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Forecasting trade flows under geopolitical uncertainty: A hybrid econometric–LSTM approach

Pronóstico de flujos comerciales bajo incertidumbre geopolítica: un enfoque híbrido econométrico-LSTM

Mariel Álvarez-Salas[*] Oscar Adrián Huitz-Montero[**] Emiliano Montalvo-Vásquez[***]

David Roberto Valenzuela-Vega[****] Carlos Emmanuel Saldaña Villanueva[*****]

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Abstract

This study develops a forecasting framework to improve the prediction of international trade flows under increasing geopolitical uncertainty, trade tensions, and global value chain fragmentation. The framework combines econometric and machine learning techniques. Stochastic convergence algorithms are used to identify convergence clubs among countries trading with China and the United States. Principal Components Analysis (PCA) and LASSO regression reduce dimensionality and select relevant predictors, which are then incorporated into a Long Short-Term Memory (LSTM) network. The proposed model outperforms comparable LSTM benchmark specifications across multiple forecast horizons. Panel Diebold-Mariano tests indicate statistically significant forecasting improvements for one-month-ahead predictions in most cases, particularly relative to models that include exogenous variables but exclude convergence club formation. The investigation demonstrates that incorporating cross-country convergence structures enhances forecast accuracy, improves dataset management and model specification, and provides a scalable framework that preserves the flexibility and nonlinear capabilities of deep learning models.

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Resumen

Este estudio desarrolla un pronóstico para mejorar la predicción de los flujos comerciales internacionales en un contexto de creciente incertidumbre geopolítica, tensiones comerciales y fragmentación de las cadenas globales de valor. La metodología combina técnicas econométricas y de aprendizaje automático. Mediante algoritmos de convergencia estocástica se identifican clubes de convergencia entre socios comerciales de China y Estados Unidos. Posteriormente, el Análisis de Componentes Principales (PCA) y la regresión LASSO permiten reducir la dimensionalidad y seleccionar las variables más relevantes, para incorporarlas a una red Long Short-Term Memory (LSTM). El modelo propuesto supera a especificaciones LSTM comparables en múltiples horizontes de pronóstico. Las pruebas de Diebold-Mariano para datos de panel muestran mejoras estadísticamente significativas en los pronósticos a un mes, especialmente en modelos que incluyen variables exógenas, pero no la formación de clubes de convergencia. El estudio demuestra que incorporar estructuras de convergencia entre países mejora la precisión predictiva, optimiza la gestión de datos y la especificación del modelo, y proporciona un marco escalable que conserva la flexibilidad y capacidad para capturar relaciones no lineales propias del aprendizaje profundo.

[*] Tecnológico de Monterrey
marielalvarezsalas@protonmail.com
https://orcid.org/0009-0001-7577-7872

[**] Universidad Autónoma de Nuevo León
ohuitz88@gmail.com
https://orcid.org/0009-0000-6665-5972

[***] Corresponding author
Tecnológico de Monterrey
emilianomontalvo118@gmail.com
https://orcid.org/0009-0002-2940-7704

[****] Tecnológico de Monterrey
david.valenzuela@tec.mx
https://orcid.org/0000-0002-5494-0132

[*****] Tecnológico de Monterrey
carlos.s@tec.mx
https://orcid.org/0000-0002-3044-6789

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1. Introduction

Recent geopolitical tensions and renewed trade protectionism have increased the need for reliable methods to forecast trade flows under uncertainty and structural change. Accurate trade forecasts are essential for policymakers facing recurrent shocks. However, traditional approaches based on historical trends or gravity models perform poorly under structural breaks (Borin et al, 2024), while general equilibrium models better capture policy shocks but lack scalability across countries and products (Bekkers & Teh, 2019; Bekkers et al., 2020). This paper addresses these challenges by proposing a hybrid reduced-form framework that combines stochastic convergence algorithms, dimensionality reduction, and LSTM networks. The convergence club procedure groups trade series with similar dynamics, enabling club-specific model estimation that preserves heterogeneity without sacrificing scalability. Within each club, PCA and LASSO regressions are used to construct parsimonious feature sets, which are then fed into an LSTM network to capture nonlinear temporal patterns. The framework is evaluated against two comparable LSTM benchmarks, allowing us to isolate the incremental contribution of the convergence club approach. Results are assessed using both descriptive metrics and a panel Diebold-Mariano test for statistical significance.

The remainder of the paper is organized as follows. Section 2 presents the literature review; Section 3 describes the data, dimensionality reduction methods (PCA and Lasso), the stochastic convergence–based club-formation procedure, and the LSTM forecasting model. Section 4 presents the main results, and Section 5 concludes and gives policy-oriented recommendations.

2. Literature review

Recent studies on forecasting international trade flows combine gravity-model fundamentals with machine learning (ML) and deep learning (DL) architectures. At the bilateral level, ML often outperforms classical gravity models, particularly when high-dimensional covariates and nonlinearities are present (Jošić & Žmuk, 2022; Bosone & Giudici, 2024). Forecasting in highly uncertain policy environments further motivates the use of flexible techniques such as ML, given the limited guidance on modeling uncertainty (Gopinath et al., 2021).

The level of data aggregation matters for forecast quality; HS-level panels frequently incorporate economic complexity features to stabilize forecasts (Tiits et al., 2024). Additional covariates increasingly complement core gravity variables. The treatment of shock windows and policy variables also affects forecasting outcomes. Gopinath et al. (2021) include tariffs as inputs in bilateral ML forecasts to test prediction sensitivity under alternative scenarios.

Methodologically, the growing complexity of global trade motivates the use of nonlinear approaches (Huang et al., 2023). Hybrid models, combining econometric structure with ML flexibility, have shown strong forecasting performance (Rowland, 2020). In particular, SARIMA–LSTM residual learning outperforms single models in monthly China–Russia trade data, while recent work combining Transformers with ARIMA further highlights promising directions for forecasting under high uncertainty (Ding, 2022; Wang, 2025).

Our approach contributes to this literature by introducing convergence club formation as a structured method for organizing heterogeneous trade panels prior to estimation, an intermediate step between full pooling and full disaggregation that has not been systematically explored in trade forecasting.

3. Data and methodology

3.1 Data

3.1.1 Trade data

Bilateral trade flow data were obtained from the Observatory of Economic Complexity (OEC) and consist of monthly observations from 2023 to 2025 (Simoes & Hidalgo, 2011). Each observation identifies the reporter and partner countries, trade flow type (imports or exports), product category at the HS6 level, quantity in standardized units, and trade value in U.S. dollars; product classifications were subsequently aggregated to the HS4 level.

The sample is restricted to the 20 countries with the largest bilateral trade flows with China and the United States, conditional on trading at least 200 distinct HS4 products over the sample period.

3.1.2 Explanatory variables

Explanatory variables follow standard macroeconomic fundamentals in the trade forecasting literature, including measures of production, consumption, real effective exchange rates (REER), and commodity prices. To capture uncertainty and changing market conditions, we also include leading indicators such as Composite Leading Indicators (CLIs), the Baltic Dry Index, and the Economic Policy Uncertainty Index (EPU). The complete set of variables, definitions, and sources is reported in Table 1.

Table 1: Explanatory variables.

Variable	Source	Justification
Industrial Production Index for the U.S. (INDPRO)	Federal Reserve Economic Data (FRED)	Proxy for economic activity (GDP).
Private Consumption Index for the U.S. (PCI)	FRED	Measure of import demand.
United States PMI Indicator	FRED	Proxy for economic activity.
Global Economic Activity Indicator for Mexico	INEGI	Proxy for economic activity.
China PMI Global Indicator	NBS of China	Proxy for economic activity.
European PMI Global Indicator	Eurostat	Proxy for economic activity.
China Real Effective Exchange Rate	IMF	Measures trade competitiveness.
European Union Real Effective Exchange Rate	IMF	Measures trade competitiveness.
United States Real Effective Exchange Rate	IMF	Measures trade competitiveness.
Mexico Real Effective Exchange Rate	IMF	Measures trade competitiveness.
International Price of WTI Crude Oil	FRED	Cost transmitter of production and consumption.
International Price of Liquefied Natural Gas	FRED	Cost transmitter of production and consumption.
International Price of Aluminum	FRED	Cost transmitter of production and consumption.
International Price of Copper	FRED	Cost transmitter of production and consumption.
International Price of Corn	FRED	Cost transmitter of production and consumption.
International Price of Wheat	FRED	Cost transmitter of production and consumption.
U.S. Trade Policy Uncertainty Index	Policy Uncertainty	Leading indicator of policy uncertainty.
China Trade Policy Uncertainty Index	Policy Uncertainty	Leading indicator of policy uncertainty.
Equity Market Volatility Index	Policy Uncertainty	Measures financial market volatility.
Baltic Dry Index	Investing.com	Leading indicator of global trade activity.
U.S. Composite Leading Indicator	OECD	Anticipates business cycle turning points.
European Union CLI	OECD	Anticipates business cycle turning points.

Table 1: Explanatory variables. (continued).

Variable	Source	Justification
Asian CLI	OECD	Anticipates business cycle turning points.
G20 CLI	OECD	Anticipates business cycle turning points.

Source: Own elaboration.

3.1.3 Dimensionality reduction

To address multicollinearity and reduce dimensionality, variables are grouped into four economically meaningful categories (Table 2) and summarized via PCA, following Hotelling (1933) and Stock and Watson (2002). For each group, components are retained sequentially if they explain at least 10% of the group's variance and satisfy the Kaiser criterion, until cumulative explained variance reaches 80%.

Table 2: PCA groups.

Group	Variables
Macroeconomic indicators for the U.S.	INDPRO, PCI, PMI U.S.
Commodity prices	International Price of WTI Crude Oil, International Price of Liquified Natural Gas, International Price of Aluminum, International Price of Copper, International Price of Corn, International Price of Wheat.
Real Effective Exchange Rate Indices (reer)	Mexico, U.S, E.U. and China REER Indices
Leading Indicators	U.S Trade Policy Uncertainty Index, China Trade Policy Uncertainty Index, Equity Market Volatility Index, U.S. Composite Leading Indicator, China Composite Leading Indicator, European Union Composite Leading Indicator, G20 Composite Leading Indicator.

Source: Own elaboration.

Feature selection is then performed using LASSO regression within each club, applying an L1 penalty that shrinks irrelevant coefficients to zero (Pabuccu & Barbu, 2024). The model uses three-fold temporal cross-validation, prior standardization, 80 values of the regularization parameter, and up to 5,000 iterations. Variables with non-zero coefficients were retained as inputs for the LSTM models.

3.2 Club formation

To identify groups of series sharing similar long-run dynamics, we apply the log-t convergence test developed by Phillips and Sul (2007), which allows for heterogeneous transitional dynamics without imposing ex ante convergence.

The procedure relies on testing the convergence of time-varying factor loadings and enables the endogenous identification of convergence clubs. Club membership is determined using the standard club formation algorithm proposed by Phillips and Sul, which proceeds as follows:

1. Series are ordered in descending order by their average over the last third of the sample.
2. The first k series is selected to form an initial core group G_k. A log-t regression is estimated for this group, and k is chosen to maximize the associated t-statistic.
3. The remaining series are sequentially added to the core group and retained if their corresponding t-statistic exceeds the critical value $c^* = 0$.

4. The procedure is then applied recursively to the set of series not included in the initial group to identify additional convergence clubs. If no valid core group can be formed at any stage, the remaining series are classified as divergent.

The procedure is implemented in R using the *ConvergenceClubs* package (Sichera & Pizzuto, 2019), applying *findClubs* and *mergeClubs* to identify statistically similar groups. This yields 24 convergence clubs for the United States and 11 for China. The full set of club assignments is reported in the appendix. Some series from the original data are excluded from this procedure due to insufficient observations.

3.3 Forecasting models

We employ LSTM networks to capture non-linear temporal patterns that standard linear benchmarks fail to identify, particularly under elevated uncertainty. LSTMs are recurrent neural networks with feedback connections that enable nonlinear, time-variant prediction on sequential data (Lindemann et al., 2012; Machlev, 2024)

Given the heterogeneity in trade values across series, the target variable is modeled in logarithmic differences to stabilize variance:

$$\Delta log(y_t) = log(y_t) - log(y_{t-1})$$

Model inputs consist of a six-month rolling window, containing lagged $log(1 + y_t)$ and LASSO-selected exogenous variables. Predicted log differences are mapped back to the original trade values $\hat{y}_{t+h}$. Full architecture and hyperparameter details are provided in Table A2 in the appendix.

3.4 Evaluating performance

The proposed model is compared against two LSTM benchmarks to isolate the contribution of the convergence club structure. We refer to the first one as Global-LSTM, a standard LSTM without club formation or exogenous variables. The second model, Global-LSTM-Exog, excludes club formation but incorporates PCA components selected via LASSO, separately within each panel.

Given the considerable scale heterogeneity across series, forecast accuracy is evaluated using symmetric absolute percentage error (sMAPE) and mean absolute scaled error (MASE), both of which are scale-free measures (Hyndman & Koehler, 2006). sMAPE ranges from 0 to 100, with lower values indicating better performance; MASE is benchmarked against a naïve forecast, with values below one indicating the model outperforms the naïve benchmark.

To assess whether the proposed model statistically outperforms benchmark forecasts, we evaluate predictive accuracy using a panel version of the Diebold-Mariano test (1995) proposed by Pesaran et al (2009), suited for panels with large cross-sectional and short time dimensions. We compute the Absolute Forecast Error (AE) for series i as:

$$AE(i, t) = |y_{i,t+1} - \hat{y}_{i,t+1|t}|$$

Where y_{t+1} is the actual value and $\hat{y}_{t+1|t}$ is the model forecast. The absolute loss function is preferred to quadratic alternatives given the panel's high heterogeneity and the presence of outliers. Testing is restricted to 1-month ahead for two reasons: the loss differentials can be assumed serially uncorrelated at h=1, requiring no adjustment; and, for 1-month-ahead forecasts, we have $T = 5$ observations per series, whereas for $h > 1$ we do not have enough observations to carry out the test reliably. Now consider the loss differential for series i using model A relative to model B:

$$z_{i,t} = \left[AE_{A,t}(i,t) - AE_{B,t}(i,t)\right]$$
$$\text{A} = \text{Proposed model}$$
$$\text{B} = \text{Benchmark model}$$

The Panel DM test structure is then:

$$z_{i,t} = \mu + \varepsilon_{i,t}$$
$$H_0 : \mu = 0$$
$$H_1 : \mu < 0$$

A negative statistic indicates lower AE for the proposed model, making the one-sided test appropriate. Standard errors are clustered at the series level to account for heteroskedasticity across series.

4. Results and discussion

Table 3 summarizes sMAPE and MASE at 1-, 3-, and 6-month horizons by panel. At the one-month horizon, the proposed model outperforms the benchmarks in all panels. Performance deteriorates at longer horizons for all models, as expected under uncertainty. The proposed model's advantages are most evident relative to Global-LSTM-Exog; Global-LSTM is the most competitive benchmark, with MASE values close to or below those of the proposed model at 3 and 6 months across several levels.

Table 3: Forecasting performance metrics by models aggregated in panels and horizons.

	Proposed model sMAPE (%)	Global LSTM sMAPE (%)	Global LSTM Exog MAPE (%)	Proposed model MASE	Global LSTM MASE	Global LSTM Exog MASE
			1 Month horizon			
China Exports	17.370	18.88	18.41	0.772	0.952	1.145
China Imports	22.504	25.196	23.72	0.643	0.977	1.209
U.S. Exports	21.366	24.592	21.406	0.851	1.004	0.921
U.S. Imports	18.478	20.998	21.447	0.901	0.988	1.018
			3 Month horizon			
China Exports	21.987	21.559	29.94	0.902	0.88	1.526
China Imports	25.524	27.099	28.507	0.812	0.974	1.509
U.S. Exports	22.720	25.879	26.968	0.924	0.949	1.184
U.S. Imports	20.642	22.301	31.651	1.113	0.951	1.51
			6 Month horizon			
China Exports	24.880	26.227	34.723	1.003	0.915	1.63
China Imports	30.978	29.761	31.687	0.868	0.951	1.449
U.S. Exports	23.873	26.796	30.35	0.923	0.988	1.411
U.S. Imports	23.102	24.011	25.151	1.681	0.983	1.562

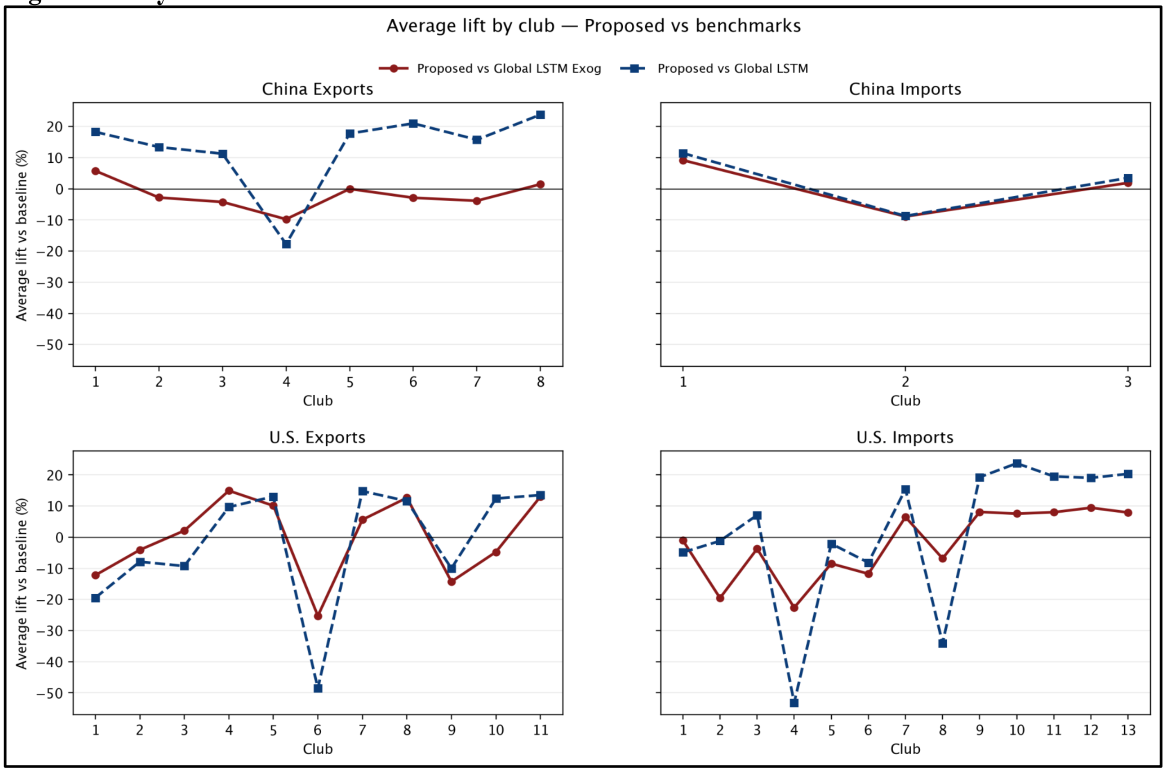
Source: Own elaboration with OEC data.

For certain panel-horizon combinations, notably US imports and China exports at 6 months, MASE exceeds unity, indicating that the proposed model does not outperform the naïve benchmark. To examine the relative performance in detail, we compute the percentage lift in sMAPE for the proposed model relative to each benchmark.

$$LIFT_{sMAPE}(\%) = \frac{sMAPE_{baseline} - sMAPE_{proposed}}{sMAPE_{baseline}} \times 100$$

Positive values indicate improvement over the benchmark; negative values indicate a deterioration.

Figure 1: Percentage lift in sMAPE of the proposed model relative to benchmark models, segmented by club.



Source: Own elaboration with OEC data.

Figure 1 illustrates performance heterogeneity across clubs, panels, and horizons, with a detailed breakdown by forecast horizon provided in Figure A1 (see Appendix). Several clubs show consistent positive gains, particularly against Global-LSTM-Exog in China Exports and against Global-LSTM in US Imports. However, improvements are not uniform: some clubs exhibit negative lift, suggesting that the benefits of group size and cohesion are not realized. Clubs with fewer series or lower convergence stability appear more sensitive to specification errors, resulting in greater lift volatility.

Table 4 presents Panel DM test results for 1-month-ahead forecasts at the aggregate level and across four panels.

Table 4: Panel DM statistics of the proposed model relative to benchmarks.

Group	US imports	US exports	China imports	China exports	All trade flows
			Proposed model vs. Global -LSTM-Exog		
DM statistic	−9.31***	0.37	−3.03***	−8.46***	−7.55***
			Proposed model vs. Global-LSTM		
DM statistic	−5.74***	−4.53***	1.25	1.82**	−3.55***

Note: Negative values indicate lower absolute forecast errors for the proposed model. Critical values for a one-sided test: −2.326 (1%) and −1.645 (5%). *** $p < 0.01$ ** $p < 0.05$.
Source: Own elaboration with OEC data.

Against Global-LSTM-Exog, the proposed model significantly outperforms at the aggregate level and for US Imports, China Imports, and China Exports, all at the 1% significance level. The only exception is US Exports, where the difference is not statistically significant. Against Global-LSTM, the proposed model outperforms at the aggregate level and across both US trade flow groups. For China, however, results are reversed: the DM statistic is positive for China Imports at the 5% level, indicating that Global-LSTM performs better for Chinese series.

Taken together, the proposed model more consistently outperforms Global-LSTM-Exog than Global-LSTM does, particularly for China's trade flows. This suggests that adding exogenous variables to an LSTM may be counterproductive if cross-sectional heterogeneity is not accounted for first. The convergence club structure addresses this by enabling club-specific estimation, and the Panel DM results provide direct evidence that this structure, rather than the use of LSTM networks or exogenous information, is an important driver of predictive gains.

4.1 Limitations

This study is limited by a short time span of monthly data, ranging from January 2023 to March 2025, which restricts the identification of long-term dynamics and cyclical patterns. Therefore, this analysis excludes some critical shocks, such as the COVID-19 pandemic. The short sample size might affect the stability of convergence club assignments, as this concept is inherently linked to long-run dynamics. This motivates future studies using longer, more frequent data and ensures robustness across country pairs and product aggregations.

Additionally, nowcasting approaches offer clear advantages for short-term prediction by incorporating high-frequency, real-time data and could be considered in this context (Giannone et al., 2008; Hopp, 2022; Arslanalp et al., 2019). Our framework partially addresses this dimension by including leading indicators within our monthly series. Extending to a full nowcasting setting, however, would require overcoming significant data availability and computational challenges, given the high level of disaggregation in our dataset across more than 20 countries and thousands of HS4 product categories. We consider this a promising direction for future research, albeit one that involves serious trade-offs between predictive performance and scalability.

5. Conclusions and recommendations

This paper proposes a forecasting framework integrating stochastic convergence clubs, dimensionality reduction, and LSTM networks to forecast bilateral trade flows under uncertainty. The key contribution lies in using club formation as a structured intermediate step between full pooling and full disaggregation, grouping heterogeneous panels with similar long-run dynamics to improve model specification and feature selection prior to estimation.

Empirical results show that the proposed model consistently outperforms benchmark models at the one-month horizon across all panels. Panel DM tests confirm that improvements are statistically significant in the majority of cases and are driven primarily by the convergence structure rather than by exogenous variables or the LSTM architecture alone. This is evidenced by the stronger outperformance against the benchmark that incorporates exogenous variables but omits club formation.

Results are more mixed at longer horizons and for China's trade flows, suggesting that the benefit of club formation depends on group cohesion and sample stability. Extending the sample period and investigating whether Chinese series exhibit structural dynamics that challenge the stochastic convergence assumption represent productive directions for future research.

From a policy perspective, the framework supports scenario analysis, inventory management, tariff impact assessment, and early detection of trade disruptions — applications of growing value as trade policy becomes increasingly unpredictable.

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Data availability statement

The U.S.–China trade dataset used in this article was sourced from the Observatory of Economic Complexity (OEC). The data can be obtained from the OEC website (oec.world) under the conditions specified by the provider. Access to the full dataset may require a premium account. The sources of the data used as explanatory variables are clearly identified in the document.

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Appendix

Table A1: Stochastic convergence club assignments.

Panel	Club	Unique Series
China Exports	1	8726
	2	5
	3	38
	4	4
	5	89
	6	496
	7	851
	8	5792
China Imports	1	2454
	2	77
	3	4848
U.S. Exports	1	6
	2	16
	3	19
	4	67
	5	98
	6	4
	7	66

Table A1: Stochastic convergence club assignments. (continued).

Panel	Club	Unique Series
U.S. Exports	8	4626
	9	43
	10	565
	11	5478
U.S. Imports	1	79
	2	6
	3	3
	4	20
	5	48
	6	30
	7	4
	8	7
	9	223
	10	794
	11	2257
	12	4237
	13	2851

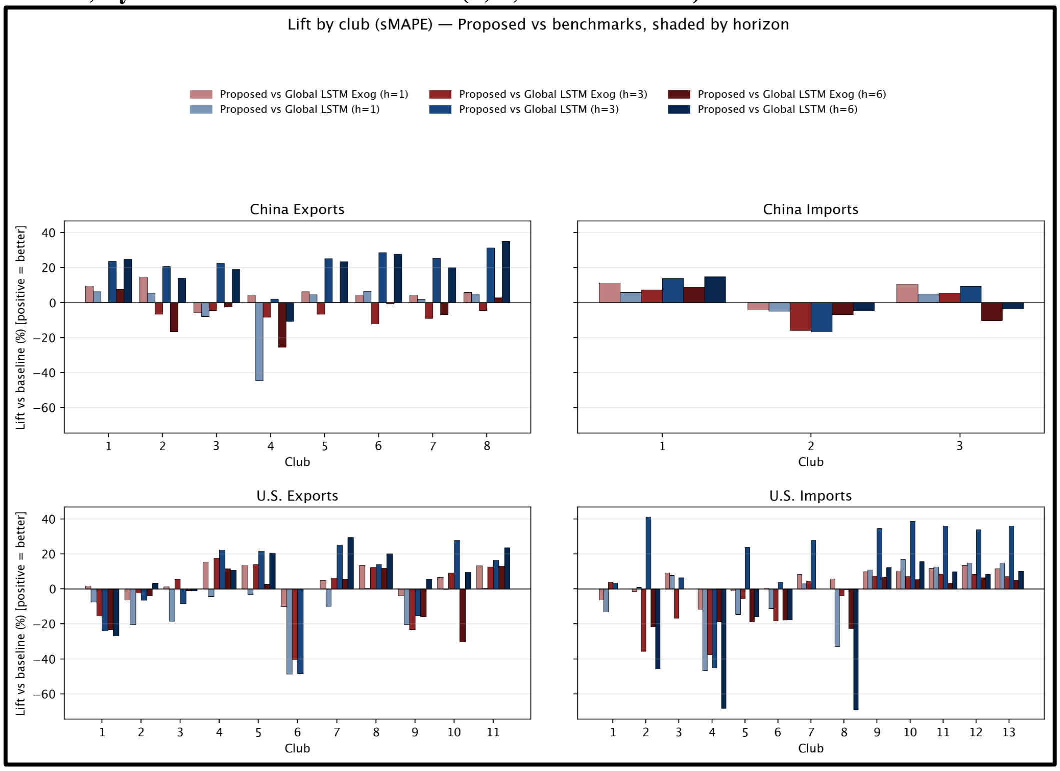
Source: Own elaboration with OEC data.

Table A2: LSTM model architecture and hyperparameters.

Category	Item	Value
Architecture	LSTM layers	1
	LSTM units	24
	Dropout layer	Yes
	Dropout rate	0.15
	Output layer	Dense
	Output units	1
	Output target	Predicted log-difference
Parameters	Rolling window	6 months
	Forecast horizon	3 months
	Optimizer	Adam
	Learning rate	0.0007
	Loss function	Huber loss
	Huber delta	1.0
	Maximum epochs	50
	Batch size	64
	Validation split	0.20
	Early stopping patience	7
	Restore best weights	Yes
	Minimum training samples	20
	Input standardization	Mean and standard deviation from training set
	Prediction clipping	[-2.0, 2.0]
	Exogenous feature threshold	Non-zero LASSO coefficients, threshold = 0.0

Source: Own elaboration.

Figure A1: Percentage lift in sMAPE of the proposed model relative to benchmark models, by club and forecast horizon (1, 3, and 6 months).



Source: Own elaboration with OEC data.