Agent-Based Modeling of Gun Ownership Trends in New York City

Andalib Samandari[1], Kevin Slote[1], Advisors: Dr. Igor Belykh[1] and Dr. Maurizio Porfiri[2]

1) Georgia State University, 2) New York University

Abstract

Gun violence is one of America's most pressing issues, with tens of thousands lives lost annually. In an effort to aid reduction of gun violence, we seek to understand driving factors behind gun purchases in New York City. Taking data from the US Census, NYC historical redlining schematics and CDC data on gun-related deaths, we created an agent-based model of NYC and used it to test our hypothesis that three main factors contribute to and modulate gun purchases: crimes, social influence, and social grouping based on demographics. Specifically, we hypothesize that people are more likely to buy guns when the local crime rate is higher, and also when their friends and neighbors are purchasing guns. Additionally, we hypothesize that the interpersonal connections governing the social influence parameter are related to demographics.

Methodology

Our model draws on two primary concepts: agent-based modeling (ABM) and the susceptible-infected (SI) model from mathematical biology.

ABM is a computational paradigm to simulate actions and interactions of distinct entities, or "agents". They are also used to examine emergent phenomena in the dynamical system resulting from the interactions of groups of agents [1][2].

The SI model is used to model the spread of disease in a very simplified context, where all members of the population are in either the "susceptible" or "infected" category. Recovery or death of infected individuals is ignored in this simplified model, meaning that as an SI model runs forever, the entire population will become infected.

In our model, each agent is a census tract of NYC, and these agents are nodes in a graph of the entire city. Nodes are connected in a rook graph, i.e., to their bordering neighbors. We assume all the people in a census tract have similar responses to local events, and therefore represent them as a single agent. Edges between nodes represent social interactions between their respective populations.

Figure 1 NYC census tracts divided into clustered subgraphs, via K-Means clustering on race, median household income and redlining attributes.

We further divided this graph into 5 subgraphs identified through similarity of the demographic variables of race, median household income and historic redlining. We assume that social connections are strongest among individuals with similar demographics as in the Schelling model of segregation [3]; but we note that this is merely a model and may not capture all social interactions accurately. After this subdivision, nodes are only connected to their immediate neighbors of the same cluster type. The resulting graph is shown in **Figure 1**. Finally, we represented the purchase of guns as an "infection" propagating across our node subnetworks and evaluated trends in gun purchase rates using the SI model.

Our model is written in Python using the Mesa agent-based modeling library, NetworkX for the graph representation and various data science libraries (e.g., NumPy, GeoPandas, Matplotlib) for other calculations and map generation.

Mathematical model

Agent-based models operate by checking the "rules" of individual agents at each discrete time step. Behavior at the collective level emerges from individual actions.

For each node *i*, we generate two uniform random variables at every time step:

$$x_1, x_2 \sim U[0,1]$$

We apply two rules to compare the values of these variables, a network rule and a local rule. For a given node at a particular time step, if either variable is below or at the threshold set by its corresponding rule, that node becomes infected.

Network rule: *I* is the number of infected neighboring nodes and *n* is total neighbors. *p* modulates the strength of this rule (bigger *p* = stronger rule).

$$x_1 \leq p * \frac{I}{n}$$

Local rule: *P(crime)* is calculated by what proportion of violent crimes in NYC in the last ~30 years occurred in a given node. It has been normalized for population density of the node. *q* modulates the strength of this rule.

$$x_2 \leq q * P(crime)$$

ABM validation

We evaluated the realism of our model output by comparing it to an established [4] proxy data for gun ownership rates, suicide-by-gun rates, in NYC. While it is possible to compare the results of our model with this data numerically, we only had access to a map of the data at this time. As a note, gun violence research in the US is uniquely challenging from a data science perspective, as a firearm registry is unconstitutional and therefore only proxy data can be used for gun counts. Our validation data is shown in **Figure 2**.

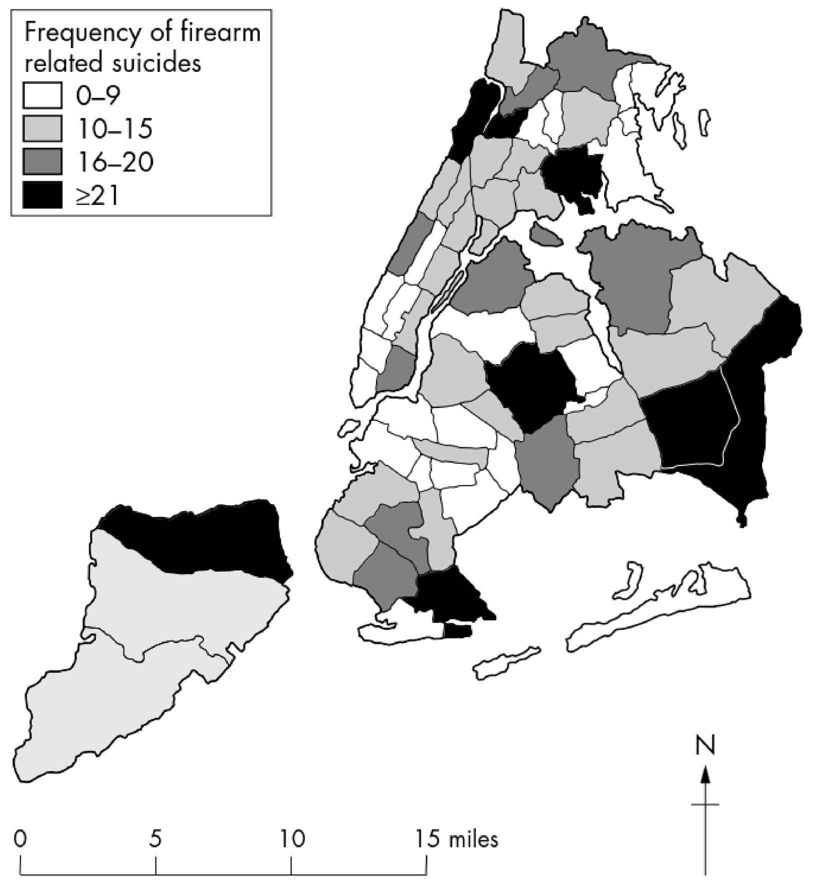

Figure 2 Frequency of firearm-related suicides by place of residence in NYC for the years 1999-2000. [5]

Results

We ran our model in four configurations: randomly infecting 9% of nodes at the start, and ignoring clusters; randomly infecting 9%, but disconnecting nodes of different clusters; infecting the top 9% of nodes by crime rate and ignoring clusters; and infecting the top 9% while also disconnecting based on clusters. Each model ran for 44 steps, based on the smallest characteristic time across all configurations, and results were then averaged over 1000 independent trials of each configuration. We compared the averaged output of each configuration to see how many nodes were consistently infected. Results are in **Figures 3-6**.

References

[1] Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. International Journal of Research in Marketing, 28(3), 181–193. https://doi.org/10.1016/j.ijresmar.2011.04.002
[2] Romano, D. M., Lomax, L., & Richmond, P. (2009). NARCSim an agent-based illegal drug market simulation. 2009 International IEEE Consumer Electronics Society's Games Innovations Conference. https://doi.org/10.1109/icegic.2009.5293584
[3] A., B. L. M. (2021). Introduction to urban science: Evidence and theory of cities as Complex Systems. MIT Press.
[4] Barak-Ventura, R., Marín, M. R., & Porfiri, M. (2022). A spatiotemporal model of firearm ownership in the United States. Patterns, 3(8), 100546. https://doi.org/10.1016/j.patter.2022.100546
[5] Piper, T. M., Tracy, M., Bucciarelli, A., Tardiff, K., & Galea, S. (2006). Firearm suicide in New York City in the 1990s. Injury Prevention, 12(1), 41–45. https://doi.org/10.1136/ip.2005.008953

Key: After averaging results across 1000 trials, *red nodes were infected more than half the time, while blue nodes were not*. Grey areas correspond to census tracts with 0 population and were not considered as nodes in the agent-based simulation.

In **Figure 3**, 10.2% of nodes remained infected.

In **Figure 4**, 6.0% of nodes remained infected.

In **Figure 5**, 20.6% of nodes remained infected.

In **Figure 6**, 17.8% of nodes remained infected.

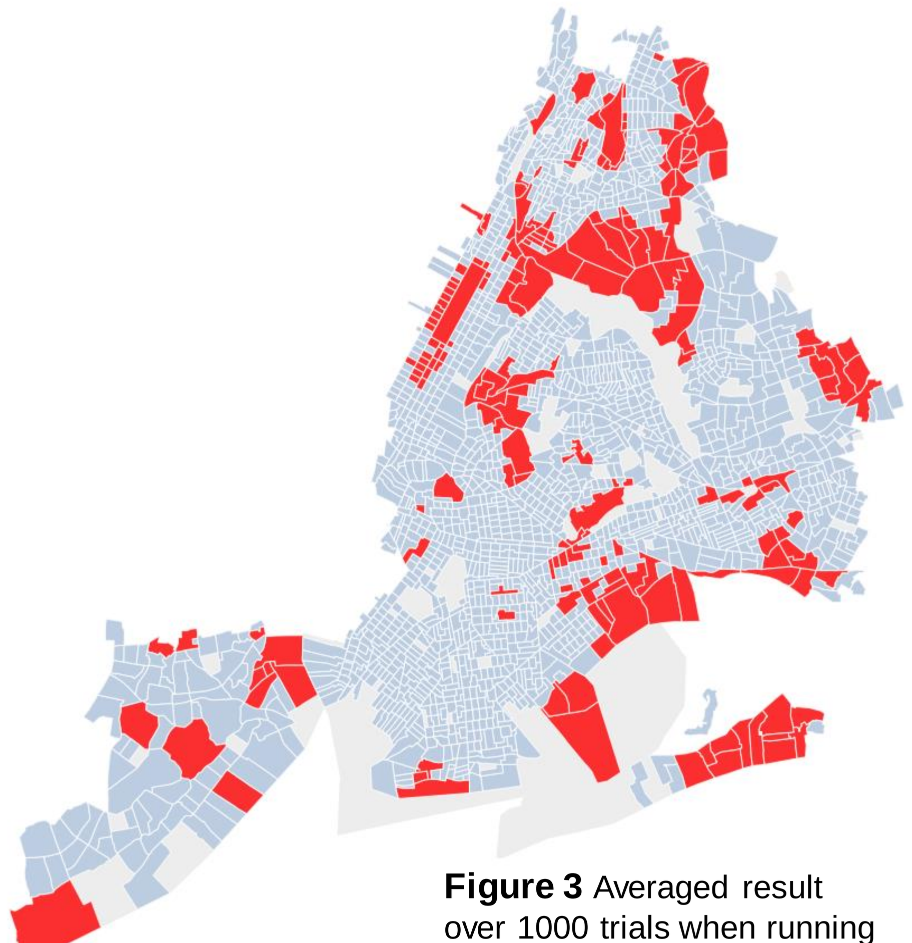

Figure 3 Averaged result over 1000 trials when running our model with random initial conditions and no clusters.

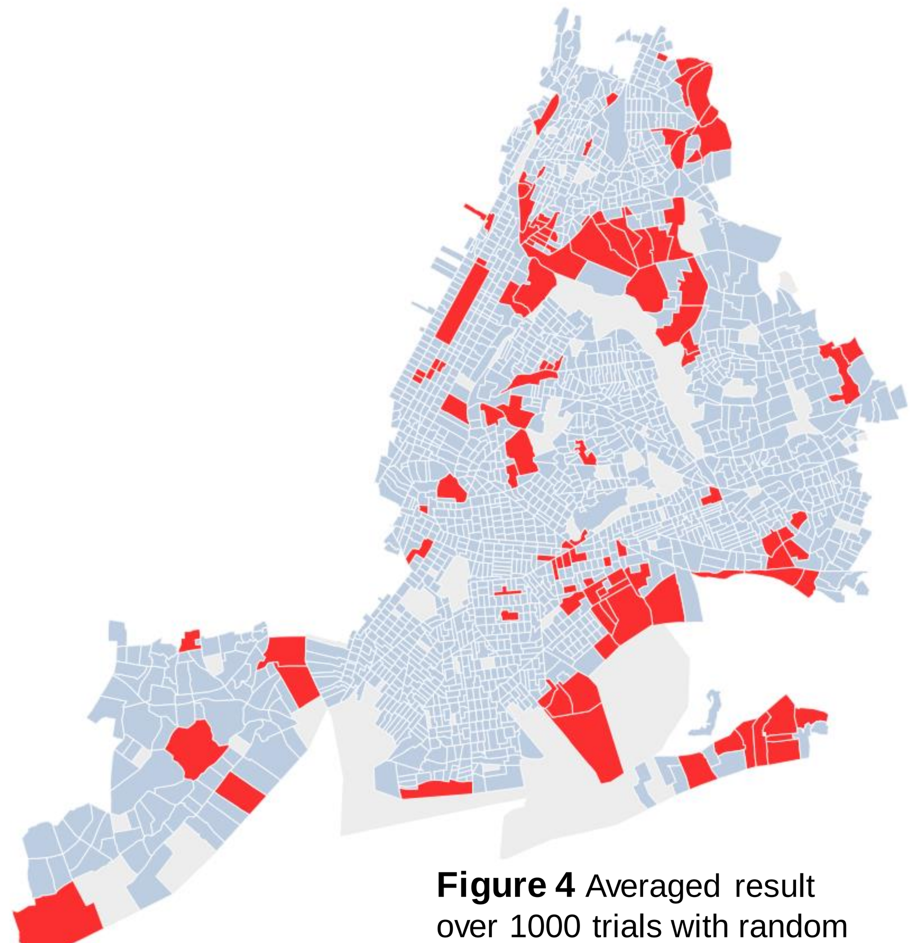

Figure 4 Averaged result over 1000 trials with random initial conditions and demographic clusters.

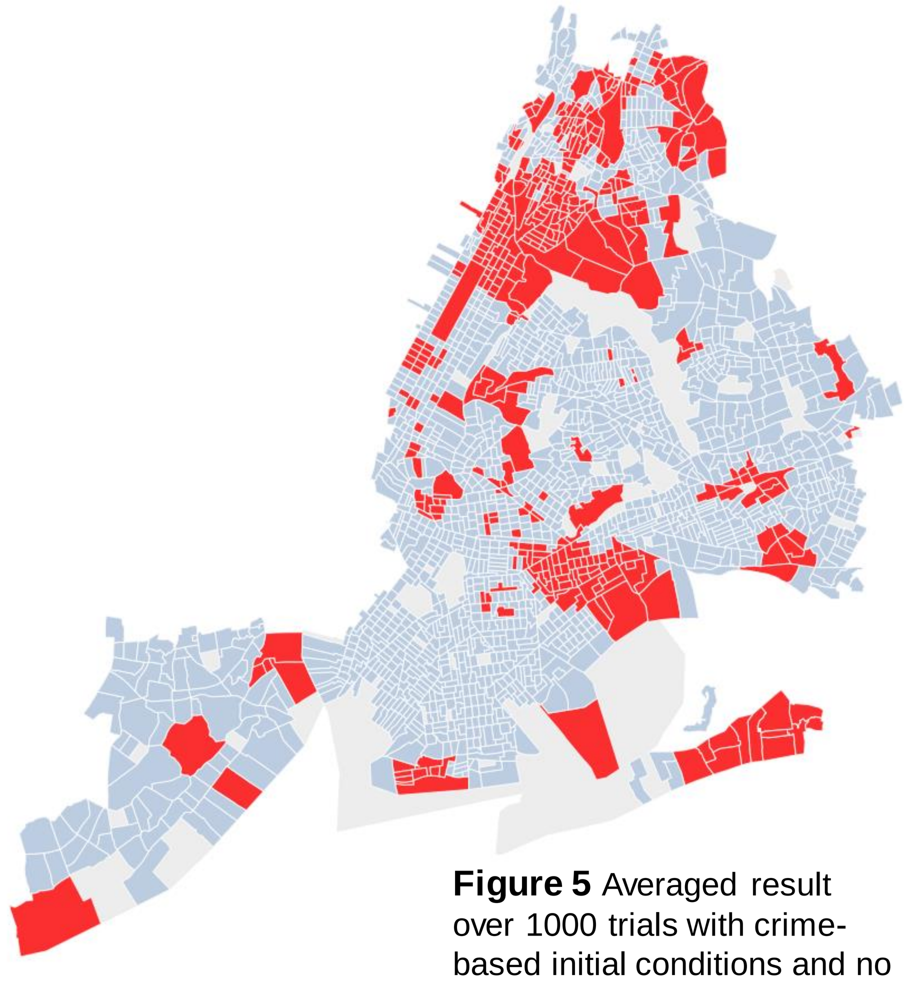

Figure 5 Averaged result over 1000 trials with crime-based initial conditions and no clusters.

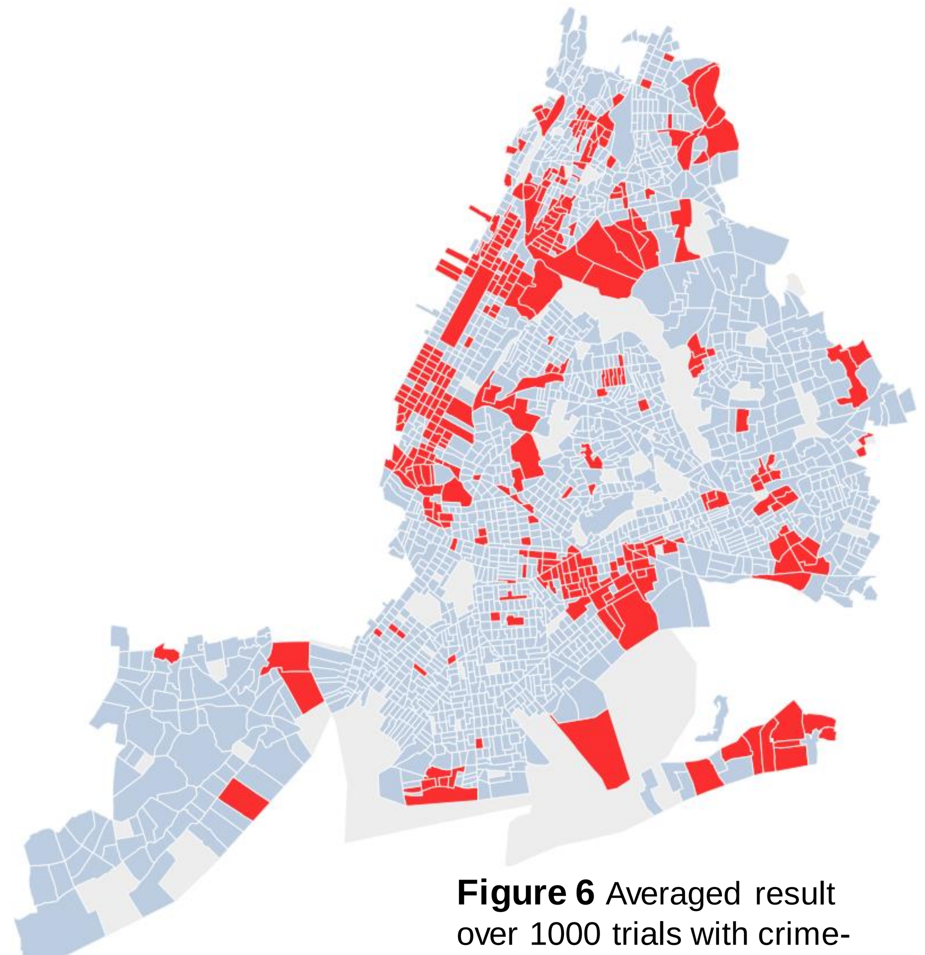

Figure 6 Averaged result over 1000 trials with crime-based initial conditions and demographic clusters.

Conclusions

Our results suggest that local crime rate is a significant driver of gun purchases, and that restricting social pressure to demographic clusters hampers the spread of gun purchasing behavior. However, without access to the suicide data we were unable to validate our model and determine if it accurately depicts trends in NYC. While further validation testing is required, agent-based modeling appears to be a promising method to explore drivers of gun purchases. Future work may include identifying "immune" nodes, which never become infected, that result in the desired output being reached in the long run. We could then analyze empirical data for possible explanations of node immunity. We hope to develop a model that can be used to understand trends and drivers of gun purchases in general American urban environments and help bring insight on gun violence and gun-related crimes.

Acknowledgements

I am grateful to Dr. Belykh for his mentorship working on this project, and to his PhD student Kevin Slote who wrote the original version of the model and helped me work on this one. I am also grateful to the LSAMP Fellowship for sponsoring me this year, and to the NSF grant (no. CMMI-1953135) supporting the Belykh Lab at GSU.