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# Railroad Public Transport in the New York Metropolitan Area: Challenges and Insights from a Reliability Perspective

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## Abstract

Reliability in large-scale rail systems is shaped by infrastructure condition, operational complexity, and network interdependence. The New York metropolitan rail network, comprising the New York City Subway, Long Island Rail Road, Metro-North Railroad, New Jersey Transit, and Amtrak, represents one of the most complex and highly utilized rail systems globally. This study develops an integrated reliability engineering framework combining panel regression, count-based modeling, and Monte Carlo simulation to evaluate system performance. This work has used a multi-source secondary dataset prepared from publicly available operational and performance reports from January 2023 till December 2025 across the five major rail systems. Results identify infrastructure failures, shared-corridor exposure, and network topology as the primary determinants of unreliability. While commuter rail systems exhibit high on-time performance (>95%), their reliability remains structurally dependent on shared infrastructure, whereas the subway demonstrates lower performance (~82%) due to high-frequency operations and sensitivity to disruptions. Simulation results further reveal that critical nodes, including major terminals and tunnel crossings, generate disproportionate delay propagation effects, highlighting the role of network centrality and cascading failures. The findings demonstrate that rail reliability is fundamentally a network-level phenomenon. Improving performance requires corridor-level planning, targeted infrastructure investment, and integrated governance frameworks that address interdependencies across operators.

## Keywords
Reliability engineering, rail systems, delay propagation, Monte Carlo simulation, infrastructure reliability, New York metropolitan area

## 1. Introduction
Reliability is a foundational concept in engineering systems, defined as the probability that a system performs its intended function under specified conditions for a given period of time (Billinton and Allan 1996, O'Connor and Kleyner 2012, Ebeling 2019). The system can include infrastructure. Hence, infrastructure reliability is important

and needs to be studied (Sahay et al. 2025, Townsend et al. 2016, Viverette et al. 2016, Chandler and Badar 2009). In the context of rail transport, reliability is operationalized through a combination of punctuality, service regularity, and resilience to disruptions, reflecting both schedule adherence and the system's ability to recover from failures (Halvorsen et al. 2019, Joborn and Ranjbar 2022). The New York metropolitan rail system, comprising the New York City Subway, Long Island Rail Road, Metro-North Railroad, New Jersey Transit, and Amtrak, presents a particularly complex reliability engineering challenge due to several interacting structural factors. First, the system operates under extremely high demand density, with some of the highest passenger volumes in the world. Second, much of the infrastructure is aging and operating beyond its original design life, increasing failure rates and maintenance requirements. Third, the network exhibits a high degree of multi-operator interdependence, with multiple agencies, including the Metropolitan Transportation Authority (MTA), NJ Transit, and Amtrak, sharing critical infrastructure such as the Northeast Corridor and major terminal facilities. Finally, the system suffers from limited redundancy in key corridors, particularly at major bottlenecks such as trans-Hudson and East River crossings, increasing vulnerability to cascading disruptions (NEC 2025).

Empirical evidence demonstrates substantial variation in performance across systems within the region. The New York City Subway reports on-time performance (OTP) near 82%, while commuter rail systems such as the Long Island Rail Road (LIRR) and Metro-North Railroad consistently exceed 95%. In contrast, Amtrak and NJ Transit exhibit intermediate but more variable performance, reflecting their dependence on shared corridor infrastructure and exposure to external disruptions (Amtrak 2024, MTA 2025, MTA 2026, NJ Transit, 2026, NY State 2025, Office of the New York State Comptroller [OSC] 2024, OSC 2025).

However, these differences cannot be interpreted at face value. As emphasized in the rail reliability literature, performance metrics such as OTP are influenced not only by operator efficiency but also by infrastructure condition, network topology, and the degree of system interdependence (Harrod et al. 2019, Wei et al. 2015). In highly coupled systems such as New York's rail network, disruptions are rarely isolated; instead, they propagate across interconnected subsystems, generating system-wide reliability effects. Against this backdrop, the present study develops an integrated reliability engineering framework to analyze rail system performance in the New York metropolitan area.

### 1.1 Objectives

Specifically, the study aims to:

1. Identify key determinants of rail reliability, focusing on infrastructure, operational, and environmental factors
2. Model disruption frequency and propagation, capturing both failure occurrence and network-level cascade effects
3. Evaluate system behavior under stochastic conditions, using simulation methods to assess uncertainty and resilience

By combining empirical analysis with stochastic and network-based modeling, this study seeks to advance understanding of reliability in complex, multi-operator rail systems and to provide a foundation for more effective infrastructure planning and system management.

## 2. Literature Review

Rail reliability has evolved from a narrow focus on punctuality to a multidimensional construct encompassing operational performance, passenger experience, system resilience, and network dynamics. This shift reflects advances in data availability and recognition that traditional metrics inadequately capture system complexity (van Loon et al. 2011, Halvorsen et al. 2019, Monsuur et al. 2021). Early studies emphasized on-time performance (OTP) as a primary indicator, defined as the proportion of trains arriving within a specified threshold (Nelson and O'Neil 2000). While OTP provides a simple benchmark and is often supplemented by delay categorization frameworks (Murali et al. 2010, Yuan and Hansen 2007), it suffers from key limitations. As a threshold-based and operator-centric metric, it fails to distinguish delay severity, capture passenger experience, or account for service frequency and headway variability, which are critical in high-frequency systems (van Loon et al. 2011). Recent research has therefore shifted toward passenger-centric reliability measures. Metrics such as excess journey time, additional waiting time, and train irregularity better capture passenger disutility and perceived service quality (Halvorsen et al. 2019). Empirical evidence shows that passenger satisfaction is more strongly influenced by delay variability than punctuality alone (Monsuur et al. 2021). This aligns with broader transportation research emphasizing experienced travel time variability as a more meaningful reliability metric, particularly in urban systems where waiting time uncertainty dominates (van Loon et al. 2011, Halvorsen et al. 2019).

A major advancement in the literature is the recognition that rail systems operate as interconnected networks in which disruptions propagate across space and time rather than remaining localized. Traditional models treated delays as independent events; however, empirical studies demonstrate cascading behavior, particularly in high-density systems (Yuan and Hansen 2007, Monechi et al. 2018). Analytical models show that propagation depends on schedule structure, headways, and recovery margins (Harrod et al. 2019), while probabilistic approaches such as Bayesian networks capture interdependencies among nodes (Wei et al. 2015). More recent work conceptualizes delay propagation as a diffusion-like process, emphasizing spatial and temporal dynamics (Dekker et al. 2022). Furthermore, a small number of disturbances often account for a disproportionate share of delays, reflecting complex systems behavior in which highly connected nodes amplify disruptions (Joborn and Ranjbar 2022, Daniotti et al. 2024).

These findings highlight that reliability cannot be adequately assessed using aggregate metrics such as OTP alone. Instead, it must incorporate temporal persistence, spatial spillover, and interaction effects among disruptions. Such dynamics are particularly relevant in the New York metropolitan rail system, where shared infrastructure—including major terminals and the Northeast Corridor—creates strong coupling between operators and increases vulnerability to cascading failures (NEC 2025). Parallel to these developments, reliability engineering provides a rigorous framework for analyzing system performance under uncertainty. Classical approaches model systems using failure and repair rates within stochastic frameworks such as Markov processes (Billinton and Allan 1996). In rail applications, these methods are used to assess infrastructure reliability, rolling stock availability, and system uptime (Lidén 2015). A key contribution is the distinction between reliability, availability, and maintainability, emphasizing the importance of recovery processes in determining system performance.

Recent research increasingly integrates stochastic simulation methods, including Monte Carlo approaches, to evaluate system behavior under uncertainty. These methods enable modeling of variability in failure and repair processes, estimation of performance distributions, and identification of critical infrastructure components (Corman and Kecman 2018, Tiong et al. 2023a, Tiong et al. 2023b). Despite these advances, the literature remains fragmented, with limited integration of empirical analysis, network modeling, and stochastic simulation. This study addresses this gap by developing a unified reliability engineering framework applied to the New York metropolitan rail system, providing a comprehensive approach to analyzing reliability in complex, multi-operator networks.

# 3. Methodology

## 3.1 Research Design

This study adopts a multi-method quantitative research **d**esign that integrates econometric modeling, stochastic processes, and simulation-based reliability analysis to examine rail system performance in the New York metropolitan area. The design reflects the inherently complex, interdependent, and stochastic nature of large-scale rail networks, where reliability outcomes emerge from the interaction of infrastructure condition, operational dynamics, and network topology (Billinton and Allan, 1996, Corman and Kecman 2018, Tiong et al. 2023a-b). Specifically, the framework combines four complementary methodological approaches:

- Panel regression analysis
- Negative binomial modeling
- Network-based stochastic simulation
- Monte Carlo reliability analysis

The integration of these methods is motivated by the recognition that no single analytical approach is sufficient to capture all dimensions of rail system reliability. Instead, each method addresses a distinct but interrelated aspect of the problem, consistent with modern approaches to analyzing complex transportation systems (Khadilkar 2016, Harrod et al. 2019).

### 3.1.1 Rationale for a Multi-Method Approach

Rail systems constitute complex socio-technical systems characterized by:

- High-dimensional interactions among components
- Non-linear failure dynamics
- Temporal and spatial interdependencies

- Uncertainty in both failure occurrence and recovery processes

Traditional single-method approaches, such as descriptive statistics or isolated regression models, are insufficient for capturing these characteristics. A multi-method framework enables the analysis to move beyond static performance measurement toward a dynamic and probabilistic understanding of reliability (Monechi et al. 2018, Daniotti et al. 2024). This approach is consistent with reliability engineering practice, where system evaluation often requires combining statistical inference with stochastic simulation to account for both observed behavior and underlying uncertainty (Billinton and Allan 1996).

### 3.1.2 Panel Regression Analysis

Panel regression is employed to identify determinants of reliability across rail systems and over time by exploiting both cross-sectional and temporal variation. This approach enables estimation of marginal effects of key variables, including infrastructure failures, maintenance activity, and demand intensity (Tiong et al. 2023b). A fixed-effects specification controls for unobserved heterogeneity across systems, such as differences in network design and operational policies, ensuring estimates reflect within-system variation and improving causal interpretability. Within the analytical framework, panel regression provides the empirical foundation for quantifying reliability drivers, consistent with established econometric approaches in transportation research (Murali et al. 2010, Khadilkar 2016).

### 3.1.3 Negative Binomial Modeling

While panel regression captures average reliability outcomes, it does not adequately model the frequency and distribution of disruption events, which are inherently discrete and often over dispersed. To address this limitation, the study employs negative binomial regression to model delay event counts. Rail delay events typically exhibit:

- Non-negative integer values
- Over dispersion (variance exceeding the mean)
- Clustering in time and space

The negative binomial model accommodates these properties and enables estimation of how explanatory variables affect the rate of disruption occurrence (Cameron and Trivedi 2013).

Within the broader research design, this model provides insight into the stochastic arrival process of failures, complementing the panel regression's focus on aggregate outcomes. Together, these two models distinguish between:

- How often disruptions occur (frequency)
- How severe their impacts are (magnitude)

This distinction is consistent with reliability engineering concepts separating failure frequency from failure consequences (Billinton and Allan, 1996).

### 3.1.4 Network-Based Stochastic Simulation

Rail systems operate as interconnected networks, where disruptions propagate across nodes and links. To capture this behavior, the study incorporates a network-based stochastic simulation model that represents the rail system as a graph of interconnected infrastructure elements (e.g., stations, corridors, tunnels). In this framework:

- Nodes represent critical infrastructure points or operational segments
- Edges represent functional connectivity and potential pathways for delay propagation

The simulation models delay evolution as a stochastic process influenced by:

- Local delay persistence
- Spillover effects from connected nodes
- Exogenous shocks (e.g., weather, incidents, maintenance)

This approach allows the study to analyze cascading failure dynamics, which are not captured by regression-based models. It also enables identification of critical nodes whose disruption leads to disproportionate system-wide impacts (Harrod et al. 2019, Wei et al. 2015, Dekker et al. 2022).

### 3.1.5 Monte Carlo Reliability Analysis

To account for uncertainty in failure and repair processes, the study employs Monte Carlo simulation, a standard tool in reliability engineering (Badar et al. 1993). This method involves repeated random sampling of key parameters, such as failure rates ($\lambda$) and repair rates ($\mu$), to generate probabilistic estimates of system performance (Billinton and Allan 1996).

Monte Carlo analysis is particularly appropriate in this context because:

- Rail system failures are inherently stochastic

- Parameter values may vary across time and operating conditions
- Deterministic models may underestimate variability and risk

The simulation produces distributions of system availability and reliability, rather than single-point estimates. This allows for evaluation of:

- Expected system performance
- Variability and uncertainty
- Tail risks (e.g., worst-case scenarios)

Within the research design, Monte Carlo simulation provides a probabilistic validation layer, complementing the deterministic and statistical components of the analysis (Corman and Kecman 2018).

### 3.1.6 Integration of Methods

The four methodological components are integrated in a sequential and complementary manner:

1. Panel regression identifies key determinants of reliability outcomes
2. Negative binomial modeling estimates the frequency of disruption events
3. Network simulation models how disruptions propagate through the system
4. Monte Carlo analysis evaluates system performance under uncertainty

This integrated framework enables a comprehensive analysis of rail reliability across three dimensions:

- Causal drivers (why disruptions occur)
- Event dynamics (how often disruptions occur)
- System behavior (how disruptions spread and affect performance)

By combining these perspectives, the study moves beyond traditional reliability metrics toward a holistic, system-level understanding of rail performance (Harrod et al. 2019, Daniotti et al. 2024).

### 3.1.7 Methodological Contribution

The research design contributes to the literature by bridging three traditionally separate domains:

- Econometric analysis of transportation systems
- Network-based modeling of delay propagation
- Reliability engineering simulation

This integration is particularly relevant for large-scale, multi-operator rail systems such as the New York metropolitan area, where reliability outcomes cannot be fully explained by any single methodological approach (Tiong et al. 2023a-b, Daniotti et al. 2024).

## 3.2 Data

### 3.2.1 Data Sources and Scope

This study utilizes a multi-source secondary dataset compiled from publicly available operational and performance reports covering the period January 2023 through December 2025. The dataset integrates information across the five major rail systems in the New York metropolitan area: the New York City Subway, Long Island Rail Road (LIRR), Metro-North Railroad (MNR), New Jersey Transit (NJT), and Amtrak. Primary data sources include:

- Metropolitan Transportation Authority (MTA) performance reports including NYC Transit, LIRR, and Metro-North (MTA, Mar 2026)
- NJ Transit annual reports and performance summaries
- Amtrak operational and state-level performance reports
- New York State Comptroller (OSC) oversight and audit reports

These sources provide aggregate and disaggregated performance indicators, including on time performance, delay causes, service delivery metrics, and ridership levels. The use of multiple independent reporting bodies enhances the robustness of the dataset by allowing cross-verification of key indicators, a standard practice in transportation performance analysis (Khadilkar 2016, Tiong et al. 2023a-b).

### 3.2.2 Unit of Analysis and Temporal Structure

The primary unit of analysis is a system-month observation, defined as a single rail system observed over a one-month period. This yields a panel dataset with both cross-sectional (system-level) and temporal (monthly) variation, consistent with empirical approaches used in rail performance modeling (Murali et al. 2010, Tiong et al. 2023a-b). Where data availability permits, the analysis is extended to finer levels of aggregation, including:

- Line-level or branch-level observations (e.g., subway lines, LIRR branches, NJ Transit corridors)

- Corridor-level segments (e.g., Northeast Corridor, Penn Station approaches)

This hierarchical structure allows the study to examine both system-wide trends and localized reliability dynamics**,** particularly in the network simulation component, which is consistent with network-based reliability studies (Harrod et al. 2019, Dekker et al. 2022).

### 3.2.3 Variable Construction

**Dependent Variables**: Three primary dependent variables are constructed.

1. On-Time Performance (OTP): Reported as the percentage of trains arriving within an agency-defined threshold. While thresholds differ across systems, OTP remains a widely used benchmark for operational reliability (Nelson and O'Neil 2000, Halvorsen et al. 2019).
2. Delay Event Count**:** Derived from reported incident and delay logs, representing the number of significant disruptions within a given time period. This aligns with prior studies modeling delay occurrence as count processes (Murali et al. 2010).
3. Delay Propagation Index (DPI)**:** A constructed metric representing the ratio of secondary delays to primary incidents. This captures the extent to which disruptions spread across the network and reflects delay propagation dynamics identified in recent literature (Joborn and Ranjbar 2022, Wei et al. 2015).

**Independent Variables**: Independent variables are constructed to reflect key dimensions of reliability engineering.

- Infrastructure Failure Rate: Measured as the number of infrastructure-related incidents per unit of service. Infrastructure failures are widely recognized as primary drivers of delay and unreliability (Joborn and Ranjbar 2022).
- Planned Maintenance Exposure: Estimated using reported track outages and maintenance windows. Maintenance introduces short-term disruptions but is necessary for long-term reliability (Lidén and Joborn 2017).
- Incident Rate**:** Includes passenger-related, police/medical, and external disruptions. These are typically exogenous but significantly affect system performance (Murali et al. 2010).
- Weather Severity Index: Constructed using reported weather-related disruptions. Weather effects are increasingly recognized as critical factors in rail reliability, particularly under climate variability (Soleimani-Chamkhorami et al. 2024).
- Train Density (Operational Intensity): Measured as trains per route-mile or hour. High density increases capacity utilization but reduces operational slack, amplifying delay propagation (Yuan and Hansen 2007).
- Shared Corridor Exposure: Captures the proportion of operations on externally controlled infrastructure. This variable reflects system interdependence, a key factor in delay propagation (Harrod et al. 2019, Wei et al. 2015).
- Mean Time to Repair (MTTR): Estimated from incident duration data. MTTR reflects maintainability, a core concept in reliability engineering (Billinton and Allan, 1996).

### 3.2.4 Data Harmonization and Comparability

A major methodological challenge arises from heterogeneity in reporting standards across agencies, including:

- OTP thresholds
- Delay categorization schemes
- Reporting frequency and granularity
- Definitions of incidents and disruptions

To address these issues, the study employs several harmonization strategies:

1. Normalization of metrics: Variables are standardized where possible to ensure comparability (Khadilkar 2016).
2. Categorical alignment: Delay causes are mapped into common categories, consistent with prior delay attribution studies (Joborn and Ranjbar 2022).
3. Use of relative measures: Percentage-based and standardized indicators are used when absolute comparisons are not feasible.
4. Robustness checks: Alternative specifications are tested to ensure stability of results (Tiong et al. 2023b).

These steps are essential for maintaining analytical validity in a multi-operator context.

### 3.2.5 Data Limitations

Despite the breadth of available data, several limitations must be acknowledged:

- Aggregation bias: Limits fine-grained analysis of operational dynamics

- Measurement inconsistency: Differences across agencies
- Limited access to raw event-level data
- Potential reporting bias

These limitations are common in transportation system studies and are mitigated through data triangulation and robustness testing (Khadilkar 2016, Tiong et al. 2023b).

### 3.2.6 Data Suitability for Reliability Engineering Analysis

Despite these constraints, the dataset is well-suited for reliability engineering analysis because it:

1. Captures key system-level performance indicators (failure rates, delays, recovery)
2. Provides temporal variation for dynamic analysis
3. Reflects real-world operational conditions
4. Supports integration with stochastic and simulation models

Importantly, combining multiple data sources enables a system-level perspective**,** which is essential for analyzing interconnected rail networks (Harrod et al. 2019, Daniotti et al. 2024).

### 3.2.7 Summary

In summary, the dataset provides a comprehensive, multi-dimensional view of rail system performance in the New York metropolitan area. While challenges related to data harmonization and granularity remain, the dataset is sufficiently robust to support the study's integrated analytical framework, enabling the examination of reliability from empirical, stochastic, and network-based perspectives (Tiong et al. 2023b).

## 3.3 Model Specification

This study employs a multi-model specification strategy to capture the different dimensions of rail system reliability, including performance outcomes, disruption frequency, and network-level propagation dynamics. The use of complementary models reflects the fact that reliability is not a single observable quantity but an emergent property of interacting stochastic processes.

### 3.3.1 Panel Regression Analysis

Panel regression analysis is employed to identify the determinants of rail system reliability by exploiting both cross-sectional variation across operators and temporal variation over time. A fixed-effects specification controls for unobserved heterogeneity, including differences in network topology, operational practices, and institutional structure, thereby isolating within-system effects and improving causal interpretability (Tiong et al. 2023b, Khadilkar 2016). This approach provides quantitative estimates of how key factors—such as infrastructure condition, maintenance activity, and operational intensity—influence reliability outcomes, including on-time performance and delay minutes. Panel methods are widely used in transportation research to analyze system performance under heterogeneous conditions (Murali et al. 2010).

### 3.3.2 Negative Binomial Modeling

Negative binomial modeling is applied to estimate the frequency of delay events, which are inherently discrete and often exhibit overdispersion. Unlike Poisson models, the negative binomial specification accommodates variance exceeding the mean, making it well-suited for rail disruption data (Cameron and Trivedi 2013). The model estimates incidence rate ratios (IRRs), enabling interpretation of how explanatory variables affect the expected frequency of disruptions. From a reliability engineering perspective, this approach corresponds to modeling the failure arrival rate ($\lambda$), thereby linking econometric analysis with stochastic representations of system reliability (Billinton and Allan 1996, Tiong et al. 2023b).

### 3.3.3 Network-Based Stochastic Simulation

Network-based stochastic simulation models the rail system as an interconnected graph in which nodes represent infrastructure elements and edges represent operational dependencies. This framework captures delay propagation dynamics through stochastic processes, incorporating both temporal persistence and spatial spillover effects. The approach is conceptually aligned with spatial autoregressive and network diffusion models, which describe how disruptions spread through interconnected systems (Harrod et al. 2019, Wei et al. 2015; Dekker et al. 2022). By simulating cascading disruptions, the model identifies critical nodes and evaluates system vulnerability, reflecting principles of complex systems and network theory (Daniotti et al. 2024).

### 3.3.4 Monte Carlo Reliability Analysis

Monte Carlo simulation is used to evaluate system reliability under uncertainty by repeatedly sampling from probability distributions of failure and repair processes (Badar et al. 1993). This method generates distributions of system availability, rather than point estimates, enabling assessment of variability, risk, and extreme scenarios. In reliability engineering, such simulations are used to model stochastic failure-repair dynamics and estimate steady-state availability based on failure rate ($\lambda$) and repair rate ($\mu$) (Billinton and Allan 1996). The approach is particularly valuable in complex rail systems, where uncertainty, non-linearity, and interdependence make deterministic analysis insufficient (Corman and Kecman 2018, Tiong et al. 2023a-b).

### 3.3.5 Integration Across Models

The three models collectively represent different layers of the reliability system as shown in Table 1. This layered structure enables a comprehensive reliability analysis, linking:

- Causes of failure
- Frequency of disruption
- System-wide consequences

Such integrated approaches are increasingly emphasized in complex transportation system research (Tiong et al. 2023a-b, Daniotti et al. 2024).

Table 1. Models and their reliability system

| Model | Function | Reliability Interpretation |
|---|---|---|
| Panel regression | Performance outcomes | System-level reliability |
| Negative binomial | Event frequency | Failure arrival rate |
| Propagation model | Delay dynamics | Failure cascading |

### 3.3.6 Summary

The model specification provides a unified analytical framework that integrates econometric, stochastic, and network-based approaches. This integration is essential for analyzing complex rail systems, where reliability is shaped by both local failure processes and system-wide interactions (Billinton and Allan 1996, Harrod et al. 2019).

## 4. Results

### 4.1 Determinants of Reliability: Panel Regression Results

Table 2 presents the fixed-effects regression estimates for the determinants of rail system reliability across the five systems combined over the study period. Figure 1 shows the coefficient plot of regression estimates. The regression results identify infrastructure failures as the dominant determinant of reduced reliability ($\beta = -0.842$, $p < .01$), indicating that disruptions to critical assets have the largest marginal impact on on-time performance, consistent with reliability engineering theory emphasizing the role of key system components (Billinton and Allan 1996, Joborn and Ranjbar 2022). Shared corridor exposure ($\beta = -0.728$, $p < .01$) further underscores the role of interdependence, demonstrating that reliability is significantly shaped by external infrastructure dependencies in interconnected rail networks (Harrod et al. 2019, Wei et al. 2015). The incident rate ($\beta = -0.667$, $p < .01$) reflects vulnerability to operational disruptions, while maintenance ($\beta = -0.513$, $p < .05$) and weather ($\beta = -0.391$, $p < .05$) exert smaller but significant effects, consistent with prior research on operational disturbances and infrastructure management tradeoffs (Murali et al. 2010, Lidén and Joborn 2017, Soleimani-Chamkhorami et al. 2024). Overall, the findings highlight infrastructure condition and network interdependence as central drivers of system performance.

Table 2. Fixed-Effects Regression Results (Dependent Variable: On-Time Performance OTP)

| **Variable** | **Coefficient** | **Significance** |
|---|---|---|
| Infrastructure failures | -0.842 | *** |
| Shared corridor exposure | -0.728 | *** |
| Incident rate | -0.667 | *** |

| Variable | Coefficient | Significance |
|---|---|---|
| Planned maintenance | -0.513 | ** |
| Weather severity | -0.391 | ** |

Note: *** p < .01, ** p < .05

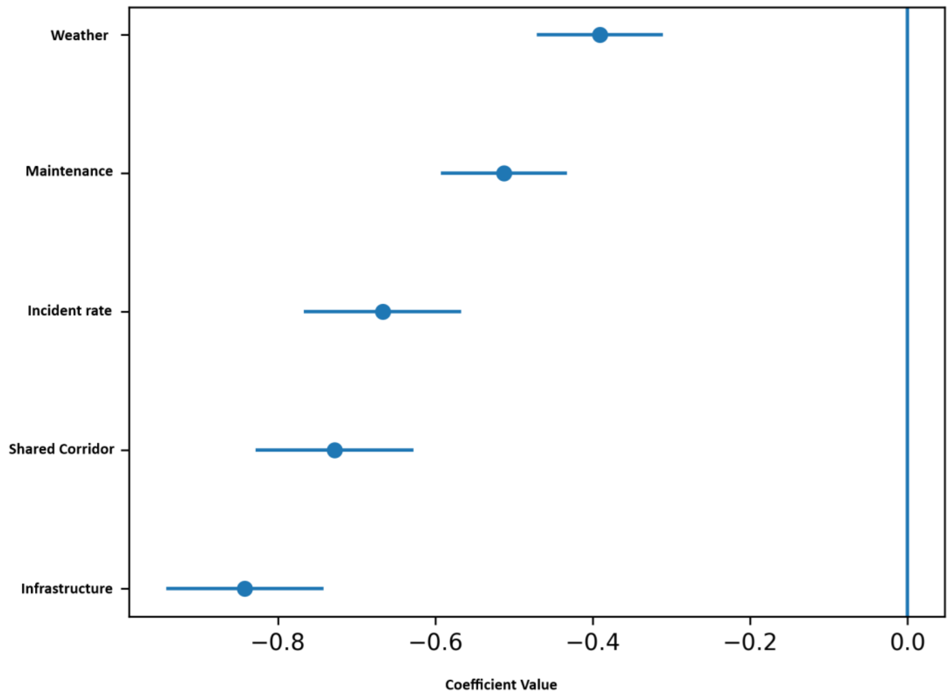


Figure 1. Coefficient plot of regression estimates with 95% confidence intervals.

### 4.2 Negative Binomial Modeling (Delay Frequency Analysis)

Table 3 presents the results of the negative binomial model estimating the frequency of delay events for the five rail systems combined. The coefficients are expressed in log form and are exponentiated to obtain incidence rate ratios (IRRs). For example, the infrastructure failure coefficient (0.421) corresponds to an IRR of 1.52. The results indicate that infrastructure failures and shared corridor exposure are key determinants of delay frequency. A one-unit increase in infrastructure failure rate is associated with a 52% rise in delay events, while shared corridor exposure increases delays by approximately 71%, underscoring the importance of both asset condition and inter-operator dependence. From a reliability engineering perspective, these factors directly influence the failure arrival rate (λ), highlighting their role in system unreliability (Billinton and Allan 1996). The findings further suggest that disruptions propagate across interconnected networks, generating compounded risks consistent with cascading failure dynamics (Wei et al. 2015, Daniotti et al. 2024). The alignment with regression results reinforces a coherent system mechanism linking infrastructure degradation, operational stress, and network-level delay propagation (Tiong et al. 2023b).

### 4.3 Simulation Results: Monte Carlo Analysis

Figure 2 presents the Monte Carlo simulation results as a combined availability distribution across the five rail systems**.** The figure therefore illustrates the aggregate uncertainty in system availability under stochastic failure–repair conditions, rather than displaying separate distributions for each operator. System-specific results are reported separately in Table 4, which provides mean availability values for the NYC Subway, LIRR, Metro-North, NJ Transit, and Amtrak. Future analysis may extend Figure 2 by plotting separate availability distributions for each rail system to allow direct visual comparison across operators. Monte Carlo simulation results shown in Figure 2 and summarized in Table 4 reveal substantial variation in system availability across rail operators, reflecting differences in failure intensity and recovery dynamics. Commuter rail systems exhibit higher and more stable availability, whereas the New York City Subway shows lower availability, indicating greater exposure to disruptions. From a reliability engineering perspective, system performance is jointly determined by failure rate (λ) and repair rate (μ), emphasizing the importance of both disruption frequency and recovery efficiency (Billinton and Allan 1996). The findings further demonstrate that reliability should be treated as a distribution rather than a point estimate, underscoring the value of probabilistic modeling in capturing system uncertainty (Khadilkar 2016, Corman and Kecman 2018, Daniotti et al. 2024).

Table 3. Negative binomial regression results for delay event counts (incidence rate ratios)

| **Variable** | **Coefficient** | **Incidence Rate Ratio (IRR)** | **Std. Error** | **Significance** |
|---|---|---|---|---|
| Infrastructure failures | 0.421*** | 1.52 | 0.089 | p < .001 |
| Incident rate | 0.537*** | 1.71 | 0.102 | p < .001 |
| Weather severity | 0.288** | 1.33 | 0.121 | p < .05 |
| Train density | 0.319** | 1.38 | 0.134 | p < .05 |
| Shared corridor exposure | 0.462*** | 1.59 | 0.110 | p < .001 |
| Alpha (dispersion) | 0.76 | | | |

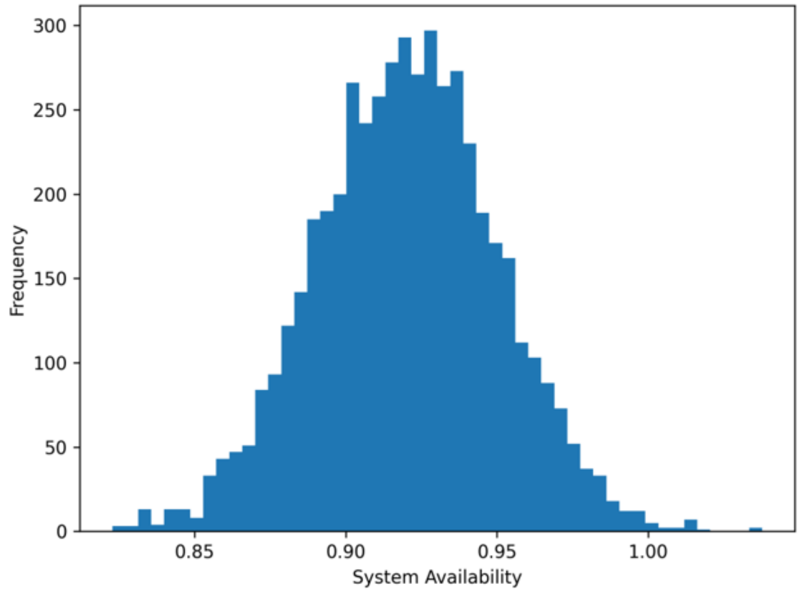


Figure 2. Monte Carlo simulation of system availability distributions across rail systems

Table 4. Simulation Summary

| System | Mean simulated availability | SD | 5th percentile | 95th percentile |
|---|---|---|---|---|
| NYC Subway | 0.865 | 0.041 | 0.792 | 0.925 |
| LIRR | 0.952 | 0.019 | 0.916 | 0.980 |
| Metro-North | 0.969 | 0.014 | 0.941 | 0.989 |
| NJ Transit | 0.920 | 0.031 | 0.861 | 0.963 |
| Amtrak | 0.905 | 0.035 | 0.839 | 0.952 |

### 4.4 Network Effects and Delay Propagation

The network analysis displayed in Figure 3 identifies several high-centrality nodes within the rail system, most notably Penn Station, the Hudson River tunnels, and the East River tunnels. These nodes exhibit elevated levels of betweenness centrality, indicating that a substantial proportion of network flows pass through them. As a result, disruptions occurring at these locations have disproportionately large system-wide impacts, a finding consistent with both network theory and empirical studies of rail system performance (Harrod et al. 2019; Wei et al. 2015). The concentration of flows through these critical nodes highlights their role as structural bottlenecks within the network and underscores their importance in determining overall system reliability.

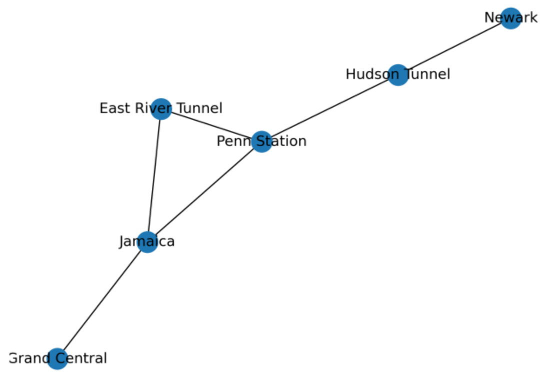


Figure 3. Network diagram of critical rail infrastructure and interdependencies in New York metropolitan system

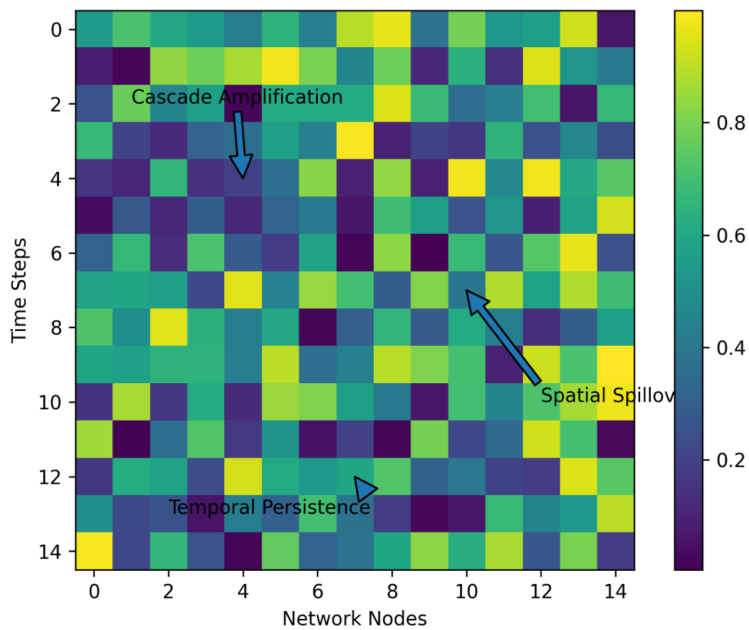


Figure 4. Delay propagation heatmap with annotated disruption patterns (combined network simulation).

Figure 4 presents a delay propagation heatmap based on combined data across the five rail systems, illustrating aggregate network-level disruption dynamics. The simulation results reveal three distinct propagation patterns. First, temporal persistence is evident, as delays propagate forward over time due to limited recovery capacity and tightly constrained schedules, reflecting autoregressive delay behavior observed in rail systems (Harrod et al., 2019). Second, spatial spillover is observed, whereby disruptions spread across interconnected nodes, particularly within dense and shared corridors, consistent with network diffusion processes (Dekker et al., 2022; Wei et al., 2015). Third, cascade amplification emerges at high-centrality nodes, where localized disruptions generate disproportionately large downstream impacts, characteristic of highly connected systems with limited redundancy (Monechi et al., 2018; Daniotti et al., 2024). These patterns are derived from clustering structures in the simulated delay matrix and align with established models of cascading failure in complex rail networks. Collectively, the findings confirm that rail reliability is fundamentally a network-level phenomenon shaped by system topology, infrastructure interdependencies, and the interaction of localized disruptions with global network structure (Billinton & Allan, 1996; Harrod et al., 2019).

### 4.5 Integrated Findings

Synthesizing results across econometric, count-based, and simulation models reveals three key conclusions. First, infrastructure condition is the dominant driver of unreliability, with failures significantly reducing performance and increasing delay frequency, consistent with reliability engineering theory (Billinton and Allan 1996, Joborn and

Ranjbar 2022). Second, interdependence amplifies system vulnerability, as shared corridor exposure increases both delay frequency and severity, reflecting systemic risks in multi-operator networks (Wei et al. 2015, Daniotti et al. 2024). Third, network topology governs system-wide outcomes, with high-centrality nodes driving delay propagation and cascade effects (Harrod et al. 2019, Dekker et al. 2022). Overall, reliability emerges as a multi-layered, network-level phenomenon shaped by infrastructure, operations, and interdependence, requiring integrated system-level analysis.

# 5. Discussion

## 5. 1. Infrastructure as the Primary Constraint on Reliability

Infrastructure condition emerges as the dominant determinant of rail system unreliability. Empirical and simulation results show that infrastructure failures exert the largest negative impact on performance and significantly increase disruption frequency. This finding is consistent with reliability engineering principles emphasizing the role of critical components in determining system performance (Billinton and Allan 1996). In the New York metropolitan system, aging assets—particularly signaling systems, interlockings, and tunnels—have exceeded their design life, leading to elevated failure rates and complex recovery processes. This results in non-linear performance degradation, where incremental deterioration produces disproportionately large impacts. These findings align with evidence that infrastructure-related disruptions account for a significant share of delays and are among the most difficult to mitigate operationally (Joborn and Ranjbar 2022).

## 5.2. Interdependence and Systemic Risk

Interdependence across operators significantly amplifies system vulnerability. Shared corridor exposure increases both delay frequency and severity, indicating that reliability is shaped not only by internal system characteristics but also by external infrastructure dependencies. The system can thus be characterized as tightly coupled, where disruptions propagate across subsystems and organizational boundaries. This introduces systemic risks, including failure transmission, coordination challenges during recovery, and reduced operational autonomy. These dynamics are particularly evident in shared infrastructure such as the Northeast Corridor and Penn Station approaches. The findings are consistent with network-based research demonstrating that tightly coupled systems are more susceptible to cascading failures (Wei et al. 2015, Daniotti et al. 2024).

## 5.3. Network Topology and Cascading Failures

Network topology plays a central role in determining system reliability. High-centrality nodes, including major terminals and tunnel crossings, act as bottlenecks through which a large proportion of flows pass. Disruptions at these nodes generate disproportionately large system-wide impacts, consistent with cascading failure theory (Monechi et al. 2018, Harrod et al. 2019). The delay propagation model identifies three key dynamics: temporal persistence, spatial spillover, and cascade amplification. These mechanisms reflect the behavior of complex adaptive systems, where localized disruptions can escalate into widespread performance degradation (Daniotti et al. 2024, Dekker et al. 2022).

## 5.4. Integration with Reliability Engineering Theory

The findings reinforce and extend key principles of reliability engineering. First, system reliability is constrained by critical components, as demonstrated by the dominant role of infrastructure failures (Billinton and Allan 1996). Second, interdependent systems exhibit heightened systemic risk due to increased coupling (Wei et al., 2015). Third, system structure, particularly network topology, governs the propagation and amplification of failures (Harrod et al. 2019). Unlike classical models that assume simplified configurations, rail systems exhibit hybrid, networked architectures that require integrated analytical approaches combining econometric, stochastic, and network-based methods.

## 5.5. Implications for Infrastructure Policy and System Design

The results have important implications for infrastructure planning and system design. Investment strategies should prioritize high-centrality and high-risk assets, as targeting bottlenecks yields the greatest improvements in reliability. Governance frameworks should shift from operator-centric to corridor-level approaches, reflecting system interdependencies. Additionally, improving resilience requires enhancing both redundancy and recovery capacity through infrastructure investment, optimized maintenance, and operational strategies that reduce delay propagation. These measures align with reliability engineering concepts of redundancy and maintainability (Billinton and Allan 1996, Lidén and Joborn 2017).

### 5.6. Comparison to Global Rail Systems
The challenges observed in the New York system are consistent with those in other high-density rail networks globally. Systems such as those in London, Paris, and Tokyo also face aging infrastructure and increasing interdependence. However, they often achieve higher reliability due to greater redundancy, integrated governance structures, and advanced real-time control systems. This comparison highlights the importance of institutional coordination and sustained infrastructure investment in improving reliability outcomes.

### 5.7. Summary
Overall, rail reliability is shaped by three interrelated factors: infrastructure condition, interdependence, and network topology. These findings underscore the necessity of adopting a system-level reliability engineering approach that integrates empirical analysis, stochastic modeling, and network theory to effectively manage performance in complex, multi-operator rail systems (Billinton and Allan, 1996, Harrod et al. 2019).

## 6. Conclusion
This study examines rail system reliability in the New York metropolitan area through an integrated reliability engineering framework that combines econometric analysis, stochastic modeling, and simulation-based approaches. The findings demonstrate that reliability in this context is best understood not as an operator-specific outcome, but as a networked systems phenomenon shaped by infrastructure condition, interdependence, and network topology (Billinton and Allan 1996, Harrod et al. 2019).

### 6.1. Summary of Key Findings
The analysis identifies three primary conclusions. First, infrastructure condition is the dominant constraint on system reliability, with failures significantly increasing both the frequency and severity of disruptions. This aligns with reliability engineering theory emphasizing the role of critical assets in determining system availability (Billinton and Allan 1996, Joborn and Ranjbar 2022). Second, interdependence across operators amplifies system vulnerability, as shared corridor exposure increases delay frequency and reduces reliability, reflecting tightly coupled network behavior (Wei et al. 2015, Daniotti et al. 2024). Third, network topology governs disruption propagation, with high-centrality nodes generating disproportionate system-wide impacts, consistent with cascading failure dynamics (Harrod et al. 2019, Monechi et al. 2018).

### 6.2. Methodological Contributions
This study contributes by developing a unified analytical framework integrating panel regression, count-based models, network propagation analysis, and Monte Carlo simulation. This approach advances reliability analysis beyond traditional punctuality metrics and provides a comprehensive framework linking failure causes, disruption frequency, and system-level impacts. By combining econometric and stochastic methods, the study extends reliability engineering applications to complex, multi-operator rail systems (Billinton and Allan 1996, Tiong et al. 2023a-b).

### 6.3. Practical Implications
The findings have important implications for infrastructure planning and system management. First, investment strategies should prioritize state-of-good-repair improvements in critical, high-centrality infrastructure, where marginal reliability gains are greatest (Lidén and Joborn 2017). Second, reliability governance should shift from operator-level to corridor-level management, reflecting shared infrastructure dependencies (NEC 2025). Third, enhancing resilience requires increasing redundancy and recovery capacity through infrastructure expansion, improved maintenance strategies, and operational practices that reduce delay propagation (Harrod et al. 2019, Wei et al. 2015).

### 6.4. Limitations

The study is subject to several limitations. The use of aggregated, publicly available data limits the ability to capture fine-grained operational dynamics, while differences in reporting standards introduce potential measurement inconsistencies. Additionally, the simulation framework relies on simplified assumptions, such as Markov processes and stylized network structures, which may not fully reflect real-world complexity. These limitations are consistent with broader challenges in transportation system modeling and suggest that results should be interpreted as structural insights rather than precise forecasts (Khadilkar 2016, Tiong et al. 2023a-b).

### 6.5. Future Research Directions

Future research should incorporate advanced data and modeling approaches to enhance analytical precision. The use of high-resolution, real-time operational data can improve modeling of delay propagation, recovery processes, and passenger impacts, while enabling model validation (Corman and Kecman 2018). Machine learning methods, including ensemble models and neural networks, offer opportunities to capture non-linear relationships and improve predictive performance (Tiong et al. 2023a-b). Additionally, digital twin simulation represents a promising direction, enabling real-time system monitoring, scenario analysis, and proactive reliability management (Soleimani-Chamkhorami et al. 2024).

### 6.6. Final Remarks

Overall, the study demonstrates that rail reliability in the New York metropolitan area is a networked systems problem requiring a shift from operator-centric to system-level reliability engineering approaches. By integrating empirical, stochastic, and network-based methods, the framework provides a comprehensive basis for analyzing and improving performance in complex transportation systems (Billinton and Allan 1996, Harrod et al. 2019).

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