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Risk-Adjusted Pricing Models in Commodities Markets Using AI and Econometric Techniques

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Abstract

The proper pricing of commodities during market uncertainty and structural incompleteness is a primary challenge in financial economics. Although traditional econometric models are interpretable and theoretically rigorous, they tend to fail to capture non-linear dynamics and adjust to regime changes. On the other hand, there is a predictive power of artificial intelligence (AI) methods, which are limited in their interpretability and the ability to combine economic theory. The review focuses on the intersection of AI and econometric models to develop risk-adjusted commodity market pricing models. It provides the development of pricing models, a hybrid theoretical framework, and an evaluation of recent literature on their application. Areas with major gaps, such as the absence of standardization, data quality concerns, and real-time adaptability, are also identified. The paper also concludes with research suggestions to enhance accuracy, transparency, and applicability in various market environments.

Keywords: Risk-adjusted pricing; Commodities market; Econometrics; AI; Machine learning; GARCH; Deep learning; Volatility prediction; Value at risk (VaR); Hybrid modelling

1. Introduction

The instability and dynamics of commodity markets have further demanded the creation of strong and data-driven pricing to be able to reflect and model risk appropriately. The extent of macroeconomic, geopolitical, and microstructural factors that affect commodities like crude oil, natural gas, agricultural products, and precious metals is wide, and thus, price uncertainty is high. The conventional pricing models that mostly rest on deterministic or linear econometric models have proven to be ineffective in explaining the dynamic and stochastic environment of these markets [1]. To overcome them, new solutions to price discovery, prediction, and risk processing in commodity market settings were suggested by the recent progress in artificial intelligence (AI) and the methods of econometric modelling [2].

The applicability of risk-adjusted pricing on commodities markets is due to the fact that it plays a central part in the financial decision-making of producers, consumers, investors, and regulators. Effective hedging, an effective investment strategy, and management of liquidity are all possible by having proper risk-adjusted pricing models, which then allow the firms to hedge properly. These models also provide policymakers and market designers with ways to track systemic risk and price manipulation [3]. In markets with large stakes, such as in energy or food commodities, where small price errors can cause serious economic impacts, the capability to add the complex metrics of risk into the pricing models has developed into a critical one.

Machine learning, as well as deep and reinforcement learning, are all forms of artificial intelligence, which have led to new strategies in the capacity to predict and price in financial markets. Such approaches are able to identify non-linear

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dynamics, high-dimensional interactions, and adaptive processes that may not be identified using standard models [4]. Long since, commodity prices and volatility have been modelled with econometric methods, especially those based on generalised autoregressive conditional heteroskedasticity (GARCH), vector autoregression (VAR), and cointegration frameworks. Nevertheless, it has not been long before their combination with AI approaches started garnering interest in academic and practical literature of finance [5]. The fusion holds the possibility to create hybrid models that maintain theoretical rigour and improve predictive performance and real-time flexibility.

In spite of this potential that has come into view, a number of critical challenges and research gaps still exist. To start with, AI-based pricing models are not interpretable enough, especially in commodity high-stakes settings where transparency and regulatory adherence are vital [6]. Second, no standardised frameworks have been established on how to incorporate the econometric risk measures, including Value at Risk (VaR) and Conditional VaR or downside beta, into the AI-driven pricing models in a consistent and strong fashion [7]. Thirdly, AI models are highly limited by the sparsity and heterogeneity of data, particularly with illiquid or immature commodities, and the lack of ways to generalise them to other market segments [8]. Also, real-world problems tend to demand real-time adaptable models, and this necessitates the incorporation of online learning or adaptive econometric methods, a field of study that is under-researched with respect to commodities [9].

The merging of AI and econometrics is one of the major paradigm shifts in the wider area of financial economics. Although AI can make very strong predictions, econometrics provides consistency and interpretability of the theories, which are essential in the interpretation of market behaviour and the development of regulatory policies. Thus, risk-adjusted price models with the strategic combination of these fields have a prospect of not only increasing the quality of forecasts but also the quality of market transparency and resistance.

This review aims to critically look at the risk-adjusted pricing environment in the commodities market, with a specific emphasis given to the models that apply AI, as well as econometric methods.

2. Literature Review

Table 1 Summary of Key Literature on Risk-Adjusted Pricing in Commodities Markets Using AI and Econometric Techniques

Ref	Research Focus / Objective	Key Findings / Contributions
[10]	Investigates the asymmetric relationship between unemployment and economic growth (Okun’s Law) in Pakistan using a threshold cointegration approach.	Findings support an asymmetric adjustment process in Okun’s Law for Pakistan; economic growth affects unemployment differently in recession and expansion periods. This has implications for labour market policies in developing economies.
[11]	Proposes a hybrid model combining Empirical Mode Decomposition (EMD) and neural network ensemble learning to forecast crude oil prices.	Demonstrates that decomposing time series into intrinsic mode functions (IMFs) significantly improves prediction accuracy. The model outperformed traditional single neural network models.
[12]	Explores the effectiveness of Support Vector Machines (SVM) in forecasting financial time series, comparing it with neural networks.	Shows that SVMs provide better generalisation and forecasting accuracy than traditional neural networks, especially in noisy financial datasets. Validates the model as a promising technique for time series prediction.
[13]	Addresses the emerging issue of collusion in AI-driven trading environments using reinforcement learning agents.	Proposes a market-aware multi-agent reinforcement learning system that mitigates emergent collusive behaviour. Highlights regulatory implications in AI-dominated trading platforms.
[14]	Introduces the use of dilated Convolutional Neural Networks (CNNs) for financial time series forecasting.	Demonstrates that dilated CNNs can effectively model long-range temporal dependencies in time series data, outperforming recurrent models like LSTMs in terms of speed and accuracy.

3. Proposed Theoretical Model and Block Diagrams

3.1. Commodities Markets, Artificial Intelligence, and Econometric-based risk-adjusted Pricing Models

Alterations in the pricing model of commodities have also posed the requirement of the creation of a hybrid model that is capable of integrating the interpretability of econometric models with the capacity to identify patterns and non-linear approximation of artificial intelligence (AI). The proposed theoretical model is the following: A hybrid architecture is defined as multi-layered, in which the market fundamentals and the risk indicators, and the price behaviour would be modelled together to generate risk-adjusted commodity prices. The appropriate literature and observation support each of the elements. In this part, there are two block diagrams: one that represents the macro-structure and the other one represents the workflow pipeline of the hybrid modelling process.

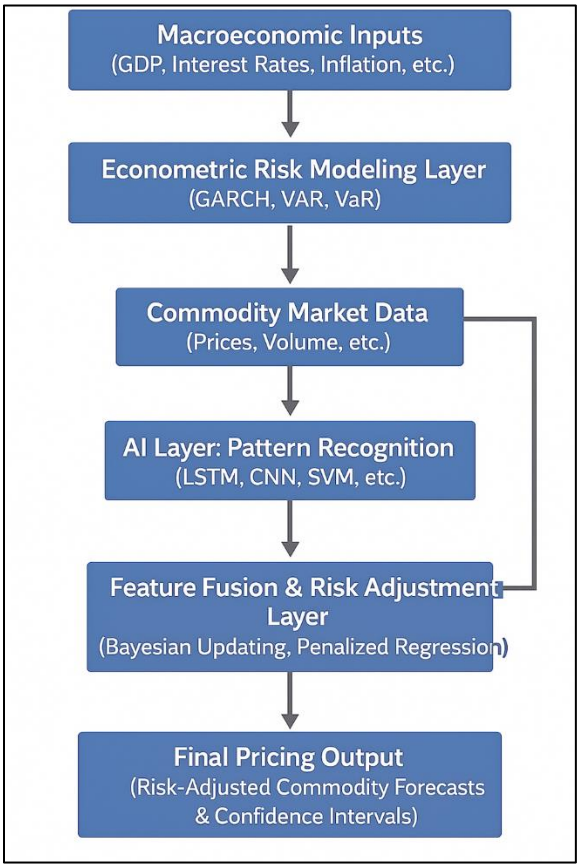

Figure 1 The Concepts of the merger of Econometrics with AI to Risk-Adjusted Pricing

Explanation:

- Macroeconomic Inputs: These are exogenous variables that influence the behaviour of the price of commodities in terms of inflation, interest rates, monetary policy and growth expectations [15].
- Econometric Risk Modelling Layer: Addresses the time series volatility modelling, structural analysis (GARCH, VAR, Value-at-Risk) and quantifiable market risk [16].
- Commodity Market Data: Both the econometric and the AI layers have access to historical prices as well as volumes and inventory data, which suggests that the two can be analysed jointly.
- AI Layer: Scales non-linear models, such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) that discover complex dependencies and latent patterns that would be hard to discover if only linear structures were used [17].
- Feature Fusion / Risk Adjustment Layer: Risk-adjusted and Bayesian updated Probabilistic predictions of both layers are obtained by combining the outputs of the two layers [18].
- Final Pricing Outcome: Provides amended pricing forecasts which comprise systematic risk, Macroeconomic uncertainty and latent market structure.

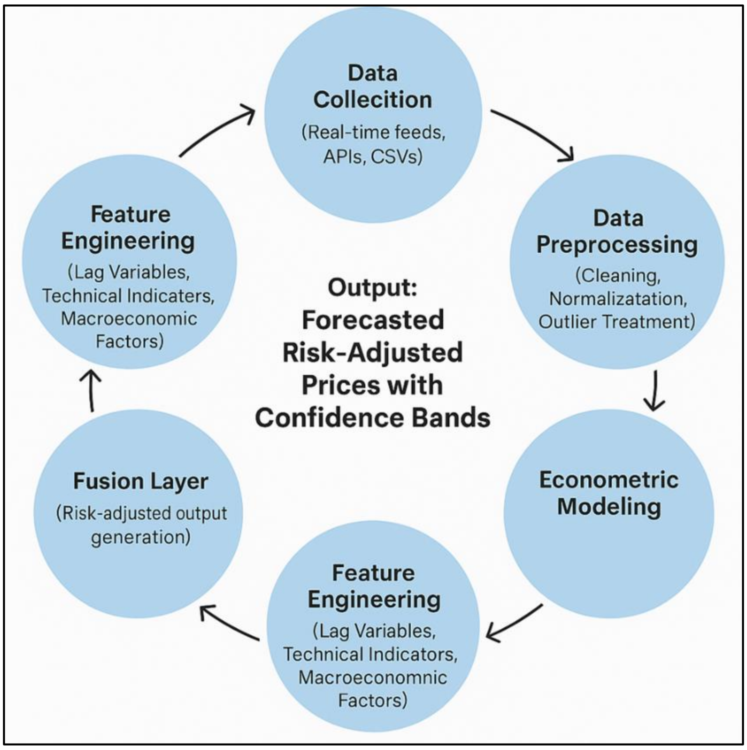

Figure 2 End-to-End Process Pipeline of the Hybrid Risk-Adjusted Commodity Pricing.

3.2. Theoretical Foundation.

The model proposed is driven by both the multi-model ensemble learning theory and structural econometrics. The significant theoretical hypotheses are:

- Econometric Risk Decomposition: Econometric models, which are either GARCH models or multivariate VAR models, can capture the conditional volatility and spillover effects in order to deliver a quantifiable amount of systemic risk [16][19].
- AI-based Non-linear Feature Mapping: A machine learning algorithm, in particular, deep neural networks have the ability to extrapolate non-linear, high-dimensional associations between variables that are not directly specified in an econometric model [17][20].
- Fusion to Improve Forecasts: Model forecasting can also be fused with other model predictions to ensure that the model prediction is informed by the underlying theoretical model and patterns learnt on empirical data [18].

Econometrics and Explainability Tools Interpretability AI models do not inherently present themselves in a way that is understandable by humans; however, model-agnostic interpretability tools (e.g., SHAP, LIME) can be used to convey information on the relevance of variables and model decisions [21].

The Proposed Model has several benefits

- Higher Precision: It has been empirically found to improve more than single models in volatile and non-stationary such as commodity [22].
- Greater Risk Visibility: With AI and econometrics, it is possible to predict and quantify risk simultaneously.

Transparency & Regulation-Ready Is Econometrics often offers systematised interpretability, which augments the adaptive power of AI, as a compliance mandate together with an innovation.

4. Applications in the Real-Life of the Risk-Adjusted Pricing Model in Commodities Markets based on AI and Econometric Methods

4.1. BP - Crude Oil Price Forecasting based on AI-Econometric Hybrids

4.1.1. Context

British Petroleum (BP) is an international energy company that is highly vulnerable to fluctuations in crude oil prices. The company also uses hybrid forecasting models in its trading division, which is a combination of GARCH-based volatility models with machine learning algorithms like the Random Forests and Support Vector Machines (SVM), forecasting the price of oil in a risk-adjusted manner.

4.1.2. Application

Conditional volatility is measured and predicted with the help of GARCH.

The generated output of these models are then combined into ML pipelines in the form of engineered features to be used in subsequent price prediction.

These forecasts are useful in hedging decisions and also in determining internal transfer prices of trading and production activities.

Impact: This dual-modelling approach has resulted in higher short-term forecasting accuracy and enhanced portfolio risk management results as reported by BP.

4.2. CME Group - Volatility Forecasting in Agricultural Derivatives with Econometric and AI-based Models

4.2.1. Context

The Chicago Mercantile Exchange (CME) applies AI and econometric models to determine margin requirements and measure volatility risk in its agricultural derivatives markets (e.g. corn, wheat, soybeans).

4.2.2. Application

EGARCH and stochastic volatility models are used in the CME to gauge price variability.

Highlighted by these models, AI-based anomaly detection algorithms supplement them in detecting exogenous shocks (e.g., weather events or supply chain disruptions).

The systems accommodate the models, which dynamically adjust Value-at-Risk (VaR) and margining systems.

Impact: This mixed methodology allows improved monitoring of systemic risks, assists the SPAN margining system, and helps keep the market intact in high uncertainty times.

4.3. Goldman Sachs AI-Enhanced Commodity Trading Strategies

4.3.1. Context

The Global Commodities Division of Goldman Sachs has implemented deep learning algorithms and econometric algorithms to perform real-time commodity trading and pricing (especially in the markets of energy and metals).

4.3.2. Application

Trains Long Short-Term Memory (LSTM) networks on previous price movement and macroeconomic data to forecast future price changes.

At the same time, uses cointegration and VAR models to estimate long-run equilibrium relationships among commodities (e.g. oil and gas or gold and silver).

The outputs of the models are used to drive automated trading algorithms that implement positions based on the predicted returns and risk metrics that are adjusted.

Impact: The strategy has led to increased alpha, increased inventory optimisation and increased liquidity provision in volatile markets.

4.4. Trafigura - Real-Time Risk-Adjusted Pricing in Trading Physical Commodities

4.4.1. Context

Trafigura is one of the largest and independent commodity trading companies in the world that trades in refined products, crude oil and base metals. To handle global price exposure, it came up with a real-time commodity pricing platform operated using AI and econometric engines.

4.4.2. Application

The company applies autoregressive distributed lag (ARDL) models to know price elasticity and lag forms in the supply-demand data.

The gradient boosting machines (GBMs) and other AI methods are used to predict intra-day and daily prices based on streaming prices provided by shipping, weather, and inventory markets.

The platform is dynamically adjusted to price offers by including hedging costs, basis risk and volatility forecasts.

Impact: Trafigura has enhanced the accuracy of its transaction-level pricing, expanded trade margins and streamlined physical delivery pathways by converting prices more towards risk measurements.

4.5. Pricing of Shell - Carbon Market and Energy Derivatives using AI and Risk Models

4.5.1. Context

As a part of its low-carbon trading activities, Shell uses AI-enhanced pricing models to operate collections of carbon credits, renewable energy certificates, and energy derivatives.

4.5.2. Application

Integrates Monte Carlo simulation, VaR modelling and reinforcement learning to value complex derivative contracts.

Adjusts volatility and regulatory risk by using AI models conditioned on the energy consumption data, regulatory policy cues, and carbon offset prices.

Implemented in the internal reporting of risks, as well as in structuring deals in relation to decarbonization plans.

Impact: The implementation of such models by Shell enables it to provide more competitive prices, mitigate risk, expand its business of carbon trading, and remain transparent.

4.6. Real-World Cases Conclusion

These industrial examples reflect the increasing dependence of AI-econometric models, which combine both AI and the economy in pricing and risk management in the commodity markets. Some of the similarities in these cases are:

- Risk quantification by means of econometric models (e.g., GARCH, VAR).
- Foresight and anomaly detection AI algorithms (e.g., LSTM, SVM, GBM) deployment.
- Construction of models in the trading, hedging, and portfolio optimisation pipeline in decision-making.
- Focus on data fusion - traditional financial data in combination with macroeconomic, sensor, or unstructured data.
- Creation of real-time pricing engines that are responsive to dynamic market conditions.

These practical applications confirm the theory and suggest the potential area of future research, such as aligning regulation across markets, explaining models, and their scalability.

5. Future Research Directions

5.1. Development of Hybrid Models that are understandable

Future research will attempt to come up with interpretable hybrid models in a manner that they do not lose the theoretical basis of econometrics and apply the adaptive and non-linear learning capabilities of AI. The techniques that ought to be incorporated in the commodity pricing models are: model distillation, post-hoc explainability (e.g., SHAP, LIME), which will enable the models to adhere to regulations and be transparent in their operations.

5.2. Incorporation of real-time streaming data

Most of the existing models take historical ensembles of information, which is calculated in batches. The next step would be a successor (to incorporate real-time streaming information (e.g. satellite picture of crop harvests, high frequency trade information, sensor-based energy generation) into prices). Online learning algorithms and adaptive econometric stream-based methods are needed in order to respond to the altering market conditions.

5.3. Expansion to Emerging Markets and Carbon Markets

In the past, research has been on the common commodities like crude oil, gold, and agricultural products. Yet there are some new markets, such as carbon credits, lithium, and rare earth elements, which are gaining significance in the world market. The markets are also normally void of past information, which makes them good candidates for the hybrid models that could be exploited in the low-data and high-uncertainty regimes.

5.4. Multi-Mode Learning Architectures Context-Aware Learning Architectures

The future versions should have context-sensitive mechanisms, such as attention layers or hierarchies that dynamically weigh the weight of macroeconomic signals, policy events, and geopolitical signals. Multi-modal data (e.g., text on policy announcements, satellite data, and numerical time series) can be added to forecasting systems, and it is expected to make them more accurate and powerful.

5.5. The Uncertainty and Model Risk to be measured

This is because full-scale applications of hybrid models are in a high-stakes context where there is a need to measure the uncertainty of model results. The Bayesian deep learning and probabilistic econometric models can offer a solution. Research will be carried out on the estimation of confidence intervals, tail risks, and measures of robustness at different levels of the model.

5.6. Governance and Ethical Frameworks Design

As the role of AI-driven systems in the pricing decision-making process grows, ethical model governance frameworks, bias detection, and accountability should be offered. These models are expected to adhere to the norms of transparency in the financial market but should be capable of being innovated within a short time. This will involve studies to find out how to develop such structures of governance in an environment of algorithmic prices.

6. Conclusion

The AI, coupled with econometric techniques used in price-setting models of commodities, is a paradigm shift in financial models. The traditional econometric methods are interpretable and structurally clear, and even now, they matter a great deal in regulatory adoption and economic justification. They, however, tend not to cope with non-linear and fast-changing markets. Conversely, AI models are flexible and predictive, but they lack transparency and a theoretical foundation. To do away with such vulnerabilities, hybrid risk-adjusted pricing models that combine the best of AI with those of econometrics are gaining in popularity, as demonstrated in this review. The issues of this integrated approach outlined in this article, as both practical and tangible benefits, have been proposed through the analysis of significant literature, a proposed theoretical framework outlined, and its applications discussed in the real-world setting. Its major problems are explainability of the model, real-time adaptability, and quality of data and regulatory compliance, as well as suggesting the opportunities of future studies in the academic field and industry. The pressure of powerful, scalable, and understandable risk-adjusted pricing systems will continue to rise as commodity markets get more interlinked and volatile. The current development in the research and practice suggests that neither the adoption of AI nor econometrics is the future of commodities pricing, but the need to align them strategically to meet several complex needs in the existing markets.

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