Drilling Deeper: Non-Linear, Non-Parametric Natural Gas Price and Volatility Forecasting

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An accurate forecasting model for natural gas pricing and forecasting is essential not only for the quantitative community in commodities trading firms, but also for gas production, storage, and distribution. Economic planning, investments in the energy sector under uncertainty, and environmental protection represent additional activities that may require reliable forecasts of gas prices and volatility. Considering the increased construction rate of gas-fired power plants over the past 10 years, such a model could assist government policy-makers in their planning efforts for electric power production and market design.

To forecast day-ahead natural gas returns and volatility, this paper employs non-linear, machine learning model architectures that allow for rather complex relationships between predictors and the dependent variable (returns and volatility) and, also, facilitate adaptive learning. We consider two major natural gas markets (Henry Hub – U.S. and Title Transfer Facility Hub – E.U.) and a diverse group of predictors that include heating oil, crude oil, fuel oil, diesel, electricity, European emission allowances, natural gas storage levels, temperature, and seasonal effects. Our data cover two sample periods: 1) sample that represents relatively stable market regime (2015-2020), and 2) sample that contains the episodes of excess volatility market regime (2020-2022). To explain the elusive non-linear relationships inherent in gas price and volatility forecasting, the explainable artificial intelligence (XAI) method is used.

The results of our empirical forecasting exercises show that the linear model and its variants (ridge, lasso, and elastic net) are inaccurate and perform no better than a random walk. In sharp contrast, our robust XAI analysis pins down the most important non-linear predictors of the Henry Hub spot price movements over the 2015-2020 period, namely crude oil price, electricity price, and temperature. Even though the findings emphasize the time-varying complexity of relationships, the model reveals that crude oil and electricity act as important drivers for natural gas. We provide compelling evidence that the oil-indexed formula likely suffers from an omitted variable bias and is an imperfect approximation of natural gas price dynamics.

We also find that the electricity price emerges as the most dominant predictor in both the E.U. and the U.S. markets, while the crude oil price seems to have lost its predictive power over the recent years. In addition, non-linear effects of the European emission allowances appear to be important for predicting the Title Transfer Facility Hub gas fluctuations.

We further examine the predictive performance of the models during periods of high uncertainty (i.e., 2020-2022), and explore in particular the impact of the COVID-19 pandemic and the Russia-Ukraine crisis. In these periods when sharp structural changes and extreme volatility occur

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in the markets, deep learning models provide better adaptability and lead to statistically significantly dominant forecast performance for both gas returns and volatility.

Our analysis sheds light on whether the machine learning methods for natural gas forecasting may represent a viable approach to practitioners, considering their high implementation cost. We highlight the potential advantages of using AI-based methods for accommodating the extreme dynamics of energy markets. More importantly, we point to the need to empirically explore the non-linear interplay between carbon price, natural gas price, oil price, electricity price and stock prices. Such an undertaking might deliver valuable lessons about the effectiveness of particular carbon policies.