System Dynamics Modeling of NYC Congestion Pricing: The Long Run Performance of Toll Schedules 2025-2031

Danni Lu[1,*], Ying Qian[3,*], Charlle LeeSy[1], Yeonkyeong Gina Park[2], Tim Fraser[1], Haoyu Wan[1], Laijun zhao[3], Haiyan Deng[1]

1. Systems Engineering, Cornell University
2. Civil and Environmental Engineering, Cornell University
3. Business School, University of Shanghai for Science and Technology

* Corresponding Author

Abstract

In 2025, New York City implemented a landmark congestion pricing policy within the Manhattan Congestion Relief Zone (CRZ). Early evidence suggests reductions in core-area traffic volumes; however, the long-run dynamic impacts remain uncertain. These extended effects include traffic diversion, multimodal behavioral adaptation, transit crowding, and evolving regional congestion patterns. This study develops a preliminary System Dynamics (SD) model to evaluate the long-term effects of the 2025, 2028, and 2031 toll schedules. The model explicitly represents feedback among toll pricing, relative driving attractiveness, traffic volume, transit ridership, peripheral congestion, and toll-revenue reinvestment. Preliminary calibration reproduces observed 2025 monthly CRZ entries and transit ridership with a mean relative error below 5%, suggesting that the model captures the short-term behavioral response to the initial pricing phase. Simulation results further indicate that policy effects are front-loaded, with the largest reductions occurring during the initial implementation period, followed by a goal-seeking stabilization driven by dominant balancing feedback. These findings suggest that the long-run performance of congestion pricing depends not only on suppressing core-area traffic, but also on transit absorption capacity and complementary reinvestment strategies.

Key words: congestion pricing; system dynamics; urban transportation; traffic congestion; public transport

1. Introduction

Urban transportation systems are shaped by complex interactions among travel behavior, infrastructure capacity, land use, and public policy. Because these systems evolve through feedback loops, stock accumulation, time delays, and nonlinear behavioral responses, transportation interventions often generate outcomes that are difficult to anticipate using static or equilibrium-based approaches [1-6]. System Dynamics (SD) has therefore become an increasingly valuable framework for transportation policy analysis, particularly for long-horizon problems involving uncertainty, behavioral adaptation, and trade-offs among congestion relief, environmental performance, and broader social outcomes [1-6, 10, 11].

These strengths are especially relevant to congestion pricing. Prior SD and dynamic simulation studies show that pricing policies do not simply reduce vehicle entries in a mechanical way; they also trigger changes in route choice, modal substitution, transit demand, and longer-run system performance [7-9, 12]. Research on sustainable urban transportation further suggests that congestion pricing is most effective when embedded in a broader policy package that includes transit enhancement, reinvestment strategies, and complementary demand-management measures [10-12]. At the same time, the wider congestion-pricing literature has highlighted effects beyond traffic reduction alone, including spillover congestion, safety implications, and distributional concerns across traveler groups and neighborhoods [12, 13].

New York City's 2025 congestion pricing program provides a timely and policy-relevant case for examining these dynamics. As the first large-scale program of its kind in the United States, it offers an opportunity to study not only immediate traffic reduction within the Manhattan Congestion Relief Zone (CRZ), but also the longer-run evolution of commuter adaptation, transit crowding, peripheral traffic diversion, and the effects of toll-revenue reinvestment [7-9, 12, 14, 15]. However, limited work has integrated phased toll escalation, multimodal behavioral response, spillover congestion, and reinvestment feedback within a single SD framework tailored to a dense multimodal metropolitan context. In response, this study develops a preliminary SD model of the Manhattan CRZ to evaluate how toll pricing, relative driving attractiveness, transit ridership, peripheral congestion, and accumulated toll revenue jointly shape the long-term performance of the policy. Consistent with the present paper's scope, the model is designed to support scenario testing across the 2025, 2028, and 2031 toll schedules and to inform more adaptive congestion-pricing strategies.

2. Methodology

This research shifts the analytical lens toward endogenous dynamic feedback modeling. We formulated Causal Loop Diagrams (CLDs) to conceptualize the interactions among key variables, including toll pricing, the relative driving attractiveness of the Congestion Relief Zone (CRZ), and toll revenue [1, 3, 4] (Figure 1). The model's structure is defined by five primary balancing loops. The exogenous toll schedule is determined by the specific policy phase, vehicle type, and time of day.

The first loop, B1 (Price Effect), represents the direct economic deterrent where toll pricing reduces the relative attractiveness of driving into the CRZ, thereby lowering trip demand and total traffic volume. B2 (Crowding Effect) captures the endogenous impact of congestion; as traffic volume increases, travel times rise, which subsequently diminishes the desire to drive within the CRZ. B3

(Spillover Effect) describes a spatial feedback loop: as the CRZ becomes less attractive and drivers opt for peripheral routes, the resulting increase in peripheral traffic volume and travel times eventually restores the relative attractiveness of driving within the CRZ. Furthermore, B4 (Transit Mode Shift) accounts for modal substitution; a decrease in driving attractiveness shifts commuters toward public transit. However, as transit occupancy increases, the resulting decline in comfort may push some users back to private vehicles. Finally, B5 (Toll Revenue Reinvestment) represents a policy-driven feedback loop where toll revenues are reinvested into transit infrastructure. This improves transit service quality and attractiveness, further reducing the relative appeal of driving in the CRZ and reinforcing the policy's long-term goals.

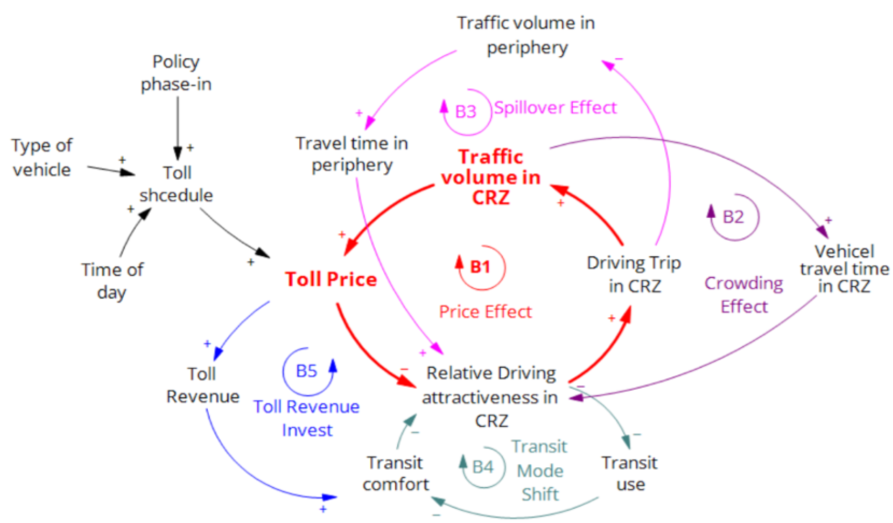


Figure 1. Causal Loop Diagram Illustrating Feedback Mechanisms of NYC Congestion Pricing Policy

To transition from the qualitative feedback identified in the CLDs (Figure 1) to a quantitative simulation, the system was formalized into a Stock and Flow Diagram (SFD) (Figure 2). This conversion process adheres to the core SD principle that behavior is generated by the accumulation of physical or information states over time.

In this model, the stocks (levels) represent the system's state at any given moment—most notably the Accumulated Toll Revenue and the Traffic Volume within the CRZ. The flows (rates), such as the Entry Rate of vehicles and the Revenue Collection Rate, represent the dynamic changes occurring within each time step (dt).

Moving beyond static equilibrium models, this research incorporates a dynamic logistic choice function to endogenize mode shift probabilities (Eq. 1). By formalizing "relative driving attractiveness" as a function of real-time system performance, the model can simulate how commuters dynamically react to evolving toll schedules. The utility function (Eq. 2) balances internal CRZ factors against external transit conditions and peripheral traffic, providing a high-fidelity representation of urban mobility responses. This function is influenced by travel time, toll levels, transit performance, and periphery congestion to accurately simulate mode shifts [5, 6, 8].

$$A_{drive}^{CRZ} = \frac{1}{1+\exp\left(-U_{drive}^{CRZ}\right)} \tag{1}$$

$$U_{drive}^{CRZ} = U_0 - \alpha\left(\frac{TT_{CRZ}}{TT_{CRZ}^{ref}} - 1\right) - \beta\left(\frac{Toll}{Toll^{ref}} - 1\right) + \gamma\left(\frac{Transit}{Transit^{ref}} - 1\right) + \delta\left(\frac{TT_{peri}}{TT_{peri}^{ref}} - 1\right) \tag{2}$$

Variables Definitions: A_{drive}^{CRZ} is relative driving attractiveness; U_{drive}^{CRZ} is the driving utility in CRZ; U_0: Baseline Driving Utility; TT_{CRZ}^{ref} represents reference vehicle travel time in CRZ; TT_{CRZ} is vehicle travel time in CRZ; $Toll^{ref}$ is reference toll pricing in CRZ; $Toll$ is toll pricing in CRZ; $Transit^{ref}$ is reference transit ridership in CRZ; $Transit$ is transit ridership in CRZ; TT_{peri}^{ref} is reference periphery travel time in CRZ; TT_{peri} is periphery travel time in CRZ; $\alpha, \beta, \gamma, \delta$ are the sensitivity to CRZ travel time, toll pricing, transit condition, periphery congestion.

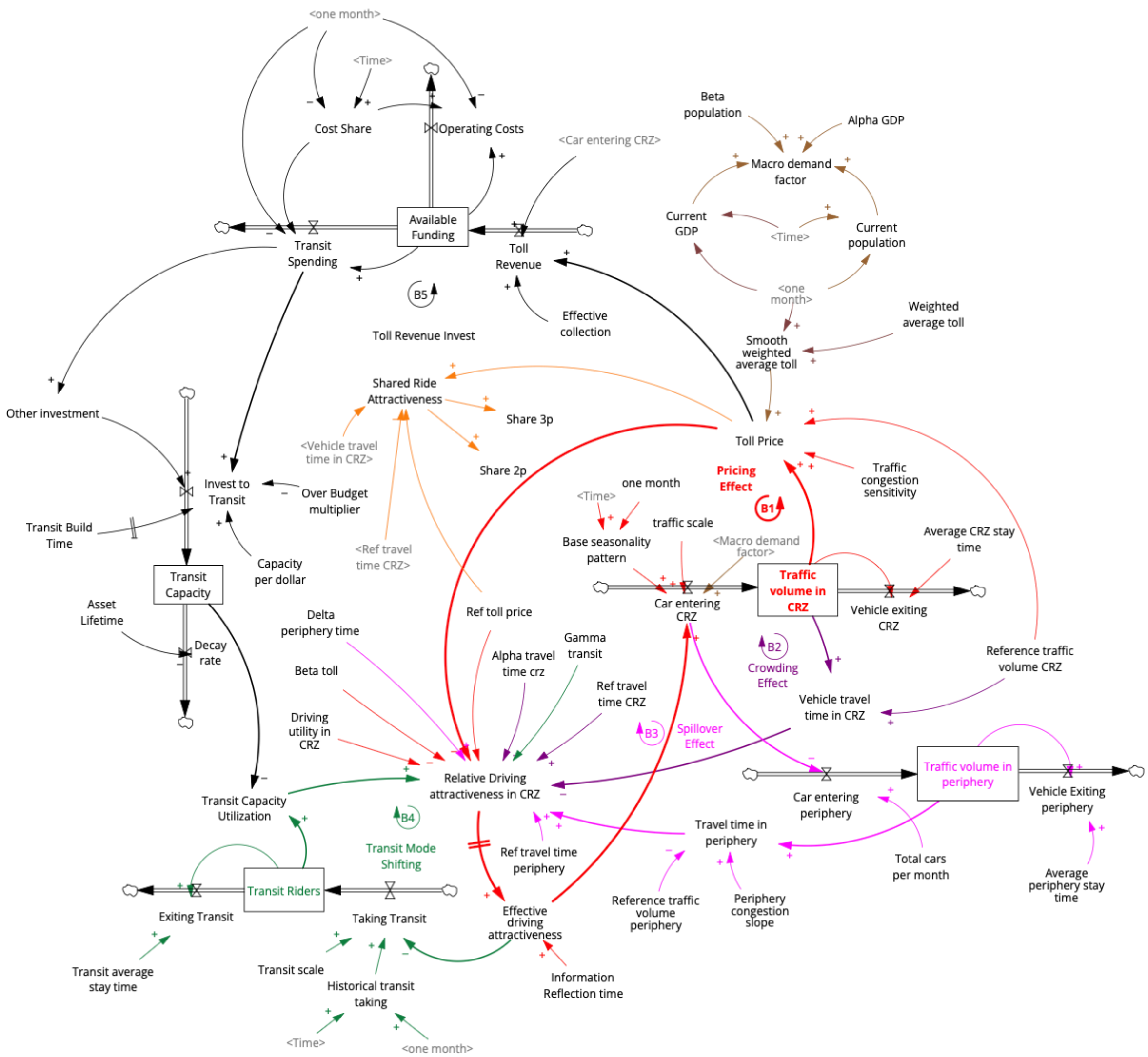


Figure 2. Stock and Flow Formalization of Multimodal Travel Behavior and Toll Revenue

Adhering to established system dynamics protocols (Figure 3), the model follows a rigorous three-stage methodological framework: calibration, validation, and scenario simulation. During the calibration phase, historical traffic volumes entering the Congestion Relief Zone (CRZ) prior to 2025 served as the baseline input for the Vensim. Model parameters were iteratively refined by benchmarking simulated outputs against empirical data from the 2025 policy implementation until the average relative error was minimized below a 5% threshold.

To ensure structural and behavioral integrity, the calibrated model was subjected to a comprehensive validation suite, including direct structural tests (e.g., boundary adequacy and dimensional consistency), structure-oriented behavior tests (e.g., sensitivity and extreme condition analysis), and behavior reproduction tests. Finally, the validated model was deployed for a decadal simulation (2023-2033). This phase utilizes step functions to exogenously represent the phased rollout of tolling policies scheduled for 2025, 2028, and 2031, allowing for a comparative analysis of their long-term impacts.

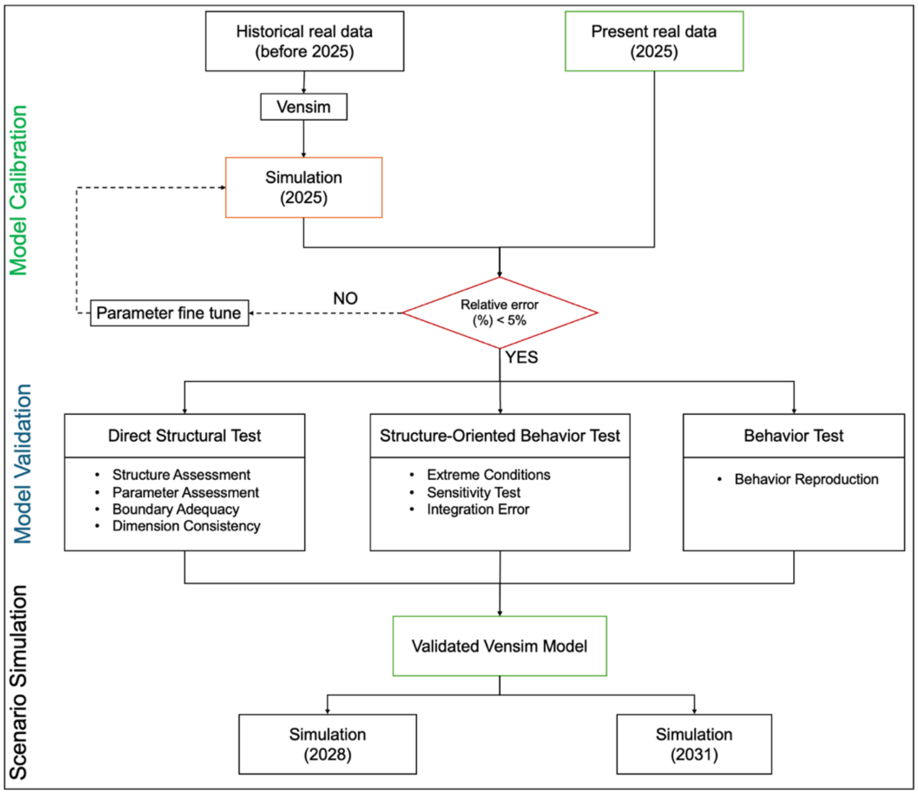
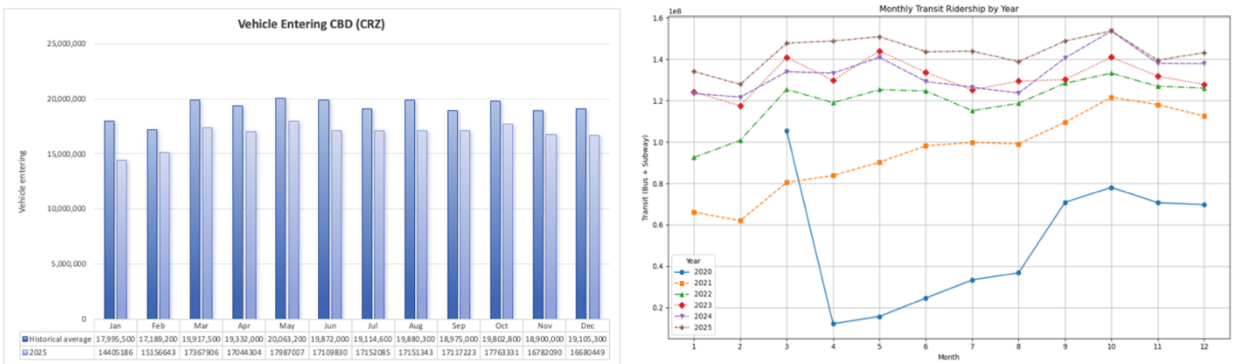


Figure 3. Methodological Framework for Model Calibration and Validation

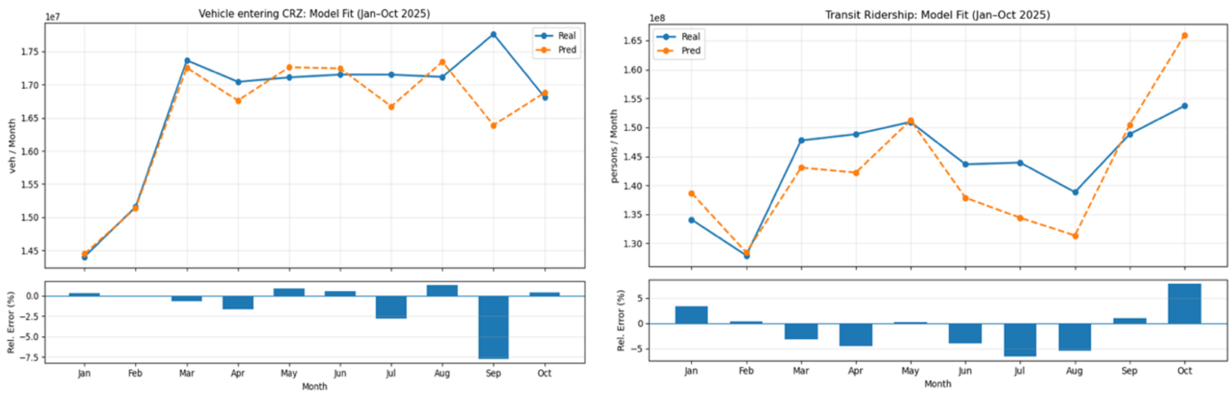
3. Results

To establish the empirical basis of the model, historical reference modes were constructed using CRZ vehicle entry data (Figure 4a) and regional transit ridership trends spanning the pre- and early post-implementation period (Figure 4b). The preliminary calibration reproduces observed 2025 monthly CRZ entries (Figure 5a) and transit ridership (Figure 5b) with a mean relative error below 5%, indicating that the current model structure can capture the short-term behavioral response of travelers to the initial congestion pricing phase. In particular, the close fit suggests that the model's endogenous treatment of relative driving attractiveness—through toll levels, travel time, transit conditions, and peripheral congestion—provides a credible representation of early mode-shift dynamics.



(a) (b)

Figure 4. Reference Modes for (a) Vehicle Entries into the CRZ and (b) Transit Ridership



(a) (b)

Figure 5. Calibration Results of Comparing Simulated and Observed Data for (a) CRZ Vehicle Entries and (b) Transit Ridership

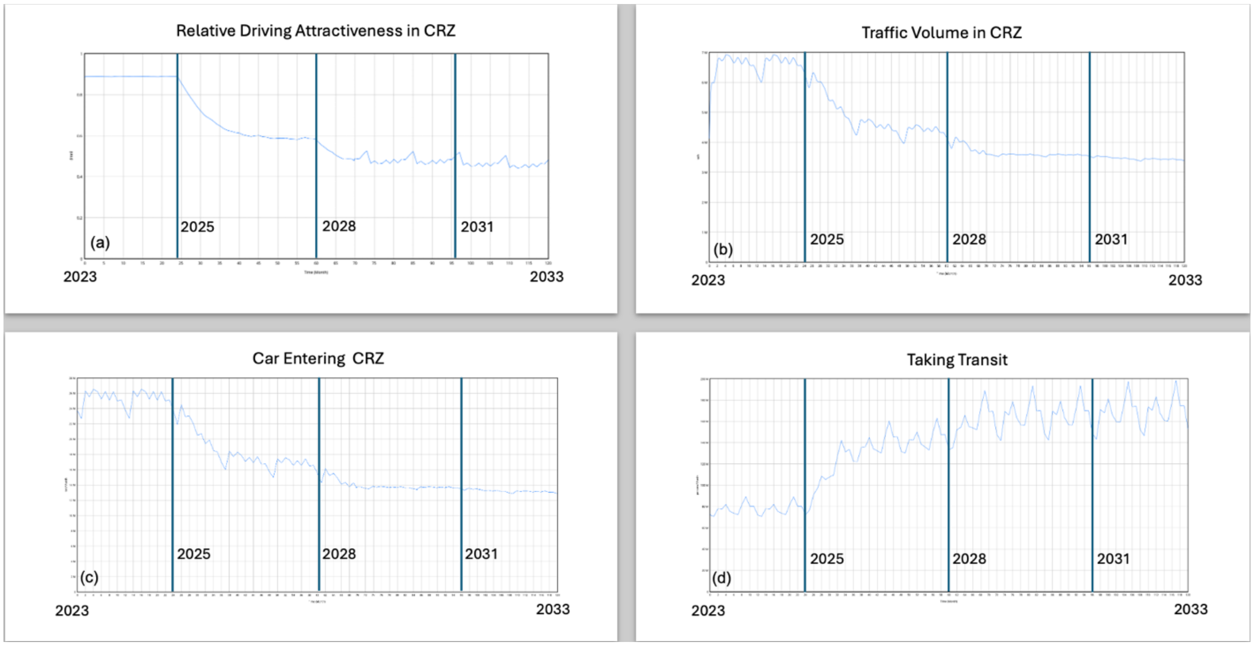


Figure 6. Dynamic Responses of Key Transportation Variables to Phased Congestion Pricing in the CRZ (2023-2033): (a) relative driving attractiveness in the CRZ, (b) traffic volume in the CRZ, (c) cars entering the CRZ, and (d) transit ridership.

Figure 6 provides a more detailed view of the system's dynamic response to phased congestion pricing. Figure 6a shows that relative driving attractiveness declines sharply following the initial 2025 toll implementation, indicating that the policy first operates by weakening the appeal of driving into the CRZ. Figure 6b and 6c show corresponding reductions in traffic volume and vehicle entries, suggesting that this decline in driving attractiveness is translated into observable system-level behavioral change rather than remaining only a latent preference shift. Figure 6d, by contrast, shows a rise in transit ridership over time, indicating that public transit functions as a primary absorption channel for displaced travel demand.

Taken together, these simulation results provide several preliminary dynamic insights. First, the policy effect appears to be strongly front-loaded: the initial implementation phase produces the steepest reduction in relative driving attractiveness and CRZ traffic volume. This suggests that early pricing intervention has the largest immediate leverage on commuter behavior. Second, the effect of subsequent policy phases is not linear. As the simulation progresses, the dominant balancing loops increasingly dampen further reductions, producing a classic goal-seeking trajectory rather than a continuously declining one. In substantive terms, this means that congestion pricing acts less as a one-time elimination mechanism and more as a stabilization policy that shifts the system toward a lower-congestion equilibrium.

The results also point to an important policy implication: reductions in CRZ traffic should not be interpreted in isolation. Because the model structure explicitly incorporates spillover congestion, transit crowding, and toll-revenue reinvestment, the long-run effectiveness of the policy depends on whether reductions in core-area traffic are matched by sufficient transit capacity and complementary reinvestment strategies. In other words, the preliminary findings suggest that the success of congestion pricing is determined not only by how much traffic is suppressed in the core, but also by how well the surrounding urban transport system absorbs the displaced demand over time. This makes reinvestment design central to policy performance in the later implementation phases.

4. Conclusion

This study develops a preliminary System Dynamics model to examine the long-term effects of New York City's congestion pricing policy in the Manhattan CRZ. The model reproduces observed 2025 CRZ vehicle entries and transit ridership with a mean relative error below 5%, providing initial confidence in its ability to capture short-term behavioral adaptation. The phased simulation results suggest that congestion pricing produces its strongest effects during the initial implementation period, after which dominant balancing feedback drive the system toward a lower congestion but more stable equilibrium. At the same time, the findings indicate that reductions in core-area traffic cannot be evaluated independently of transit crowding, peripheral spillovers, and the design of toll-revenue reinvestment. Taken together, the model provides a useful first step toward a more policy-relevant dynamic framework for evaluating congestion pricing as a long-term urban mobility transition strategy.

5. Limitations and Directions for Future Work

While the preliminary model reproduces the observed reference modes and captures the short-term effects of congestion pricing, several important extensions remain for future research. First, the current version of the model is calibrated primarily to early implementation data and should be further strengthened through additional structural and behavioral validation, including boundary adequacy tests, extreme-condition tests, and sensitivity analysis. These procedures will help assess the robustness of the nonlinear relationships embedded in mode choice, travel time penalties, and transit crowding feedback.

Second, future work will expand the policy design space beyond the currently modeled toll schedule. Subsequent model iterations will examine how alternative revenue reinvestment strategies—such as transit capacity expansion, bus service improvements, and micromobility integration—may alter the long-run effectiveness of congestion pricing. This will allow the model to move from evaluating policy impacts to supporting the design of more adaptive and equitable policy packages.

Third, additional attention is needed to capture spatial heterogeneity and spillover dynamics more explicitly. Although the present framework incorporates peripheral congestion effects, future versions should better distinguish between different borough-level responses, boundary-crossing patterns, and potential distributional consequences for travelers with limited modal alternatives. This extension is especially important for assessing whether congestion relief in the CRZ may be achieved at the expense of worsening congestion or reduced accessibility elsewhere in the region.

Finally, future research will refine the behavioral assumptions underlying relative driving attractiveness, especially the parameterization of nonlinear travel-time disutility, transit crowding perception, and delayed commuter adaptation. Strengthening these mechanisms will improve the model's transferability and make it more suitable for comparative applications in other large metropolitan areas considering congestion pricing. In this sense, the present study should be viewed as a first step toward a broader system dynamics framework for evaluating congestion pricing as a long-term urban mobility transition policy.

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