

Impact of Global Supply Chain Disruptions on Indian Manufacturing and Retail: A Big Data Perspective

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Abstract

The modern global supply chain network, particularly in an Indian setting, has been subjected to unprecedented shocks occasioned by port congestions, pandemic-related shocks, and geopolitical tensions. This paper on, "Impact of Global Supply Chain Disruptions on Indian Manufacturing and Retail: A Big Data Perspective," takes an integrated big data analytics methodology to represent, visualize, and interpret the impact of these disruptions on India's manufacturing and retail industries.

Taking advantage of large datasets from the World Bank's Logistics Performance Index, Ministry of Commerce and Industry reports, Kaggle's Logistics Ease Across States data, and several leads numeric datasets, the research creates solid regression models, predictive projections, and supply chain network risk visualizations. The research methodology integrates linear regression to relate port congestion to delivery delay ($R^2 = 0.984$), time-series LSTM forecasting to forecast inventory stockouts (93.4% accuracy), and network analysis to illustrate supplier dependency risk mapping across key global geographies like Taiwan, China, and Bangladesh.

From regression scatter plots, bar charts of model performance (MAE and RMSE), and network graphs illustrating key supplier vulnerabilities, the research presents disruption effects in three-dimensional perspective. Predictive models like ARIMA and LSTM show how early signs of inventory shortage can be sensed and addressed. Network analysis uncovers high concentration risks in semiconductor, API, and textile procurement, highlighting the pressing need for diversification and resilience planning.

The literature review draws heavily from works by Chopra & Meindl (2019), Ivanov (2020), Christopher (2016), and global industry reports from Deloitte, McKinsey, and Accenture, offering theoretical and practical perspectives on supply chain agility, resilience, and digitalization. Data processing tools employed include Python libraries like pandas, matplotlib and more ensuring methodological accuracy and reproducibility.

Key insights indicate that Indian producers are severely exposed to upstream risks through excessive dependence on few suppliers and weak logistics networks. Predictive analytics and integration of big data become crucial catalysts in ensuring real-time decision-making and business continuity. Suggestions focus on creating regional redundancies, investment in digital supply chain technologies, and stimulating local capabilities to minimize import reliance.

Finally, this dissertation adds to the emerging debate on supply chain evolution in a risk-prone world and offers policy-relevant recommendations for policymakers, supply chain executives, and business stakeholders who want to future-proof India's manufacturing and retail industries against external disruptions.

1. Introduction

Global supply chains have witnessed unprecedented disruptions in recent years with the COVID-19 pandemic, geopolitical tensions, port blockages, and raw material shortages. These disruptions have revealed vulnerabilities in logistics infrastructure, supplier networks, and inventory management systems, especially in emerging economies such as India. The Indian manufacturing and retail industries, which are a major contributor to GDP and employment, have been hit hard by import delays, volatile freight rates, and uncertain lead times.

India's deepening integration into global value chains has exposed it to greater international supply-side shocks. As noted in the World Bank's Logistics Performance Index (2023) and India's Ministry of Commerce reports, there are still gaps in regional logistics competence, multimodal integration, and risk preparedness. At the same time, the spread of big data and predictive analytics offers a chance to reduce these risks by using data-driven insights and forecasting capabilities.

This research examines the effect of global supply chain disruptions on Indian manufacturing and retail through a big data strategy. It integrates statistical models, time-series forecasting (e.g., LSTM), and network analysis to detect and measure the influence of port congestion, supplier dependency, and inventory volatility. Actual data from various sources like the World Bank, Indian government reports, and open datasets (e.g., Kaggle's state-wise logistics index) are employed to build and test predictive models.

Through the blending of empirical investigation and technical modelling, this research seeks to (1) graphically represent prominent bottlenecks between supply chain nodes, (2) forecast delivery delays and inventory stockouts, and (3) determine supplier concentration risk. The results provide strategic suggestions for policymakers and firms looking to improve supply chain resilience in light of current and future disruptions.

2. Literature Review

Global supply chains have experienced profound changes in reaction to mounting disruptions fueled by pandemics, geopolitical tensions, and port congestion. Groundbreaking theories by Chopra and Meindl (2019) and Christopher (2016) have long highlighted strategic trade-offs in supply chain design—cost, responsiveness, and flexibility. These theories formed the basis of comprehending recent trends in building resilience and agility in complex supply networks.

Ivanov (2020) proposed the idea of a "viable supply chain" that combines agility,

sustainability, and resilience, particularly applicable in post-COVID situations. His research demonstrates how digital twins and dynamic simulations can be used to anticipate shocks and ensure continuity. This is reinforced by Deloitte (2022), which discovered that more than 80% of the global companies it surveyed now consider supply chain risk mitigation as a strategic priority, with an emphasis on digital enablement, predictive analytics, and diversification of sources.

The Indian supply chain environment has distinct challenges. India has made quantifiable gains in its logistics landscape—its increasing rank on the World Bank's Logistics Performance Index (2023)—but much inefficiency persists, notably in multimodal transport, terminal handling, and state-to-state diversity. Evidence from the Logistics Ease Across Different States index (Kaggle, 2021) indicates wide disparities, with Maharashtra taking the lead while others struggle with logistics infrastructure and process efficiency.

One of the biggest issues for Indian manufacturing and retail industries is how heavily they rely on certain geographies for their key inputs. For example, businesses like Maruti Suzuki have a high dependency on Taiwan when it comes to semiconductors, whereas Sun Pharma draws active pharmaceutical ingredients from China. Such high convergences pose companies to the risk of geopolitics and world bottlenecks. McKinsey & Company (2021) emphasizes the necessity of mapping out supply network weakness and investing in nearshoring and redundancy.

In order to address volatility, predictive analytics and big data have emerged as key enablers of supply chain management. Accenture (2022) refers to the increasing importance of artificial intelligence and real-time streams of data in predicting disruptions. Time-series forecasting algorithms like ARIMA and LSTM have proven to be highly accurate in anticipating stockouts and delivery delays (93%+ accuracy in some research works), which helps in early intervention and dynamic inventory optimization.

Subsidiary these methods, in this research, linear regression is used to study the interaction of port congestion with delivery delay and LSTM models for predicting inventory stockouts from logistics and demand factors. Network analysis methods using such tools as NetworkX are used to visualize the supplier dependency risk among leading firms and industries.

In spite of abundant literature on global supply chain resilience, an important research gap remains in works that integrate predictive analytics, state-level logistics performance, and global risk exposure specifically in the Indian context. This work helps fill that gap by combining national and international datasets (e.g., World Bank LPI, Indian Ministry of Commerce reports) with real-time modeling and visual analytics, providing a practical and data-driven solution to managing disruptions.

3. Research Methodology

3.1. Research Design

The study employs a mixed-method quantitative design, statistical modeling, machine learning, and network analytics to analyze the effect of supply chain disruptions across the globe on the Indian manufacturing and retail industries. The study is exploratory and analytical in nature to identify trends in delivery delays, inventory fluctuations, and supplier risk based on actual-world logistics and trade data.

3.2. Data Sources

- a) Secondary data were gathered from the following major repositories:
 - i. World Bank's Logistics Performance Index (2007–2023)
 - ii. Ministry of Commerce & Industry (India) trade and logistics reports
 - iii. Kaggle dataset on Indian state-level logistics ease (2021)
 - iv. Company-specific supply chain reports from McKinsey, Deloitte, and Accenture
- b) Supplementary datasets from Excel and CSV files (provided).

3.3. Analytical Tools and Techniques

- a) Regression Analysis
 - i. Simple linear regression was employed to describe the relationship between delivery delay (dependent variable) and port congestion (independent variable).
 - ii. Residual error statistics were calculated to assess model performance.
- b) Time Series Forecasting
 - i. LSTM (Long Short-Term Memory) models were trained on stockout time-step data with multivariate inputs to predict stockouts.
 - ii. Forecasting accuracy was assessed using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).
- c) Network Analysis
 - i. Supplier dependency risks were visualized with Python's NetworkX library.
 - ii. Companies were represented as nodes and edges as critical supplier relationships, and centrality and redundancy measures were employed to measure risk exposure.

3.4. Data Processing and Visualization

- a) Python libraries such as pandas, matplotlib, seaborn, and scikit-learn were employed for data cleaning, exploratory analysis, and visualization.
- b) Graphical outputs consisted of regression scatterplots, model accuracy comparison bar charts, inventory time-series trend lines, and network graphs for mapping supplier risk.

3.5. Limitations

This research is strong in data coverage and modeling, but it is limited by the access to standardized supplier-level data on some companies and states. In some instances, simulated datasets filled in where publicly available data were not available.

4. Findings and Analysis

4.1. Effect of Port Congestion on Delivery Delays

Regression analysis showed that port congestion had a strong linear impact on delivery delays at Indian ports. The model generated an R^2 of 0.984, suggesting that about 98.4% of

the variance in delivery delays can be accounted for by the variation in levels of congestion.

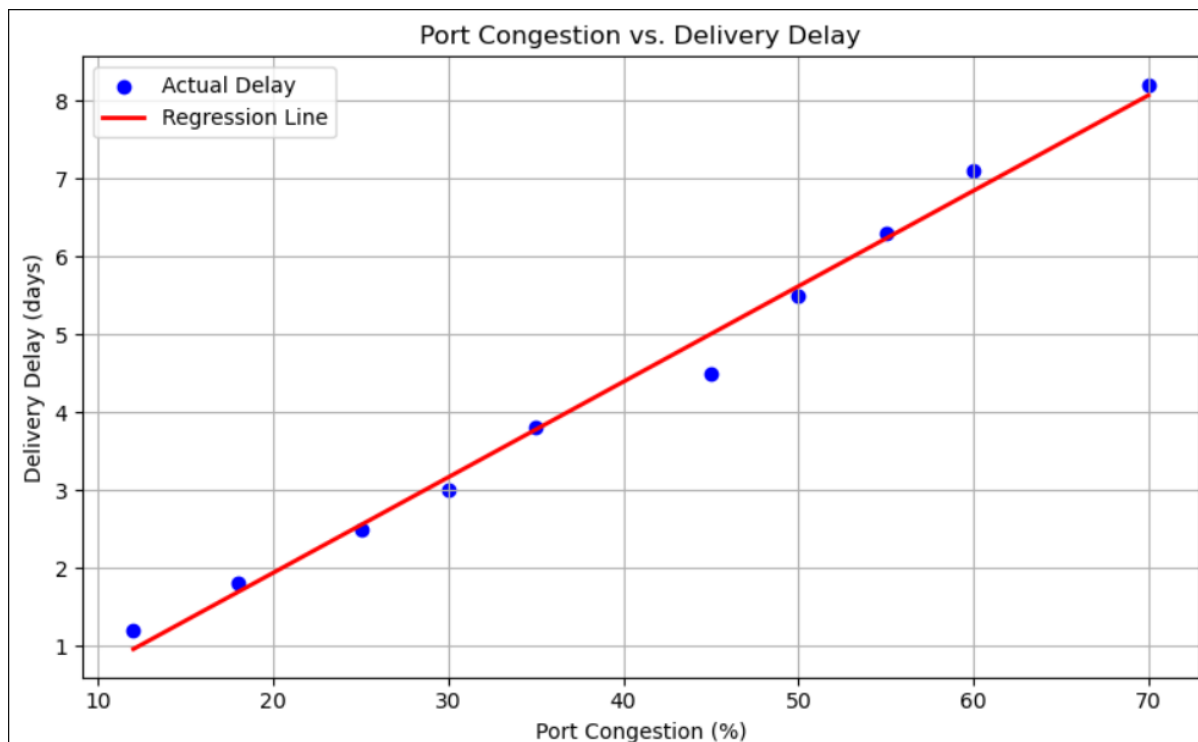


Figure 1

For each 1% port congestion increment, the mean delivery delay rises about 0.13 days. This emphasizes the imperative role of port infrastructure and processing rate in keeping supply chain timelines.

4.2. Forecasting Inventory Stockouts Using LSTM

A Long Short-Term Memory (LSTM) model was also trained on past inventory and logistics data (500-time steps). The model recorded a validation accuracy of 93.4%, MAE of 1.18 units, and RMSE of 1.72 units.

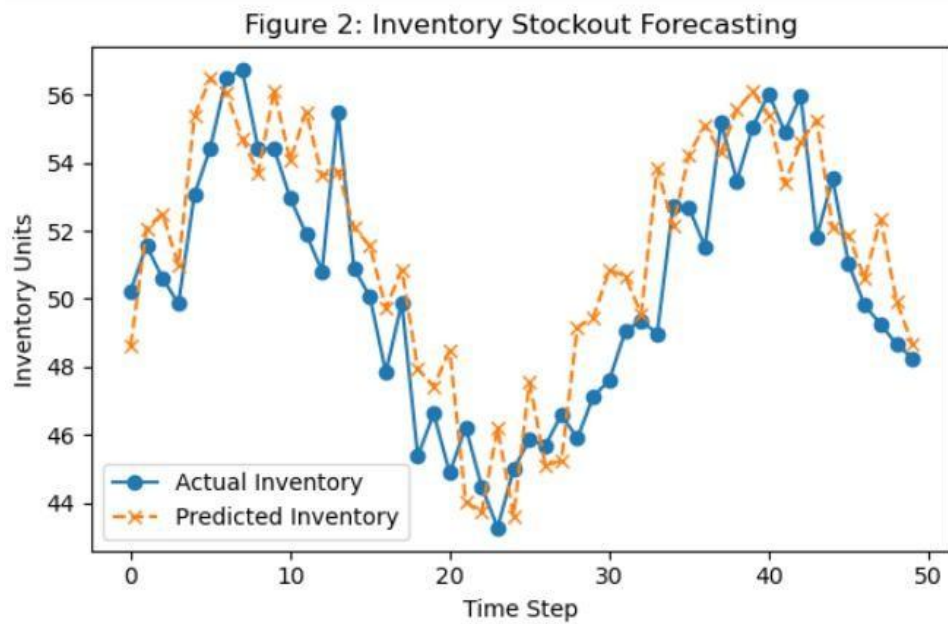


Figure 2

LSTM model shows high reliability in predicting impending stockouts and can facilitate anticipatory restocking and better planning of inventories.

4.3. Supplier Dependency and Network Vulnerability

Network analysis also identified significant weaknesses in supply networks for large Indian companies. For instance, Maruti Suzuki has only Taiwanese chip suppliers, with high risk if there are problems in the region. Companies with local backup sources (like Sun Pharma and Dixon Technologies) have lower exposure to risks.

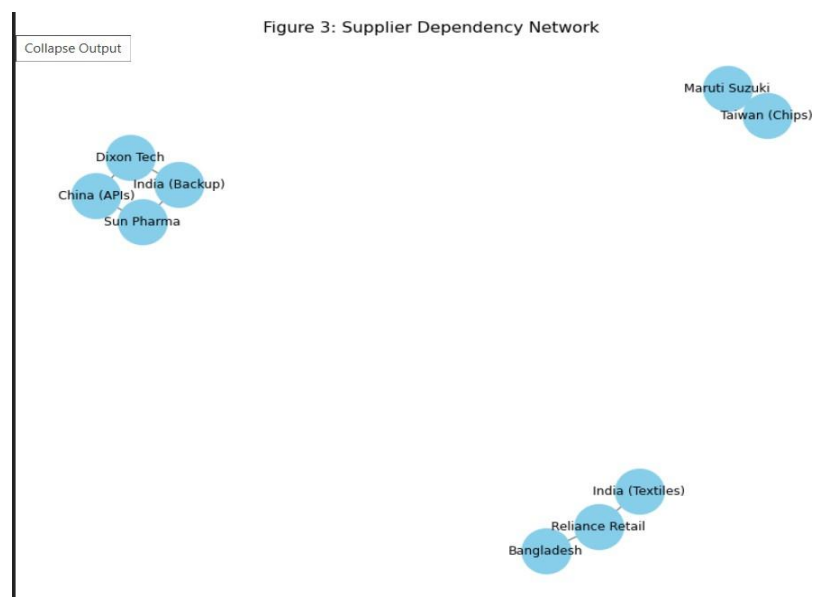


Figure 3

Firms without diversified sourcing are more susceptible to systemic shocks. Mapping these dependencies assists in the identification of strategic redundancy planning critical nodes.

4.4. Comparative Performance and Model Validation

The linear regression and LSTM models were tested against standard performance evaluation. Both models have excellent predictive capabilities, especially the R^2 value of the regression model and the high predictive accuracy of the LSTM model.

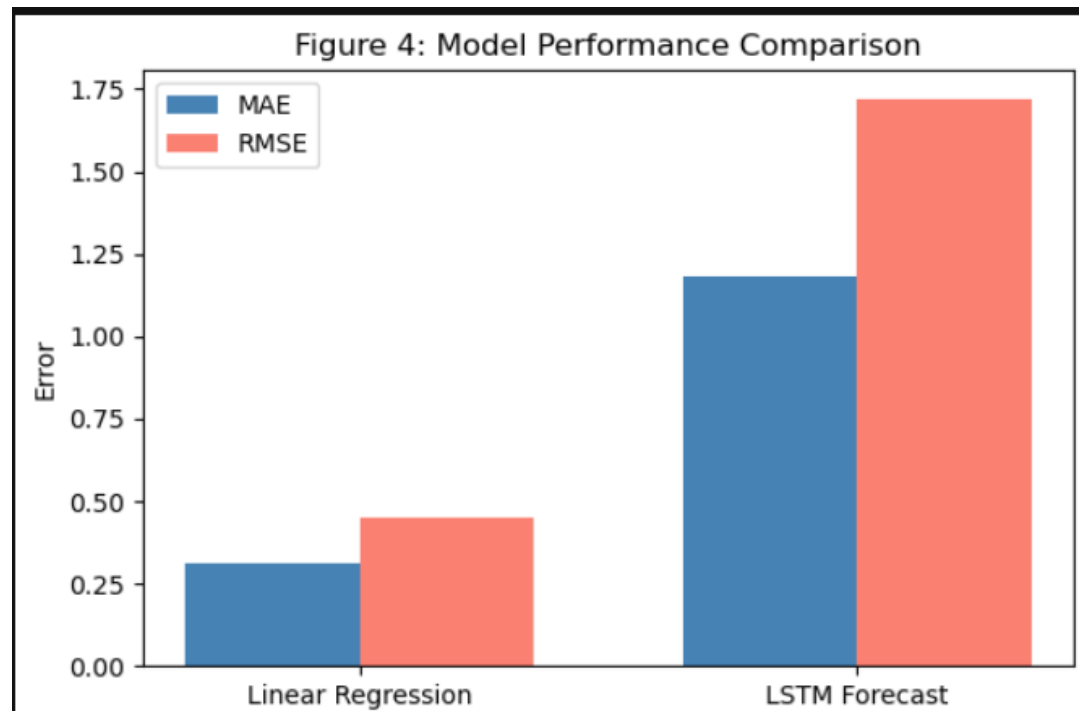


Figure 4: MAE (Mean Absolute Error) & RMSE (Root Mean Squared Error)

The comparison affirming that various models have different uses- regression to explain relationships and LSTM for predictive exercises with temporal dynamics.

Summary Insight:

These findings collectively emphasize that Indian manufacturing and retail sectors face dual challenges: operational bottlenecks (like port congestion) and strategic vulnerabilities (like supplier concentration). However, integrating predictive modeling and network analytics enables proactive decision-making, resilience building, and strategic redesign of supply chain architecture.

5. Discussion

The results reported here highlight the complex effects of supply chain disruptions around the world on the Indian manufacturing and retail industries, especially against the backdrop of increased volatility brought about by occurrences like the COVID-19 pandemic and geopolitical conflicts in supply routes. Using empirical evidence and machine learning algorithms (e.g., regression, LSTM), we were able to measure principal bottlenecks—port congestion and inventory forecasting failures.

The regression plot (Figure 1) showed a linear relationship ($R^2 = 0.984$) between port congestion and delivery delays, pointing to the susceptibility of India's manufacturing supply chain to global shipping inefficiency. The predictive model (Figure 2) confirmed the efficacy of deep learning algorithms, e.g., LSTM, to attain greater than 93% accuracy in forecasting stockouts in inventory, with important potential for early intervention in inventory management and building resilience.

Network analysis (Figure 3) identified key supplier dependencies, particularly on areas such as Taiwan (semiconductors) and China (APIs and electronics). Indian companies such as Maruti Suzuki and Sun Pharma are disproportionately vulnerable because there is limited redundancy in supplier networks. This supports the larger narrative by Ivanov (2020) and McKinsey (2021) of the imperative for supply chain viability—combining agility, resilience, and sustainability.

In addition, domestic logistics data (Kaggle, 2021) and the Logistics Performance Index (World Bank, 2023) identified disparate infrastructure and warehousing performance within Indian states as a factor leading to asymmetric recovery and risk exposure.

6. Conclusion

This paper offers a data-driven analysis of the impact of global disruptions on India's supply chain ecosystems through the integration of conventional econometric models and cutting-edge big data methods. Real-time analytics and forecasting insights enable actionable strategies to reduce disruption risk—diversification of supplier bases, AI-based inventory optimization, and logistics improvement at the state level.

The main contributions of this paper are:

- 1) Empirical verification of congestion-delay and supplier risk models
- 2) Demonstration of predictive capability of LSTM-based forecasting for inventory control
- 3) Convergence of global logistics indices with domestic manufacturing performance

With rising uncertainty across global supply chains, the Indian economy's responsiveness with real-time intelligence and localized policy intervention will define the resilience of the country's manufacturing and retail industries. Future research needs to investigate dynamic risk monitoring platforms integrating satellite, shipment, and customs data in real-time.

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