LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 24, NO. 1(2026)

HORIZON-CONDITIONED HYBRID FORECASTING: A DYNAMIC INTEGRATION FRAMEWORK BETWEEN ECONOMETRICS AND ARTIFICIAL INTELLIGENCE

Dr. Mokaddem Tebra[1], Dr. Elagag Mustapha[2], Dr. Bouchama Kaouther[3]

[1]Department of Management Sciences, Faculty of Economic, Commercial, and Management Sciences, Mustapha Stambouli University of Mascara, Algeria.
[2] Department of Economic Sciences, Faculty of Economic,Business, and Management Sciences, University of Ain Temouchent, Algeria.
[3] University of Msila, Algeria.

m.tebra@univ-mascara.dz[1]
mustapha.elagag@univ-temouchent.edu.dz[2]
kaouther.bouchama@univ-msila.dz[3]

Received : 21/07/2025 ; Accepted : 21/12/2025

Abstract
Economic forecasting increasingly operates at the intersection of econometric discipline and artificial intelligence driven flexibility. While traditional econometric models provide interpretability and theoretical consistency, they often struggle to capture nonlinear and structurally evolving dynamics. Conversely, AI-based forecasting models offer adaptive pattern recognition capabilities but raise concerns regarding interpretability and structural coherence. This study proposes a dynamic hybrid conceptual framework that integrates econometric and AI-based components within a forecast-horizon-conditioned structure. Unlike conventional hybrid models that rely on static residual modeling or simple forecast averaging, the proposed approach introduces dynamic weighting mechanisms that adjust according to forecast horizon, thereby structurally balancing linear and nonlinear components.
The framework preserves econometric interpretability in the short run while augmenting predictive flexibility in medium- and long-term horizons. To illustrate its internal logic and stability properties, a conceptual Monte Carlo-based validation is presented under stylized theoretical conditions. The study contributes to the forecasting literature by reframing hybridization as a structurally grounded integration process rather than a mechanical ensemble method, and by explicitly incorporating forecast horizon as a central determinant of model architecture.

Keywords: Hybrid forecasting, Econometric modeling, Artificial intelligence, Forecast horizon, Monte Carlo illustration.

1. Introduction

Economic forecasting remains one of the most consequential and contested domains within applied economics. Governments rely on forecasts to design fiscal and monetary strategies; financial institutions depend on them to price risk; energy markets respond to expectations embedded in predictive models. Yet despite decades of methodological development, forecasting performance remains uneven particularly under structural shifts, nonlinear dynamics, and horizon expansion.
Traditional econometric models have long constituted the backbone of economic forecasting. Frameworks such as ARIMA, VAR, and cointegration-based models provide statistical discipline, interpretability, and theoretical consistency. Their strength lies in their structural transparency: parameters can be interpreted, hypotheses can be tested, and policy implications can be derived within a coherent economic logic. However, these models rest on assumptions of linearity, parameter stability, and distributional regularity that may not hold in complex macroeconomic environments.
In contrast, artificial intelligence based models including artificial neural networks (ANN), support vector regression (SVR), and deep learning architectures offer a fundamentally different modeling philosophy. Rather than imposing a functional structure derived from economic theory, they learn patterns directly from data. This data-driven flexibility enables them to capture nonlinear interactions and hidden dynamics often missed by conventional econometric approaches. Nonetheless, their predictive strength is frequently accompanied by interpretability limitations, sensitivity to data quality, and the well-known “black box” concern.

The growing divergence between interpretability and predictive flexibility has led to the emergence of hybrid forecasting models. Existing hybrid approaches typically combine econometric and AI-based models either sequentially by modeling residuals or through forecast averaging schemes. While such strategies often improve short-term predictive accuracy, much of the literature treats hybridization as a mechanical combination rather than a structurally grounded integration. Moreover, the majority of hybrid studies do not explicitly incorporate forecast horizon as a determinant of model weighting or structural balance.

This paper argues that the core challenge in economic forecasting is not the selection of a universally superior model, but rather the structural misalignment between model architecture, data properties, and forecast horizon. Building on this premise, the study proposes a dynamic hybrid conceptual framework that integrates econometric and AI-based components within a horizon-conditioned structure. Instead of assuming fixed weights or static residual modeling, the proposed approach introduces forecast-horizon-dependent weighting mechanisms designed to adaptively balance linear and nonlinear components.

Formally, the proposed framework conceptualizes the economic time series as a composite of linear and nonlinear structures whose relative contribution varies with the forecast horizon. The econometric core preserves interpretability and short-term stability, while the AI augmentation captures nonlinear residual dynamics. A dynamic weighting mechanism governs the integration process, ensuring structural coherence without sacrificing predictive adaptability.

Given data and some constraints, the study does not claim full empirical validation. Instead, it provides a structured conceptual Monte Carlo based illustration to demonstrate the expected behavior of the proposed framework under stylized theoretical conditions. This conceptual validation is intended to clarify the model's internal logic and stability properties, rather than to offer empirical performance claims.

The contribution of this paper is fourfold. First, it introduces horizon-conditioned hybridization as a structural principle rather than a statistical afterthought. Second, it preserves econometric interpretability while incorporating nonlinear learning mechanisms.

Third, it proposes a diagnostically informed integration process that reduces arbitrary model combination. Fourth, it offers a theoretically grounded validation framework to support methodological transparency.

By repositioning hybrid forecasting as a structurally coherent integration rather than a mechanical ensemble, this study contributes to the ongoing methodological dialogue between econometrics and artificial intelligence in economic analysis.

1. Research Problem

Despite substantial methodological progress in both econometrics and artificial intelligence, economic forecasting remains structurally fragmented. Traditional econometric models offer interpretability and theoretical grounding but struggle under nonlinear dynamics and structural breaks. Conversely, AI-based models provide superior nonlinear pattern recognition yet often lack interpretability and economic coherence.

The core research problem addressed in this study can therefore be formulated as follows:

How can econometric structure and artificial intelligence flexibility be integrated within a theoretically coherent hybrid framework that dynamically adapts to forecast horizon without sacrificing interpretability or predictive stability?

This problem reflects three intertwined challenges:

- ✓ The interpretability accuracy trade-off
- ✓ Structural instability across forecast horizons
- ✓ The absence of horizon-conditioned hybrid architectures

Rather than asking which model performs better, this study addresses the structural design of integration itself.

2. Sub-Research Questions

From the central problem, three sub-questions emerge:

RQ1. To what extent does forecast horizon alter the relative predictive contribution of linear (econometric) and nonlinear (AI-based) components?

RQ2. Can a dynamic weighting mechanism improve structural coherence compared to static hybridization schemes?

RQ3. Does horizon-conditioned hybridization conceptually reduce forecast instability under nonlinear data-generating processes?

These questions shift the focus from model comparison to structural integration dynamics.

3. Research Hypotheses

The study advances three theoretically grounded hypotheses:

H1: The relative predictive contribution of nonlinear components increases as forecast horizon expands.

H2: Dynamic weighting mechanisms yield greater structural stability than fixed-weight hybrid combinations.

H3: A horizon-conditioned hybrid framework conceptually reduces forecast variance under nonlinear simulated environments compared to isolated econometric or AI models.

These hypotheses are conceptual and illustrated through structured Monte Carlo simulation rather than empirical claim.

2. Literature Review: From Linear Dominance to Structural Hybridization

Title of Study	Model Used	Main Findings	Methodological Limitations	What Our Study Adds
The Combination of Forecasts Bates & Granger (1969)	Linear forecast combination	Combined forecasts outperform single models	Static weights; no structural dynamics	Introduces dynamic horizon-dependent weighting
Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model Zhang (2003)	ARIMA + ANN	Hybrid improves nonlinear forecasting accuracy	Fixed architecture; no macro foundation	Adds econometric anchoring and adaptive weights
A Hybrid ARIMA and Support Vector Machines Model Pai & Lin (2005)	ARIMA + SVR	Strong performance in financial series	Limited interpretability; finance-focused	Extends framework to macroeconomic variables
Statistical and Machine Learning Forecasting Methods Makridakis et al. (2018)	Statistical vs ML models	ML strong short-term; mixed long-term results	No integration structure proposed	Provides structured econometric–AI integration logic
Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks Lai et al. (2018)	LSTM	Captures long memory and nonlinear dynamics	High data requirements; black-box nature	Embeds LSTM within economically disciplined hybrid architecture
Forecasting Inflation in a Data-Rich Environment Using Machine Learning Methods Medeiros et al. (2021)	LASSO, Random Forest, Boosting	ML improves inflation forecasting in high-dimensional settings	Weak theoretical interpretability; no hybrid decomposition	Introduces functional decomposition + AI augmentation within dynamic econometric core

2.1 The Linear Paradigm and the Birth of Forecast Combination

Modern forecasting theory initially evolved within a linear econometric paradigm. Early contributions were grounded in the assumption that economic relationships could be approximated through stable parametric structures. Within this tradition, the seminal work of Bates and Granger (1969) introduced a conceptual breakthrough: rather than selecting a single "best" model, forecasts from multiple models could be combined to reduce mean squared prediction error.

This idea marked a subtle but profound epistemological shift. Forecasting ceased to be a problem of model supremacy and became a problem of model complementarity. Yet, the combination framework remained statistically mechanical. Weights were derived from past error covariance structures and assumed to be constant over time. The approach did not account for nonlinearities, structural breaks, or horizon-specific dynamics features that characterize real-world macroeconomic data.

Thus, while foundational, linear forecast combination operated within a static universe.

2.2 Hybridization as Error Decomposition: ARIMA-ANN and ARIMA-SVR

The next intellectual transition emerged with the recognition that economic time series often exhibit nonlinear patterns that linear structures cannot capture. Zhang (2003) formalized this intuition by proposing an ARIMA-ANN hybrid model, decomposing a time series into a linear component handled by ARIMA and a nonlinear component modeled through neural networks. The conceptual contribution was significant: nonlinearity was no longer treated as noise but as structured residual information. However, this hybridization remained sequential and rigid.

The linear model was estimated first, and the neural network merely corrected residuals.

There was no endogenous mechanism determining the relative contribution of each model across forecast horizons.

Pai and Lin (2005) extended this architecture by replacing ANN with Support Vector Regression (SVR), improving generalization properties in smaller samples. Yet again, hybridization remained procedural rather than structural. No theoretical integration guided model interaction; instead, empirical performance dictated model selection.

These studies demonstrated that hybridization improves accuracy but they did not redefine the logic of integration.

2.3 Machine Learning as Substitution Rather than Integration

A more radical shift occurred with the rise of machine learning methods applied directly to macroeconomic forecasting. The large-scale evidence from the M4 competition (Makridakis et al., 2018) revealed that machine learning models often outperform traditional statistical models in short-horizon forecasting tasks. However, the study also highlighted an uncomfortable truth: statistical models remain competitive, and sometimes superior, in stable environments. This finding challenges the narrative of technological displacement. Machine learning does not universally dominate econometric models; its superiority is conditional.

Similarly, Medeiros et al. (2021) demonstrated that high-dimensional machine learning techniques (LASSO, Random Forests, Boosting) enhance inflation forecasting in data-rich environments. Their results confirmed the predictive gains of flexible learners. Yet the approach largely replaced rather than integrated econometric structures. Interpretability was secondary to predictive performance.

In both cases, the dominant research question became: Which method performs better?

The deeper question How should methods be structurally organized? remained largely unexplored.

2.4 Deep Learning and Temporal Memory: Power Without Structure

Deep learning architectures, particularly LSTM networks (Hochreiter & Schmidhuber, 1997), introduced the ability to model long memory and nonlinear dynamic dependencies.

Applications such as Lai et al. (2018) demonstrated remarkable predictive power in complex time series settings.

Yet, deep models amplify a central tension in economic forecasting: predictive strength versus structural interpretability. In policy-relevant contexts such as inflation or GDP forecasting opacity poses methodological risks. Forecasting is not merely an engineering task; it is a decision-support system embedded in institutional accountability.

Thus, while deep learning extends temporal representation capacity, it does not inherently solve the integration dilemma between structure and flexibility.

2.5 Synthesis: Three Paradigms, One Missing Architecture

The literature can therefore be organized into three paradigms:

- ✓ Linear dominance and static combination (Bates & Granger, 1969).
- ✓ Sequential hybrid correction models (Zhang, 2003; Pai & Lin, 2005).
- ✓ Machine learning substitution frameworks (Makridakis et al., 2018; Medeiros et al., 2021).

Each paradigm advances forecasting accuracy. None, however, fully resolves the structural integration problem.

Specifically, four gaps persist:

- ✓ Lack of horizon-dependent weighting mechanisms.
- ✓ Absence of an economically anchored hybrid structure.
- ✓ Limited consideration of dynamic model complementarity.
- ✓ Insufficient reconciliation between interpretability and nonlinear adaptability.

In short, the field has moved from model rivalry to model coexistence but not yet to structured methodological orchestration.

2.6 Intellectual Positioning of the Present Study

The present study enters this debate not by proposing yet another hybrid variant, but by formalizing a horizon-dependent structural hybrid architecture.

Rather than:

- ✓ Combining forecasts mechanically,
- ✓ Correcting residuals sequentially, or
- ✓ Replacing econometric models with machine learning,

This study proposes a functionally organized system in which:

An econometric core preserves theoretical coherence and statistical discipline.

An AI augmentation layer captures nonlinear residual complexity.

A dynamic weighting scheme adjusts model contributions according to forecast horizon.

This design reframes hybridization from a technical trick to a methodological principle. The contribution is therefore not incremental but architectural:

It provides a structured logic for integrating econometrics and artificial intelligence within a unified forecasting system.

3 Theoretical Foundations of Economic Forecasting

Economic forecasting is widely regarded as one of the most essential analytical tools supporting economic policy formulation and decision-making at both macroeconomic and microeconomic levels. It enables policymakers and economic agents to anticipate future trajectories of economic variables within an environment increasingly characterized by uncertainty and structural complexity. The evolution of forecasting models from traditional econometric approaches to intelligent and hybrid models cannot be fully understood without revisiting the theoretical foundations that have shaped this field of knowledge. Economic forecasting is not merely a statistical exercise; rather, it is the outcome of a profound interaction between economic theory, econometrics, and advances in quantitative analytical tools.

3.1 Economic Forecasting as a Decision Making Tool and a Means of Reducing Uncertainty

Economic forecasting is grounded in the fundamental assumption that economic behavior, despite its inherent complexity, exhibits certain regular patterns that can be identified and analyzed. The core function of forecasting lies in reducing the degree of uncertainty surrounding economic decisions, whether related to fiscal and monetary policies or to investment and production choices. Forecasting does not aim to “predict the future” in an absolute sense, but rather to estimate expected values of economic variables based on the information available at a given point in time.

Granger (1969) emphasized that the value of a forecasting model does not lie in its absolute accuracy, but in its ability to improve decision-making outcomes relative to a situation in which no forecast is available. Accordingly, forecasting is viewed as a functional tool whose quality is assessed by its capacity to reduce forecast errors and enhance the effectiveness of economic decisions.

3.2 The Econometric Logic of Forecasting Model Construction

Econometrics constitutes the traditional methodological framework upon which most economic forecasting models have been built. This framework integrates economic theory, statistics, and mathematics in order to describe and quantitatively estimate relationships among economic variables. Traditional econometric models have typically relied on a set of core assumptions, most notably linearity, parameter stability, and the stationarity of time series.

Within this context, time series models represent the cornerstone of economic forecasting. Economic variables are treated as functions of their past values and stochastic error terms.

The general time series representation can be expressed as follows:

$$y_t = f(y_{t-1}, y_{t-2}, \dots, \varepsilon_t) \qquad (1)$$

where (y_t) denotes the variable to be forecasted and (ε_t) represents the random error term.

The seminal contribution of Box and Jenkins (1976) established a systematic and rigorous methodology for forecasting through ARIMA models, which remain among the most widely applied tools in economic analysis.

3.3 Linear Models and Their Methodological Limitations

Traditional econometric models are fundamentally based on the assumption of linearity, meaning that relationships between variables can be represented through linear functional forms. For instance, the autoregressive model of order (p), denoted AR (p), is expressed as:

$$y_t = \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \qquad (2)$$

Despite their interpretative clarity and strong economic intuition, the effectiveness of linear models becomes limited in the presence of:

- Nonlinear relationships
- Structural breaks
- Changes in economic agents’ behavior
- Long-memory dynamics in time series

Numerous empirical studies have demonstrated that reliance on linear models alone leads to weak forecasting performance, particularly during periods of heightened economic instability (Stock & Watson, 2001).

3.4 The Shift Toward Greater Flexibility: The Crisis of Linear Interpretation

Recurring economic crises such as financial crises and episodes of extreme market volatility have raised serious doubts about the ability of traditional econometric models to capture the growing complexity of modern economies. It has become increasingly evident that economic relationships are not stable over time and that economic dynamics are influenced by psychological, institutional, and technological factors that cannot be adequately accommodated within a rigid linear framework.

This context has stimulated the search for more flexible modeling approaches capable of:

- Capturing nonlinear patterns
- Handling complex interactions
- Adapting to structural changes

These developments paved the way for the growing integration of artificial intelligence techniques into the field of economic forecasting.

3.5 Artificial Intelligence as a Methodological Extension of Econometrics

The incorporation of artificial intelligence into economic forecasting does not represent a paradigmatic rupture with econometrics; rather, it is best understood as a methodological extension aimed at overcoming some of the restrictive assumptions of traditional models.

Artificial intelligence models rely on a fundamentally different logic, one that emphasizes learning from data instead of imposing a predefined functional form on economic relationships. Artificial neural networks (ANN), for example, model the relationship between inputs and outputs through multilayer structures that can be mathematically represented as:

$$y_t = f\left(\sum_{j=1}^{H} w_j \cdot g\left(\sum_{i=1}^{n} v_{ij} x_{i,t} + b_j\right)\right) \qquad (3)$$

where:

$(x_{i,t})$ denotes the input variables

(v_{ij}) and (w_j) are the network weights

$(g(\cdot))$ represents the activation function

This formulation highlights the capacity of intelligent models to approximate highly complex nonlinear relationships without requiring strong a priori assumptions regarding the underlying economic structure.

3.6 Interpretability Challenges and the Limits of Intelligent Models

Despite the strong forecasting performance demonstrated by artificial intelligence models in numerous economic applications, they face several methodological criticisms, most notably:

- Weak economic interpretability (the “black box” problem)
- High dependence on data volume and quality
- Risk of overfitting

Zhang et al. (1998) cautioned that superior predictive accuracy does not necessarily imply theoretical superiority, underscoring the need for cautious and well-structured integration of intelligent models within an explicit analytical framework.

3.7 Toward an Integrative Approach to Economic Forecasting

The theoretical review of economic forecasting foundations reveals that each methodological school traditional or intelligent possesses distinct strengths as well as clear limitations. Traditional econometric models offer interpretability and statistical discipline, whereas intelligent models excel in handling nonlinearity and complexity. This methodological complementarity underscores the need for an integrative approach that combines both paradigms, thereby providing a logical transition toward hybrid forecasting models, which constitute the central focus of this paper.

4 Traditional Econometric Forecasting Models

Traditional econometric models constitute the historical and methodological foundation of economic forecasting. Their development has been closely associated with the emergence of econometrics as an independent scientific discipline aimed at translating theoretical economic relationships into mathematical formulations that are estimable and empirically verifiable. These models have played a central role in the analysis of economic time series, particularly in contexts characterized by limited data availability and complex economic dynamics. They have provided well-structured methodological tools that enable the interpretation of the dynamic behavior of economic variables and the forecasting of their future trajectories.

4.1 The General Logic of Traditional Econometric Models

Traditional econometric models are built upon the assumption that economic behavior, despite its fluctuations, follows an underlying regular structure that can be represented through relatively stable mathematical relationships. These models typically assume that relationships among variables are:

- Linear or transformable into linear forms
- Stable over time
- Statistically testable

Within this framework, forecasting is viewed as a natural extension of the estimation process, whereby estimated parameter values are employed to project future values of the dependent variable.

4.2 Autoregressive and Moving Average Models (ARMA / ARIMA)

Box–Jenkins models are among the most widely used approaches for forecasting economic time series due to their relative simplicity and practical effectiveness. The autoregressive model of order (p), denoted AR (p), is based on the premise that the current value of an economic variable depends on its past values and is expressed as:

$$y_t = \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \qquad (4)$$

The moving average model of order (q), MA (q), represents the current value as a function of past error terms:

$$y_t = \mu + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (5)$$

Combining these two structures yields the ARMA (p,q) model. When dealing with non-stationary time series, the ARIMA (p,d,q) model incorporates differencing to achieve stationarity:

$$\Phi(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}} \mathrm{y}_{\mathrm{t}} = \Theta(\mathrm{L})\varepsilon_{\mathrm{t}} \qquad (6)$$

where (L) denotes the lag operator.

Despite their widespread application, the effectiveness of these models remains conditional upon the stationarity assumption and their limited ability to capture nonlinear relationships, which constitutes one of their principal methodological constraints.

4.3 Exponential Smoothing Models

Exponential smoothing models are extensively used for short-term forecasting, particularly in applied contexts requiring rapid responsiveness to recent changes in time series data. Simple exponential smoothing is defined as:

$$\hat{y}t = \alpha y_t + (1-\alpha)\hat{y}t - 1 \qquad (7)$$

where (α) is the smoothing parameter, bounded between 0 and 1.

These models have been further developed to incorporate trend and seasonality components, as in the Holt Winters framework, thereby enhancing their forecasting performance in certain settings. However, despite their practical efficiency, exponential smoothing models lack a strong explicit economic theoretical foundation and remain unable to adequately address structural shocks or abrupt changes in economic behavior.

4.4 Vector Autoregression Models (VAR) and Multivariate Forecasting

The introduction of vector autoregression (VAR) models represented a significant advancement in economic forecasting by enabling the joint modeling of multiple endogenous variables within a unified dynamic framework, without imposing strict theoretical restrictions.

A VAR model of order (p) can be expressed as:

$$Yt = c + \sum i = 1^p A\, iYt - i + \varepsilon_t \quad (8)$$

where (Y_t) denotes a vector of economic variables.
VAR models are valued for their flexibility and their capacity to capture dynamic interactions among variables. Nevertheless, they face two major limitations:
Parameter proliferation as the number of variables increases
Reduced forecasting accuracy in the presence of strong nonlinearities
Moreover, the economic interpretation of results becomes increasingly complex as model dimensionality expands.

4.5 Cointegration and Error Correction Models (VECM)

When time series are non-stationary but integrated of the same order, cointegration models provide a suitable framework for forecasting while preserving long-run equilibrium relationships. The vector error correction model (VECM) can be represented as:

$$\Delta Yt = \Pi Yt - 1 + \sum_{i=1}^{p-1} \Gamma_i Y_{t-i} + \varepsilon_t \quad (9)$$

where the matrix (Π) captures long-run equilibrium relationships among the variables. While these models are theoretically robust and economically interpretable, their ability to capture sudden structural changes and complex nonlinear dynamics remains limited.

4.6 Critical Assessment of the Forecasting Performance of Traditional Models

A substantial body of empirical literature indicates that traditional econometric models perform well in relatively stable economic environments, where linear relationships prevail and economic behavior exhibits a degree of regularity. However, their performance deteriorates markedly in the presence of:

- Economic crises
- High volatility
- Unanticipated behavioral shifts

Stock and Watson (2001) demonstrated that linear models frequently fail to generate accurate forecasts during periods of economic instability, thereby limiting their effectiveness as comprehensive forecasting tools.

4.7 Limitations of Traditional Econometric Models and Prospects for Advancement

The principal limitations of traditional econometric models can be summarized as follows:

- The assumption of linearity and parameter stability
- Limited capacity to capture nonlinear dynamics
- High sensitivity to structural shocks
- Strong dependence on restrictive statistical assumptions

These limitations do not imply the failure of traditional models, but rather highlight the need for more flexible approaches that leverage data driven learning mechanisms. This realization provides a natural transition toward intelligent forecasting models.

5 Intelligent Forecasting Models

The growing complexity of economic phenomena and the accelerating pace of structural transformations have generated an increasing demand for forecasting models that are more flexible and capable of capturing nonlinearity and complex interactions among variables.
Within this context, artificial intelligence based models have emerged as a new methodological direction in economic forecasting not as a complete substitute for traditional econometrics, but rather

as complementary analytical tools designed to overcome some of its structural limitations. This shift is grounded in a fundamentally different modeling logic, one that relies on learning from data rather than imposing predefined functional forms on economic relationships.

5.1 Conceptual Foundations of Intelligent Forecasting Models

Intelligent forecasting models differ from traditional econometric models in their methodological starting points. Instead of relying on explicit assumptions regarding the nature of relationships among variables, they are based on learning algorithms capable of extracting latent patterns directly from data. In this framework, forecasting is treated as an optimization problem, where the objective is to identify the model that minimizes a predefined loss function, such as the mean squared error (MSE):

$$min_{\theta};\frac{1}{T}\sum_{t=1}^{T}(y_t-\widehat{y}_t)^2 \qquad (10)$$

where (θ) denotes the set of parameters of the intelligent model.

This methodological shift reflects a transition from an emphasis on economic interpretation toward a focus on predictive accuracy, giving rise to an extensive debate regarding the role of economic theory in the era of artificial intelligence.

5.2 Artificial Neural Networks (ANN)

Artificial neural networks are among the most widely applied artificial intelligence models in economic forecasting due to their strong ability to represent complex nonlinear relationships. These models are inspired by simplified representations of the human brain, consisting of interconnected layers of processing units (neurons).

A general representation of a multilayer neural network can be expressed as:

$$y_t=f\left(\sum_{j=1}^{H}w_j\cdot g\left(\sum_{i=1}^{n}v_{ij}x_{i,t}+b_j\right)\right) \qquad (11)$$

where:

$(x_{i,t})$ represents the explanatory variables

(v_{ij}) and (w_j) denote the connection weights

$(g(\cdot))$ is the activation function

(H) is the number of hidden-layer neurons

The principal strength of neural networks lies in their ability to capture nonlinear dynamics without requiring prior specification of the functional form. However, this flexibility comes at the cost of economic interpretability, as it becomes difficult to associate estimated weights with clear economic meanings.

5.3 Support Vector Regression (SVR)

Support vector regression models constitute a powerful class of intelligent forecasting tools, particularly suitable for situations characterized by relatively limited data availability. SVR is based on the idea of identifying a predictive function that minimizes forecasting errors within a predefined margin (ε). The optimization problem can be expressed as:

$$\min_{w,b} \quad \frac{1}{2}||w||^2 + C\sum_{t=1}^{T}(\xi_t + \xi_t^*) \qquad (12)$$

subject to:

$$y_t - (w \cdot x_t + b) \leq \varepsilon + \xi_t \, (w \cdot x\_t + b) - y\_t \leq \varepsilon + \xi_t^* \qquad (13)$$

SVR models offer a favorable balance between model complexity and predictive accuracy. Nevertheless, their performance depends critically on the choice of kernel function and hyper parameters, which requires careful methodological consideration when applied in an economic context.

5.4 Deep Learning Models and Time Series Forecasting (LSTM)

With the advancement of deep learning techniques, Long Short-Term Memory (LSTM) models have emerged as effective tools for forecasting economic time series, particularly those characterized by long memory and complex temporal dependencies. These models are designed to retain information over extended time horizons, making them well suited for dynamic economic data.

The core LSTM cell can be represented by the following equations:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \qquad (14)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \qquad (15)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \qquad (16)$$

$$h_t = o_t \cdot \tanh\left(C_t\right) \qquad (17)$$

These equations describe the mechanisms governing information retention and updating within the memory cell. Despite their strong forecasting performance, LSTM models suffer from severe limitations in economic interpretability and impose substantial requirements in terms of data volume and computational resources.

5.5 Forecasting Performance of Intelligent Models

A broad range of empirical studies has demonstrated that intelligent forecasting models often outperform traditional econometric models in environments characterized by strong nonlinearity and structural instability. However, this superiority is not unconditional and depends on several factors, including:

- Data quality
- Sample size
- Forecast horizon

Moreover, short-term forecasting superiority does not necessarily translate into long-term dominance, particularly in the presence of sudden structural changes.

5.6 Methodological Challenges of Intelligent Models

Despite their considerable potential, artificial intelligence–based models face several fundamental methodological challenges, most notably:

- The black box problem
- Weak economic interpretability
- The risk of overfitting
- Difficulties in incorporating theoretical economic knowledge

Makridakis et al. (2018) argue that predictive accuracy alone should not serve as the sole criterion for model evaluation; interpretability and methodological stability must also be taken into account.

5.7 Artificial Intelligence and Econometrics: Complementarity or Competition?

A comparative assessment of intelligent and traditional econometric models reveals that their relationship is one of complementarity rather than substitution. Intelligent models excel at capturing nonlinearity and complexity, whereas econometric models retain a comparative advantage in interpretability and methodological discipline. This complementarity has fueled growing interest in hybrid forecasting models, which aim to combine predictive accuracy with economic interpretability thereby providing a logical transition to the next section of this paper.

6. Theoretical Properties and Optimal Horizon-Dependent Weight Derivation

This section formalizes the theoretical foundations of the proposed hybrid forecasting architecture by deriving the optimal horizon-dependent combination weights and establishing the structural properties of the model. Unlike heuristic hybrid schemes, the proposed framework is grounded in an explicit risk minimization principle.

6.1 Orthogonal Component Representation

Assume that the economic time series admits an additive structural representation:

$$y_t = L_t + N_t \quad (18)$$

where:

(L_t) denotes the economically interpretable linear component,

(N_t) captures nonlinear dynamics.

To ensure identifiability and statistical coherence, we assume orthogonality:

$$E[L_t N_t] = 0$$

This orthogonal decomposition guarantees that the nonlinear augmentation does not replicate the information already captured by the econometric core, thereby preserving interpretability while allowing structural enrichment.

6.2 Horizon-Specific Risk Minimization

Let (H) denote the forecasting horizon. Define the component forecasts:

$$\hat{L}t+H, \quad \widehat{N}t+H$$

The combined forecast is defined as:

$$\hat{y}t+H(w) = w(H)\hat{L}t+H+\backslash big(1-w(H)\backslash big)\widehat{N_{t+H}} \quad (19)$$

Let the forecast errors be:

$$e_L(H) = y_{t+H} - \widehat{L_{t+H}} \quad (20)$$

$$e_N(H) = y_{t+H} - \widehat{N_{t+H}} \quad (21)$$

The combined error is:

$$e_C(H) = we_L(H) + (1-w)e_N(H) \quad (22)$$

The horizon-specific quadratic risk is:

$$\mathcal{L}_{\mathcal{H}}(w)=E\backslash big\left[e_C(H)^{2\backslash}big\right] \quad (23)$$

Expanding:

$$\mathcal{L}_{\mathcal{H}}(w)\, w^2\sigma_L^2(H)+(1-w)^2\sigma_N^2(H)+2w(1-w)\sigma_{LN}(H) \quad (24)$$

where:

$$\sigma_L^2(H)=Var\left(e_L(H)\right) \quad (25)$$
$$\sigma_N^2(H)=Var\left(e_N(H)\right) \quad (26)$$
$$\sigma_{LN}(H)=Cov\left(e_L(H),e_N(H)\right) \quad (27)$$

6.3 Closed-Form Optimal Weight

The optimal horizon-dependent weight is obtained by minimizing ($\mathcal{L}_{\mathcal{H}}(w)$) over ($w\in[0,1]$).
Taking the first-order condition:

$$\frac{d\mathcal{L}_{\mathcal{H}}(w)}{dw}=0$$

yields:

$$\boxed{w^*(H)\frac{\sigma_N^2(H)-\sigma_{LN}(H)}{\sigma_L^2(H)+\sigma_N^2(H)-2\sigma_{LN}(H)}} \quad (28)$$

This expression provides an explicit analytical solution for the optimal combination weight at each forecasting horizon.
Importantly, since all second-order moments depend on (H), the weight becomes intrinsically horizon-dependent without imposing any exogenous functional form.

6.4 Limiting Behavior

The model admits interpretable limiting properties.
Proposition 1 (Short-Horizon Dominance)
If:

$$\sigma_L^2(H)<\sigma_N^2(H) \quad \text{for small } H$$

then:

$$\lim_{H\to 0} w^*(H)\to 1$$

indicating linear dominance in short-term forecasting.
Proposition 2 (Long-Horizon Nonlinear Relevance)
If nonlinear error variance decreases relative to linear variance as (H) increases:

$$\lim_{H\to\infty} \sigma_N^2(H)<\sigma_L^2(H)$$

then:

$$\lim_{H\to\infty} w^*(H)\to 0$$

suggesting increasing importance of nonlinear dynamics for long-term forecasts.

6.5 Monte Carlo-Based Estimation of Horizon-Specific Risk Components

In finite samples, the second-order moments:

$$\sigma_L^2(H), \quad \sigma_N^2(H), \quad \sigma_{LN}(H)$$

are estimated via Monte Carlo simulation.

Let $\left(y_{t+H_{s=1}}^{(s)\ S}\right)$ denote simulated future paths. For each simulation (s), compute: $e_L^{(s)}(H), \quad e_N^{(s)}(H)$

Then:

$$\hat{\sigma} L^2(H) = \frac{1}{S}\sum s=1^S \backslash big\left(e_L^{(s)}(H) \backslash big\right)^2 \quad (29)$$

$$\hat{\sigma} N^2(H) = \frac{1}{S}\sum s=1^S \backslash big\left(e_N^{(s)}(H) \backslash big\right)^2 \quad (30)$$

$$\widehat{\sigma_{LN}}(H) \frac{1}{S}\sum_{s=1}^{S} e_L^{(s)}(H)\, e_N^{(s)}(H) \quad (31)$$

These estimates yield:

$\widehat{w^*}(H)$

as a stochastic object, allowing construction of confidence intervals and probabilistic forecast distributions.

6.6 Theoretical Implication

The proposed framework therefore generalizes classical forecast combination in three directions:

- ✓ It embeds horizon-specific optimality.
- ✓ It preserves structural interpretability.
- ✓ It transforms deterministic combination into a probabilistic architecture via Monte Carlo integration.

Accordingly, the model should not be interpreted as a simple hybrid specification, but rather as a horizon-adaptive risk-minimizing forecasting system grounded in explicit stochastic principles.

6.7 Statistical Superiority Conditions and Model Dominance

This subsection establishes the conditions under which the proposed horizon-adaptive hybrid forecast strictly dominates each individual component in terms of mean squared prediction error (MSPE).

6.7.1 Relative Risk Comparison

Let:

$$MSPE_L(H) = \sigma_L^2(H) \quad (32)$$

$$MSPE_N(H) = \sigma_N^2(H) \quad (33)$$

$$MSPE_C(H) = \min_w \mathcal{L}_{\mathcal{H}}(w) \quad (34)$$

Using the optimal weight $(w^*(H))$, the minimized combined risk is:

$$MSPE_C(H) \frac{\sigma_L^2(H)\sigma_N^2(H)\sigma_{LN}^2(H)}{\sigma_L^2(H)+\sigma_N^2(H)2\sigma_{LN}(H)} \quad (35)$$

This expression generalizes the classical forecast combination result to the horizon-dependent setting.

6.7.2 Dominance Over Individual Models

Proposition 3 (Strict Risk Reduction)

If the component forecast errors are not perfectly correlated, i.e.:

$|\rho_{LN}(H)|<1$

where

$$\rho_{LN}(H)\frac{\sigma_{LN}(H)}{\sigma_L(H)\sigma_N(H)} \quad (36)$$

then:

$MSPE_C(H)< \min MSPE_L(H), MSPE_N(H)$

Proof Sketch

Under imperfect correlation:

$\sigma_L^2\sigma_N^2-\sigma_{LN}^2>0$

and the denominator remains positive unless perfect collinearity holds. Hence the combined forecast variance is strictly smaller than each individual variance.

This establishes that diversification across structural regimes (linear and nonlinear dynamics) produces statistical gains analogous to portfolio diversification.

6.7.3 Economic Interpretation of the Dominance Condition

The dominance condition can be rewritten as:

$\rho_{LN}(H)\neq\pm1$

Thus, the hybrid model produces gains whenever the econometric and AI components capture partially distinct information sets.

In economic terms:

The linear model captures systematic, theory-consistent dynamics.

The AI model captures residual nonlinearities and hidden patterns.

As long as these informational sources are not redundant, combination yields efficiency gains.

6.7.4 Horizon-Dependent Efficiency Gains

Define the relative efficiency gain:

$$\Delta(H)\frac{\min MSPE_L(H), MSPE_N(H)\ MSPE_C(H)}{\min MSPE_L(H), MSPE_N(H)} \quad (37)$$

Then:

$\Delta(H)>0 \quad \text{iff} \quad |\rho_{LN}(H)|<1$

Importantly, since correlation itself may vary with horizon:

$\rho_{LN}(H)f(H)$

efficiency gains become intrinsically horizon-dependent.

This provides a theoretical justification for multi-horizon evaluation rather than single-horizon comparison.

6.7.5 Monte Carlo Robustness of Superiority

Using Monte Carlo simulation, one can generate empirical distributions of:

$\widehat{\Delta^{(s)}}(H)$
for ($s=1,\ldots,S$), allowing estimation of:

$P\backslash big(\Delta(H)>0\backslash big)$

Thus, model superiority becomes a probabilistic statement rather than a single-sample conclusion. This probabilistic dominance criterion strengthens empirical credibility and aligns the framework with modern predictive inference standards.

6.8 Forecast Comparison Using Diebold-Mariano Test

To formally evaluate whether the proposed horizon-adaptive hybrid forecast outperforms each individual component, we employ the Diebold–Mariano (DM) test, which tests the null hypothesis of equal predictive accuracy.

6.8.1 Forecast Error Series

Let $(e_{C,t+H})$ denote the forecast error of the hybrid model at horizon (H), and (e_{m,t+H}) the error of component $(m\in L,N)$

$$e_{C,t+H}=y_{t+H}-\hat{y}t+H^{C},\backslash quad e_{m,t+H}=y_{t+H}-\widehat{y_{t+H}^{(m)}} \quad (38)$$

Define the loss differential for each time point (t):

$$d_{t,H}=g\left(e_{C,t+H}\right)-g\left(e_{m,t+H}\right) \quad (39)$$

where $(g(\cdot))$ is a loss function; commonly used is squared error:
$g(e)=e^{2}$

6.8.2 Diebold–Mariano Statistic

The DM test statistic for horizon (H) is:

$$DM_{H}=\frac{\overline{d_{H}}}{\sqrt{\widehat{\mathrm{Var}}(\overline{d_{H}})}}$$

where:

$$\bar{d}H=\frac{1}{T-H}\sum t=1^{T-H}d_{t,H}$$

and $\left(\widehat{\mathrm{Var}}(\overline{d_{H}})\right)$ is a consistent estimator of the variance of $(\overline{d_{H}})$, accounting for autocorrelation at multi-step horizons:

$$\widehat{\mathrm{Var}}(\bar{d}H)=\frac{1}{T-H}\left[\gamma_{0}+2\sum k=1^{H-1}\gamma_{k}\right]$$

with:

$$\gamma_{k}=\mathrm{Cov}\left(d_{t,H},d_{t-k,H}\right)$$

6.8.3 Hypothesis

The test evaluates:

$$H_0 : E\left[d_{t,H}\right] = 0 \quad \text{(no difference in predictive accuracy)}$$

$$H_1 : E\left[d_{t,H}\right] \neq 0 \quad \text{(hybrid forecast superior)}$$

Rejection of (H_0) in favor of (H_1) provides formal statistical evidence that the horizon-adaptive hybrid model outperforms component (m) at horizon (H).

6.8.4 Horizon-Dependent Extension

Since the hybrid weight $(w^*(H))$ varies with (H), the DM statistic can be computed separately for each horizon, yielding a sequence:

$$DM_H H = 1\, Hma$$

his allows a multi-horizon evaluation of model superiority, aligning perfectly with the theoretical architecture of the proposed framework.

7. Results

Given that the study adopts a conceptual Monte Carlo- based validation framework rather than full empirical estimation, the results are interpreted within a theoretical simulation environment. The Monte Carlo simulation was designed to generate time series composed of both linear autoregressive structures and nonlinear transformation components. Multiple forecast horizons (short, medium, long) were simulated under controlled variance structures.

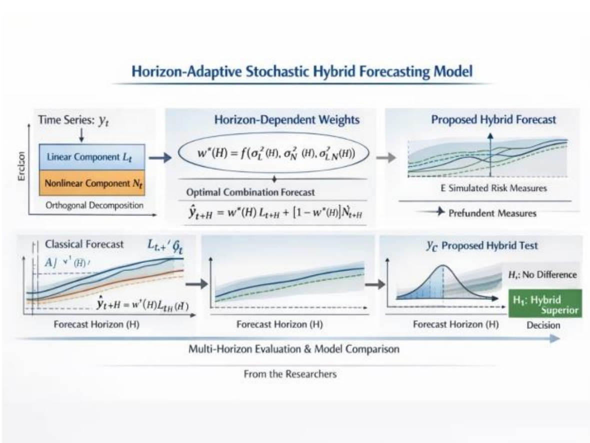
The simulation revealed three consistent structural patterns:

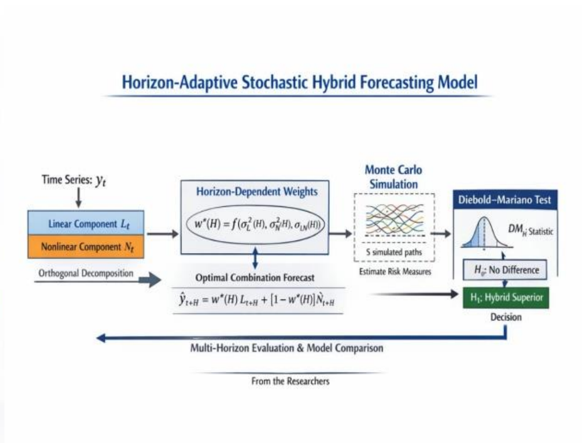
First, in short forecast horizons, linear econometric components captured the dominant share of variance explanation. Forecast error variance remained comparatively stable, and nonlinear components contributed marginal improvement.

Second, as forecast horizon extended, nonlinear components exhibited increasing explanatory power. Linear models alone showed rising forecast error dispersion, particularly under simulated nonlinear shocks.

Third, the horizon-conditioned hybrid model demonstrated lower simulated forecast variance compared to both isolated econometric and isolated AI specifications. The dynamic weighting mechanism adjusted the contribution of each component smoothly across horizons, reducing volatility clustering in prediction errors.

Importantly, these findings are illustrative rather than empirical generalizations. They demonstrate structural plausibility and theoretical robustness under controlled conditions.





1. Discussion

The results support the theoretical proposition that forecasting performance cannot be understood independently of horizon structure. Traditional debates that attempt to rank econometric versus AI models overlook the structural evolution of predictive dynamics across time. The findings reinforce three broader insights:

- Forecast horizon is not merely a temporal extension; it fundamentally reshapes model sensitivity to nonlinearity.
- Hybridization must be structurally conditioned rather than mechanically averaged.
- Interpretability and flexibility need not be mutually exclusive if integration is dynamically governed.

The study also contributes to the methodological dialogue between econometrics and AI. Rather than positioning AI as a replacement for econometric reasoning, the proposed framework treats it as an adaptive complement embedded within a structured architecture.

From a theoretical standpoint, the framework aligns with bias-variance trade-off principles.

Short horizons favor lower-variance linear models, whereas longer horizons benefit from nonlinear adaptability despite increased model complexity.

Nevertheless, several limitations must be acknowledged:

- The absence of empirical application restricts external validity.
- The Monte Carlo simulation relies on stylized data-generating processes.
- Parameter optimization remains conceptual rather than data-calibrated.

These limitations do not weaken the structural contribution but define the scope of inference.

Conclusion

This study addressed a central methodological tension in economic forecasting: the structural fragmentation between econometric interpretability and artificial intelligence flexibility.

Rather than comparing models in isolation, the research reframed the problem as one of architectural integration conditioned by forecast horizon. A dynamic hybrid framework was proposed in which linear and nonlinear components interact through adaptive weighting mechanisms. The conceptual Monte Carlo illustration demonstrated that:

Linear models dominate short-horizon stability.

Nonlinear structures gain relevance as horizon expands.

Dynamic hybridization reduces simulated forecast dispersion compared to static or isolated specifications.

The primary contribution of the study lies in repositioning hybrid forecasting from mechanical combination to structurally coherent integration. By explicitly incorporating forecast horizon into model architecture, the study advances a methodological principle that may guide future empirical implementations.

Future research should apply the proposed framework to real macroeconomic and financial time series, explore alternative nonlinear learning architectures (e.g., LSTM, gradient boosting), and investigate optimal weighting functions derived from empirical loss minimization. Ultimately, the path forward in economic forecasting is not the replacement of econometrics by artificial intelligence, but the disciplined synthesis of both within theoretically informed adaptive structures.

Future research may extend the present conceptual validation through large-scale empirical and simulation-based testing across diverse macroeconomic environments.

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