





# 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

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equivalent initial conditions, we provide compelling evidence in favor of the central 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

## 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]. Along 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 COVID-19 pandemic in urban environments, in search of characteristics that influence its spread, often toward 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 segments of the population. 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.

## 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 at the resolution of a single individual. The core framework is described in our earlier publications [34, 35, 42], to which we point the interested reader for further details.

### Database

The database of each city contains the coordinates of all the public and residential buildings along with resident demographics. With this information, we 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 US 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, as recorded by the 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 not hospitalize

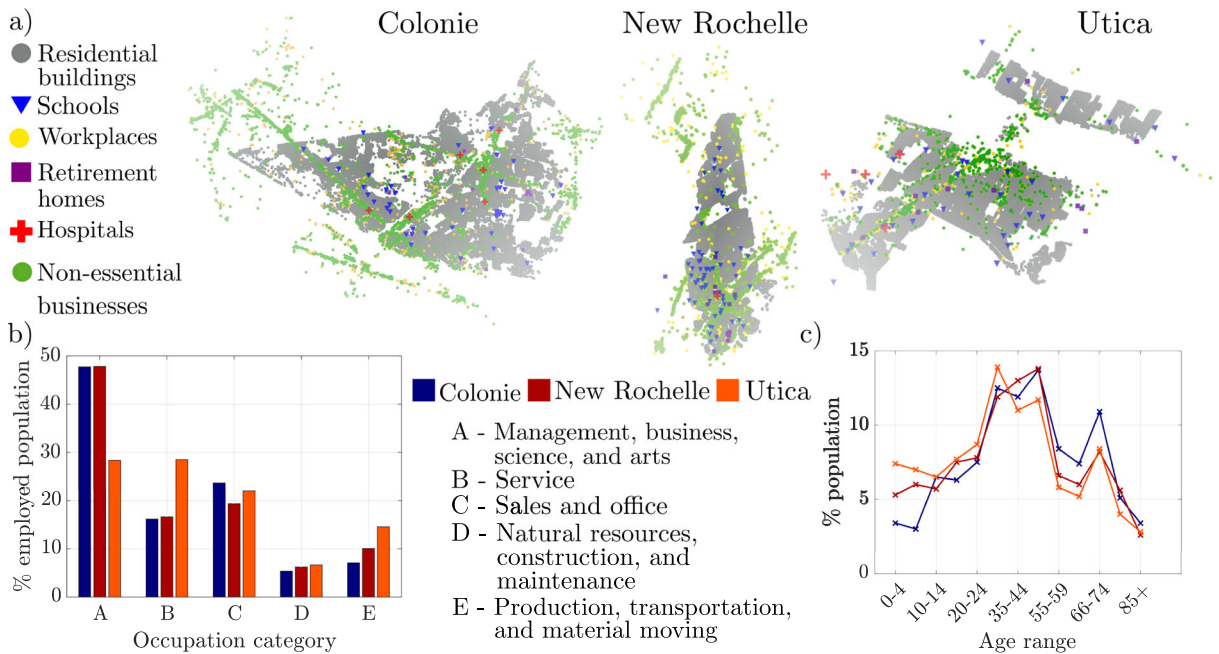
patients. Consistent with the premise of lack of hospitalization, we assumed that none of the virtual bed capacity of Colonie was allocated to patients with conditions other than COVID-19.

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 Fig. 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 there were divided into five occupational categories, as shown in Fig. 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



**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

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 of 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 the corresponding category-specific transmission rate. Overall, the employment type distribution matches the U.S. Census data [48] with details on its distribution and rate computation enclosed in the [Supplementary Material](#).

The age distributions of the cities’ residents are shown in Fig. 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.

### 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, go to school, visit non-essential businesses, visit each other, and travel to work through

**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%  |

various transit means, consistent with the database described in “[Database](#)”.

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 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 are tested with a certain probability. We refer to this likelihood as testing and detection efficacy (low, moderate, or perfect). A low efficacy corresponds to testing 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 tested, and perfect efficacy means that all infected agents are tested. Testing accounts for false positive and false negative results, as detailed in [42]. 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], the 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 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 have been incorporated within our simulation framework in a separate publication [35].

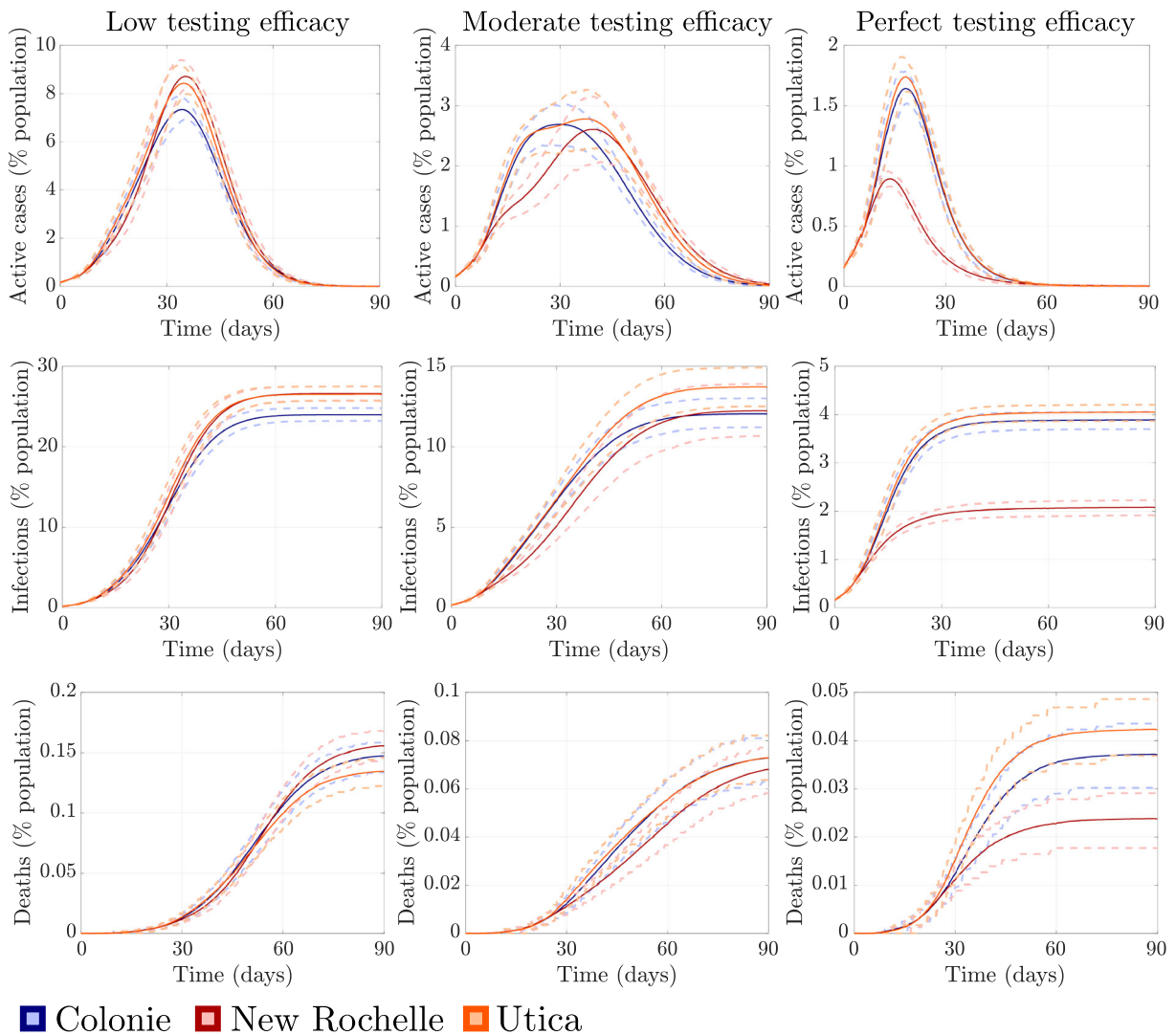
The core parameters used in the model are described in detail in our previous works. Following our most recent study [35], we simulate the Delta variant of the virus with epidemiological parameters calibrated on clinical estimations [62, 63]. Since our goal was to analyze the impact of non-epidemiological 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](#).

## Results

### COVID-19 Spread in the Three Cities

Starting from the same initial conditions, we simulated 3 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 Fig. 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.





**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 3 months, for three different testing

and detection efficacies. Solid lines represent the average of 400 independent realizations; dashed lines are the 25<sup>th</sup> and 75<sup>th</sup> percentiles

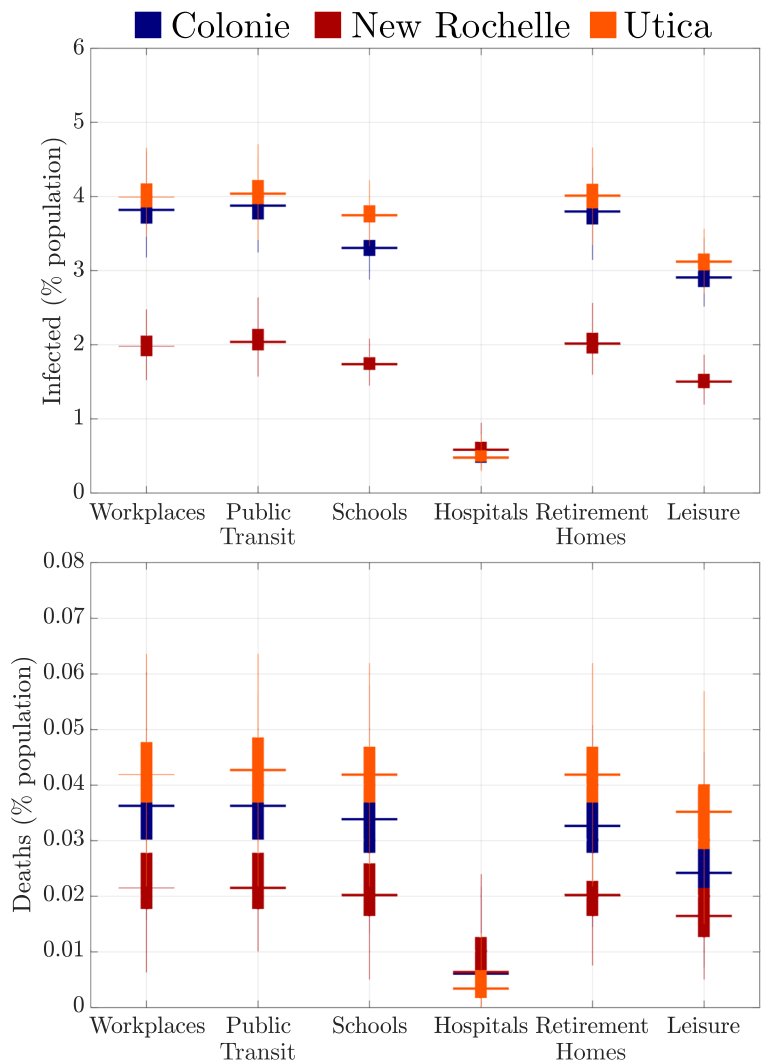
### Identification of Major COVID-19 Hubs Under Perfect Testing and Detection Efficacy

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 (technically, by setting the corresponding transmission rate to 0). Among location types, we also include public transit to delve into observed

differences among cities as reported in Table 1. In this way, we simulated the spread in the three cities without agents being infected at generic workplaces, public transportation, schools, hospitals, retirement homes, or non-essential business locations, respectively.

According to the results shown in Fig. 3, the spread in Colonie and Utica is comparable to the one in New Rochelle only if hospitals are excluded from transmission. Note that this trend is preserved even after the exclusion of infections in public transit, which is markedly more used by the residents of

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



New Rochelle than the other two towns (as reported in Table 1). 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). Thus, New Rochelle provides less routes for COVID-19 to spread

from hospital employees who are positive but still performing their duties.

While our simulation results are suggestive of a key role of hospitals 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 select types of agents in hospitals from the transmission dynamics. 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 Fig. 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, suggesting their prominent role as main spreaders within hospital facilities.

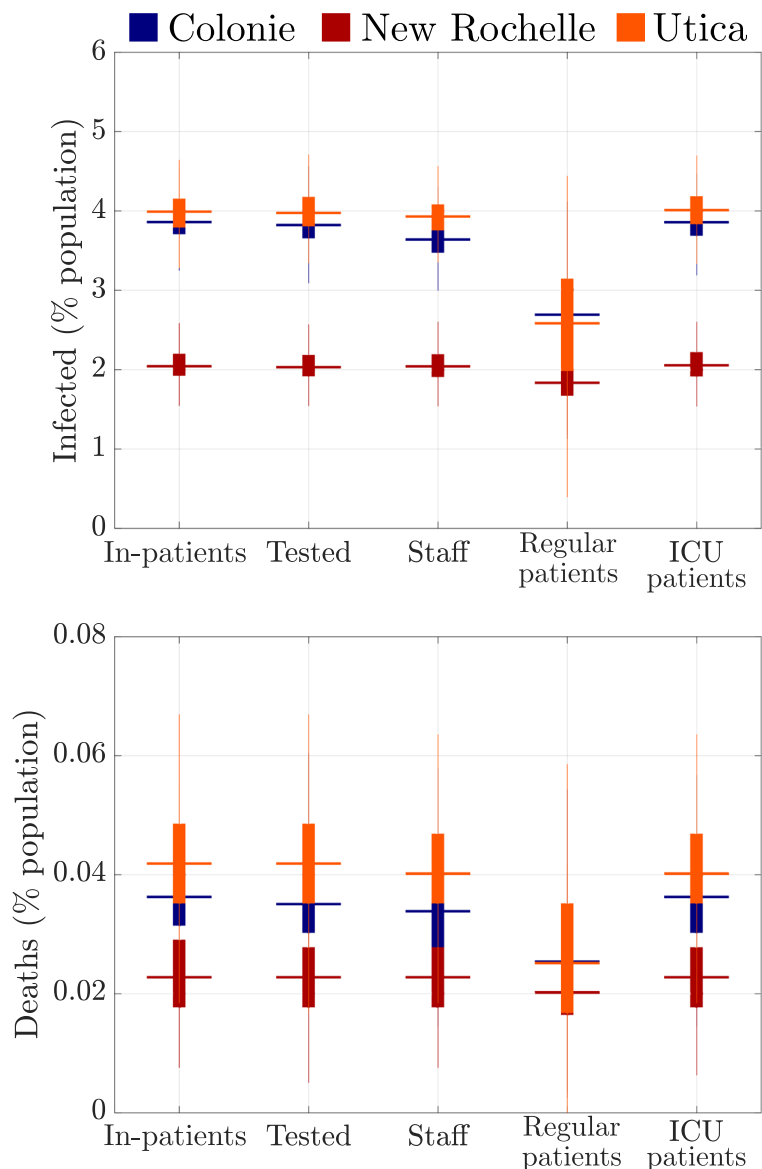
### Effect of Vaccinating Hospital Employees

Results in Fig. 4 lead us to formulate the hypothesis that an important route for COVID-19 generates from

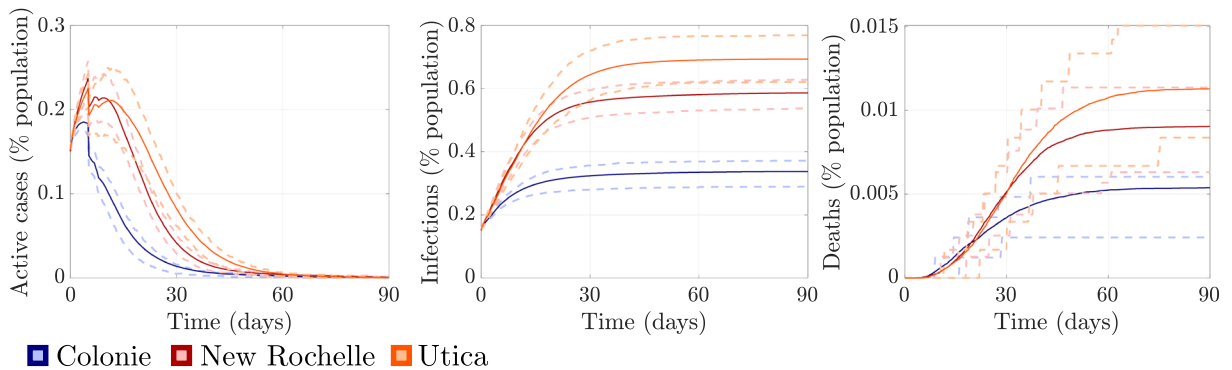
hospitals, among patients, and spreads outside, due to infected employees who could interact with others between the time the infection is contracted and the emergence of symptoms or the positive outcome of a test. Under this premise, vaccinating hospital employees becomes of paramount importance.

To further back this claim, we performed an additional simulation study in which we vaccinated all the initially healthy hospital employees. Under the assumption of perfect immunity, results in Fig. 5 confirm that vaccination of healthcare employees greatly reduces the toll of the epidemic. Importantly, the immunity of

**Fig. 4** Final COVID-19 toll (infections and deaths) after simulating a 3-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







**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 25<sup>th</sup> and 75<sup>th</sup> percentiles

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) vaccination of healthcare workers.

## 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 such a difference is mainly 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, 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 sixfold, 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 in other works [67–70], while hospitals have been identified as dominant COVID-19 hubs 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 are 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 features may partly reduce differences in the number of deaths between the three cities. However, we do not anticipate dramatic changes from the inclusion of these features.

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 Contribution** 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** 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](https://github.com/Dynamical-Systems-Laboratory/DSL_ABM-Multitown)

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