our model, each city resident is represented by a simulated agent who mirrors residents' lifestyles. The agents could live together in distinct households, retirement homes, and be admitted to hospitals. They could work,

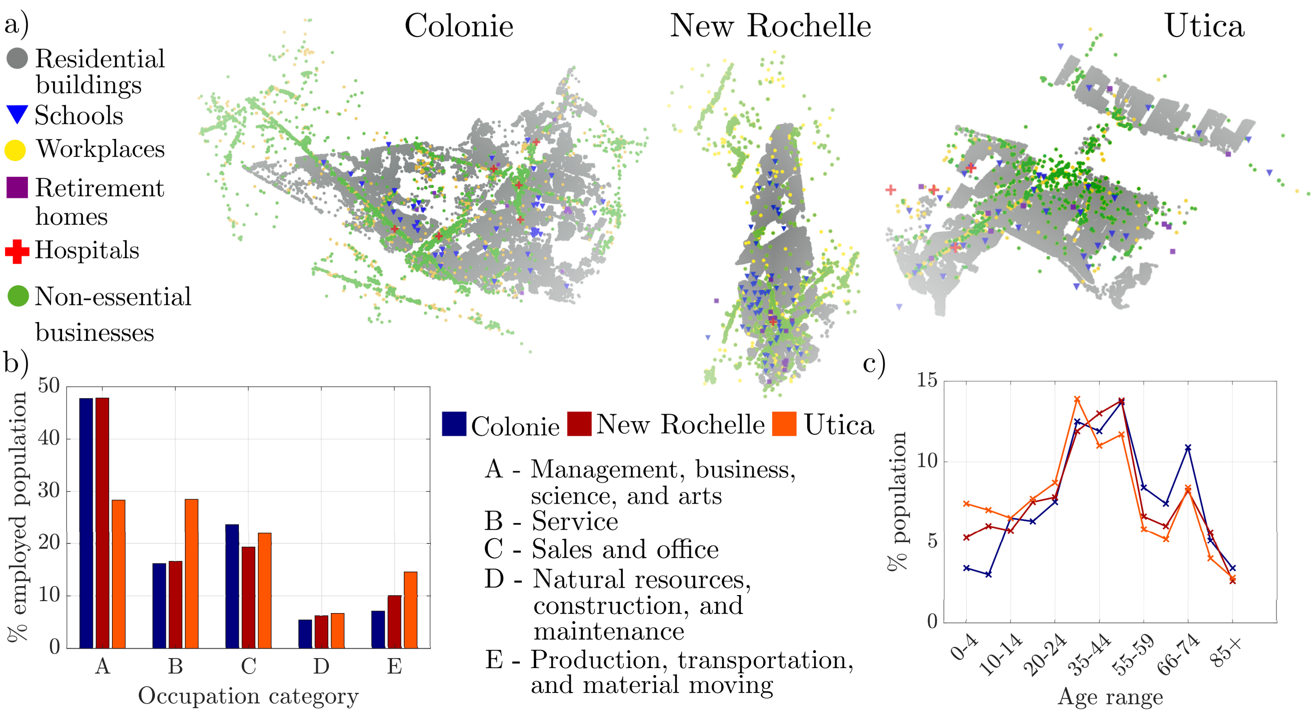

Fig. 1 a) Public and residential locations in the three cities that are considered in the model, b) occupation categories of the employed residents, and c) age distribution of the population.

Table 1 Characteristics of the three modeled cities.

	Colonie	New Rochelle	Utica
Population	82,797	79,205	59,750
Population/sqmi	1,459	7,445	3,714
Unemployment rate	3.1%	6.1%	8.2%
Use of public transit	1.02%	8.5%	0.77%
Workers out of the city	19.7%	31.2%	15.6%

go to school, visit non-essential businesses, visit each other, and travel to work through various transit means, consistent with the database described in Section 2.1.

COVID-19 spreads through contacts that agents make in the locations they visit through a probabilistic mechanism. Specifically, the transmissibility of COVID-19 is dependent on the location type and agent role and is quantified through transmission rates, as explicitly detailed in our previous work [34, 42]. To capture the transmission levels associated with different occupations, we use the empirical data published by the Washington State Department of Health [59, 60]. Details about this procedure and exact values of the infected fractions and rates are included in the Supplementary Material.

Once infected, agents can develop symptoms or remain asymptomatic. Infected agents (both asymptomatic and symptomatic) and those with symptoms similar to COVID-19 but from other diseases can be tested with a certain probability. We refer to this likelihood as testing and detection efficacy (low, moderate, or perfect). A low efficacy corresponds to the detection of 63% of the symptomatic agents and 44% of the asymptomatic, following our model calibration for the first wave [34]. Moderate efficacy implies that 82% of symptomatic and 72% of asymptomatic agents are detected, and perfect efficacy means that all infected agents are tested. With the exception of hospital employees, when an agent "signs up" for a test, they are immediately home-isolated. This mimics local practices, whereby healthcare staff do not isolate until they are confirmed COVID-19 positive or develop symptoms of the disease. Tests are performed in hospitals or in independent testing sites, where the latter locations are assumed to pose no risk of transmission. Agents who tested positive can be treated at home, through routine hospitalization, or in ICUs, depending on the severity of the disease, which is determined in a stochastic fashion, consistent with COVID-19 clinical data [61]. The disease progression terminates with either a recovery or death. The exact COVID-19 progression used in this work follows the progression model described in [42].

Similar to our previous work [42], our model contemplates vaccination for agents. In our simulations, we mimic a continuously progressing vaccination campaign. A portion of the agents is immunized at the beginning of the study and the number of vaccinated individuals increases linearly as the simulation progresses. Once

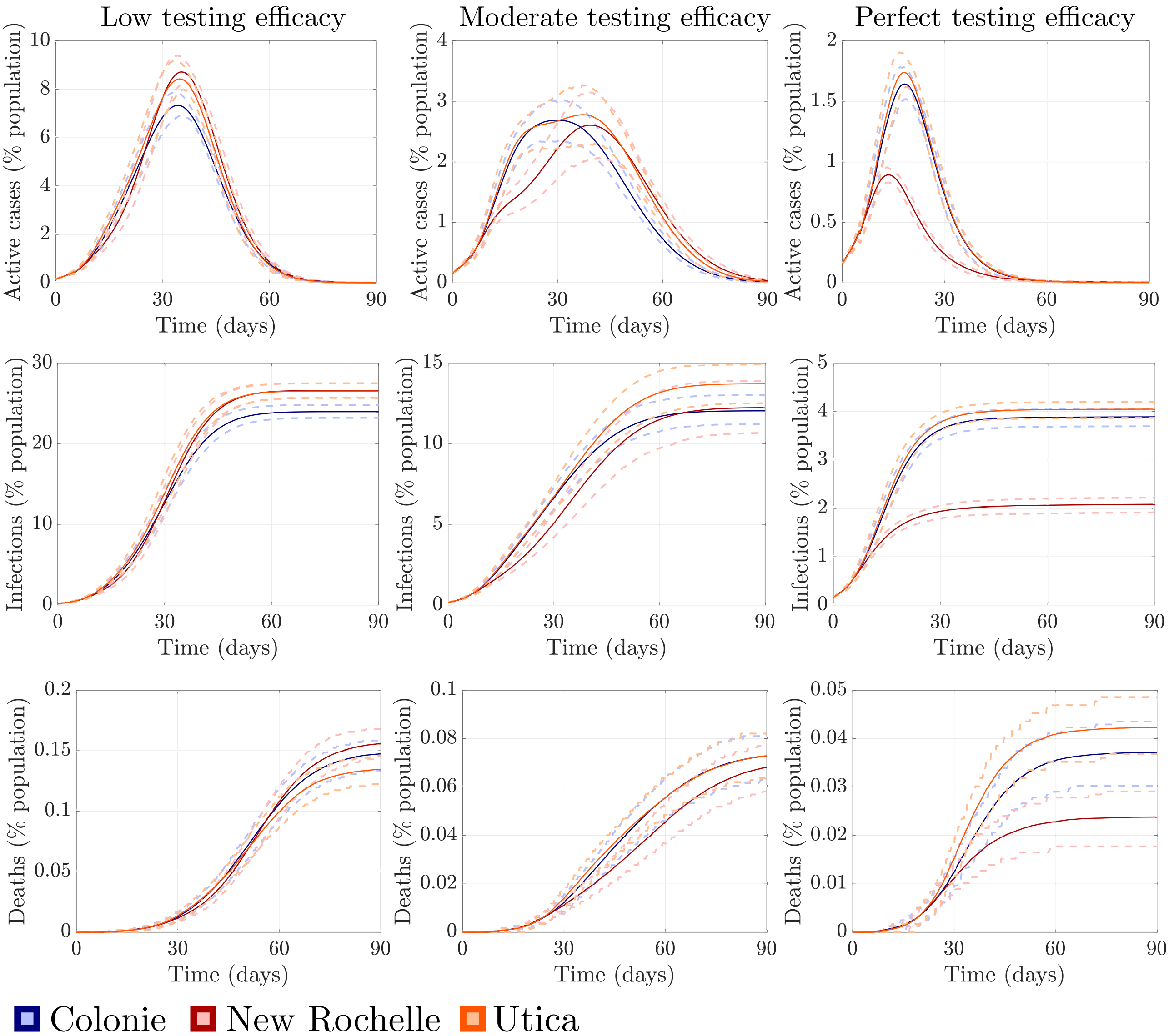

Fig. 2 Simulations of the spread of COVID-19 in Colonie (blue curves), New Rochelle (red curves), and Utica (orange curves) over a time-window of three months, for three different testing and detection efficacies. Solid lines represent the average of of 400 independent realizations; dashed lines are the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles.

vaccinated, we assume that individuals are granted full immunity to COVID-19. Despite being simplistic, such an assumption should be realistic for the short-term simulation window (through Summer 2021) considered in this work. Non-ideal effectiveness of vaccines and waning immunity has been incorporated within our simulation framework in a separate publication [35].

The core parameters used in the model are described in detail in our previous works. Following our most recent study [35], we simulate the Delta variant of the virus with epidemiological parameters calibrated on clinical estimations [62,63]. Because our goal was to analyze the impact of non-epidemiological factors, such as population density and employment distributions, on the spread of COVID-19, all three cities were simulated with the same initial percentage of infected agents, patients in various stages of COVID-19, and vaccinated agents, chosen uniformly at random in the population. All cities are assumed to have the same risk levels from travels from and to neighboring cities, transmission in public transit, and frequency of visiting non-essential business locations. The detailed parameter list is enclosed in the Supplementary Material.

3 Results

3.1 COVID-19 spread in the three cities

Starting from the same initial conditions, we simulated three months of COVID-19 spread in the three cities for different testing and detection efficacies. Since the initialization of the system and the contagion model are governed by probabilistic mechanisms, for each analyzed condition, we estimated the outcome of the spreading process via Monte Carlo simulations, by averaging over 400 independent realizations. Results shown in Figure 2 indicate that under low and moderate testing and detection efficacy, the three cities of Colonie, New Rochelle, and Utica do not experience significant differences in the COVID-19 toll, either in terms of total infections or in total deaths. However, under perfect efficacy, the case and death counts in New Rochelle are considerably smaller than in the other two cities.

3.2 Identification of major COVID-19 hubs under perfect testing and detection efficacy

To shed light on the factors that determine the significantly lower spread in New Rochelle for perfect testing and detection efficacy, we performed two additional analyses. In the first analysis, we selectively excluded different location types from the spread by assuming that no transmission can happen in that type of locations (formally, by setting the corresponding transmission rate to 0). In this way, we simulated the spread in the three cities without agents being infected at generic workplaces, schools, hospitals, retirement homes, or non-essential business locations, respectively.

According to the results shown in Figure 3, the spread in Colonie and Utica are comparable to the one in New Rochelle only if hospitals are excluded from transmission. This result can be traced back to different rules applied to hospital employees compared to the general population. Under perfect testing and detection efficacy, nearly all the agents who become infected during the simulated time-window are successfully detected. However, as opposed to any other agent, hospital employees do not home-isolate before receiving their positive test result or developing disease symptoms. As such, they are allowed a wider period for potentially spreading the infection in the hospital and outside. Furthermore, New Rochelle has only one hospital with 345 employees, which is much less than Colonie (six hospitals, 1,552 employees) and Utica (four hospitals, 962 employees). As such, New Rochelle provides less routes for COVID-19 to spread from hospital employees who are positive but still performing their duties.

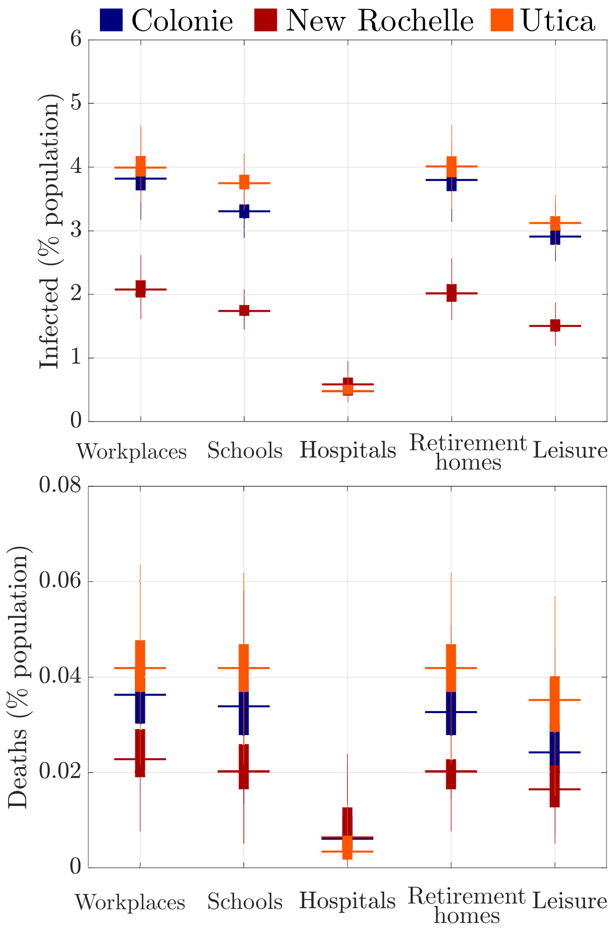

Fig. 3 Final COVID-19 toll (infections and deaths) after simulating a three-month window and excluding the indicated location types from the spread. The bottom and top edges of the box plots mark the 25^{th} and 75^{th} percentiles, the solid lines represent the median, and the whiskers span the entire, outlier-free dataset.

While our simulation results are suggestive of a key role of hospital in relaying the infection *outside* of their facilities, the question about possible causes of transmission *within* facilities, with the associated risk of generating outbreaks, remains open. To this aim, our second analysis sought to identify the types of agents that contributed the most to the spread within hospitals. In particular, we performed a series of simulations where we excluded from the transmission dynamics select types of agents in hospitals. The types of agents that we excluded were patients who were originally admitted to the hospital due to conditions other than COVID-19, agents that get tested at a hospital, hospital employees, routinely hospitalized COVID-19 patients, and patients treated for COVID-19 in an ICU, respectively. The results in Figure 4 show that the reduction of spread in Colonie and Utica is achieved only when excluding the agents who are routinely hospitalized for COVID-19,

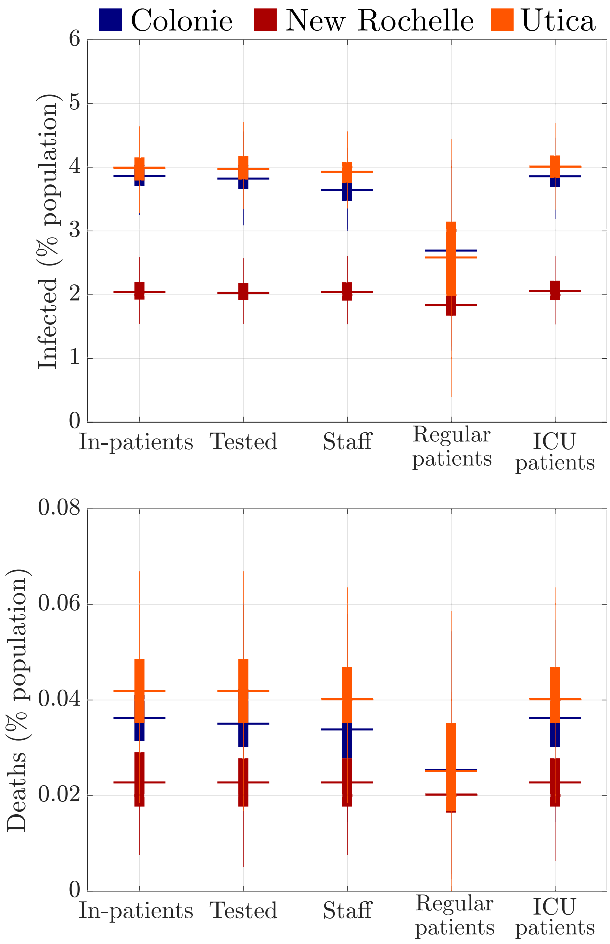

Fig. 4 Final COVID-19 toll (infections and deaths) after simulating a three-month window and excluding the indicated agent type from the spread within hospitals. *In-patients* refer to agents originally admitted to the hospital due to conditions other than COVID-19, *Tested* are agents having their test in a hospital, *Staff* are the healthcare employees, *Regular patients* are the agents routinely hospitalized for COVID-19, and *ICU patients* are the agents treated for COVID-19 in ICUs. The bottom and top edges of the box plots mark the 25th and 75th percentiles, the solid lines represent the median, and the whiskers span the entire, outlier-free dataset.

suggesting their prominent role as main spreaders within hospital facilities.

3.3 Effect of vaccinating hospital employees

Results in Figure 4 leads us to formulate the hypothesis that an important route for COVID-19 generates from hospitals, among patients, and spreads outside, due to infected employees who could interact with others between the time the infection is contracted and the emergence of symptoms or the positive outcome of a test. Under this premise, it becomes of paramount importance to vaccinate hospital employees.

To further back this claim, we performed an additional simulation in which we vaccinated all the initially healthy hospital employees. Under the assumption of perfect immunity, results in Figure 5 confirm that vaccination of healthcare employees greatly reduces the toll of the epidemic. Importantly, the immunity of hospital employees also changes the previous trends, with Colonie presenting the least number of cases due to its larger number of hospital and hospital employees. Given that the vaccines in reality do not fully protect against COVID-19 and their effects wane with time, this best-case scenario further highlights the need of mandatory (or extremely incentivized) immunization of healthcare workers.

4 Discussion

Our work offers a unique, comparative study of different U.S. cities toward elucidating the urban determinants of COVID-19 spread. Through a high-resolution agent-based model, we simulated the spread of COVID-19 in three similar-sized cities in New York state (Colonie, New Rochelle, and Utica), differing in spatial layout, population demographics and lifestyles, and occupational characteristics. We matched the initial COVID-19-related conditions in the three cities to facilitate the isolation of non-epidemiological, urban determinants. Acknowledging the critical importance of testing and detection in fighting the pandemic, our analysis included different testing and detection scenarios, from low (reminiscent of the first wave) to perfect efficacy.

Our computational results indicate that the three cities experience similar COVID-19 infections and deaths for low and moderate efficacies of testing and detection. In the case of perfect detection and testing efficacy, the COVID-19 toll in New Rochelle remarkably drops below the other two cities. Through additional analysis on the influence of different locations on the spread, we demonstrated that the reason behind this difference is due to the spread in hospitals. Specifically, we found that contagion within hospitals is dominated by routinely hospitalized COVID-19 patients and hospital employees who could serve as vectors from the hospitals out to the city. Predictably, our numerical simulations also indicate that vaccination of healthcare workers is successful in preventing these contagions, thereby reducing the COVID-19 toll in the three cities. Our results contribute a valuable outlook on testing, immunization, and isolation of infected cases in urban environments.

Overall, the results of our study highlight the importance of timely and efficacious testing and detection, consistent with claims from our previous analyses [34,

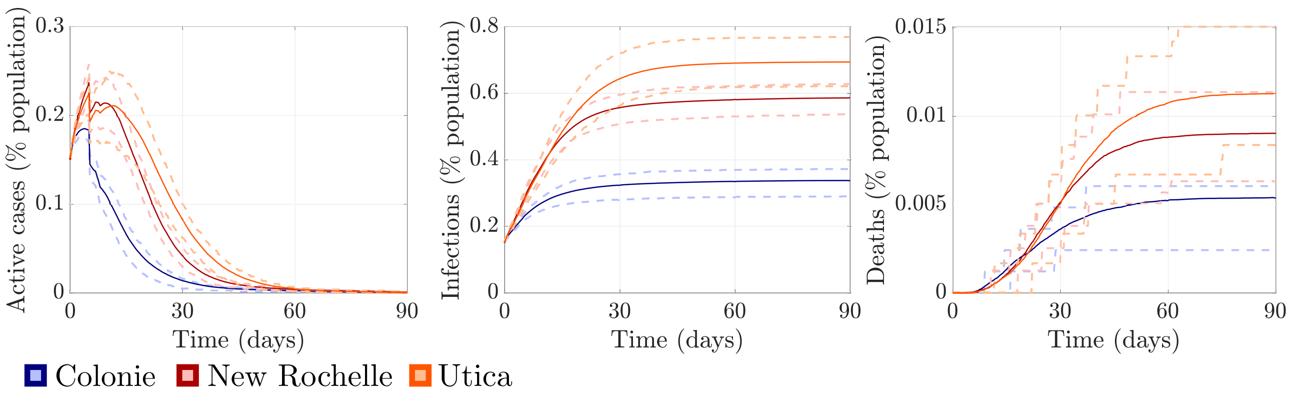

Fig. 5 Spread of COVID-19 with perfect testing and detection and fully vaccinated hospital employees. Solid lines represent the mean out of 400 independent realizations. Dashed lines are the realizations corresponding to the 25th and 75th percentiles.

35, 42] and work of other research groups [28, 64]. By improving the efficacy of testing and detection from low to perfect, the case count drops as much as six fold, resulting in up to five times fewer deaths. With reduced testing and detection, differences between the fabrics of the cities have a limited impact on COVID-19, resulting in equivalent epidemic patterns. In this vein, despite their differences, the burden of undetected cases bears similar, dramatic consequences on the three cities. These claims are aligned with strategic plans implemented world-wide in an effort to curb the COVID-19 pandemic through immunization and non-pharmaceutical interventions [65, 66].

With perfect testing and detection efficacy, New Rochelle had, on average, two times less infection cases and deaths compared to Colonie and Utica. We attribute this variation to differences in COVID-19 spread in hospitals. The severity of the spread in hospitals has been documented by other works [67–70], while hospitals have been identified as dominant COVID-19 hubs have been identified in various computational studies [47, 71]. With respect to urban planning and epidemiological crisis mitigation, our results highlight the importance of proper isolation of the hospitalized infected individuals [69, 72]. Following successful implementations [73–75], cities should consider establishing fewer, more isolated hospitals to treat COVID-19 patients. Ongoing solutions aiming to reduce COVID-19 spread from hospitals is the utilization of mobile pre-screening applications before a visit [76], and delegating some of the diagnostic services to online meetings rather than live interactions [77].

In our model, only hospital employees spread COVID-19 from the hospitals to the general population, which is consistent with restrictions that are placed in health care facilities on guests' admission and efforts to perform remote diagnosis when possible [77, 78]. The intensity of the spread is linked to the nature of their work, preventing hospital employees from quarantining unless tested positive or developing symptoms [79, 80]. Vaccinating these individuals in our simulations resulted in twenty times fewer cases and ten times less casualties. While we have assumed that vaccines grant full, long-lasting immunity, it is tenable that equivalent, albeit reduced, benefits would persist under more realistic conditions, in line with other studies [67, 68]. The importance of vaccinating healthcare workers pointed out in our study is particularly relevant, as many governments across the globe are hesitant in mandating their immunization [81, 82], facing criticism from the employees and the public.

When interpreting the results of our work, one should keep in mind several of its limitations. First, our testing and detection procedure is very conservative, with agents isolating as soon as they decide to get tested. This is likely a more optimistic scenario than what is encountered in reality, especially after relaxing local quarantine rules for the fully vaccinated [83]. Second, the model does not accommodate any form of contact tracing, which is still a major component of COVID-19 curbing. Third, the vaccines are also assumed to act in an idealized fashion, and there are no limits to their application, like agents' age or hesitancy. Fourth, our model does not account for additional deaths that may result from the overburden of hospitals and the reduction of hospital employees due to infection. Adding such a feature may partly reduce differences in the number of deaths between the three cities.

In conclusion, our study indicates that enhancing the effectiveness of testing and detection policies would make urban determinants essential factors of the epidemic outcome. Conversely, prioritizing urban modifications over improvement on testing may nullify such an effort. In the absence of highly efficacious testing and detection, cities appear to be equivalently vulnerable to COVID-19 spread. If highly efficacious testing and detection are practiced, our analysis points to hospitals as major sources of epidemic spread, with hospitalized individuals causing local outbreaks and employees facilitating the spread across the community. Our results imply that an epidemiologically resilient city should possess well-developed detection infrastructure providing high-quality and timely tests; fewer, dedicated healthcare facilities that provide good isolation of treated individuals; and strongly incentivized vaccination of its healthcare workers.

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Author contributions Conceptualization: AT, LZ, SB, AR, MP; data curation: AT, MF, SW; methodology: AT, MF, SW, LZ, SB, AR, MP; software: AT, MF, SW; validation: AT, MF, SW; formal analysis: AT, LZ, SB, AR, MP; investigation: all the authors; resources: MP; writing—original draft preparation: AT, LZ, SB, AR, MP; writing—review and editing: EC, ZPJ; visualization: AT, MF, SW; supervision: SB, AR, MP; project administration: MP; funding acquisition: SB, ZPJ, AR, MP.

Data availability statement The database is accessible at `https://github.com/Dynamical-Systems-Laboratory/Multitown-Population-ABM` and the software used for the simulations is available at `https://github.com/Dynamical-Systems-Laboratory/DSL_ABM-Multitown`

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Supplementary Information for **Urban determinants of COVID-19 spread: A comparative study across three cities in New York State**

S1: Creation of households

All agents who are not residents of retirement homes or hospital patients are assigned a household. Household structure follows the U.S. Census data on housing statistics [17] on household size, percentage of families, single and two-parent families, and fraction of households with senior citizens. Households can be stand-alone buildings or be a part of multiunit structures. Agent location is the same as the geographic coordinates of the household they are assigned to. The geographic coordinates are used to assign each agent a workplace and several non-essential businesses that they may frequent as described in our previous publication [14]. The frequency with which agents visit non-essential businesses is selected as the average value of available records across the three cities, collected during early spring 2021.

To spatially distribute the households, we use the U.S. Census on single and multiunit residential buildings listed in Table S1. Below, we outline the algorithm for generating households and their coordinates

1. **Collect coordinates of all residential buildings**
   Spatial coordinates of the buildings are collected manually using ArcGIS [3].

2. **Create single unit households**
   The number of single unit households, $N_{1\mathrm{H}}$, in our model is

$$N_{1\mathrm{H}} = N_{1-\mathrm{A}} + N_{1-\mathrm{D}} + N_{\mathrm{M}} + N_{\mathrm{O}}, \tag{S1}$$

   which corresponds to the total number of the relevant U.S. Census categories outlined in Table S1: 1-unit attached ($N_{1-\mathrm{A}}$), 1-unit detached ($N_{1-\mathrm{D}}$), mobile homes (N_{M}), and other (N_{O}), which represents boats, RVs, etc. In this step, we randomly choose locations collected in Step 1 and turn them into single households.

3. **Create two-unit households**
   The number of buildings with two households, $N_{2\mathrm{H}}$, is computed following the data in Table S1 as:

$$N_{2\mathrm{H}} = \left\lfloor \frac{n_{\mathrm{u},2}}{2} \right\rfloor, \tag{S2}$$

   where $n_{\mathrm{u},2}$ is the number of households located in two unit buildings and $\lfloor \cdot \rfloor$ indicates rounding off to the lowest integer. The buildings are then randomly assigned to the locations that were not selected as 1-unit in Step 2. Each of such geographic locations will thus have two households assigned to it.

4. **Create households characterized by ranges of units**
Part of the multi-unit structures in the U.S. Census data are characterized by a range of units, for example, 5–9. To create those households, we
   (a) Select the average number of units in the building, $n_{\rm i}$ that is within the reported range as listed in Table S1.
   (b) Calculate the number of buildings with $n_{\rm i}$ units, $N_{\rm iH}$:
$$N_{\rm iH} = \left\lfloor \frac{n_{\rm u,i}}{n_{\rm i}} \right\rfloor, \tag{S3}$$
   where $n_{\rm u,i}$ is the number of units in buildings with $n_{\rm i}$ households.
   (c) If enough locations are available after assigning single- and two-unit households, randomly assign $N_{\rm iH}$ buildings to a subset of the same
   (d) If there are not enough available locations, randomly select $N_{\rm iH}$ buildings with more than one unit and add $n_{\rm i}$ households to them.

5. **Generate households with more than 20 units**
For multi-unit buildings that represent complexes with 20 or more households, we follow a procedure similar to that summarized above, specifically,
   (a) Calculate the number of buildings with at least 20 units, $N_{\rm 20H}$:
$$N_{\rm 20H} = \left\lfloor \frac{n_{\rm u,20}}{20} \right\rfloor + N_{\rm E}. \tag{S4}$$
   where $n_{\rm u,20}$ is the number of units in buildings with 20 or more households and $N_{\rm E}$ is the number of buildings remaining due to rounding operations in the previous steps.
   (b) If there are enough available locations, randomly assign $N_{\rm 20H}$ buildings to have 20 household each and create the households.
   (c) If there are not enough locations, randomly select $N_{\rm 20H}$ buildings with more than one unit and add 20 households to them. This will create buildings with more than 20 households, which is still consistent with the data reported in U.S. Census.

The approach described here is different from how residential building capacity was collected in our previous work [13]. Specifically, in our previous work, multi-unit buildings were identified manually and the number of units within them were estimated based on the floor count of each structure. While our current approach involves significantly less manual assignment, it also results in a more evenly distributed population. To verify that this coarser approach of household assignment does not skew our analysis, we compare the spread of infection along three different testing efficacies in the city of New Rochelle created using manual assignment of household capacity with that using the approach described here. Figure S1 shows the number of active cases, infections, and deaths over a three-month period for three different testing and detection efficacies. Results indicate close agreement between the two approaches, effectively validating the simplified strategy for household capacity assignment for small urban areas.

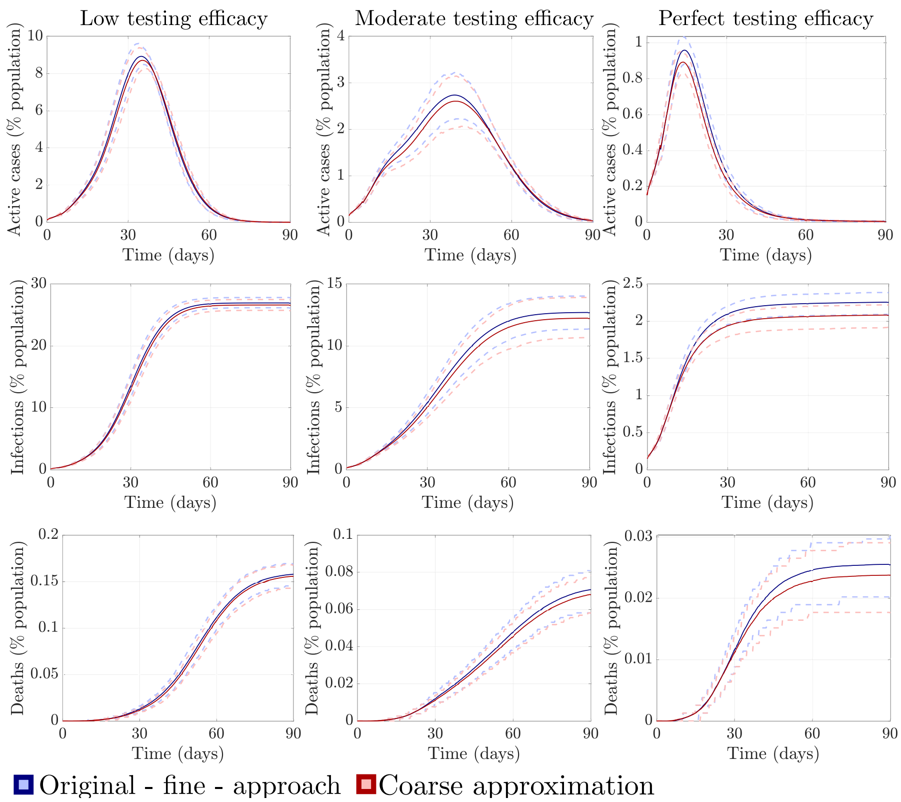

Figure S1: Simulation of the spread of COVID-19 in New Rochelle using manual assignment of household capacity and location, as implemented in our previous study [13], (blue curves) and the random assignment proposed in this work (red curves) over a time-window of three months, for three different testing and detection efficacies. Solid lines represent the average of of 400 independent realizations; dashed lines are the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles.

Units in structure	n_i	**Colonie,** $n_{u,i}$	**New Rochelle,** $n_{u,i}$	**Utica,** $n_{u,i}$
1-unit attached, N_{1-A}	1	1,150	1,364	959
1-unit detached, N_{1-D}	1	23,273	10,316	10,774
Mobile home, N_M	1	448	0	79
Other, N_O	1	0	0	0
2 units	2	2,152	1,749	7,881
3-4 units	3	1,240	3,676	3,428
5-9 units	7	1,269	623	1,646
10-19 units	14	2,481	1,127	699
20+ units	20	4,551	10,791	2,703

Table S1: U.S. Census data on housing units characteristics used in this work. We do not cite the exact tables as the reported data is subject to regular changes.

Occupation category	**Colonie**, %	**New Rochelle**, %	**Utica**, %
Management, business, science, and art	47.75	47.84	28.35
Service	16.15	16.59	28.5
Sales and office	23.67	19.31	21.98
Natural resources, construction, and maintenance	5.37	6.19	6.63
Production, transportation, and material moving	7.07	10.05	14.55

Table S2: U.S. Census occupational data in the three cities used in our work.

S2: distribution of agent occupation types

Here, we summarize the procedure for assigning occupation types to the agents using U.S. Census statistics. Occupation types and percentages of people employed in them are listed in Table S2.

Agents are assigned workplaces as follows: we first assign occupations to in-city employees; next, we determine occupations of the agents working out-of-city such as to match the U.S. Census statistics on occupational types shown in Table S2.

S3: transmission rates for different occupational categories

Agents modeling employees can either work in the city or in its vicinity, with workplaces contributing to an agent's total risk of infection. At any time step, a working susceptible agent can get infected with COVID-19 at time t with the probability

$$p_i(t) := 1 - e^{-\Delta t \Lambda_i(t)}, \tag{S5}$$

where $\Delta t = 0.25$ day is the duration of a time-step. $\Lambda_i(t)$ represents a combined risk from all the locations that the agent i is associated with,

$$\begin{aligned}\Lambda_i(t) :=& \lambda_{\mathrm{Hh},f_{\mathrm{Hh}}(i)}(t) + \lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t) + \lambda_{\mathrm{Sc},f_{\mathrm{Sc}}(i)}(t) + \lambda_{\mathrm{Rh},f_{\mathrm{Rh}}(i)}(t) \\ &+ \lambda_{\mathrm{Hsp},f_{\mathrm{Hsp}}(i)}(t) + \lambda_{\mathrm{Tr},f_{\mathrm{Tr}}(i)}(t) + \lambda_{\mathrm{N},f_{\mathrm{N}}(i,t)}(t),\end{aligned} \tag{S6}$$

where $\lambda_{\bullet,\ell}(t)$ represents the risk of infection at location ℓ at time t. The possible types of locations are: households - Hh, workplaces - W, schools - Sc, retirement homes - Rh, hospitals - Hsp, public transit and carpooling - Tr, and non-essential businesses - N. Function $f_\bullet(i)$ selects the location type that agent i is assigned to. Below, we explain the workplace contribution, $\lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t)$, and the reader is referred to our previous publications for further details [13–15].

The infection risk contribution for retirement home, hospital, and school employees is associated with corresponding dedicated terms, $\lambda_{\mathrm{Rh},f_{\mathrm{Rh}}(i)}(t)$, $\lambda_{\mathrm{Hsp},f_{\mathrm{Hsp}}(i)}(t)$, and $\lambda_{\mathrm{Sc},f_{\mathrm{Sc}}(i)}(t)$ respectively. In those cases, the generic workplace contribution is set to zero, that is, $\lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t) = 0$. If an agent works in a generic workplace, $\lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t) \neq 0$ while other contributions will depend if they are a student and are getting tested or treated for COVID-19. The form of the contribution $\lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t)$ itself depends on whether the agent works in the city or in the region around it.

The workplaces inside the cities have an occupational type assigned to them based on the SafeGraph data used to locate them [12]. The contribution $\lambda_{\mathrm{W},f_{\mathrm{W}}(i)}(t)$ of such a workplace becomes a function of all other agents working at that location,

$$\lambda_{\mathrm{W},\ell}(t) = \frac{1}{n_\ell} \sum_{j:f_{\mathrm{W}}(i)=\ell} \left(E_{j,\mathrm{W}}(t) \rho_j \beta_{\mathrm{W}}^k + Sy_{j,\mathrm{W}}(t) c_j \rho_j \psi_{\mathrm{W}} \beta_{\mathrm{W}}^k \right), \tag{S7}$$

where E_j and Sy_j are indicator functions that identify when an agent is exposed or symptomatic, respectively; $\rho_j \geq 0$ accounts for the variability in infectiousness among the agents; $c_j > 1$ reflects the increased infectiousness of a symptomatic agent compared to an exposed one; ψ_{W} denotes the fraction of agents who will still be present at their workplace, regardless of having COVID-19 symptoms; and β_{W}^k is the transmission rate of the workplace of occupational type k, as outlined in Table S2. This transmission rate may, in principle, differ among workplaces of various types, reflecting the unequal infection risk in them. For in-city workplaces, β_{W}^k is tied to a specific location and applies to any agent working in that particular workplace. That is, for agent i working in an in-city workplace, the β_{W}^k in Equation S7 has the value that corresponds to that workplace occupational type.

Infection risk from working out-of-city is approximated as

$$\lambda_{\mathrm{WO}} = \beta_{\mathrm{W}}^k \chi_I, \tag{S8}$$

where β^k_{W} is the transmission rate for occupation type k and χ_I is the regional COVID-19 prevalence, estimated from officially reported data for the entire region in vicinity of the city, where the agents work.

In our model, all agent occupations are characterized by their own transmission rates, β^k_{W}, reflecting different working conditions and their associated infection risks. To compute them, we use empirical data published by the Washington State Department of Health [20, 21] on positivity rates recorded within different occupational categories. The report groups occupations using the North American Industry Classification System (NAICS) [18], as opposed to our categorization which relies on U.S. Census Bureau Occupational Codes [16]. To utilize the results from the report, we group the NAICS occupations into the U.S. Census defined categories utilized in our model, as outlined in Table S3. We then set the positivity rate associated with each category to an average value across all grouped occupations as detailed in Table S4.

To calculate the infection rates for each occupational type k, we use scaling relative to the healthcare employees,

$$\beta^i_{\mathrm{W}} = \frac{\overline{\chi}^i}{\chi^{\mathrm{HSP}}} \beta_{\mathrm{HSP}}. \tag{S9}$$

Here, $\overline{\chi}^i$ is the average percentage of COVID-19 cases reported for industry categories classified under occupation i, χ^{HSP} is the percentage of infected healthcare workers, and β_{HSP} is our previously established healthcare employees transmission rate.

For consistency, we apply this procedure to recompute the original infection rates for school and retirement home employees. The NAICS classification and rates for these categories are also shown in Tables S3 and S4.

S4: Model parameters

The model parameters used in our work can be found in our previous publication [14]. Here, we list only the parameters that unique to this work except the workplace-related transmission rates that are already detailed in Section . Specifically, we report transmission rates adjusted to reflect the spread of the more infectious Delta variant [7].

[1] Scaled down to city size, time-step, and doubled following calibrated percentage of asymptomatic adults in Ref. [13], used as a proxy for underdetection.

[2] Scaled down to city size, time-step, and doubled following calibrated percentage of asymptomatic adults in Ref. [13], used as a proxy for underdetection; computed based on the total number of cases recovering from COVID-19 during an average recovery period used in Ref. [13]

[3] Scaled down to city size and time-step.

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Occupational category from U.S. Census [16] and this work	**NAICS categories [18]**
Management, business, science, and art	• Finance and insurance • Public administration • Professional, scientific, and technical services • Information
Service	• Other services • Arts, entertainment, and recreation • Accommodation and food services • Administrative, support, waste management, and remediation services
Sales and office	• Retail trade • Wholesale trade • Information • Professional, scientific, and technical services
Natural resources, construction, and maintenance	• Agriculture, forestry, fishing, and hunting • Construction • Mining
Production, transportation, and material moving	• Manufacturing • Transportation and warehousing
School employees	Educational services
Retirement home employees	• Healthcare and social assistance • Accommodation and food services • Other services

Table S3: Grouping of NAICS categories into occupation classification used in this work.

Occupational category	**Transmission rate**, β_{W}^{k}
Healthcare employees	2.05
Management, business, science, and art	0.2347
Service	0.3413
Sales and office	0.3627
Natural resources, construction, and maintenance	0.7253
Production, transportation, and material moving	0.6827
School employees	0.3413
Retirement home employees	0.9958

Table S4: Grouping of NAICS categories into occupation classification used in this work.

Parameter	**Value**	**References**
Household transmission rate - untreated	1.1 day^{-1}	[4] scaled by 1.41
Household transmission rate - home-isolated	0.768 day^{-1}	Assumption
Retirement home resident transmission rate - untreated	1.1 day^{-1}	Assumption
Retirement home resident transmission rate - home-isolated	0.768 day^{-1}	Assumption
School student transmission rate	2.13 day^{-1}	[4] scaled by 1.41
Transmission rate of hospital patients with a condition different than COVID-19	2.21 day^{-1}	Estimated based on data from a clinical consultant
Transmission rate of hospitalized agents	1.63 day^{-1}	Estimated based on data from a clinical consultant
Transmission rate of ICU hospitalized agents	2.14 day^{-1}	Estimated based on data from a clinical consultant
Transmission rate of infected hospital visitors being tested for COVID-19	2.8 day^{-1}	Estimated based on data from a clinical consultant
Transmission rate of agents in a carpool	1.1 day^{-1}	Assumed to be equal to $\beta_{\text{Hh,Ut}}$
Transmission rate of agents visiting other agents households	1.1 day^{-1}	Assumed to be equal to $\beta_{\text{Hh,Ut}}$
Transmission rate of agents visiting non-essential businesses	0.3648 day^{-1}	[8]

Table S5: COVID-19 transmission parameters. Assumed values were based on discussions with Clinical consultant. Transmission rates where additionally scaled by a factor of 1.6 to reflect the increased infectiousness of the then dominant Delta variant [7].

Parameter	Value	References
Latency period	log-normal distribution with 1.225 mean and 0.418 standard deviation, days	[9, 10]
Fraction of the population initially infected in the city	1.32×10^{-4}	[2][1]
Fraction of agents that are initially active COVID-19 cases	1.39×10^{-3}	[6][2]
Fraction of agents that are initially vaccinated	0.217	[11][3]
Current vaccination rate in the city, %(population)/day	0.58	[11]
Fraction of the population that is estimated to be infected in the area at a time-step, χ_I	1.32×10^{-4}	[1, 2, 19][4]
Current capacity of public transit compared to its maximum capacity, ζ	0.697	[5] for public transit
Fraction of the nominal transmission rate at workplaces, public transit, carpools, and leisure locations associated with current reopening stage (Phase 4)	0.63	[5] for workplaces
Initial fraction of agents going to leisure locations at each time-step, $\underline{\beta}_{\mathrm{N}}$	0.2	Assumption
Final fraction of agents going to leisure locations at each time-step, $\underline{\beta}_{\mathrm{N}}$	0.2	Assumption

Table S6: Other parameters. The fractions and the vaccination rate are averages of reported data across the three cities. The city populations are 82,797, 79,205, and 59,750 for Colonie, New Rochelle, and Utica, respectively [17].