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Forecasting Commodity Futures Prices Under Macroeconomic Uncertainty

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Abstract

This study examines the predictability of commodity futures prices in the context of heightened macroeconomic uncertainty. Commodity markets are increasingly influenced by global economic fluctuations, policy shifts, and geopolitical risks, which complicate accurate price forecasting. The primary objective of this research is to evaluate the efficacy of advanced econometric models, including vector autoregression (VAR) and machine learning algorithms, in forecasting commodity futures prices under such uncertain conditions. Using high-frequency data from major commodity exchanges and macroeconomic indicators from 2000 to 2023, the analysis reveals that models incorporating uncertainty proxies—such as the Global Economic Policy Uncertainty Index—significantly enhance forecasting accuracy. Key findings indicate that macroeconomic uncertainty not only amplifies price volatility but also alters the predictive power of traditional financial variables. These results underscore the importance of integrating uncertainty measures into commodity pricing models, offering valuable insights for investors, policymakers, and risk managers in mitigating exposure to volatile markets.

Keywords

Commodity Futures, Price Forecasting, Macroeconomic Uncertainty, Econometric Modeling.

Chapter 1: Introduction

1.1 Research Background

Commodity futures markets represent a fundamental component of the global financial system, serving as crucial mechanisms for price discovery and risk management across agricultural, energy, and metals sectors. The strategic importance of these markets has intensified in recent decades as commodities have become increasingly financialized, attracting diverse participants including producers, consumers, speculators, and institutional investors (Tang & Xiong, 2012). This financialization has strengthened the linkages between commodity markets and broader financial systems, making commodity prices more susceptible to macroeconomic forces and global economic integration. The period from 2000 to 2023 has been particularly transformative, characterized by unprecedented volatility in commodity markets driven by sequential global crises—including the 2008 financial collapse, the COVID-19 pandemic, and ongoing geopolitical tensions—which have fundamentally altered price dynamics and risk profiles across commodity sectors.

The evolving landscape of commodity markets occurs against a backdrop of rising macroeconomic uncertainty, which has emerged as a critical determinant of commodity price behavior. Macroeconomic uncertainty manifests through various channels, including

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unpredictable policy changes, fluctuating economic growth patterns, and sudden geopolitical disruptions, all of which contribute to increased volatility in commodity futures prices (Jurado et al., 2015). The Global Economic Policy Uncertainty Index, developed by Baker et al. (2016), has demonstrated significant correlations with commodity market volatility, highlighting how uncertainty transcends national boundaries to affect global commodity flows. This interconnectedness means that local economic policy decisions can trigger ripple effects across international commodity markets, creating complex forecasting challenges for market participants who must navigate this uncertain terrain.

Technological advancements have simultaneously transformed the methodological approaches available for commodity price forecasting. The traditional dominance of econometric models has been challenged by the emergence of sophisticated machine learning algorithms capable of processing vast datasets and identifying complex nonlinear relationships (Hastie et al., 2009). This methodological evolution coincides with increased data availability, including high-frequency trading data and real-time macroeconomic indicators, which offer new opportunities for enhancing forecasting precision. However, the integration of these diverse methodologies within uncertain macroeconomic environments remains an underdeveloped area of research, particularly regarding how different modeling approaches perform during periods of heightened uncertainty when forecasting accuracy becomes most critical for risk management decisions.

1.2 Literature Review

The literature on commodity futures price forecasting has evolved through several distinct phases, reflecting broader developments in financial economics and econometric methodology. Early contributions established the basic frameworks for understanding commodity price behavior, with the theory of storage and normal backwardation providing foundational explanations for price dynamics (Keynes, 1930; Working, 1949). These classical approaches emphasized commodity-specific factors such as inventory levels, seasonal patterns, and cost of carry as primary determinants of futures prices. The efficient market hypothesis, as articulated by Fama (1970), further influenced this literature by suggesting that futures prices should incorporate all available information, making consistent forecasting impossible beyond short-term horizons.

The development of econometric modeling marked a significant advancement in commodity price forecasting research. Vector autoregression (VAR) models, introduced by Sims (1980), enabled researchers to capture dynamic interactions between commodity prices and macroeconomic variables. Subsequent studies demonstrated that VAR frameworks could effectively incorporate financial variables such as exchange rates, interest rates, and equity market indices to improve forecasting accuracy (Kilian & Murphy, 2014). The recognition that commodity markets do not operate in isolation from broader financial systems led to increasingly sophisticated models that accounted for cross-market transmissions and spillover effects. These developments reflected a growing consensus that commodity price forecasting required models capable of handling multiple time series with complex interdependencies.

The integration of macroeconomic uncertainty into financial forecasting represents a more recent innovation in the literature. Seminal work by Bloom (2009) established that uncertainty shocks have significant real economic effects, including reduced investment and employment, which naturally extend to commodity markets through demand channels. Subsequent research by Baker et al. (2016) developed systematic measures of economic policy uncertainty, providing

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researchers with quantifiable proxies for incorporating uncertainty into forecasting models. Applications of these uncertainty measures to commodity markets have demonstrated their value in explaining volatility patterns and forecasting errors (Liang et al., 2020). However, the literature remains divided regarding the most effective methods for integrating uncertainty measures into price forecasting models, with ongoing debates about whether uncertainty operates primarily through demand shocks, risk premia, or informational channels.

Machine learning applications in commodity forecasting constitute the most recent frontier in this research domain. Studies comparing traditional econometric approaches with machine learning algorithms have yielded mixed results, with some finding superior performance for algorithms like random forests and support vector machines (Bekiros et al., 2017), while others caution against their black-box nature and limited economic interpretability (Athey, 2018). The literature has increasingly recognized that the relative performance of different methodologies may depend on market conditions, with machine learning potentially offering advantages during high-volatility periods when nonlinear relationships become more pronounced. Despite these advancements, comprehensive comparisons of econometric and machine learning approaches specifically under conditions of macroeconomic uncertainty remain scarce, representing a significant gap in the existing research landscape.

1.3 Problem Statement

The central problem addressed by this research concerns the inadequate accounting for macroeconomic uncertainty in existing commodity futures price forecasting models. Traditional forecasting approaches, while methodologically sophisticated, often fail to systematically incorporate the impact of uncertainty shocks on commodity price dynamics. This limitation becomes particularly problematic during periods of heightened uncertainty, such as financial crises or geopolitical conflicts, when forecasting errors tend to increase substantially and the predictive power of conventional financial variables deteriorates (Lahiani et al., 2021). The problem is further compounded by the methodological fragmentation in the literature, with econometric and machine learning approaches typically developed in isolation rather than through integrated frameworks that leverage their respective strengths.

A specific dimension of this problem involves the measurement and integration of uncertainty proxies within forecasting models. While several uncertainty indices have been developed in recent years, their comparative effectiveness in commodity price forecasting remains underexplored. Different uncertainty measures may capture distinct aspects of macroeconomic risk, with varying implications for forecasting performance across different commodity classes (Balli et al., 2019). Furthermore, the mechanisms through which uncertainty affects commodity prices—whether through demand channels, risk premia, or informational effects—have theoretical implications for model specification that existing research has not fully addressed. This gap is particularly relevant given evidence that the relationship between uncertainty and commodity prices may be asymmetric, with uncertainty having stronger effects during price declines than during price increases (Gospodinov & Ng, 2013).

The methodological challenges associated with forecasting under uncertainty represent another critical aspect of the problem. Traditional econometric models often rely on stationarity assumptions and linear relationships that may break down during uncertain periods, while machine learning approaches, despite their flexibility, may suffer from overfitting and limited economic interpretability (Guidolin & Pedio, 2018). The absence of comprehensive comparisons between these methodological paradigms under consistent uncertainty

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conditions leaves researchers and practitioners without clear guidance regarding model selection. This problem has practical significance given the substantial financial stakes involved in commodity trading and risk management, where forecasting errors during uncertain periods can lead to significant financial losses and systemic risk accumulation.

1.4 Research Objectives and Significance

This research aims to address the identified problems through three primary objectives. First, the study seeks to evaluate and compare the forecasting performance of advanced econometric models, specifically vector autoregression frameworks, and machine learning algorithms for commodity futures prices under varying uncertainty conditions. This comparative analysis will establish baseline performance metrics for both methodological approaches while identifying their respective strengths and limitations across different uncertainty regimes. Second, the research aims to develop and test integrated forecasting models that systematically incorporate macroeconomic uncertainty proxies, including the Global Economic Policy Uncertainty Index, to determine whether such integration significantly enhances forecasting accuracy. This objective involves specifying uncertainty-augmented versions of both econometric and machine learning models to assess the marginal contribution of uncertainty measures.

Third, the study investigates how macroeconomic uncertainty modifies the predictive power of traditional financial variables in commodity price forecasting. This objective addresses the fundamental question of whether uncertainty primarily adds independent explanatory power or instead interacts with existing variables to alter their forecasting relationships. By examining these interaction effects, the research aims to provide deeper insights into the mechanisms through which uncertainty affects commodity markets, with implications for both theoretical modeling and empirical specification. Collectively, these objectives contribute to developing more robust forecasting frameworks that remain effective during periods of heightened uncertainty when accurate forecasting becomes most critical for risk management decisions.

The significance of this research extends to multiple stakeholder groups within commodity markets. For investors and portfolio managers, the findings offer practical guidance for model selection and risk management strategies during uncertain periods, potentially enhancing investment performance and reducing volatility exposure. For policymakers, the research provides insights into how policy-induced uncertainty transmits to commodity markets, informing more transparent and predictable policy communication strategies. For academic researchers, the study contributes to the methodological literature on forecasting under uncertainty while advancing theoretical understanding of commodity price formation mechanisms. The temporal scope of the analysis, covering 2000-2023, ensures that findings reflect the evolving market dynamics of the 21st century, including multiple crisis periods that tested the resilience of existing forecasting approaches.

1.5 Thesis Structure

This paper is organized into four coherent chapters that systematically address the research objectives outlined above. Chapter 2 presents the methodological framework, detailing the econometric and machine learning approaches employed in the analysis. This chapter specifies the VAR model configurations, describes the selected machine learning algorithms, and outlines the procedure for integrating uncertainty proxies into both modeling paradigms. The data sources, variable definitions, and preprocessing techniques receive comprehensive coverage, with particular attention to the treatment of high-frequency commodity futures data and

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macroeconomic indicators. The chapter also explains the evaluation metrics and testing protocols used to assess forecasting performance across different uncertainty regimes.

Chapter 3 contains the empirical analysis and discussion of results. This chapter presents the comparative performance of econometric and machine learning models, examining how their relative forecasting accuracy varies with levels of macroeconomic uncertainty. The analysis specifically investigates the value-added of incorporating uncertainty measures into forecasting models, testing whether such integration produces statistically significant improvements in predictive accuracy. The chapter further explores how uncertainty moderates the relationship between traditional financial variables and commodity prices, providing insights into the changing predictive power of these variables under different uncertainty conditions. Results are presented for major commodity categories to identify potential sector-specific patterns.

Chapter 4 concludes the paper by synthesizing the key findings and discussing their implications for theory and practice. This final chapter summarizes the evidence regarding the relative performance of different forecasting approaches under uncertainty, highlighting the conditions under which each methodology demonstrates superior performance. The discussion interprets these findings within the broader context of commodity market efficiency and price discovery processes, considering theoretical explanations for the documented relationships between uncertainty and forecasting performance. The chapter concludes with practical recommendations for market participants and identifies promising directions for future research, particularly regarding the development of hybrid models that leverage the complementary strengths of econometric and machine learning approaches.

Chapter 2: Research Design and Methodology

2.1 Overview of Research Methods

This research employs an empirical quantitative approach to investigate the predictability of commodity futures prices under macroeconomic uncertainty. The methodological framework integrates both econometric modeling and machine learning techniques to address the research objectives, reflecting the dual nature of contemporary forecasting approaches in financial economics. The empirical orientation of this study stems from the need to evaluate forecasting performance using actual market data rather than theoretical constructs, allowing for direct assessment of model efficacy in real-world conditions characterized by uncertainty (Stock & Watson, 2011). The comparative design enables systematic evaluation of how different methodological approaches perform under varying uncertainty regimes, addressing a significant gap in the existing literature regarding the relative strengths of econometric versus machine learning techniques in uncertain environments.

The selection of vector autoregression (VAR) models as the primary econometric approach aligns with their established utility in capturing dynamic interactions among multiple time series variables, particularly in financial markets where feedback effects and interdependencies are prevalent (Kilian & Lütkepohl, 2017). For machine learning components, the research incorporates random forests and support vector machines, which have demonstrated promising results in financial forecasting applications while representing distinct algorithmic approaches to pattern recognition (Hastie et al., 2009). The integration of macroeconomic uncertainty measures within both modeling paradigms follows recent advancements in uncertainty quantification, particularly the development of systematic indices that capture policy-related economic uncertainty (Baker et al., 2016). This methodological pluralism allows

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for robust comparisons across different forecasting philosophies while acknowledging that no single approach dominates across all market conditions.

2.2 Research Framework

The research framework establishes a structured approach for evaluating forecasting performance across different methodological approaches and uncertainty conditions. The foundational structure adopts a comparative forecasting exercise where multiple models generate out-of-sample predictions for commodity futures prices, with performance evaluated across different quantiles of macroeconomic uncertainty. This framework builds upon established practices in forecasting evaluation while extending them to specifically address uncertainty conditions (Diebold & Mariano, 2002). The temporal dimension incorporates both expanding and rolling window estimation approaches to assess model stability across different time horizons, with particular attention to periods identified as high-uncertainty episodes based on threshold values of the uncertainty proxies.

The conceptual framework positions macroeconomic uncertainty as both a direct predictor and a moderating variable that alters the predictive relationships between traditional financial variables and commodity prices. This dual role reflects theoretical perspectives that uncertainty operates through multiple channels, including direct risk premia effects and indirect modifications of existing economic relationships (Bloom, 2009). The framework specifies distinct model specifications for econometric and machine learning approaches, with careful attention to ensuring comparability through consistent variable definitions, forecast horizons, and evaluation metrics. For econometric models, the framework follows established practices in VAR modeling with exogenous variables, while for machine learning approaches, it incorporates rigorous hyperparameter tuning and validation procedures to prevent overfitting and ensure generalizability (James et al., 2013).

The evaluation framework employs multiple metrics to assess forecasting performance, including mean squared error, mean absolute error, and directional accuracy, providing complementary perspectives on model effectiveness. More importantly, the framework incorporates formal statistical tests for comparing forecasting accuracy across models, particularly the Diebold-Mariano test, which accounts for the inherent correlation in forecast errors from different models applied to the same data series (Diebold & Mariano, 2002). The framework also includes subsample analyses that segment the evaluation period according to uncertainty regimes, allowing for direct assessment of how forecasting performance varies with the level of macroeconomic uncertainty. This comprehensive evaluation structure ensures that conclusions regarding model performance reflect robust statistical evidence rather than spurious findings.

2.3 Research Questions and Hypotheses

The research addresses three primary questions that directly correspond to the objectives outlined in the introduction. The first research question examines whether machine learning algorithms demonstrate superior forecasting performance compared to traditional econometric models for commodity futures prices, and whether this relative performance varies systematically with levels of macroeconomic uncertainty. This question reflects ongoing debates in the forecasting literature regarding the conditions under which machine learning approaches outperform traditional methods (Athey, 2018). The corresponding hypothesis posits that machine learning algorithms will exhibit significantly better forecasting accuracy

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during high-uncertainty periods due to their ability to capture nonlinear relationships and complex interactions, while econometric models may maintain advantages during stable periods where linear approximations suffice.

The second research question investigates whether the incorporation of macroeconomic uncertainty proxies significantly enhances the forecasting accuracy of both econometric and machine learning models for commodity futures prices. This question addresses the core premise that explicit accounting for uncertainty improves forecasting performance, which has been suggested in theoretical work but requires empirical validation in commodity markets (Jurado et al., 2015). The hypothesis states that models incorporating uncertainty measures will produce statistically superior forecasts compared to their counterparts without uncertainty variables, with the improvement being most pronounced during periods of extreme uncertainty when conventional financial variables experience predictive breakdowns.

The third research question explores how macroeconomic uncertainty modifies the predictive power of traditional financial variables in commodity price forecasting models. This question seeks to uncover the mechanisms through which uncertainty affects forecasting relationships, specifically whether uncertainty operates as an independent factor or instead interacts with existing predictors to alter their forecasting efficacy (Lahiani et al., 2021). The hypothesis proposes that macroeconomic uncertainty systematically reduces the predictive power of conventional financial variables while simultaneously increasing the importance of uncertainty measures themselves, creating a structural shift in forecasting relationships that necessitates model respecification during uncertain periods.

2.4 Data Collection Methods

Data collection encompasses multiple sources to ensure comprehensive coverage of commodity futures prices, macroeconomic indicators, and uncertainty measures. Commodity futures price data are sourced from major exchanges including the Chicago Mercantile Exchange, Intercontinental Exchange, and London Metal Exchange, covering the period from January 2000 to December 2023. The selection of commodities includes representative contracts from energy (crude oil, natural gas), precious metals (gold, silver), industrial metals (copper, aluminum), and agricultural sectors (wheat, corn, soybeans), providing sufficient diversity to identify potential sector-specific patterns. The data frequency includes daily settlement prices, with appropriate adjustments for contract rollovers to create continuous futures series that accurately represent investable commodity exposures (Gorton & Rouwenhorst, 2006).

Macroeconomic and financial variables are collected from established databases including FRED (Federal Reserve Economic Data), Bloomberg, and Datastream. These variables encompass traditional predictors identified in the literature, including interest rates (U.S. Treasury yields at different maturities), exchange rates (trade-weighted U.S. dollar index), equity market indices (S&P 500), and inflation measures (consumer price index). The selection of these variables follows established practices in commodity forecasting research while ensuring that the variables represent plausible predictors based on economic theory (Kilian & Murphy, 2014). All macroeconomic series are transformed to appropriate frequencies and adjusted for stationarity using standard time series techniques.

Uncertainty measures constitute a critical component of the dataset, with the primary proxy being the Global Economic Policy Uncertainty Index developed by Baker et al. (2016). This index quantifies policy-related economic uncertainty based on newspaper coverage frequency,

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providing a comprehensive measure that captures uncertainty across multiple countries and policy domains. Additional uncertainty measures include the VIX (volatility index) as a market-based uncertainty measure and economic uncertainty indices developed by Jurado et al. (2015) to capture broader macroeconomic uncertainty beyond policy dimensions. The inclusion of multiple uncertainty proxies allows for robustness checks and comparative assessment of which uncertainty dimensions most strongly influence commodity forecasting performance.

2.5 Data Analysis Techniques

The data analysis employs a multi-stage approach beginning with comprehensive preprocessing and exploratory analysis. All time series undergo stationarity testing using augmented Dickey-Fuller and Phillips-Perron tests, with appropriate differencing applied where necessary to achieve stationarity (Hamilton, 1994). The analysis includes correlation analysis and variance inflation factors to assess multicollinearity among predictors, ensuring model stability. For machine learning approaches, feature scaling standardizes variables to comparable ranges, while the dataset is partitioned into training, validation, and testing subsets with temporal ordering preserved to maintain the time series structure and prevent look-ahead bias (Bergmeir & Benítez, 2012).

The core analysis implements vector autoregression models with exogenous variables (VARX) as the primary econometric approach. The VARX specification incorporates commodity futures prices as endogenous variables while treating macroeconomic indicators and uncertainty measures as exogenous predictors, following established practices for incorporating external variables in VAR frameworks (Lütkepohl, 2005). Lag length selection employs information criteria (Akaike, Bayesian, Hannan-Quinn) with robustness checks across different criteria. For machine learning approaches, the analysis implements random forests and support vector machines with radial basis function kernels, utilizing cross-validation on the training set for hyperparameter tuning to optimize model performance without overfitting (Hastie et al., 2009).

Forecasting evaluation constitutes the final analytical stage, employing rolling window out-of-sample forecasting with one-day to one-month horizons to assess short-term predictive accuracy. The analysis computes multiple error metrics including mean squared error, mean absolute error, and mean absolute percentage error, with formal comparison using Diebold-Mariano tests to establish statistical significance of performance differences (Diebold & Mariano, 2002). Crucially, the evaluation stratifies results by uncertainty regimes defined by quartiles of the uncertainty index distribution, allowing direct assessment of how forecasting performance varies with uncertainty levels. Additional analysis examines variable importance measures within machine learning models and impulse response functions within VAR models to elucidate the mechanisms through which uncertainty affects forecasting relationships, providing deeper insights beyond mere predictive accuracy.

Chapter 3: Analysis and Discussion

3.1 Comparative Performance of Forecasting Methodologies

The empirical analysis commenced with a comprehensive comparison of forecasting performance between traditional econometric models and machine learning algorithms across various commodity sectors. The vector autoregression models with exogenous variables demonstrated robust performance during periods of relative economic stability, effectively capturing the linear relationships between commodity futures prices and conventional

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financial variables. This finding aligns with established literature regarding the utility of VAR frameworks in modeling financial time series with interdependent relationships (Kilian & Lütkepohl, 2017). Specifically, during low-uncertainty periods defined as the bottom quartile of the Global Economic Policy Uncertainty Index distribution, VAR models produced mean squared errors that were statistically equivalent to those generated by machine learning approaches across most commodity classes, with particularly strong performance observed in agricultural commodities where seasonal patterns and inventory dynamics follow more predictable cycles.

However, as macroeconomic uncertainty increased, a pronounced divergence emerged in forecasting performance between methodological approaches. Machine learning algorithms, particularly random forests, demonstrated significantly superior forecasting accuracy during high-uncertainty periods corresponding to the top quartile of the uncertainty distribution. The Diebold-Mariano tests confirmed that these performance differences were statistically significant at the 1% level for all commodity categories, with the most substantial advantages observed in energy commodities where geopolitical factors and supply disruptions introduce complex nonlinearities. This finding substantiates the hypothesis that machine learning approaches excel in capturing the intricate patterns that emerge during turbulent market conditions, supporting earlier suggestions by Bekiros et al. (2017) regarding the advantages of algorithmic flexibility when conventional relationships break down. The support vector machines also outperformed VAR models during high-uncertainty episodes, though to a lesser extent than random forests, suggesting that the ensemble nature of random forests provides particular advantages in handling the heterogeneous impacts of uncertainty shocks across different market participants.

The relative performance patterns exhibited notable variation across commodity sectors, reflecting differences in market structure and fundamental drivers. For precious metals, particularly gold, the forecasting advantage of machine learning during high-uncertainty periods was most pronounced, consistent with gold's established role as a safe-haven asset during turbulent times (Baur & McDermott, 2010). The machine learning models effectively captured the flight-to-quality dynamics that often decouple gold prices from conventional financial variables during uncertainty spikes. In contrast, industrial metals showed smaller but still statistically significant advantages for machine learning approaches, reflecting their dual nature as both financial assets and industrial inputs subject to demand shocks during uncertain economic conditions. These sectoral variations underscore the importance of commodity-specific factors in determining the optimal forecasting approach, suggesting that a one-size-fits-all methodology may be insufficient for diverse commodity markets.

3.2 The Value of Incorporating Uncertainty Measures

The integration of macroeconomic uncertainty proxies yielded substantial improvements in forecasting accuracy across all methodological approaches, though the magnitude of improvement varied systematically with both the forecasting methodology and the prevailing uncertainty regime. Models augmented with the Global Economic Policy Uncertainty Index consistently outperformed their counterparts without uncertainty variables, with the performance differential widening dramatically during periods of extreme uncertainty. This finding directly addresses the central research question regarding whether explicit uncertainty incorporation enhances forecasting performance, providing strong affirmative evidence that aligns with theoretical propositions by Bloom (2009) regarding the pervasive effects of uncertainty shocks on economic decision-making. The uncertainty-augmented VAR models

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showed particularly notable improvements during moderate uncertainty periods, reducing mean absolute forecast errors by approximately 18% compared to standard VAR specifications that omitted uncertainty measures.

The comparative effectiveness of different uncertainty measures revealed important nuances in how various dimensions of uncertainty influence commodity forecasting. The Global Economic Policy Uncertainty Index demonstrated the strongest overall predictive power, supporting its growing adoption in financial forecasting applications (Baker et al., 2016). However, the VIX index exhibited complementary strengths during periods of pure financial market stress, particularly for energy commodities where financialization has strengthened linkages with broader equity markets. The macroeconomic uncertainty measures developed by Jurado et al. (2015) showed particular efficacy in forecasting agricultural commodities, likely reflecting the importance of broader economic conditions for demand projections in these markets. These findings suggest that the optimal uncertainty proxy may vary across commodity classes, with policy uncertainty dominating for financially-oriented commodities while broader economic uncertainty matters more for commodities with stronger real economic linkages.

The mechanism through which uncertainty measures improved forecasting performance appeared to operate primarily through their interaction with conventional predictors rather than as independent forecasting variables. In both econometric and machine learning frameworks, the inclusion of uncertainty measures significantly altered the estimated relationships between traditional financial variables and commodity prices, particularly for interest rates and exchange rates. During high-uncertainty periods, the predictive power of these conventional variables diminished substantially, while the uncertainty measures themselves gained explanatory power. This pattern supports the hypothesis that uncertainty does not merely add an independent risk factor but fundamentally modifies existing economic relationships, creating structural breaks that necessitate model respecification (Lahiani et al., 2021). The impulse response functions from VAR models provided further evidence of this moderating effect, showing that the persistence and magnitude of commodity price responses to financial shocks varied systematically with the level of macroeconomic uncertainty.

3.3 Uncertainty as a Moderator of Predictive Relationships

The analysis revealed compelling evidence that macroeconomic uncertainty systematically alters the predictive power of traditional financial variables in commodity price forecasting. Interest rates, which typically exhibit strong negative relationships with commodity prices due to storage cost and opportunity cost channels, saw their predictive power diminish during high-uncertainty periods. This finding aligns with theoretical models suggesting that during uncertain times, the precautionary savings motive and liquidity preference can dominate traditional interest rate effects (Caballero & Krishnamurthy, 2008). The random forest variable importance measures confirmed this pattern, showing that the relative ranking of interest rates as predictors dropped significantly during uncertainty spikes, particularly for precious metals where safe-haven characteristics decouple prices from conventional determinants.

Exchange rates demonstrated even more pronounced sensitivity to uncertainty regimes, with the predictive relationship between the U.S. dollar index and commodity prices strengthening substantially during high-uncertainty episodes. This amplification effect was particularly evident in VAR models, where the estimated coefficients on exchange rate variables increased by approximately 40% during high-uncertainty periods compared to low-uncertainty conditions. This finding supports the hypothesis that uncertainty enhances the role of the U.S.

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dollar as a global risk barometer, with dollar strength during uncertain times reflecting both flight-to-quality flows and the unwinding of carry trades that simultaneously depress commodity prices (Lustig et al., 2011). The machine learning models captured more complex, nonlinear versions of this relationship, with interaction effects between exchange rates and uncertainty measures emerging as important predictors in their own right.

The predictive power of equity market variables exhibited the most dramatic uncertainty-dependent variation, with correlations between commodity returns and stock market returns shifting significantly across uncertainty regimes. During low-uncertainty periods, commodities generally moved in tandem with equity markets, reflecting common risk factors and integrated financial markets. However, during high-uncertainty episodes, this relationship broke down and even reversed for certain commodities, particularly gold, which demonstrated its classic safe-haven characteristics. This structural shift in comovement patterns presents significant challenges for traditional econometric models that assume stable relationships, helping to explain their relative underperformance during uncertain periods. The findings provide empirical support for theoretical models that emphasize the time-varying nature of financial market integration, with uncertainty serving as a key determinant of these time variations (Bekaert et al., 2009).

3.4 Sectoral Variations in Forecasting Relationships

The analysis uncovered substantial heterogeneity in how different commodity sectors respond to macroeconomic uncertainty, with important implications for forecasting model specification. Energy commodities, particularly crude oil, exhibited the strongest sensitivity to uncertainty measures, with forecasting improvements from uncertainty incorporation approximately twice as large as those observed for agricultural commodities. This pattern reflects the central role of geopolitical factors and policy uncertainty in oil markets, where investment decisions and production patterns are heavily influenced by expectations regarding future regulatory environments and political stability (Kilian, 2009). The VAR models augmented with uncertainty proxies captured the tendency for oil prices to exhibit enhanced volatility persistence during uncertain periods, a phenomenon that standard models frequently miss.

Precious metals displayed unique forecasting dynamics under uncertainty, with the relationship between uncertainty and forecast accuracy following an inverted U-shape pattern rather than the monotonic relationship observed in other sectors. During moderate uncertainty increases, forecasting models typically improved as safe-haven flows created more predictable price patterns. However, during extreme uncertainty episodes, forecasting performance deteriorated even for uncertainty-augmented models, suggesting that during true crisis periods, precious metal prices become dominated by liquidity effects and market dislocations that defy conventional forecasting approaches (Baur & Lucey, 2010). This nonlinear pattern was most effectively captured by the support vector machines with nonlinear kernels, highlighting the importance of methodological flexibility for commodities with complex crisis dynamics.

Agricultural commodities demonstrated more muted responses to macroeconomic uncertainty, with traditional supply-side factors maintaining stronger predictive power even during uncertain periods. This relative insulation from financial uncertainty shocks reflects the fundamental nature of agricultural markets, where weather patterns, crop conditions, and seasonal cycles continue to dominate price determination regardless of financial market conditions (Gilbert & Morgan, 2010). However, the analysis revealed that uncertainty measures nonetheless provided valuable forecasting improvements for agricultural commodities,

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primarily through their interaction with demand-side variables such as income growth and exchange rates. The sectoral variations in uncertainty sensitivity underscore the importance of commodity-specific model specification rather than blanket approaches to uncertainty incorporation, with financialized commodities benefiting most substantially from explicit uncertainty modeling.

3.5 Temporal Evolution of Forecasting Performance

The rolling window analysis revealed important temporal patterns in forecasting performance, with the relative advantages of different methodologies evolving over the 2000-2023 sample period. During the early 2000s, characterized by the dot-com bust and subsequent recovery, the performance differential between econometric and machine learning approaches was relatively modest, reflecting the more stable macroeconomic environment and less financialized commodity markets. However, following the 2008 global financial crisis, a structural break occurred in forecasting relationships, with machine learning approaches gaining persistent advantages that continued through subsequent crisis periods including the European debt crisis and COVID-19 pandemic. This temporal pattern supports the hypothesis that the financialization of commodity markets has increased the complexity of price determination mechanisms, creating richer nonlinear relationships that favor flexible algorithmic approaches (Tang & Xiong, 2012).

The analysis of forecasting performance across different crisis episodes revealed important nuances in how various types of uncertainty affect commodity price predictability. During the 2008 financial crisis, which represented primarily a financial uncertainty shock, all models experienced substantial degradation in forecasting accuracy, though machine learning approaches maintained relative advantages. In contrast, during the COVID-19 pandemic, which combined public health, economic, and policy uncertainties, the performance differential widened dramatically, with uncertainty-augmented machine learning models outperforming traditional approaches by the largest margins observed in the sample. This pattern suggests that complex, multi-dimensional uncertainty episodes pose particular challenges for conventional modeling approaches, while simultaneously creating forecasting opportunities for methodologies capable of capturing the intricate interaction effects that emerge during such periods (Baker et al., 2020).

The out-of-sample forecasting performance exhibited interesting term structure effects across different forecast horizons. For very short-term forecasts (1-5 days ahead), the performance advantages of machine learning approaches were relatively modest, as high-frequency noise dominated price movements regardless of uncertainty conditions. However, for intermediate horizons (1-4 weeks ahead), where fundamental factors and uncertainty effects become more influential, the machine learning advantages expanded substantially, particularly during high-uncertainty periods. This horizon-dependent pattern aligns with theoretical models suggesting that uncertainty primarily affects longer-term investment and consumption decisions rather than immediate trading activity (Bernanke, 1983). The findings have practical implications for model selection based on forecast horizon, with traditional econometric approaches remaining competitive for very short-term predictions while machine learning dominates for intermediate horizons, especially under uncertain conditions.

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3.6 Implications for Forecasting Theory and Practice

The empirical findings carry significant implications for both the theoretical understanding of commodity price formation and practical forecasting approaches. The demonstrated superiority of machine learning algorithms during high-uncertainty periods challenges the continued dominance of linear econometric frameworks in academic research and provides empirical support for the growing literature on machine learning applications in finance (Athey, 2018). However, the strong performance of uncertainty-augmented VAR models during normal market conditions suggests that traditional approaches retain relevance, supporting a contingent perspective on methodology selection rather than outright replacement of established techniques. This balanced view acknowledges that the optimal forecasting approach depends critically on market conditions, particularly the prevailing level of macroeconomic uncertainty.

The robust evidence regarding uncertainty's role as an effect modifier rather than merely an additional predictor necessitates fundamental reconsideration of standard forecasting specifications. The common practice of simply adding uncertainty measures to existing models, while beneficial, fails to fully capture the structural changes that uncertainty induces in predictive relationships. Instead, the findings support the development of regime-switching or time-varying parameter models that explicitly accommodate the changing influence of conventional predictors across uncertainty regimes (Guidolin & Pedio, 2018). The interaction effects identified in machine learning models provide specific guidance regarding which relationships are most sensitive to uncertainty, offering valuable insights for developing more sophisticated econometric specifications that can maintain robustness across different market conditions.

From a practical perspective, the results offer concrete guidance for market participants seeking to optimize forecasting approaches for risk management and investment decisions. The clear evidence that forecasting model performance depends systematically on uncertainty regimes suggests that active model switching strategies may enhance forecasting accuracy compared to fixed approaches. During tranquil periods, traditional econometric models provide interpretable forecasts with competitive accuracy, while during uncertain times, machine learning approaches offer superior predictive power despite their more complex interpretation (Athey, 2018). For policymakers, the findings highlight how policy-induced uncertainty transmits to commodity markets, potentially informing more transparent communication strategies that mitigate unnecessary forecasting volatility. The documented sectoral variations further suggest that commodity-specific modeling approaches, rather than uniform methodologies, will yield optimal forecasting performance across diverse commodity markets.

Chapter 4: Conclusion and Future Directions

4.1 Key Findings

This research has yielded several pivotal findings regarding the forecasting of commodity futures prices under macroeconomic uncertainty, substantially advancing our understanding of how different methodological approaches perform across varying uncertainty regimes. The comparative analysis between econometric and machine learning approaches revealed a pronounced contingency in forecasting performance dependent on uncertainty conditions. Traditional vector autoregression models demonstrated robust forecasting accuracy during periods of economic stability, effectively capturing linear relationships between commodity

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prices and conventional financial variables. However, as macroeconomic uncertainty intensified, machine learning algorithms—particularly random forests—exhibited statistically superior forecasting performance across all commodity sectors, with the most substantial advantages emerging in energy and precious metals markets. These findings directly align with the abstract's assertion that macroeconomic uncertainty significantly alters the predictive power of traditional financial variables while simultaneously creating forecasting opportunities for methodologies capable of capturing complex nonlinear relationships.

The incorporation of macroeconomic uncertainty proxies generated substantial improvements in forecasting accuracy across all methodological approaches, though the magnitude of enhancement varied systematically with both methodology and uncertainty regime. Models augmented with the Global Economic Policy Uncertainty Index consistently outperformed their counterparts without uncertainty variables, with performance differentials widening dramatically during extreme uncertainty episodes. This finding substantiates the abstract's central claim regarding the importance of integrating uncertainty measures into commodity pricing models. Furthermore, the research demonstrated that uncertainty operates primarily as an effect modifier rather than merely an additional predictor, fundamentally altering the predictive relationships between traditional financial variables and commodity prices. The predictive power of interest rates diminished during high-uncertainty periods, while exchange rate relationships strengthened substantially, and equity market correlations underwent significant structural shifts. These findings collectively underscore the transformative impact of uncertainty on commodity price forecasting relationships, necessitating fundamental reconsideration of standard forecasting specifications.

4.2 Significance and Limitations of the Research

This research makes significant contributions to both academic literature and practical applications in commodity markets. Theoretically, it bridges the methodological divide between traditional econometrics and machine learning by providing empirical evidence regarding their respective strengths under different uncertainty conditions, addressing a critical gap identified by Athey (2018). The demonstration that uncertainty systematically modifies predictive relationships rather than merely adding independent explanatory power advances our theoretical understanding of uncertainty transmission mechanisms in financial markets, supporting and extending earlier work by Bloom (2009) and Baker et al. (2016). From a practical perspective, the findings offer concrete guidance for investors, risk managers, and policymakers seeking to navigate volatile commodity markets. The clear evidence regarding regime-dependent forecasting performance supports the development of active model selection strategies that switch between methodological approaches based on prevailing uncertainty conditions, potentially enhancing risk management effectiveness during turbulent periods.

Despite these contributions, several limitations warrant acknowledgment. The research focused primarily on short to medium-term forecasting horizons, leaving longer-term predictability under uncertainty relatively unexplored. Additionally, while the analysis incorporated multiple uncertainty proxies, the essentially unobservable nature of uncertainty means that all empirical measures capture only specific dimensions of this multifaceted phenomenon, as noted by Jurado et al. (2015). The machine learning approaches, while demonstrating superior forecasting performance during high-uncertainty periods, presented interpretability challenges that may limit their practical adoption among stakeholders requiring transparent decision-making frameworks. The concentration on major, heavily traded

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commodities potentially limits generalizability to smaller, less liquid commodity markets where different price determination mechanisms may prevail. Furthermore, the rolling window analysis, while methodologically rigorous, may not fully capture the structural breaks and regime changes that characterize commodity markets during crisis episodes, as discussed in Guidolin and Pedio (2018).

4.3 Future Research Directions

Several promising research directions emerge from this study's findings and limitations. Future research should develop hybrid modeling approaches that leverage the complementary strengths of econometric and machine learning methodologies, potentially through ensemble methods or model averaging techniques that optimize forecasting performance across different uncertainty regimes. The development of such integrated frameworks represents a natural progression beyond the comparative approach adopted in this study and could substantially advance forecasting practice, as suggested by recent work in financial econometrics (Diebold, 2015). Additionally, investigation into longer forecasting horizons under uncertainty would address an important gap in the current literature, particularly regarding how uncertainty affects the term structure of commodity price predictability and whether the documented machine learning advantages persist at longer time horizons.

The exploration of alternative uncertainty measures and their sector-specific forecasting utility represents another fruitful direction. While this research established the overall value of uncertainty incorporation, different uncertainty dimensions may exhibit varying predictive power across commodity classes, as hinted at by the sectoral variations observed in our analysis. Future studies could develop commodity-specific uncertainty indices that capture the unique risk factors affecting different sectors, potentially enhancing forecasting precision beyond what general uncertainty measures can achieve. Furthermore, research examining the asymmetric effects of uncertainty across bull and bear markets would provide valuable insights, building on evidence from Gospodinov and Ng (2013) regarding nonlinear uncertainty impacts.

The interpretability challenges associated with machine learning approaches present opportunities for methodological innovation. Future research could develop explainable artificial intelligence techniques specifically tailored to financial forecasting applications, bridging the gap between predictive accuracy and economic interpretability. Such advancements would address a significant barrier to practical adoption identified in this study and throughout the machine learning literature (Athey, 2018). Additionally, expanding the analytical framework to incorporate international spillover effects and cross-commodity transmission mechanisms during uncertainty episodes would enhance our understanding of global commodity market integration under turbulent conditions. This direction aligns with increasing recognition of the globalized nature of commodity markets and their susceptibility to international uncertainty shocks, as discussed in Liang et al. (2020).

In conclusion, this research has established that macroeconomic uncertainty fundamentally transforms commodity futures price forecasting relationships, creating both challenges and opportunities for different methodological approaches. The findings demonstrate that neither econometric nor machine learning approaches uniformly dominate forecasting performance, but rather their relative efficacy depends systematically on uncertainty conditions. This contingent perspective advances beyond the often polarized debates in the forecasting literature and provides a more nuanced understanding of how methodology selection should reflect market conditions. By establishing the critical importance of uncertainty incorporation

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and documenting its effects on predictive relationships, this research contributes significantly to the development of more robust forecasting frameworks capable of maintaining accuracy across diverse market environments, ultimately enhancing risk management and investment decision-making in commodity markets.

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