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Deep Learning-Based Demand Forecasting and Logistics Velocity: An Interrupted Time Series and DuPont Analysis of Amazon (2008-2025)

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Abstract.

This study quantitatively evaluates the impact of deep learning-based demand forecasting on logistics velocity and profitability at Amazon. Using quarterly financial data extracted from SEC EDGAR filings for 2008–2025 (72 observations), the deployment of the Multi-Horizon Quantile Recurrent Neural Network (MQ-RNN) in the first quarter of 2018 is treated as an intervention point. An Interrupted Time Series Analysis (ITSA) with Newey-West robust standard errors shows that the intervention produced an immediate reduction of 6.9 days in Days Sales of Inventory (DSI) and almost completely halted the upward trend in DSI observed before 2018. DuPont analysis indicates that this reduction released approximately $2.36 billion of capital tied up in inventory, reduced holding costs by $117.94 million and raised the quarterly net profit margin by 0.23 percentage points.

Keywords

artificial intelligence, deep learning, demand forecasting, MQ-RNN, days sales of inventory, interrupted time series analysis, DuPont analysis, Amazon.

Annotatsiya.

Ushbu tadqiqotda chuqur o‘qitishga asoslangan talabni prognozlash tizimining Amazon kompaniyasi logistika tezligi va rentabelligiga ta’siri miqdoriy baholanadi. SEC EDGAR bazasidan olingan 2008–2025-yillarga oid choraklik moliyaviy ma’lumotlar (72 ta kuzatuv) asosida 2018-yil I choragida Ko‘p gorizontli kvantil rekurrent neyron tarmog‘i (MQ-RNN) joriy etilishi intervensiya nuqtasi sifatida qabul qilingan. Newey-West barqaror standart xatolari bilan bajarilgan uzilgan vaqt qatorlari tahlili (ITSA) intervensiya tovar-moddiy zaxiralarning aylanish muddatini (DSI) darhol 6,9 kunga qisqartirganini va 2018-yilgacha kuzatilgan DSI ning o‘sish tendensiyasini deyarli to‘xtatganini ko‘rsatdi. DuPont tahliliga ko‘ra, bu qisqarish zaxiralarda band bo‘lgan taxminan 2,36 mlrd dollar kapitalni bo‘shatgan, saqlash xarajatlarini 117,94 mln

dollarga kamaytirgan va choraklik sof foyda me’yorini 0,23 foiz punktga oshirgan.

Kalit so‘zlar: sun’iy intellekt, chuqur o‘qitish, talabni prognozlash, MQ-RNN, tovar-moddiy zaxiralar aylanish muddati, uzilgan vaqt qatorlari tahlili, DuPont tahlili, Amazon.

Research Objective and Intervention Context. Modern organizations increasingly rely on advanced information technologies to improve their supply chain and logistics operations [1]. Demand forecasting systems are a key factor that determines how efficiently a company operates and how stable its financial position remains [2]. This study aims to examine how the deployment of artificial intelligence (AI) based on deep neural networks affected logistics velocity and inventory management at Amazon by conducting a quantitative and financial evaluation of its effects.

Amazon’s logistics network has always had to handle highly complex operations. Until 2018, the company’s Supply Chain Optimization Technologies (SCOT) division relied on traditional machine learning methods. These models achieved high accuracy for top-selling items, but they depended on human experts to construct input features through feature engineering, and data scientists had to define the variables explicitly before the algorithm could process them [3]. As a result, the models systematically failed to predict demand for the “long tail”, the large number of catalog items that generate minimal sales [4]. This technological limitation required large safety stocks, which left substantial capital resources idle.

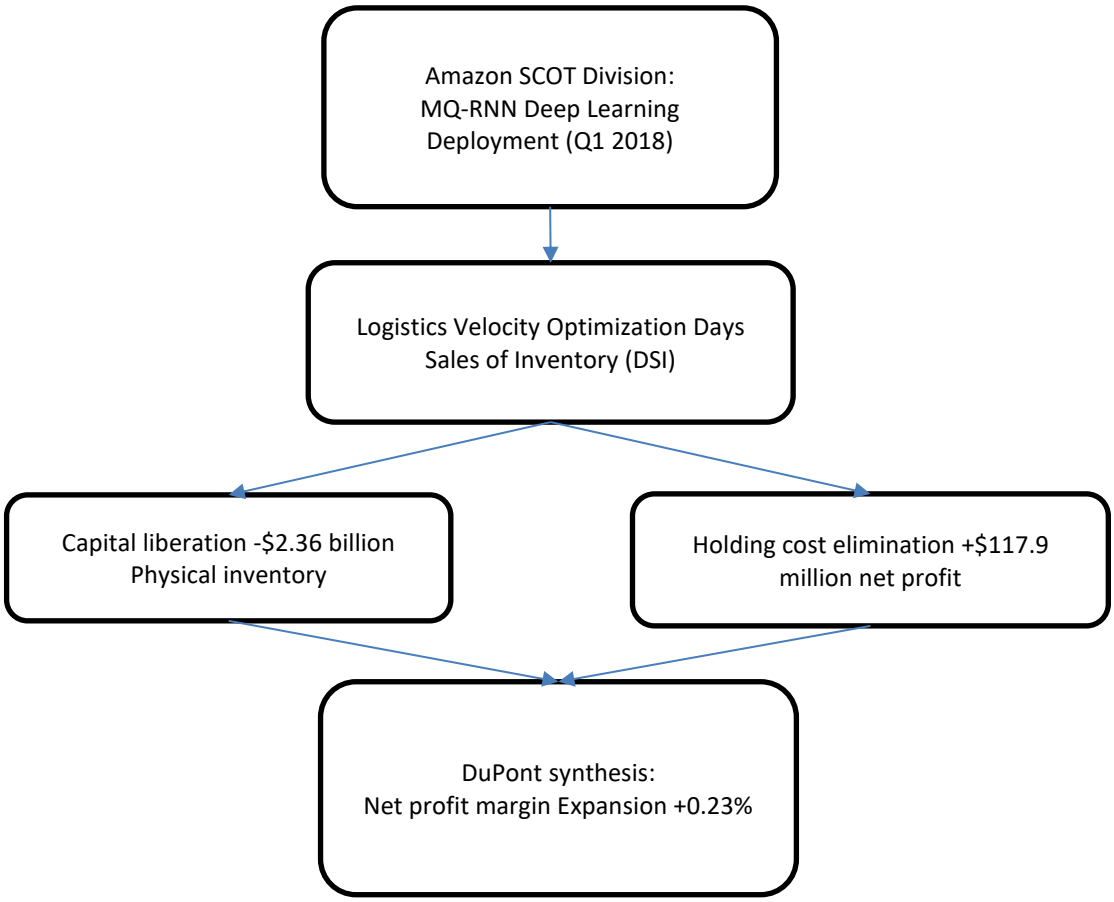

Figure 1. **Deep learning intervention and DuPont impact framework**

The conceptual framework shown in the flowchart in Figure 1 establishes a causal chain that runs from AI implementation to increased profit margins. In the first quarter of 2018, Amazon began a major organizational change by moving from human-designed machine learning models to a fully automated deep learning system, the Multi-Horizon Quantile Recurrent Neural Network (MQ-RNN) [5, 6]. The key feature of this system is that it removed the need for human experts to construct features: the neural network uses unstructured historical data to automatically discover hidden demand patterns at multiple time horizons across the entire product catalog. The Q1 2018 deployment therefore serves as the external intervention point that this study uses to assess how deep learning changes logistics speed and generates specific financial benefits.

Data Collection Methodology and Systems Engineering. To ensure a transparent and replicable analysis of corporate operations, all financial and operational metrics were extracted from the U.S. Securities and Exchange Commission (SEC) EDGAR database [7]. The resulting longitudinal dataset covers the period from the first quarter of 2008 to the fourth quarter of 2025 and contains 72 quarterly observations. Raw data were

extracted programmatically from standardized XBRL 10-K (annual) and 10-Q (quarterly) filings through the SEC REST API.

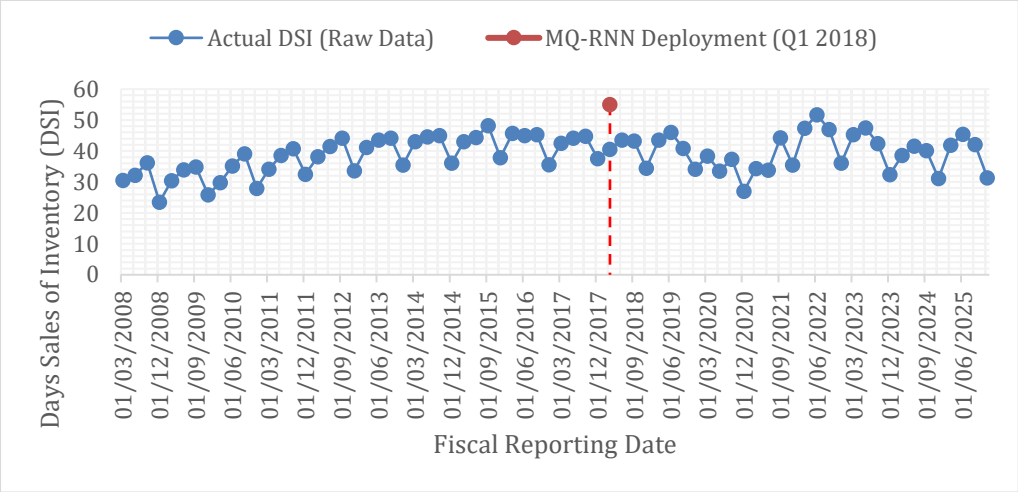

Figure 2. **Amazon Days Sales of Inventory (2008-2025)**

Highlighting Q4 Seasonal Shocks and AI Intervention Date

Building a continuous time series required two structural accounting issues to be resolved. First, the revenue recognition standard ASC 606, which took effect in 2018, split the historical revenue data into two separate records [8]. To create a single continuous revenue series, the legacy and the current XBRL revenue tags were merged. Second, Amazon does not report fourth-quarter flow metrics separately in its SEC filings. An algorithm was therefore developed to identify the missing Q4 values and derive them by subtracting the sum of the first three quarters from the cumulative annual 10-K totals: $Q_4 = Annual_{Total} - \sum_{i=1}^{3} Q_i$. Figure 2 shows the resulting time series, which demonstrates both the extreme Q4 holiday shocks and the exact moment when the deep learning system began operating.

Variable Operationalization. For the econometric analysis, total financial amounts were converted into standardized operational metrics. Days Sales of Inventory (DSI) was chosen as the primary dependent variable (Y_t) representing logistics velocity [9]. Because the dataset is quarterly, the standard annual DSI formula was calibrated to a 90-day window:

$$DSI = \frac{InventoryNet}{Cost\ of\ Goods\ Sold} \times 90 \quad (1)$$

For the Interrupted Time Series Analysis (ITSA), four independent variables were constructed [10, 11]:

1. **Time (T_t):** A continuous baseline trend counter spanning the entire temporal range.
2. **Intervention (X_t):** A binary dummy variable (0 prior to Q1 2018, and 1 thereafter).
3. **Post-Intervention Trend ($T_t \times X_t$):** An interaction term measuring quarters elapsed since the AI deployment.
4. **Seasonality Control (Q_{4t}):** A binary dummy variable designed to mathematically isolate and filter the systemic supply chain distortions caused by the Q4 holiday volume shock.

Table 1.

Summary Statistics for Key Financial and Operational Variables (2008 – 2025)

(Note: Financial figures are in Millions of USD, except DSI which is in days, and Margin which is a ratio.)

Variable	Obs. (N)	Mean	Std. Dev.	Minimum	Maximum
Days Sales of Inventory (DSI)	72	38.93	6.03	23.50	51.69
Total Revenue	72	63,718	58,311	4,063	213,386
Cost of Goods Sold (COGS)	72	36,376	29,978	3,096	109,959
Net Profit Margin	72	0.033	0.034	-0.033	0.117

Interrupted Time Series Analysis (ITSA) Results and Autocorrelation Diagnostics

To isolate the exact operational influence of the deep learning architecture, an initial segmented Ordinary Least Squares (OLS) regression [12] was estimated using the following equation:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_2 (T_t \times X_t) + \beta_4 Q_{4t} + \epsilon_t \quad (3)$$

The baseline model showed a good fit, with an R^2 value of 0.705, meaning that it explains 70.5% of the variation in Amazon's inventory turnover. However, supply chain time series are prone to serial correlation, because inventory accumulated in one quarter continues to affect subsequent quarters. The Durbin-Watson statistic of the initial model was 0.766, which indicates positive autocorrelation [13]. To prevent artificially low

standard errors, the model was re-estimated with Newey-West heteroskedasticity and autocorrelation consistent (HAC) robust standard errors [14], using 4 lags to cover the annual retail cycle.

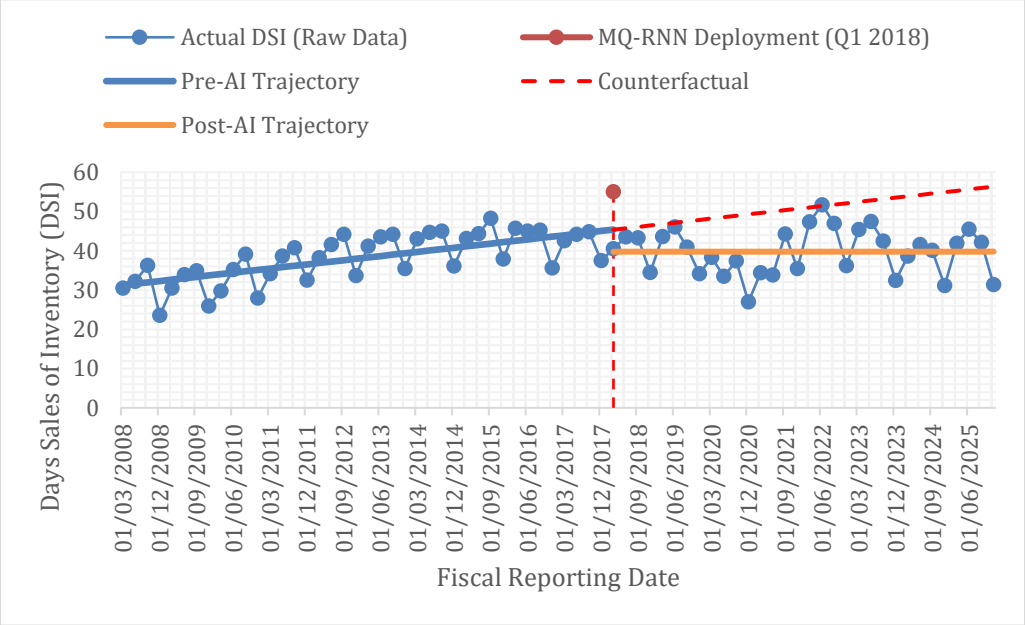

Figure 3. **Interrupted Time Series Analysis (ITSA)**

Segmented Regression with Robust Trend Lines

Figure 3 visualizes these robust trends, showing the actual, predicted and counterfactual trajectories of DSI. All independent variables remained statistically significant after the robust correction (Table 2). The baseline intercept ($\beta_0 = 32.319$) indicates that Amazon's inventory turnover period at the start of the sample was about 32.3 days. The pre-intervention time coefficient ($\beta_1 = 0.397$, $p < 0.001$) shows that, until 2018, logistics efficiency was steadily declining, with DSI rising by about 0.4 days per quarter. The seasonality control ($\beta_4 = -8.812$, $p < 0.001$) separates the Q4 holiday effect from the trend: in fourth quarters, DSI is on average 8.8 days lower than in other quarters. Visual inspection of Figure 3 also shows that DSI began to decline in mid-to-late 2016. In time-series econometrics, this pattern is known as a "phase-in effect": during this period, Amazon's SCOT division was testing early neural network systems on selected product lines.

Table 2.

Segmented Regression Results with Newey-West HAC Robust Standard Errors

Dependent Variable: Days Sales of Inventory (DSI)

Model Fit: R-squared = 0.705, Observations = 72, Durbin-Watson = 0.766

Variable (ITSA Parameters)	**Coefficient (β)**	**Robust Std. Error**	**z-Statistic**	**P-Value (p)**
Baseline Intercept (β_0)	32.319	1.010	31.988	< 0.001***
Pre-Intervention Time Trend (β_1)	0.397	0.051	7.744	< 0.001***
AI Intervention Dummy (β_2)	-6.907	2.370	-2.915	**0.004****
Post-Intervention Trend (β_3)	-0.356	0.088	-4.034	< 0.001***
Seasonality Control - Q4 (β_4)	-8.812	0.464	-18.996	< 0.001***

*** *denotes statistical significance at the 1% level. Standard errors are heteroskedasticity and autocorrelation robust (Newey-West, 4 lags).*

The pilot projects conducted at selected locations in 2016 and 2017 produced small efficiency gains but did not fundamentally change operational procedures. The model therefore uses Q1 2018 as the intervention date, because this point marks the stage at which the MQ-RNN architecture was unified and applied across the entire fulfillment network, allowing its full effect to be assessed. The AI intervention coefficients confirm the core hypothesis of the study with high statistical confidence. The immediate intervention dummy (β_2 = -6.907) has a robust standard error of 2.370 and a p-value of 0.004. This shows, at the 1% significance level, that the activation of the MQ-RNN architecture caused a direct structural reduction of 6.9 days in inventory holding time. The post-intervention trend coefficient (β_3 = -0.356, $p < 0.001$) shows that the company's trajectory changed fundamentally: the quarterly increase in DSI fell from about 0.40 days before 2018 to only about 0.04 days afterwards (0.397 – 0.356), meaning that the neural network almost completely halted the deterioration in inventory efficiency observed over the previous decade.

DuPont Financial Synthesis: Calculating the Economic Value. A reduction of almost

seven days in inventory holding time reflects a substantial increase in operational speed. DuPont analysis makes it possible to convert this time saving into specific financial benefits [15]. The decrease in DSI shows how much capital was released from inventory held at fulfillment centers.

Applying the Q1 2018 intervention shock ($\boldsymbol{\Delta\, DSI\ =\ -6.907}$) to Amazon's actual Cost of Goods Sold for that quarter ($30.73 billion), the capital liberation equation yields:

$$\boldsymbol{\Delta Inventory = \frac{6.907 \times \$30.73\ Billion}{90} = \$2.36\ Billion} \quad (3)$$

As a result of the transition to deep learning, Amazon released approximately $2.36 billion of capital that had previously been tied up in slow-moving inventory.

This capital reduction directly affected the income statement through the elimination of inventory holding costs (warehousing, depreciation and labor). Assuming a quarterly holding cost rate of 5% (H = 0.05), which corresponds to the annual rate of about 20% commonly used in inventory management [9, 16], the operational savings generated by the AI system were calculated as follows:

$$\boldsymbol{\Delta Net\ Profit = \$2.36\ Billion \times 0.05 = \$117.94\ Million} \quad (4)$$

Based on these results, a counterfactual DuPont baseline was constructed to estimate the effect of the intervention on corporate profitability. Without the AI system, the additional holding costs of $117.94 million would have reduced Amazon's Q1 2018 net profit margin to 2.96%. The actual reported net profit margin was 3.19%, which means that the deep learning logistics intervention increased the net profit margin by 0.23 percentage points (Table 3).

Table 3. **Economic Impact and Counterfactual Baseline (Q1 2018 AI Deployment)**
(Financial figures in Millions of USD)

Metric	Counterfactual Baseline (Without AI)	Actual Reported (With AI)	AI-Generated Variance (Δ)
Days Sales of Inventory (DSI)	45.25 days	38.34 days	**-6.90 days**
Physical Inventory (Capital Trapped)	$16,198.84	$13,840.00	-$2,358.84

Inventory Holding Costs (Operational Waste)	$809.94	$692.00	-$117.94
Net Income	$1,511.06	$1,629.00	+$117.94
Net Profit Margin	2.96%	3.19%	**+0.23 p.p.**

Conclusion

The results support the hypothesis that autonomous artificial intelligence systems provide significant advantages over human-designed logistics forecasting systems. The combination of Interrupted Time Series Analysis and DuPont synthesis demonstrates that deep learning models act as important drivers of capital release rather than simple software upgrades. By improving demand forecasting for long-tail products, the MQ-RNN system removed 6.9 days of idle inventory from Amazon's fulfillment network, released approximately $2.36 billion of capital and generated about $118 million in quarterly operational savings, increasing the net profit margin by 0.23 percentage points. The study has several limitations. It is based on a single company, so the results cannot be directly generalized to other firms. The intervention date is identified from publicly available information, and the phase-in effect observed in 2016–2017 suggests that part of the impact occurred before Q1 2018. In addition, the financial effect relies on an assumed holding cost rate of 5% per quarter. Future research could extend this approach to a panel of logistics and retail companies and test the sensitivity of the results to alternative holding cost assumptions.

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