Fixed vs. Dynamic Price Cap and Commodity Market Dynamics: the Case of EU-Russia Gas Market

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Abstract

We study the price cap impact on the commodity market dynamics by exploring price and volatility transmission effects. Focusing on the recent EU-Russia gas market turmoil, we run Filtered Historical Simulations and conditional Extreme Value Theory in a multivariate setting, then controlling for market co-movements. By comparing no-price intervention vs. Fixed- and Dynamic Price Cap scenarios, we show that (i) Fixed Price Cap leads to a rapid and consistent dis-inflationary effect on nearly all the commodities, albeit at the cost of high market volatility; (ii) Dynamic Price Cap while having a modest and gradual price impact on a limited subset of commodities, it results in lower overall market volatility. Our findings are particularly important as they suggest the use of Fixed Price Cap as an extraordinary policy measure, while the Dynamic Price Cap offers a more sustainable, long-term framework for reducing inefficiencies in the energy market.

1 Introduction

The price cap mechanism has come under the spotlight in the recent EU-Russia gas market turmoil reigniting the debate on the best price mitigation measure, while maintaining high domestic welfare. Much of the literature to date is concerned with industrial organization economics, specifically on how to reduce the monopolist's market power and increase domestic welfare when foreign monopolists operate within domestic markets.

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Just focusing on the EU-Russia gas market, Ehrhart et al. (2023) prove that price caps Pareto-dominates the tariff, yielding higher domestic welfare and higher foreign monopoly profits. This is in line with other studies confirming the price cap as the best policy measure compared to tariffs or subsidies (e.g., De Meza (1979); Tower (1983); Kowalczyk, 1994). Other studies explored the effectiveness of the price caps by comparing the equilibrium points before and after the caps (e.g., Vossler et al. (2009); Reynolds and Rietzke (2018)). Still others explored conditional dependence between stock markets, commodity futures and prices in a univariate, multivariate, Value-at-Risk and portfolio optimization contexts using ARMA, GARCH, Extreme Value Theory, and copulae (e.g., Hussain and Li (2018), Marimoutou et al. (2009), Ohashi and Okimoto (2016), and Ghorbel and Trabelsi (2014)).

Focusing on the recent EU-Russia gas market turmoil, we complement this literature by exploring the price and volatility transmission effects induced by the Fixed and Dynamic price cap mechanisms.

Efficiently modeling commodity dynamics is particularly challenging due to the complex interplay between product trading and supply-demand imbalances resulting from economic conditions (Giot and Laurent (2003)). Moreover, the commodity market has been increasingly characterized by a financialization process (Cheng and Xiong, 2014), through which commodity derivatives and replicating financial securities became popular assets within investment portfolios, with scant or no positions on the underlying physical assets. As a result, commodity price dynamics have been extremely sensitive to financial market dynamics, business cycles, political and climate risk factors, thereby exhibiting large price fluctuations. The 2007-2008 Financial Crisis, when the Producer Price Index of All Commodities exhibited a year-on-year increase of 17.36% on July 2008, followed by a drop of 16.05% in July 2009 [1], as well as the recent COVID-19 pandemic and the Russian-Ukrainian conflict, highlight the fundamental importance to better inspect how commodity prices move and comove over time, especially during extreme, systemic events, and which are the most efficient price mitigation measures that policymakers could implement.

In this study we explore the impacts of Fixed vs. Dynamic price cap mechanisms in the

[1] U.S. Bureau of Labor Statistics, Producer Price Index by Commodity: All Commodities [PPIACO], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PPIACO, November 10, 2022)

European natural gas spot price on the other commodity prices and volatilities. Over the period from January 2013 to October 2022, and using a 250-day forecasting time window from November 2022 to August 2023, we analyze the interconnections between natural gas and other commodities, also assessing the mitigation effects on price and volatility over the short-term.

We employ a univariate time-series approach to model the conditional mean and volatility of commodity returns, next using multivariate Filtered Historical Simulations (FHS) and conditional Extreme Value Theory (EVT) with copulae to model the conditional dependence structure between natural gas prices and other commodities. In doing this, we capture inter-dependencies and forecast joint conditional distributions of commodity returns, in particular when extreme events materialize, thereby obtaining probabilistic relationships between prices and volatilities without making explicit assumptions on the underlying causal mechanisms.

We compare Fixed- with Dynamic-Price Cap Scenarios, both imposed on the Dutch TTF gas price, and contrast with the no-price intervention baseline. The Fixed Price Cap Scenario assumes a fixed price as the upper limit of TTF for the entire forecasting window, while the Dynamic Price Cap Scenario imposes a limit on the volatility of the gas price rather than the price level itself.

To assess how the Natural Gas Dutch TTF spot price dynamics, under Fixed or Dynamic Price Cap mechanisms, affects the prices and volatilities of other commodities, we run numerical simulations under the three scenarios based on the conditional dependence structure estimated via FHS and EVT.

Our findings reveal that Fixed Price Cap leads to a rapid and consistent dis-inflationary effect on nearly all the commodities, albeit at the cost of high market volatility. On the other hand, Dynamic Price Cap while having a modest and gradual price impact on a limited subset of commodities, reflects on lower overall market volatility. These results have important policy messages, as they suggest that Fixed Price Cap mechanism could be planned as a extraordinary policy measure, to take in extreme crisis scenarios, while the Dynamic Price Cap, having a long-term impact on volatility, could be used within a long-run strategy to make more sustainable the energy market and to contain its inefficiencies.

This paper is organized as follows: Section 2 we introduce the Institutional Background. Section 3 describes the Gas Scenarios, while Section 4 introduces the Methodology. Data description is in Section 5, and Results are in Section 6. Finally, Section 7 presents the conclusions.

2 Institutional Background

The Title Transfer Facility (TTF) is a virtual platform for natural gas in the Netherlands, which serves as the main benchmark to define the price of gas. The TTF has gained global attention after Russia cut gas deliveries to Europe following its invasion of Ukraine leading gas prices to hit record levels. According to the European Commission, the TTF was ... *no longer an adequate reflection of market realities as it is unduly influenced by pipeline infrastructure bottlenecks in North-Western Europe and therefore Russian manipulation of natural gas supplies to the EU*[2]. The European Commission, recognizing the need for intervention, then began to evaluate possible price cap mechanisms in the form of Fixed vs. Dynamic Price Cap, with the end to mitigate and prevent potential distortions to energy markets.

After several discussions about taming gas prices, EU countries agreed in December 2022 to trigger a price cap on TTF gas hub's front-month contract when prices exceed 180 euros (191.11 USD) per megawatt hour for three days. Moreover, the TTF price must be 35 eur/mwh higher than a reference price based on existing liquefied natural gas (LNG) price assessments for three days. Once the mechanism is activated, gas transactions above the "dynamic bidding limit" will not be allowed to take place. Such a limit is defined as the reference price calculated on the basis of global LNG price indices, plus a maximum of 35 euro/mwh. However, the agreement provides that if the reference price of LNG is below 145 euros, the dynamic bidding limit will remain at the sum of 145 euros and 35 euros (to reach the threshold of 180) [3]. The cap mechanism entered in force on 15 February 2023 and has been applied to TTF derivatives, which account for more than 90 percent of natural gas derivatives traded on regulated markets in the EU. At the time we

[2]European Commission, Questions and Answers on proposals to fight high energy prices and ensure security of supply, https://ec.europa.eu/commission/presscorner/detail/en/qanda_22_6226, 18 October 2022, Strasbourg.

[3]Once activated, the dynamic bidding limit will apply for at least 20 working days. If the dynamic bidding limit is below 180€/mwh for last three consecutive working days, it will be automatically deactivated

are writing this paper, the cap mechanism is designed to be temporary, applying until January 2024.

3 Gas Price Scenarios

To explore price and volatility transmission effects induced by different policy interventions, we consider three scenarios depending on the cap mechanism we impose on the TTF gas price path: (i) the Baseline Scenario, (ii) the Fixed Price Cap Scenario, and (iii) the Dynamic Price Cap Scenario.

To formalize our methodological approach we first introduce our econometric framework, then presenting the model we use to inspect price and volatility impacts in a multivariate setting.

3.1 Econometric Framewok

We consider N commodities and assume that their prices are observed in T consecutive (daily) realizations. For each $i = 1, \dots, N$ and $t = 1, \dots, T$, we denote with P_t^i the price of commodity i at time t. We define the logarithmic return of commodity i at time t as $r_t^i = \ln\left(P_t^i / P_{t-1}^i\right)$ and its conditional volatility as σ_t^i. Let $\{z_t^i\}_{t=1,\dots,T}^{i=1,\dots,N}$ be an iid sequence of standardized innovations for commodity price i with $\mathbb{E}\left[z_t^i\right] = 0$ and $\mathbb{V}\left[z_t^i\right] = 1$.

To investigate the dynamics of commodities returns, we consider three conditional models[4]:

1. the ARMA(1,1)-GARCH(1,1) (Bollerslev (1986)), which combines an autoregressive moving average (ARMA) process for the mean with a generalized autoregressive conditional heteroskedasticity (GARCH) process for the variance:

$$\begin{aligned} r_t &= \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \\ \varepsilon_t &= \sigma_t z_t, \\ \sigma_t^2 &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2. \end{aligned} \tag{1}$$

   As known, the ARMA(1,1) process has three parameters: ϕ_0 represents the constant mean of the return series, while ϕ_1 and θ_1 represent the autoregressive and moving

[4] To simplify the notation we consider a generic commodity i, and then we suppress the superscript from the general notation (e.g., we write r_t instead of r_t^i).

average coefficients, respectively. The condition $|\phi_1| < 1$ must hold for stationarity. The GARCH(1,1) process has three parameters: $\omega > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$, which represent the constant, the weight of past squared innovations (ARCH component coefficient), and the weight of past conditional variances (GARCH component coefficient), respectively. To preserve stationarity, we need to impose the condition $\alpha_1 + \beta_1 < 1$.

2. The ARMA(1,1)-EGARCH(1,1) (Nelson (1991)), which combines an ARMA process for the mean with an exponential form for the variance equation to ensure non-negative values. The model allows for asymmetric volatility responses to positive and negative shocks by introducing a logarithmic transformation of the variance process and an additional parameter capturing the impact of negative shocks:

$$\begin{aligned} r_t &= \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, \\ \varepsilon_t &= \sigma_t z_t, \\ \ln(\sigma_t^2) &= \omega + \alpha_1 \left[|z_{t-1}| - \mathbb{E}\left[|z_{t-1}|\right]\right] + \beta_1 \ln(\sigma_{t-1}^2) + \xi_1 z_{t-1}. \end{aligned} \tag{2}$$

This model has the same autoregressive and moving average parameters together with the same constraints as the ARMA(1,1)-GARCH(1,1) model. The EGARCH(1,1) process has four parameters: ω, α_1, β_1, and ξ_1, which represent the constant, the weight of past squared standardized innovations (ARCH component coefficient), the weight of past conditional variances (GARCH component coefficient) on the logarithmic scale, and the impact of past negative shocks (leverage component coefficient), respectively.

3. The ARMA(1,1)-GJR(1,1) (Glosten et al. (1993)), which is an extension of the GARCH model that allows for an asymmetric response of the variance to positive and negative shocks. It introduces an additional parameter capturing the impact of negative shocks on the conditional variance:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t, notag \tag{3}$$

$$\varepsilon_t = \sigma_t z_t, \tag{4}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, + \gamma_1 \mathbb{I}_{\{\varepsilon_{t-1} < 0\}} \varepsilon_{t-1}^2.$$

As for the ARMA(1,1)-GARCH(1,1), this model has the same contraints as well as the same autoregressive and moving average parameters. The GJR(1,1) process has four parameters: $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\gamma_1 \in \mathbb{R}$, which represent the constant, the weight of past squared innovations (ARCH component coefficient), the weight of past conditional variances (GARCH component coefficient), and the weight of past squared, negative innovations (leverage component coefficient), respectively. The condition $\alpha_1 + \gamma_1 \geq 0$ and $\alpha_1 + \beta_1 + \gamma_1 < 1$ ensures the model to be stationary.

3.2 Scenarios

The conditional models for commodities returns are used to inspect the price and volatility dynamics in the three scenarios over a pre-specified forecasting time window. We consider a forecasting time window of length H, and define P_h^i be the predicted daily price of commodity $i = 1, \ldots, N$ at time $h = T+1, \ldots, T+H$; denoting by σ_h^i the predicted daily conditional volatility of commodity i at time h, each scenario is formalized as described below.

3.2.1 Baseline Scenario

The Baseline Scenario serves as a benchmark for comparison with the other two scenarios. Here, no authority intervention or constraints are imposed on the predicted gas price. As a result, gas price vary over time without restrictions, while maintaining in non-negative territory[5]:

$$BS = \{P_h^{TTF} | P_h^{TTF} \in [0, +\infty]\}_{h=T+1,\ldots,T+H}. \tag{5}$$

In the Baseline Scenario BS, the univariate expected value and corresponding conditional volatility of the returns for commodity i at time T are:

$$\begin{cases} \mathbb{E}_T\left[P_h^i | BS\right] = \mathbb{E}_T\left[P_h^i\right], \\ \mathbb{E}_T\left[\sigma_h^i | BS\right] = \mathbb{E}_T\left[\sigma_h^i\right]. \end{cases} \tag{6}$$

3.2.2 Fixed Price Cap Scenario

The Fixed Price Cap introduces an upper limit, denoted as $\bar{P}^{TTF}$, on the daily TTF gas price. This constraint ensures that the TTF gas price remains within the specified range throughout the forecasting time horizon:

$$FS = \{P_h^{TTF} | P_h^{TTF} \in \left[0, \bar{P}^{TTF}\right]\}_{h=T+1,\ldots,T+H}. \tag{7}$$

[5] In our study we do not consider negative commodity prices, being out of our scope.

The Fixed Price Cap serves as a mechanism to control and limit the upward movement of the gas price. The upper bound on (predicted) TTF price, then preventing potential excessive price spikes, is the first policy intervention option we consider. Being the benchmark to define the price of gas, the TTF price plays a pivotal role also for other commodities. Therefore, the constraint may impact the price of other commodities:

$$\{P_h^i|FS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N \tag{8}$$

and conditional volatilities:

$$\{\sigma_h^i|FS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N. \tag{9}$$

3.2.3 Dynamic Price Cap Scenario

The Dynamic Price Cap aims to limit the volatility of the TTF gas price. In this scenario, we propose restricting the conditional volatility of TTF. Based on historical estimates, we define a stability criteria for its conditional volatility forecasts, based on the median, average, and maximum historical conditional volatility. The following rules on the predicted conditional volatility apply for the Dynamic Price Cap:

1. the median forecasted TTF conditional volatility must not exceed the median historical conditional volatility;

2. the average forecasted TTF conditional volatility must not exceed the mean historical conditional volatility;

3. the TTF volatility at any point in the forecasting time window must not exceed the maximum historical conditional volatility.

Finally, the predicted TTF price should not exceed the maximum historical price at any point in the forecasting time window.

Let $q_{0.50}(\hat{\sigma}_t^{TTF})$, $\overline{\hat{\sigma}}_t^{TTF}$, $\max_{t \in T} \hat{\sigma}_t^{TTF}$, be the median, the average and the maximum value of historical conditional volatility, respectively, and let $\max_{t \in T} P_t^{TTF}$ be the maximum price of TTF gas. The Dynamic Price Cap Scenario can be defined as:

$$DS = \left\{ (P_h^{TTF}, \sigma_h^{TTF}) \middle| \begin{array}{c} q_{0.50}(\sigma_h^{TTF}) \leq q_{0.50}(\hat{\sigma}_t^{TTF}) \\ \overline{\sigma}_h^{TTF} \leq \overline{\hat{\sigma}}_t^{TTF} \\ \max_{h \in H} \sigma_h^{TTF} \leq \max_{t \in T} \hat{\sigma}_t^{TTF} \\ \{P_h^{TTF}\}_{h \in H} \in \left[0, \max_{t \in T} P_t^{TTF}\right) \end{array} \right\} \quad \forall h = T+1, \ldots, T+H. \quad (10)$$

In a sense, the term "Dynamic Price Cap" is not self-explanatory, since the cap mechanism acts through the volatility rather than the price directly. Formally, the dynamics of commodity prices under this price rule are:

$$\{P_h^i | DS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N \quad (11)$$

and conditional volatilities:

$$\{\sigma_h^i | DS\} \qquad \forall h = T+1, \ldots, T+H \text{ and } i = 1, \ldots, N. \quad (12)$$

3.2.4 Comparative Analysis

Having specified the processes for price and volatilities with (Fixed and Dynamic Price Caps) and without (Baseline) the price cap mechanisms, we next examine the effects of the different price dynamics on other commodity prices and volatilities under the three scenarios. Formally:

$$\begin{cases} \mathbb{E}_T \left[P_h^i | BS\right] \gtreqless \mathbb{E}_T \left[P_h^i | FS\right] \gtreqless \mathbb{E}_T \left[P_h^i | DS\right] \\ \mathbb{E}_T \left[\sigma_h^i | BS\right] \gtreqless \mathbb{E}_T \left[\sigma_h^i | FS\right] \gtreqless \mathbb{E}_T \left[\sigma_h^i | DS\right] \end{cases}. \quad (13)$$

By contrasting the two cap rules with the Baseline Scenario, we offer a 'what if analysis' for commodity markets under different policy intervention options. Moreover, since we focus on price and volatility impacts and transmissions, our study offer also important insights for market practitioners in terms of possible investment and hedging decisions, conditional on price cap mechanism.

4 Methodology

4.1 Model Estimation

We first estimate the conditional models parameters, as described in Section 3.1. The parameters in the mean return equation, the equation for the conditional standard deviation, and the probability distribution for return innovations are jointly estimated through Maximum Likelihood. To account for the heavier tails often observed in commodity price data, we employ the Student-t to model innovation distribution. Specifically, we assume that standardized residuals $\{z_t^i\}_{t=1,\dots,T}^{i=1,\dots,N}$ are iid following a Student-t distribution with ν degrees of freedom. We preliminary checked the iid assumption by running standard diagnostic tests, specifically examining the standardized residuals and their squared values for each time series and model.

4.2 Scenario Simulations

Having calibrated the parameters of the conditional models, we then generate joint forecasts for each commodity in the sample. We employ two simulation techniques, namely the multivariate Filtered Historical Simulations (FHS) and the conditional Extreme Value Theory (EVT) with copula models[6]. The FHS and EVT methods allow us to generate $B = 5000$ joint forecasts (scenarios) over a forecasting horizon of $H = 250$ days. These simulation methods incorporate observed market co-movements and estimated dependence structure among commodity prices. In this way, we realize our Baseline Scenario, which consists of the univariate forecasts for each commodity price and conditional volatility.

To provide predictions for TTF price and volatility, we define the Fixed and Dynamic Price Cap scenarios as subsets of realizations of the Baseline Scenario:

$$FS = \{b = 1, \dots, B | P_{hb}^{TTF} \in \big[0, \bar{P}^{TTF}\big]\}, \tag{14}$$

and

$$DS = \left\{ b = 1, \dots, B | \begin{array}{c} q_{0.50}(\sigma_{hb}^{TTF}) \leq q_{0.50}(\hat{\sigma}_t^{TTF}) \\ \overline{\sigma}_{hb}^{TTF} \leq \overline{\hat{\sigma}}_t^{TTF} \\ \max\limits_{h \in H} \sigma_{hb}^{TTF} \leq \max\limits_{t \in T} \hat{\sigma}_t^{TTF} \\ \{P_{hb}^{TTF}\}_{h \in H}^{b \in B} \in \left[0, \max\limits_{t \in T} P_t^{TTF}\right) \end{array} \right\} \tag{15}$$

where P_{hb}^{TTF} is the predicted daily price of gas at time h in simulation scenario b. Similarly, σ_{hb}^{TTF} is the predicted daily conditional volatility of gas at time h in simulation scenario b.

[6] Detailed explanations of the Filtered Historical Simulations and conditional Extreme Value Theory with copula models are in the Appendix.

While EU countries agreed in December 2022 to trigger a price cap on TTF gas at 180 euros (191.11 USD)/mwh, we used $\bar{P}^{TTF} = 114.79$ as the upper bound for the Fixed Price Cap scenario. Indeed, before the decision, rumors have placed the Fixed Price Cap between 105 USD/mwh and 115 USD/mwh, and market price decreased to 114.79 USD/mwh on 4 November 2022[7]. In this way we explore the effects of a price cap more restrictive and in line with the market expectations, which is line with our forecasting exercise.

For the Dynamic Price Cap, we consider the years 2013–2019 as a reference TTF's stable volatility period, which excludes financial instability from the pandemic and the Russian-Ukrainian conflict. As for the maximum historical price of the TTF gas, the reference value corresponds to 339.20 USD/mwh recorded on August 26, 2022, encompassing the entire time series.

For each cap mechanism, we exclude joint multivariate simulation scenarios from the set B if the predicted TTF price or volatility in any of those scenarios does not comply with the selected cap. In other terms, if the gas price in a specific simulation scenario b^* does not meet, for e.g., the requirements for the Fixed Price Cap rule, we exclude all the realizations of that particular scenario b^* for all commodities in the sample. This ensures that the analysis includes only those simulation scenarios closed to the selected cap for all commodities.

5 Data

The data used in this study comprises the following:

- Dutch TTF Gas Monthly Near-Term (NDEX USD/mwh) daily spot price obtained from Intercontinental Exchange (ICE) and ICE Endex. The term "Monthly" refers to the delivery period[8], which runs from 06:00 (CET) on the first day of the month until 06:00 (CET) on the first day of the next month.

[7]It should be noticed that TTF and other commodities are USD-denominated , while the actual TTF and European Gas Futures are EUR-denominated. Changes in the EUR/USD exchange rate are neglected and are not within the scope of our work.

[8]The time series is daily, the term term "Monthly" derives from the fact that: *Intercontinental Exchange (ICE) EUR/mwh Contracts are for physical delivery through the transfer of rights in respect of Natural Gas at the TTF Virtual Trading Point, operated by Gasunie Transport Services (GTS), the transmission system operator in the Netherlands. Delivery is made equally each hour throughout the delivery*

- S&P GSCI single-commodity spot indices[9] for the following commodities: *Energy*, *Petroleum*, *Grains*, *Gasoil*, *Aluminum*, *Nickel*, *Zinc*, *Brent Crude* oil and *Precious Metals*[10].

The data come from FactSet over the period from 07/10/2013 to 04/11/2022 for a total of $T = 2288$ observations per variable. We select commodities that were more sensitive to the Russian-Ukrainian conflict, according to the reports realized by the World Bank (Word Bank Special Focus, *Pandemic, war, recession: Drivers of aluminum and copper prices*, Word Bank (2022b)[11] and Word Bank Special Focus, *The Impact of the War in Ukraine on Commodity Markets*, Word Bank (2022a)[12]).

Figure 4 (left panel) presents the normalized price paths to unity for each commodity. Notably, the TTF Gas spot index experienced a substantial surge in both price and volatility, beginning in the last quarter of 2021. Figure 4 (right panel) provides a detailed analysis of the returns over time, revealing the presence of volatility clustering in commodity returns, particularly during the periods surrounding the pandemic and the Russian-Ukrainian conflict.

5.1 Summary Statistics

Table 1 presents the annualized summary statistics for commodity returns. In the first sub-period (2013-2016), all commodities, except for *Zinc*, experienced on average negative returns. Among them, *TTFGas* exhibited the lowest overall minimum and the highest overall maximum returns, indicating a potentially fat-tailed distribution. *TTFGas*, *Energy*, and *Petroleum* were the most volatile commodities. Except for *Nickel*, all commodities displayed right-skewed returns, with *TTFGas* having the highest positive

period from 06:00 (CET) on the first day of the month until 06:00 (CET) on the first day of the next month., ICE Endex, Dutch TTF Gas Futures, https://www.theice.com/products/27996665/Dutch-TTF-Gas-Futures, 11 November 2022.

[9] S&P Dow Jones Indices, https://www.spglobal.com/spdji/en/index-family/commodities/, 11 November 2022.

[10] For more details about the indices methodology see:
https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-gsci.pdf.

[11] Word Bank, Commodity Markets, https://www.worldbank.org/en/research/commodity-markets, 11 November 2022

[12] Word Bank, Commodity Markets, https://www.worldbank.org/en/research/commodity-markets, 11 November 2022

skewness. This suggests that the distribution of returns for *TTFGas* and other commodities had longer right tails with more extreme positive outliers. Furthermore, all commodities exhibited elevated positive excess kurtosis, with *TTFGas* having the highest value (9.6146).

In the second sub-period (2017-2019), all commodities, except for *TTFGas* and *Zinc*, exhibited positive average daily returns. Similar to the first sub-period, *TTFGas* displayed the lowest overall minimum and the highest overall maximum returns, then indicating a persistent fat-tailed distribution. The volatility of the *TTFGas* is approximately double the volatility of other commodities. The skewness of *TTFGas* was notably larger than in the first sub-period, which is significantly greater than that of other commodities (24.4606), confirming its right-skewed leptokurtic distribution. The high excess kurtosis of *TTFGas* confirms this finding.

In the third sub-period (2020-2022), the commodity market faced the impact of both the pandemic and the Russian-Ukrainian conflict. These events had contrasting effects on commodity prices: the pandemic caused a demand shock, while the conflict led to a supply shock. Energy-related commodities, in particular, witnessed an unprecedented drop in demand during the pandemic, with West Texas Intermediate crude oil prices reaching an all-time low of -37 USD/barrel. In contrast, energy-related commodities and *Nickel* recorded the highest maximum daily returns, which could be attributed to supply reductions caused by the Russian-Ukrainian conflict. Russia accounted for 15.2% of global production of *Nickel*, which is used in the production of lithium-ion batteries. The sub-period was characterized by high volatility for all commodities, with *TTFGas* displaying the highest daily volatility, nearly twice the value of other commodities. All commodities exhibited negative skewness, except for *TTFGas* and *Nickel*. The excess kurtosis of all commodities was higher compared to the previous sub-period, indicating a higher degree of fat-tailedness in their distribution due to an increase in the frequency and magnitude of tail events.

The analysis of TTF gas returns reveals a significantly non-normal distribution, characterized by positive skewness and high excess kurtosis. The behavior of *TTFGas* differs significantly from other commodities, suggesting potential market inefficiencies and low liquidity. The reason is because the natural gas market is characterized by a small number of price-setters and inelastic demand, particularly during colder months. European countries, which are largely dependent on natural gas imports, are price-takers and are thus susceptible to geopolitical risks and price discrimination. These factors highlight the importance of understanding the idiosyncrasies of the natural gas market and its potential impacts on the economy as a whole.

5.2 Correlation Analysis

To preliminary inspect dependencies among commodity returns over the entire time period we computed linear (Pearson) correlations and Kendall's Tau; results are in in Table 2.

Linear correlations denote weak dependency between *TTFGas* returns and *Gasoil* (20.18%), *Energy* (15.25%), *Petroleum* (14.41%), and *Brent Crude* (13.92%). On the other hand, textitTTFGas returns appear strongly correlated with energy-related commodities (over 90%).

Energy-related commodities are known to be highly interdependent, resulting in strong positive correlations among them. However, the correlation between the regional *TTFGas* and global energy-related commodities may not be particularly high. This is likely due to the global nature of the S&P GSCI indices compared to the regional impact of *TTFGas* on global price movements.

Kendall's Tau, which measures the discrepancy between the number of concordant and discordant pairs, was also used to calculate the dependencies between *TTFGas* and other commodities. The results show that *TTFGas* returns are weakly correlated with energy commodities, with lower coefficients than those obtained with the Pearson correlation coefficient. The index is 13.84% for *Gasoil*, 11.06% for *Energy*, 10.34% for *Petroleum*, and 9.84% for *Brent Crude*. Lastly, the Spearman rank correlation coefficient, which is a rank-based version of the Pearson coefficient, was used to calculate the correlations between *TTFGas* and other energy commodities. Again, the results show that *TTFGas* is weakly correlated with the other energy commodities: *Gasoil* (20.09%), *Energy* (16.22%), *Petroleum* (15.14%), and *Brent Crude* (14.43%).

Figure 5 depicts the 250 days-rolling Pearson correlations between *TTFGas* returns and other commodities returns. From 2014 to 2016, the correlations between European natural gas and other commodities are within ±20%. The non-energy-related correlations with European natural gas appear to be stable and rarely exceeding the ±10% boundaries from 2014 to the end of 2019. The dynamics of correlations between energy-related commodities are more volatile over time and changes tend to occur in the same direction. In 2020, the dynamics shrink, suggesting that the pandemic crisis reduced commodities correlations with *TTFGas*, except for *Petroleum*. However, at the beginning of 2022, all the dynamics peaked in the same direction and remained positive, albeit not at the highest level, from that point until the end of the period.

6 Results

6.1 Model Estimates

The following sections present estimates for the conditional models, the GPD paremeters fitted on the standardized resituals and estimates for the copulae dependence structure.

6.1.1 ARMA-GARCH Type Models

In Table 3 we report ARMA-GARCH-type models estimation. Results from conditional mean estimates are as follows:

- intercepts for *TTFGas* and other commodities are not statisically significant, except for ARMA(1,1)-GARCH(1,1) for *Energy* and *Petroleum*;
- for the ARMA(1,1)-GARCH(1,1) models, the *AR* and *MA* coefficients are statistically significant for *Energy*, *Petroleum*, *Grains*, and *Gasoil*. In the case of the ARMA(1,1)-EGARCH(1,1) only the *MA* coefficient is significant for *TTFGas*, the *AR* and *MA* coefficients are statistically significant for *Energy*, *Petroleum*, *Gasoil*, and *Aluminum*;
- *AR* and *MA* coefficients for ARMA(1,1)-GJR(1,1) are statistically significant for *Energy*, *Petroleum*, *Gasoil*, *Aluminum*, *Zinc*, and *Brent Crude*.

Regarding conditional volatility estimates, main results are as follows:

- the intercept is close to zero and statistically significant for all commodities with ARMA(1,1)-GARCH(1,1) model and ARMA(1,1)-GJR(1,1), except for *PreciousMetals* in the ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-GJR(1,1) models.
- with ARMA(1,1)-EGARCH(1,1), the intercept is negative and statistically significant for all commodities;

- *ARCH* and *GARCH* coefficients are statistically significant for all commodities and all models;
- For the ARMA(1,1)-EGARCH1(1,1) the leverage term is negative and statistically significant for *Energy*, *Petroleum*, *Gasoil* and *Brent Crude*; instead, for *Aluminum* and *Precious Metals*.the parameter is positive (and statistically significant);
- For the ARMA(1,1)-GJR(1,1), the leverage term is statistically significant and negative for *Energy*, *Aluminum* and *Precious Metals*, *Petroleum*, *Gasoil* and *Brent Crude*.

As a whole, these results provide evidence on model estimates' robustness. Coefficients are indeed statistically significant and almost consistent in terms of sign and magnitude moving from ARMA(1,1)-GARCH(1,1) to ARMA(1,1)-EGARCH(1,1) and ARMA(1,1)-GJR(1,1). Single commodities denote different leverage effects both in magnitude and direction, then implying greater influence on future volatility with positive and negative correlations between returns and volatility for some commodities, while for other such effect seems silent; this is the case for *TTFGas*, *Grains*, *Nickel* and *Zinc*.

6.1.2 Generalized Pareto Distribution Parameters

Table 4 reports tGPD parameter estimates for left and right tail of the standardized residuals distribution. The portion of tail data T_u/T we process in our analysis is selected through an automated threshold selection procedure. The threshold selection is indeed a critical issue in the framework of EVT, and for this reason we propose a procedure which selects the lowest threshold based on the best fit of the tail data as described in the Appendix. This approach offers a good balance between bias and variation. Indeed, a too low threshold leads to violate the asymptotic basis of the model (bias). On the other hand, a threshold being too high results on few tail data thus increasing the variance of the estimators

The Table denotes substantial variability of the portion of tail data across different commodities, which implies different thickness of tails which in turns reflects on varying probability of extreme events in the return disributions.

Conditional models have no substantial impact on tail data, as the value of T_u/T is basically the same across different conditional models, both for the left and right tails.

In more detail, textitAluminum, *Grains*, and *TTFGas* exhibit thicker left tails, as indicated by a higher percentage of observations lying in the left tail, then implying a higher likelihood of extreme negative returns. On the other hand, *Gasoil*, *Brent Crude*, and *Energy* show thicker right tails (lower percentage of observations lying in the right tail), suggesting higher probability of extreme positive returns.

The shape parameter or tail index, ξ, in the GPD plays a crucial role in understanding the tail behavior of the distribution. For $\xi < 0$, the parameter indicates a bounded distribution with no heavy tails. This suggests that extreme events are less likely to occur, and the distribution follows a more "close-to-normal" pattern. On the other hand, when $0 < \xi < 1$, the parameter indicates heavy tails distribution: extreme events are more likely to occur relative to a normal distribution, and the tail of the distribution decays relatively slowly. Finally, for $\xi > 1$, the distribution exhibits extremely heavy tails with very high probability of extreme events, and the tail of the distribution decays very slowly, also being able not to decrease at all.

An in depth analysis of Table 4 reveals interesting insights regarding the left tail behavior of different commodities. Notably, the left tail index for *TTFGas*, *Grains*, and industrial metals is negative, suggesting a bounded distribution with no heavy tails. In the case of *Gasoil*, the left tail index is negative for ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-EGARCH,(1,1), while left tail index is close to 0 for ARMA(1,1)-GJR(1,1), thereby suggesting some sensitivity of left tail behavior of *Gasoil* to the conditional model under study. On the other hand, both *Energy* and *Brent Crude* exhibit higher left tail indices compared to other commodities. Among all the commodities analyzed, the right tail indices of *TTFGas*, *Nickel*, and *Zinc* are the only ones that exhibit positive values. Notably, both *TTFGas* and *Nickel* denote large values for the tail index, indicating the presence of heavy tails in their distributions. The substantial right tail indices observed for *TTFGas* and *Nickel* suggest that extreme positive price movements are more likely to occur in these commodities compared to others.

6.1.3 Dependence Structure

Table 5 reports estimates of t copula parameters giving information on dependency structure between different commodities. The results indicate that *TTFGas* returns are weakly dependent with *Gasoil* (21.67%), *Energy* (17.97%), *Petroleum* (17.29%), and *Brent Crude*

(17.05%). More specifically, some important insights result:

- The estimated dependencies for most commodity pairs are consistent across different conditional models., then proving robustness of the approch in measuring the dependence structure.

- *TTFGas*, *Energy*, *Petroleum*, and *Brent Crude* consistently exhibit high positive correlations (approximately 98%), thereby suggesting common exposure to market and macroeconomic factors.

- Some commodity exhibit relatively weaker positive correlations (around 18%). For instance, *Grains* and *Precious Metals* show weaker positive correlations across the different conditional models.

- Interestingly, for some commodities the correlation estimates are negative then suggesting potential for commodity diversification portfolio strategy.This is the case for *Precious Metals* and *TTFGas* (–4.22%).

6.2 Baseline Scenario

Tables 6 - 16 and Figures 6 - 15 present the simulation results. In the Baseline Scenario, there is no authority intervention that influences the *TTFGas* price. The first two plots of Figure 6 show the forecasted price of the Baseline Scenario for European natural gas. The top dotted line, representing the 95th percentile, is characterized by an exponential shape. The price forecasts from the ARMA(1,1)-EGARCH(1,1) model convey a lower 95th percentile than the other two conditional approaches. Differences between FHS and EVT seems to be negligible. Table 6 displays the predicted compounded *TTFGas* return over 1, 3, 6, 9, and 12 months. As before, FHS and EVT forecasts are not significantly different: after one month, the *TTFGas* price is expected to grow, on average, by 3.83% (FHS) and by 3.47% (EVT). After 12 months, the average growth of *TTFGas* prices is expected to be 30.62% (FHS) and 31.87% (EVT).

Energy-related commodity prices are expected to decrease at a constant marginal rate, as indicated by the average percentage changes after three months: *Energy* (-1.77% for FHS and –1.95% for EVT), *Petroleum* (-1.89% for FHS and –2.08% for EVT), *Gasoil* (-2.28% for FHS and –2.35% for EVT), and *Brent crude oil* (-1.94% for FHS and –2.09% for

EVT). These trends are depicted in the first row of Figures 7, 8, 10, and 14. Conversely, forecasts for *Grains*, *Metals*, and *Precious Metals* indicate an expected price increase, albeit less pronounced than the increase in European natural gas price.

Average conditional models descriptive statistics for estimated and predicted conditional daily volatility are presented in Table 16. The average estimated conditional volatility for *TTFGas* over the period 2013 – 2022 is 3.39%, while the average volatility is 4.99% for FHS and 4.95% for EVT. This is the largest increase in expected volatility. However, for other commodities, the average and median predicted volatility are generally higher but close to their historical estimates. For example, the historical average conditional volatility for *Grains* is 1.26%, while the average forecasted volatility is 1.30% (for both FHS and EVT). Therefore, in the Baseline Scenario, the overall commodity market volatility is expected to slightly increase, and except for *TTFGas*, differences between estimated average volatility and expected average daily volatility quite low (under 10 basis points).

6.3 Fixed Price Cap

Figure 6 (plots of the third and fourth rows) presents a clear visual representation of how the Fixed Price Cap scenario affects forecasts of *TTFGas* prices from the conditional models. In both the FHS and EVT cases, the forecasts for the prices remain consistently below the cap, indicating a significant impact of the cap on TTF market dynamics. The impact on *TTFGas* conditional volatility forecasts is also sizeble, with the upper 95% bound being significantly lower compared to the Baseline Scenario. This reduction in volatility is consistent with a straight Fixed Price Cap, which leads to an initial spike in volatility then stabilizing as the market adjusts to the new constraints.

In Table 6 we report descriptive statistics for compounded returns of expected *TTFGas*. The data show an expected significant drop of –40.96% (FHS) and –40.27% (EVT) after one month, with further reductions over the remaining months of the forecasting window; the largest price decreases are expected to occur within six months. These findings suggest that the imposition of a Fixed Price Cap have significant, and definitive impacts on *TTFGas* market dynamics.

Fixed Price Cap on the *TTFGas* market results in higher energy-related commodity price reductions relative to Baseline Scenario. The average compounded percentage changes predicted after three months are –4.47% (FHS) and –5.27% (EVT) for *Energy*, –4.55% (FHS) and –5.39% (EVT) for *Petroleum*, –7.53% (FHS) and –7.29% (EVT) for *Gasoil*, which is the highest impact, and –4.65% (FHS) and –5.51% (EVT) for *Brent crude* oil. Table 9 highlights an interesting pattern for predicted *Grains* price changes, as the increase is significantly lower than in the Baseline Scenario for FHS and higher for EVT. This difference is the most substantial observed among all commodities. The predicted one-month-ahead average *Grains* return changes from positive in the Baseline Scenario to negative. A similar change in sign occurs for *Nickel* and *Zinc*, while the increase in the average expected return for *Precious Metals* appears to be slightly more pronounced.

Note in Table 16 that the expected daily conditional volatility for *TTFGas* returns which is lower than the Baseline Scenario, but higher than its historical estimate over the 2013 – 2022 period (3.64% for both FHS and EVT versus 3.39%). On the other hand, the average daily volatility forecasts for all other commodities are higher than observed for Baseline Scenario, except for *Grains* which has no difference in volatility: this is the effect from a sudden and substantial price reduction imposed on the European natural gas. The same picture arises from comparing expected with historical volatilies, both for FHS and EVT.

6.4 Dynamic Price Cap

Figure 6 depicts the expected *TTFGas* prices and conditional volatilities under the Dynamic Price Cap scenario. Unlike what oserved for Fixed Price Cap, the impact of the Dynamic Price Cap is less pronounced, albeit still visible.

The predicted price of gas is not as low as in the case of the Fixed Price Cap, but it does not attain the same level as the Ibbotson Cone in the Baseline Scenario. From January 2023 onwards, the upper bounds of gas prices appear to be around 200 USD/mwh. The conditional volatility forecasts for *TTFGas* in the Dynamic Price Cap scenario are consistently lower than both the Baseline Scenario and the Fixed Price Cap scenario and even lower than its historical estimate. Specifically, the expected daily conditional volatilities are 2.69% (FHS) and 2.70% (EVT) compared to the historical estimate of 3.39%. This is a reasonable value since the average historical volatility over the 2013 – 2022 period includes the extreme values of the last two years, while the rule imposed on gas prices takes into account volatility over the 2013 – 2019 period.

Table 6 presents descriptive statistics for the compounded returns in the Dynamic Price Cap scenario. The table shows that *TTFGas* prices are expected to decrease by –2.80% (FHS) and –3.53% (EVT) after one month. Similar to the Fixed Price Cap scenario, the largest marginal decreases in gas prices are expected within six months. Overall, the Dynamic Price Cap scenario appears to have a milder effect on gas prices and volatility compared to the Fixed Price Cap scenario.

The Dynamic Price Cap mechanism has a relatively smaller impact on the reduction of energy-related commodity prices compared to the Fixed Price Cap, but higher than the Baseline. Specifically, after three months, the average percentage changes in compounded returns are –2.44% (FHS) and –2.62% (EVT) for *Energy*, –2.58% (FHS) and –2.75% (EVT) for *Petroleum*, –4.03% (FHS) and –3.90% (EVT) for *Gasoil*, and –2.67% (FHS) and –2.70% (EVT) for *Brent crude oil*. The impact on *Grains* prices is not significantly different from the Baseline Scenario and exhibits contrasting predictions between the two approaches, possibly due to a lack of direct dependence between *Grains* and *TTFGas* prices. The expected compound returns for industrial metals are generally lower than the Baseline Scenario but higher trelative to the Fixed Price Cap scenario; *Precious Metals* prices are expected to increase, particularly in the EVT scenario.

A more detailed analysis of Table 16 reveals that the reduction in expected conditional volatility is the main effect of the Dynamic Price Cap scenario. Although the dis-inflationary impact on commodity returns is smaller compared to the Fixed Price Cap scenario, it is fully compensated by the reduction in expected conditional volatility. Moreover, expected conditional volatility in the Dynamic Price Cap scenario is consistently lower for all commodities in the sample compared to both the Fixed Price Cap and Baseline Scenarios. The differences from historical estimates are mostly negligible, except for *Gasoil* and *Zinc*, and of course *TTFGas*.

Overall, these results suggest that the Dynamic Price Cap approach can provide a better balance between price volatility abatement and volatility spillover mitigation relative to both the Fixed Price Cap mechanism and the option to refrain from any policy intervention (Baseline Scenario).

6.5 Discussion

The effects of gas price cap mechanisms prove that the imposition of price restrictions significantly affects the dynamics of other commodities with different magnitudes. Energy-related commodities are the most sensitive to regulatory price intervention. Assuming no-price intervention, a price reduction for *Energy* in order of –0.52% (FHS) and –0.58% (EVT) over one-month time horizon, corresponds to higher mitigation effects on price dynamics when considering price cap mechnisms: under the Fixed Price Cap our estimates are between –2.28% (FHS) and –3.05% (EVT), while under the Dynamic Price Cap, between –0.80% (FHS) and –0.87% (EVT).

On the other hand, an expected *Grains* price increase between 1.06% (FHS) and 1.02% (EVT) after three months (under the Baseline Scenario) corresponds to a much lower growth with Fixed Price Cap, between 0.12% (FHS) and 1.22% (EVT), while under the Dynamic Price Cap, the increase is expected between 0.64% (FHS) and 0.98% (EVT). EVT estimates appear to be more reliable, as historical data suggest that *Grains* prices were not influenced by gas prices until recently, when extreme values were observed for both commodities.

Similar behavior is with *Zinc*, where the effect of price regulation on other industrial metals results in lower marginal increases. The predicted returns of industrial metals appear to be more sensitive to the Fixed Price Cap than the Dynamic Price Cap, while the latter assesses the impact of price regulation on volatility.

Interestingly, *Precious Metals* do not appear to be affected by the price rule, with slight increases in their prices under both the Fixed and Dynamic Price Cap scenarios. Their volatility remains approximately constant between different scenarios and does not seem to be influenced by regulatory intervention.

7 Conclusions

In this paper, we study the short-term effects of a regulatory intervention on the European natural gas spot price on the commodity market using multivariate FHS and EVT methods. We focus on Fixed and Dynamic Price Cap scenario in a retrospective empirical exercise over the period 2013–2022, using the time window November 2022–August 2023 for a simulation excercise in a "what-if" analysis spirit. Using price data for *TTF-*

Gas, (*Energy*, *Petroleum*, *Grains*, *Gasoil*, *Aluminum*, *Nickel*, *Zinc*, *Brent Crude oil*, and *Precious Metals*), our main results are as follows:

- With no-price cap mechanism (Baseline Scenario), the European Gas price would has been expected to increase, while most of energy-related commodity prices would come down. The exceptions are industrial and *Precious Metals* together with *Grains* prices, all expected to increase. Furthermore, the overall commodity market volatility would exhibit a slightly increase, greater than the corresponding historical estimates;

- Fixed Price Cap is expected to exert a price mitigation effects mainly over the first three months. The energy-related commodity prices are expected to decrease at higher rates compared to the Baseline Scenario, and the effect on *Grains* is ambiguous. The industrial metals are expected to increase at lower rates, and *Precious Metals* increase at a slightly higher rate. The overall commodity market volatility is expected to increase significantly more than the Baseline Scenario and its historical estimates;

- Dynamic Price Cap mechanism exert a price mitigation too, but lower than the Fixed Price Cap. The effect on *Grains* remains ambiguous, and industrial metals are expected to increase at equal or slightly lower rates than the Baseline Scenario. *Precious Metals*, however, seem unaffected by the Dynamic Price Cap. The major impact is on commodity market volatility, which is expected to be approximately constant with respect of its historical estimates and therefore lower than both the Baseline and the Fixed Price Cap scenarios.

Overall, our results suggest that the Dynamic Price Cap could contribute to maintain market volatility under control over the long-run, then acting as a market stability policy measure. The Fixed Price Cap, having an immediate and consistent dis-inflationary effect on most of the commodities, may act as extraordinary and urgent measure to introduce only in the short-term with the objective to control price spikes, since its side effect is on high market volatility. This price vs. volatility conflicting objective problem open the door to a complex and challenging policy dilemma when extreme price spikes occur, as the main problem is to better combine Dynamic with Fixed Price Cap in terms of when and for how long the intervention mechanism should be used.

References

Bader, B., Yan, J., and Zhang, X. (2018). Automated threshold selection for extreme value analysis via ordered goodness-of-fit tests with adjustment for false discovery rate. *The Annals of Applied Statistics*, 12(1):310–329.

Balkema, A. A. and De Haan, L. (1974). Residual life time at great age. *The Annals of probability*, 2(5):792–804.

Barone-Adesi, G., Giannopoulos, K., and Vosper, L. (1999). Var without correlations for portfolios of derivative securities. *Journal of Futures Markets*, 19(5):583–602.

Barone-Adesi, G., Giannopoulos, K., and Vosper, L. (2000). Filtering historical simulation. backtest analysis. *Manuscript, March*.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327.

Bücher, A. and Zhou, C. (2018). A horse racing between the block maxima method and the peak-over-threshold approach. *arXiv preprint arXiv:1807.00282*.

Cantelli, F. (1933a). Considerazioni sulla legge uniforme dei grandi numeri e sulla generalizzazione di un fondamentale teorema del sig. *Paul Levy. Giorn. Ist. Ital. Attuari*, 4(3):327–50.

Cantelli, F. P. (1933b). Sulla determinazione empirica delle leggi di probabilita. *Giorn. Ist. Ital. Attuari*, 4(421-424).

Cheng, I.-H. and Xiong, W. (2014). Financialization of commodity markets. *Annu. Rev. Financ. Econ.*, 6(1):419–441.

Cherubini, U., Luciano, E., and Vecchiato, W. (2004). *Copula methods in finance*. John Wiley & Sons.

Choulakian, V. and Stephens, M. A. (2001). Goodness-of-fit tests for the generalized pareto distribution. *Technometrics*, 43(4):478–484.

Christoffersen, P. (2011). *Elements of financial risk management*. Academic press.

De Meza, D. (1979). Commercial policy towards multinational monopolies—reservations on katrak. *Oxford Economic Papers*, 31(2):334–337.

Demarta, S. and McNeil, A. J. (2005). The t copula and related copulas. *International statistical review*, 73(1):111–129.

Ehrhart, K.-M., Schlecht, I., Schmitz, J., and Wang, R. (2023). Comparison of price caps and tariffs to counter a foreign monopoly. *Economics Letters*, 227:111128.

Embrechts, P., Klüppelberg, C., and Mikosch, T. (2013). *Modelling extremal events: for insurance and finance*, volume 33. Springer Science & Business Media.

Fernandes, M. C., Dias, J. C., and Nunes, J. P. V. (2021). Modeling energy prices under energy transition: A novel stochastic-copula approach. *Economic Modelling*, 105:105671.

Ferreira, A. and De Haan, L. (2015). On the block maxima method in extreme value theory: Pwm estimators. *The Annals of statistics*, 43(1):276–298.

Ghorbel, A. and Trabelsi, A. (2014). Energy portfolio risk management using time-varying extreme value copula methods. *Economic Modelling*, 38:470–485.

Giot, P. and Laurent, S. (2003). Market risk in commodity markets: a var approach. *Energy Economics*, 25(5):435–457.

Glosten, L. R., Jagannathan, R., and Runkle, D. (1993). On the relationship between garch and symmetric stable process: Finding the source of fat tails in data. *Journal of Finance*, 48(5):1779–1802.

Grimshaw, S. D. (1993). Computing maximum likelihood estimates for the generalized pareto distribution. *Technometrics*, 35(2):185–191.

G'Sell, M. G., Wager, S., Chouldechova, A., and Tibshirani, R. (2016). Sequential selection procedures and false discovery rate control. *Journal of the royal statistical society: series B (statistical methodology)*, 78(2):423–444.

Gumbel, E. (2004). (1958): Statistics of extremes. *NewYork: Columbia*.

Hussain, S. I. and Li, S. (2018). The dependence structure between chinese and other major stock markets using extreme values and copulas. *International Review of Economics & Finance*, 56:421–437.

Marimoutou, V., Raggad, B., and Trabelsi, A. (2009). Extreme value theory and value at risk: application to oil market. *Energy Economics*, 31(4):519–530.

McNeil, A. J. and Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of empirical finance*, 7(3-4):271–300.

McNeil, A. J., Frey, R., and Embrechts, P. (2015). *Quantitative risk management: concepts, techniques and tools-revised edition*. Princeton university press.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, pages 347–370.

Ohashi, K. and Okimoto, T. (2016). Increasing trends in the excess comovement of commodity prices. *Journal of Commodity Markets*, 1(1):48–64.

Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International economic review*, 47(2):527–556.

Pickands, J. (1975). Statistical inference using extreme order statistics. *the Annals of Statistics*, pages 119–131.

Reynolds, S. S. and Rietzke, D. (2018). Price caps, oligopoly, and entry. *Economic Theory*, 66:707–745.

Thompson, P., Cai, Y., Reeve, D., and Stander, J. (2009). Automated threshold selection methods for extreme wave analysis. *Coastal Engineering*, 56(10):1013–1021.

Tower, E. (1983). On the best use of trade controls in the presence of foreign market power. *Journal of International Economics*, 15(3-4):349–365.

Vossler, C. A., Mount, T. D., Thomas, R. J., and Zimmerman, R. D. (2009). An experimental investigation of soft price caps in uniform price auction markets for wholesale electricity. *Journal of Regulatory Economics*, 36:44–59.

Word Bank (2022a). The impact of the war in ukraine on commodity markets.

Word Bank (2022b). Pandemic, war, recession: Drivers of aluminum and copper prices.

Zhao, X., Zhang, Z., Cheng, W., and Zhang, P. (2019). A new parameter estimator for the generalized pareto distribution under the peaks over threshold framework. *Mathematics*, 7(5):406.

A Filtered Historical Simulations

Barone-Adesi et al. (1999) and Barone-Adesi et al. (2000) introduced FHS, a simulation approach that combines historical and Monte Carlo techniques to forecast daily log returns. It utilizes statistical bootstrap with replacement to simulate future standardized residuals without assuming their distribution. FHS models filtered returns instead of raw returns and preserves observed co-movements between entities in a multivariate extension. A key advantage is the ability to compound daily returns for forecasts over extended horizons.

Let r_t^i represents the daily return of commodity $i = 1, \ldots, N$ at time $t = 1, \ldots, T$, where T denotes the time series sample size. Assume the returns dynamics are driven by the following equation:

$$r_t^i = \mu_t^i + \sigma_t^i z_t^i \tag{16}$$

where μ_t^i is the daily conditional mean and σ_t^i is the daily conditional volatility of commodity i at time t. Let $\hat{z}_t^i$ represents the estimated standardized residuals of an ARMA-GARCH-type model for commodity i at time t. An algorithm for FHS involves the following steps[13]:

1. take the scenario simulation $b = 1$ and sample the sequence of length H of standardized residuals, $\{\hat{z}_{hb}^*\}_{h=1,\ldots,T+H}$, from the historical estimates with replacement (bootstrap);

2. consider the last historical estimates of the model as pre-sample values: $\sigma_0^* = \hat{\sigma}_T, r_0^* = r_T$;

3. filter the bootstrapped standardized residuals based on the pre-sample values and obtain the simulated predicted returns, $\{r_{hb}^*\}_{h=1,\ldots,T+H}$;

4. repeat the procedure for $b = 2, \ldots, B$ to get a bootstrapped matrix of size $H \times 1 \times B$ for the standardized residuals, residuals, variances, and returns of each commodity i in the sample.

The multivariate extension of FHS involves drawing with replacement a complete cross-section of commodities estimated standardized residuals at a random date to generate a

[13]From here the index i is omitted for clarity.

matrix of size $H \times N \times B$ of returns and conditional volatilities, preserving the observed market co-movements between the commodities.

B Extreme Value Theory

EVT is concerned with modeling and inferring the probability distributions of extreme events. It provides a theoretical framework for the tails of distributions and the probabilities of observing extreme values beyond typical observations. Two commonly used approaches in EVT are Block Maxima (BM) and Peaks Over Threshold (POT). BM divides observations into non-overlapping blocks and selects the maximum value, while POT identifies extreme values above a threshold. The POT approach is generally considered more efficient and suitable for estimating tail risk as it utilizes all available information. In this work, we focus on the POT approach which fits a Generalized Pareto Distribution to the exceedance data.

Let $X_1, \ldots, X_N$ be iid random sample taken from a generic random variable X with distribution function $F(x)$ and right endpoint x_F. The support of X is assumed to be the discrete set $S_X = \{u_1, \ldots, u_K\}$. The distribution function of exceedances above threshold $u < x_F$ is denoted as $F_u(x)$. It can be expressed as:

$$F_u(x) = \mathbb{P}\{X - u \leq x | X > u\} = \frac{\mathbb{P}\{u < X < x + u\}}{\mathbb{P}\{X > u\}} = \begin{cases} \frac{F(x)-F(u)}{1-F(u)} & x \geq 0 \\ 0 & \text{else} \end{cases}.$$

According to the Pickands-Balkema-De Haan theorem (Pickands, 1975; Balkema and De Haan, 1974), for a sufficiently large threshold u, the excess loss $Y = X - u | X > u$ converges to the Generalized Pareto Distribution (GPD) with shape parameter $\xi > 0$. The distribution of exceedances above u can be well approximated by the GPD:

$$F_u(x) \approx G_{\xi,\sigma_u}(x),$$

where G_{ξ,σ_u} is the GPD. The threshold stability property ensures that $F_v(x) = G_{\xi,\sigma+\xi(v-u)}(x)$ holds for u large enough.

Pickands (1975) introduced the *Generalized Pareto Distribution* (GPD), where loss exceedances over some high threshold have PDF:

$$f_{\xi,\sigma_u}(x) = \begin{cases} \frac{1}{\sigma_u}\left(1 + \xi \frac{x-u}{\sigma_u}\right)^{\left(-\frac{1}{\xi}-1\right)}, & \xi \neq 0 \\ \frac{1}{\sigma_u}\exp\left(-\frac{x-u}{\sigma_u}\right), & \xi = 0 \end{cases} \tag{17}$$

and CDF:

$$G_{\xi,\sigma_u}(x) = \begin{cases} 1 - \left(1 + \xi \frac{x-u}{\sigma_u}\right)^{-1/\xi}, & \xi \neq 0 \\ 1 - \exp\left(-\frac{x-u}{\sigma_u}\right), & \xi = 0. \end{cases} \tag{18}$$

where $\sigma_u > 0$, $x - u \geq 0$ when $\xi \geq 0$ and $u \leq x \leq u - \sigma_u/\xi$ when $\xi < 0$. The parameter ξ is referred as the *shape* or *tail index*, the parameter σ_u is referred as the *scale*, and the parameter u is referred as the *threshold* or the *location*.

When the threshold u is known and both σ and ξ are unknown, the parameters of the GPD model can be estimated. The log-likelihood function is given by:

$$l(\xi, \sigma) = -T_u \ln \sigma - \left(1 + \frac{1}{\xi}\right) \sum_{k=1}^{T_u} \ln \left(1 + \xi \frac{x_k - u}{\sigma}\right). \tag{19}$$

The log-likelihood function is maximized subject to the constraints $\sigma > 0$ and $1+\xi/\sigma(x_k - u) > 0$ for all k. The resulting GPD model is denoted as $G_{\hat{\xi},\hat{\sigma},u}$.

B.1 Threshold Identification

Threshold identification is a critical aspect of modeling with the GPD. As pointed out by Christoffersen (2011), the selection of an appropriate threshold is the "Achilles heel" of Extreme Value Theory (EVT) using GPD. This step involves a trade-off between bias and variance. If the threshold is set too high, only a few data points remain in the tail, resulting in a noisy estimate of the tail parameter, ξ. On the other hand, if the threshold is set too low, the GPD fit may be poor and the estimate of ξ becomes biased.

To address this challenge, Bader et al. (2018) proposed an automated threshold selection procedure based on sequential goodness-of-fit (GoF) tests. The procedure, named ForwardStop, is applied to the random sample $X_1, \ldots, X_k, \ldots, X_N$. For simplicity, we assume that the labels $1, \ldots, k, \ldots, N$ point to ranks, so that $Prob(X_1 < \cdots < X_k < \cdots < X_N) = 1$.

According to the Pickands-Balkema-De Haan theorem (Pickands, 1975; Balkema and De Haan, 1974), the exceedances $Y_k = X_k - u$, for $k = 1, \ldots, N$, follow a GPD distribution when $u \in S_X$ is large enough.

The goal is to find the optimal threshold $u^* = u_{\hat{k}+1} \in S_X$ that balances the bias-variance trade-off.

The ForwardStop rule is applied by performing GoF tests, such as the Anderson-Darling test, on a sequence of candidate thresholds $u_1 < u_2 < \cdots < u_k < \cdots < u_K$. The null hypotheses for these tests are as follows:

$$\begin{cases} H_0^{(k)} : F_{u_k}(x) = GPD(u_k, \sigma_k, \xi_k) \\ H_0^{(k)} : F_{u_k}(x) \neq GPD(u_k, \sigma_k, \xi_k) \end{cases} . \tag{20}$$

where $F_{u_k}(x)$ represents the distribution function of X above the threshold u_k, and $GPD(u_k, \sigma_k, \xi_k)$ is the GPD distribution with threshold u_k, scale parameter σ_k, and shape parameter ξ_k.

The ForwardStop rule is defined as:

$$\hat{k} = \max\left\{k \in \{1, 2, ..., K\} : -\frac{1}{k}\sum_{i=1}^{k} \log(1 - p_i) \leq \alpha\right\}, \tag{21}$$

where α is a pre-specified significance level. The optimal threshold is the cutoff point where $H_0^{(1)}, H_0^{(i)}, \ldots, H_0^{(\hat{k})}$ are rejected defined as $u = x_{\hat{k}+1}$: from that point the exceedances follows a GPD since GoF tests fail to reject the null hypotheses and before that point GoF tests reject the null hypothesis at the specified significance level α. If $\nexists\, \hat{k} \in \{1, \ldots, K\}$ no rejection is made and $T_u = T$.

By applying the ForwardStop rule, rejection of the null hypotheses up to a certain threshold implies rejection for all lower thresholds. The sequential nature of the tests accounts for the ordered statistics.

B.2 Conditional and Multivariate EVT

Let r_t^i represents the daily return of commodity $i = 1, \ldots, N$ at time $t = 1, \ldots, T$, where T denotes the time series sample size. Assume the returns dynamics are driven by the following equation:

$$r_t^i = \mu_t^i + \sigma_t^i z_t^i \tag{22}$$

where μ_t^i is the daily conditional mean and σ_t^i is the daily conditional volatility of commodity i at time t. Let $\hat{z}_t^i$ represents the estimated standardized residuals of an ARMA-GARCH-type model for commodity i at time t. To apply conditional EVT following the procedure proposed by McNeil and Frey (2000), we fit a piece-wise cumulative distribution with Generalized Pareto tails to the standardized residuals of each commodity i in the sample[14]:

$$F(\hat{z}_t) = \begin{cases} \frac{T_{u_L}}{T}\left(1+\xi_L\frac{u_L-\hat{z}_t}{\sigma_L}\right)^{-\frac{1}{\xi_L}}, & \text{for } \hat{z}_t < u_L \\ \frac{1}{T\gamma}\sum_{s=1}^{T} K\left(\frac{\hat{z}_t-\hat{z}_s}{\gamma}\right), & \text{for } u_L < \hat{z}_t < u_R \\ 1-\frac{T_{u_R}}{T}\left(1+\xi_R\frac{\hat{z}_t-u_R}{\sigma_R}\right)^{-\frac{1}{\xi_R}}, & \text{for } \hat{z}_t > u_R \end{cases} \tag{23}$$

where the subscript L, R denote the left and the right tails, T is the number of observations, T_u is the number of observations exceeding the threshold u, $\sigma > 0$, $x - u \geq 0$ when $\xi \geq 0$ and $u \leq x \leq u - \sigma/\xi$ when $\xi < 0$.

In multivariate EVT, marginal distributions are estimated using a conditional univariate piece-wise CDF with GPD tails, while the dependence structure is modeled using a copula. We used the t-copula, which is better suited for financial time series due to its ability to handle heavier tails and outliers. In contrast, the Gaussian copula assumes a normal distribution that may not be appropriate. Vine copulas, although useful for complex dependencies, are less commonly used in financial time series, especially for extreme market events, and can be harder to interpret than the t-copula. Studies have consistently shown the superior performance of the Student-t copula in risk management and portfolio optimization during extreme market conditions (Patton, 2006; McNeil et al., 2015; Demarta and McNeil, 2005; Cherubini et al., 2004; Fernandes et al., 2021).

An algorithm for multivariate EVT involves the following steps:

1. fit a piece-wise CDF with GPD tails to the estimated standardized residuals, $\{\hat{z}_t^i\}_{t=1,\dots,T}$, and repeat the procedure for each commodity i in the sample N;

2. calibrate the t-copula parameters on the semi-parametric CDFs with GPD tails marginals of the standardized residuals matrix, $\{\hat{z}_t^i\}_{t=1,\dots,T}^{i=1,\dots,N}$, estimated at point 1;

3. take the scenario simulation $b = 1$ and sample a matrix, $\{\hat{z}_{hb}^{*i}\}_{h=1,\dots,T+H}^{i=1,\dots,N}$, of jointly dependent standardized residuals, based on the dependence structure from the previous step;

4. consider the last historical estimates of the model as pre-sample values: $\sigma_0^* = \hat{\sigma}_T, r_0^* = r_T$;

5. filter the bootstrapped standardized residuals based on the pre-sample values and obtain the simulated predicted returns matrix, $\{r_{hb}^{*i}\}_{h=1,\dots,T+H}^{i=1,\dots,N}$;

[14]For clarity, the index i is omitted from this point onward.

6. repeat the procedure from point 3. for $b = 2, \ldots, B$ to get a simulated matrix of size $H \times N \times B$ of returns and conditional volatilities, preserving the estimated dependence structure between the commodities.

C Tables

Table 1: Descriptive statistics of commodities returns.

Commodity	Mean	Min	Median	Max	StdDev	Skew	Kurt
2013 - 2016							
TTFGas	-0.0049	-0.1169	-0.0174	0.1385	0.0692	0.6389	9.6146
Energy	-0.0087	-0.0883	-0.0146	0.0835	0.0701	0.2136	4.8206
Petroleum	-0.0091	-0.0900	-0.0146	0.0901	0.0733	0.2721	4.9053
Grains	-0.0052	-0.0439	-0.0053	0.0578	0.0417	0.0712	3.8579
Gasoil	-0.0089	-0.0814	-0.0058	0.0855	0.0646	0.4410	5.5659
Aluminum	-0.0012	-0.0296	-0.0023	0.0344	0.0364	0.2247	3.1643
Nickel	-0.0049	-0.0889	-0.0003	0.0624	0.0634	-0.1886	4.8155
Zinc	0.0048	-0.0683	0.0012	0.0942	0.0498	0.3227	6.2681
Brent Crude	-0.0096	-0.0967	-0.0143	0.0937	0.0785	0.2139	5.1920
Precious Metals	-0.0024	-0.0384	-0.0100	0.0426	0.0349	0.2127	5.0040
2017 - 2019							
TTFGas	-0.0077	-0.1318	-0.0054	0.3170	0.1038	2.0790	24.4606
Energy	0.0016	-0.0708	0.0234	0.1214	0.0569	-0.1518	8.3981
Petroleum	0.0021	-0.0748	0.0248	0.1264	0.0594	-0.1598	8.4522
Grains	0.0018	-0.0467	-0.0027	0.0413	0.0391	0.0694	4.2458
Gasoil	0.0031	-0.0545	0.0095	0.0947	0.0520	0.0261	5.4013
Aluminum	0.0010	-0.0766	0.0000	0.0536	0.0392	0.0978	7.4549
Nickel	0.0054	-0.0587	0.0024	0.0851	0.0609	0.0890	4.4591
Zinc	-0.0019	-0.0652	0.0000	0.0532	0.0505	0.0160	3.6588
Brent Crude	0.0024	-0.0780	0.0251	0.1330	0.0619	-0.1787	8.8908
Precious Metals	0.0042	-0.0255	0.0068	0.0350	0.0246	0.0118	4.7845
2020 - 2022							
TTFGas	0.0377	-0.3524	0.0000	0.4128	0.2249	0.1611	9.1168
Energy	0.0082	-0.3018	0.0313	0.1599	0.1106	-1.8455	21.2012
Petroleum	0.0076	-0.3328	0.0346	0.1736	0.1175	-1.9903	23.0728
Grains	0.0084	-0.0630	0.0055	0.0618	0.0531	-0.1255	5.0131
Gasoil	0.0093	-0.1630	0.0371	0.1151	0.1054	-0.7360	7.1230
Aluminum	0.0045	-0.0694	0.0000	0.0568	0.0529	-0.2469	4.6181
Nickel	0.0088	-0.1618	0.0075	0.4960	0.1050	5.8269	103.8200
Zinc	0.0040	-0.0626	0.0060	0.0743	0.0576	-0.1906	4.6248
Brent Crude	0.0067	-0.2683	0.0333	0.1908	0.1092	-1.3464	18.0334
Precious Metals	0.0017	-0.0543	0.0068	0.0572	0.0412	-0.3811	6.7597

The table reports summary statistics for commodities over sub-periods: *Mean* is the average daily return (not annualized). *Min* and *Max* are the minimum and the maximum daily return, respectively. *Median* is the median daily return (not annualized). *StdDev* is the periodal standard deviation (not annualized). *Skew* and *Kurt* are the skewness and the excess kurtosis.

Table 2: Correlations between commodities.

	TTFGas	*Energy*	*Petroleum*	*Grains*	*Gasoil*	*Aluminum*	*Nickel*	*Zinc*	*Brent Crude*	*Precious Metals*
Pearson										
TTFGas	1.0000	0.1525	0.1441	0.0819	0.2018	0.0723	0.0812	0.0781	0.1392	-0.0093
Energy	0.1525	1.0000	0.9960	0.2077	0.7624	0.2468	0.1982	0.2231	0.9741	0.1251
Petroleum	0.1441	0.9960	1.0000	0.2037	0.7634	0.2420	0.1957	0.2209	0.9754	0.1252
Grains	0.0819	0.2077	0.2037	1.0000	0.1921	0.1486	0.1425	0.1352	0.2068	0.1208
Gasoil	0.2018	0.7624	0.7634	0.1921	1.0000	0.2491	0.2189	0.2635	0.7310	0.1126
Aluminum	0.0723	0.2468	0.2420	0.1486	0.2491	1.0000	0.3154	0.4595	0.2460	0.1530
Nickel	0.0812	0.1982	0.1957	0.1425	0.2189	0.3154	1.0000	0.4156	0.2006	0.1603
Zinc	0.0781	0.2231	0.2209	0.1352	0.2635	0.4595	0.4156	1.0000	0.2211	0.1449
Brent Crude	0.1392	0.9741	0.9754	0.2068	0.7310	0.2460	0.2006	0.2211	1.0000	0.1168
Precious Metals	-0.0093	0.1251	0.1252	0.1208	0.1126	0.1530	0.1603	0.1449	0.1168	1.0000
Kendall										
TTFGas	1.0000	0.1106	0.1034	0.0147	0.1384	0.0324	0.0216	0.0318	0.0984	-0.0351
Energy	0.1106	1.0000	0.9348	0.1288	0.5423	0.1657	0.1598	0.1423	0.8737	0.0679
Petroleum	0.1034	0.9348	1.0000	0.1285	0.5465	0.1633	0.1589	0.1442	0.8966	0.0698
Grains	0.0147	0.1288	0.1285	1.0000	0.1048	0.0916	0.0887	0.0774	0.1255	0.0735
Gasoil	0.1384	0.5423	0.5465	0.1048	1.0000	0.1630	0.1557	0.1649	0.5066	0.0640
Aluminum	0.0324	0.1657	0.1633	0.0916	0.1630	1.0000	0.2810	0.3161	0.1601	0.0973
Nickel	0.0216	0.1598	0.1589	0.0887	0.1557	0.2810	1.0000	0.3320	0.1553	0.1182
Zinc	0.0318	0.1423	0.1442	0.0774	0.1649	0.3161	0.3320	1.0000	0.1372	0.0895
Brent Crude	0.0984	0.8737	0.8966	0.1255	0.5066	0.1601	0.1553	0.1372	1.0000	0.0678
Precious Metals	-0.0351	0.0679	0.0698	0.0735	0.0640	0.0973	0.1182	0.0895	0.0678	1.0000
Spearman										
TTFGas	1.0000	0.1622	0.1514	0.0216	0.2009	0.0472	0.0322	0.0471	0.1443	-0.0519
Energy	0.1622	1.0000	0.9919	0.1915	0.7168	0.2442	0.2361	0.2103	0.9741	0.0999
Petroleum	0.1514	0.9919	1.0000	0.1910	0.7203	0.2410	0.2345	0.2129	0.9821	0.1027
Grains	0.0216	0.1915	0.1910	1.0000	0.1556	0.1363	0.1321	0.1154	0.1866	0.1095
Gasoil	0.2009	0.7168	0.7203	0.1556	1.0000	0.2383	0.2291	0.2420	0.6749	0.0940
Aluminum	0.0472	0.2442	0.2410	0.1363	0.2383	1.0000	0.4072	0.4526	0.2362	0.1442
Nickel	0.0322	0.2361	0.2345	0.1321	0.2291	0.4072	1.0000	0.4760	0.2290	0.1750
Zinc	0.0471	0.2103	0.2129	0.1154	0.2420	0.4526	0.4760	1.0000	0.2023	0.1324
Brent Crude	0.1443	0.9741	0.9821	0.1866	0.6749	0.2362	0.2290	0.2023	1.0000	0.0999
Precious Metals	-0.0519	0.0999	0.1027	0.1095	0.0940	0.1442	0.1750	0.1324	0.0999	1.0000

The table represents correlation between commodities calculated over the entire time window. *Pearson* is Pearson correlation coefficient. *Kendall* is Kendall's Tau non-parametric correlation coefficient. *Spearman* is Spearman rank correlation coefficient.

Table 3: Parameter estimates.

ARMA(1,1)-GARCH(1,1)	**const1**	**AR**	**MA**	**const2**	**GARCH**	**ARCH**	**Leverage**	**DoF**	**AIC**	**BIC**
TTFGas	-0.0007	-0.2863	0.3542	0.0000***	0.8477***	0.1523***	–	5.1644***	-10009.4145	-9969.2665
Energy	0.0012**	-0.9745***	0.9706***	0.0000***	0.8987***	0.1013***	–	4.7994***	-11814.8425	-11774.6945
Petroleum	0.0013**	-0.9812***	0.9770***	0.0000***	0.8943***	0.1057***	–	4.8149***	-11624.7972	-11584.6491
Grains	0.0000	-0.8552***	0.8720***	0.0000**	0.9162***	0.0686***	–	10.2341***	-13702.6143	-13662.4663
Gasoil	0.0005	-0.8426***	0.8383***	0.0000**	0.9185***	0.0787***	–	5.7987***	-11882.5875	-11842.4395
Aluminum	0.0000	0.5539	-0.5380	0.0000***	0.9018***	0.0718***	–	13.4477***	-13920.5189	-13880.3708
Nickel	0.0002	0.5420	-0.5571	0.0000***	0.7955***	0.0869***	–	5.5592***	-11771.4226	-11731.2745
Zinc	0.0006	-0.5613	0.5617	0.0000*	0.9509***	0.0380***	–	9.1864***	-12851.1584	-12811.0103
Brent Crude	0.0007	-0.3066	0.2494	0.0000**	0.9010***	0.0990***	–	4.8438***	-11508.8338	-11468.6858
Precious Metals	0.0002	-0.0516	0.0114	0.0000	0.9711***	0.0244***	–	3.9784***	-15055.7143	-15015.5663
ARMA(1,1)-EGARCH(1,1)	**const1**	**AR**	**MA**	**const2**	**GARCH**	**ARCH**	**Leverage**	**DoF**	**AIC**	**BIC**
TTFGas	-0.0007	-0.3401	0.4080*	-0.0984***	0.9859***	0.2802***	0.0109	4.6662***	-10037.1127	-9991.2292
Energy	0.0007	-0.9741***	0.9712***	-0.1074***	0.9866***	0.1669***	-0.0635***	5.1146***	-11844.2586	-11798.3751
Petroleum	0.0007	-0.9815***	0.9789***	-0.1132***	0.9858***	0.1722***	-0.0648***	5.1034***	-11652.8931	-11607.0097
Grains	0.0000	0.6880	-0.6821	-0.1602***	0.9818***	0.1490***	0.0103	10.1572***	-13700.3347	-13654.4513
Gasoil	0.0000	0.8575***	-0.8305***	-0.0769***	0.9903***	0.1571***	-0.0591***	6.2657***	-11903.9371	-11858.0537
Aluminum	0.0004	-0.9738***	0.9775***	-0.1090**	0.9877***	0.1163***	0.0254**	13.5647***	-13917.5219	-13871.6384
Nickel	0.0002	0.5004	-0.5160	-0.1701***	0.9784***	0.1018***	0.0160	5.5711***	-11768.115	-11722.2315
Zinc	0.0006	-0.6561	0.6531	-0.1164**	0.9861***	0.0991***	-0.0049	9.2702***	-12859.0118	-12813.1283
Brent Crude	0.0004	0.0016	-0.0563	-0.1049***	0.9868***	0.1649***	-0.0603***	5.0447***	-11538.6407	-11492.7572
Precious Metals	0.0002	-0.0175	-0.0228	-0.0799**	0.9913***	0.0740***	0.0198*	3.9400***	-15057.3381	-15011.4546
ARMA(1,1)-GJR(1,1)	**const1**	**AR**	**MA**	**const2**	**GARCH**	**ARCH**	**Leverage**	**DoF**	**AIC**	**BIC**
TTFGas	-0.0007	-0.2849	0.3528	0.0000***	0.8468***	0.1566***	-0.0068	5.1636***	-10007.4761	-9961.5926
Energy	0.0009	-0.9081***	0.8993***	0.0000***	0.9053***	0.0564***	-0.0684***	4,9387***	-11822.7813	-11776.8978
Petroleum	0.0010	-0.9810***	0.9768***	0.0000***	0.8999***	0.0602***	0.0715***	4.9266***	-11634.2046	-11588.3212
Grains	0.0000	0.7152	-0.7135	0.0000**	0.9185***	0.0732***	-0.0130	10.3225***	-13699.6259	-13653.7424
Gasoil	0.0000	0.8294***	-0.8072***	0.0000*	0.9273***	0.0393***	0.0650***	6.1125***	-11894.7755	-11848.892
Aluminum	0.0003	-0.9660***	0.9698***	0.0000**	0.9080***	0.0859***	-0.0377**	14.4879***	-13929.1628	-13883.2793
Nickel	0.0002	0.5416	-0.5569	0.0000***	0.7975***	0.0888***	-0.0048	5.5648***	-11769.4471	-11723.5637
Zinc	0.0008	-0.9479***	0.9557***	0.0000*	0.9521***	0.0317***	0.0100	9.1054***	-12850.5491	-12804.6656
Brent Crude	0.0008	-0.5845**	0.5409*	0.0000**	0.9081***	0.0561***	0.0645***	4.9002***	-11517.2923	-11471.4089
Precious Metals	0.0002	-0.0355	-0.0062	0.0000	0.9672***	0.0397***	-0.0233*	3.9635***	-15057.6066	-15011.7231

The table shows parameter estimates for ARMA-GARCH-type models. *const1* is the constant of the conditional mean model. *AR* is the auto-regressive coefficient estimate. *MA* is the moving-average coefficient estimate. *const2* is the constant of the conditional volatility model. *GARCH* is the GARCH coefficient estimate. *ARCH* is the ARCH coefficient estimate. *Leverage* is the leverage coefficient estimate, included only in EGARCH and GJR models. *DoF* is the estimated Degrees of Freedom of the Student-t distribution. *AIC* is the Akaike Information Criteria. *BIC* is the Bayesian (Schwarz) Information Criteria. ***, ** and * denote significance at 0.01, 0.05 and 0.10 level, respectively.

Table 4: Estimated GPD parameters for the tails of standardized residuals.

ARMA(1,1)-GARCH(1,1)	$T_{\hat{u}_L}/T$	$\hat{\xi}_L$	$\hat{\sigma}_L$	$T_{\hat{u}_R}/T$	$\hat{\xi}_R$	$\hat{\sigma}_R$
TTFGas	0.2902	-0.0180	0.6164	0.7915	0.1237	0.5967
Energy	0.1993	0.0887	0.6512	0.7365	-0.0186	0.5613
Petroleum	0.2784	0.0497	0.6976	0.7386	-0.0295	0.5785
Grains	0.2950	-0.0901	0.6513	0.7784	-0.1149	0.7202
Gasoil	0.1770	-0.0112	0.7161	0.7281	-0.0462	0.6037
Aluminium	0.3003	-0.1429	0.6874	0.8816	-0.0747	0.6170
Nickel	0.2780	-0.0517	0.6765	0.8728	0.2170	0.4851
Zinc	0.2574	-0.1038	0.6949	0.8785	0.0122	0.5638
Brent Crude	0.2705	0.0632	0.6812	0.7312	-0.0104	0.5732
Precious Metals	0.0747	0.0242	0.6954	0.8033	-0.0217	0.6513
ARMA(1,1)-EGARCH(1,1)	$T_{\hat{u}_L}/T$	$\hat{\xi}_L$	$\hat{\sigma}_L$	$T_{\hat{u}_R}/T$	$\hat{\xi}_R$	$\hat{\sigma}_R$
TTFGas	0.2906	-0.0343	0.6212	0.7920	0.1200	0.5833
Energy	0.1879	0.1173	0.6101	0.7356	-0.0252	0.5614
Petroleum	0.2762	0.0505	0.6879	0.7356	-0.0353	0.5746
Grains	0.2976	-0.0998	0.6612	0.7928	-0.1102	0.7061
Gasoil	0.1490	0.0104	0.6453	0.7181	-0.0644	0.6231
Aluminium	0.3042	-0.1452	0.6915	0.8781	-0.0486	0.6028
Nickel	0.2784	-0.0546	0.6767	0.8680	0.1904	0.5018
Zinc	0.2583	-0.0967	0.6883	0.8820	0.0039	0.5671
Brent Crude	0.2745	0.0581	0.6742	0.7343	-0.0137	0.5687
Precious Metals	0.0752	0.0014	0.7369	0.8016	-0.0098	0.6436
ARMA(1,1)-GJR(1,1)	$T_{\hat{u}_L}/T$	$\hat{\xi}_L$	$\hat{\sigma}_L$	$T_{\hat{u}_R}/T$	$\hat{\xi}_R$	$\hat{\sigma}_R$
TTFGas	0.2906	-0.0191	0.6178	0.7915	0.1247	0.5949
Energy	0.2640	0.0414	0.6948	0.7426	-0.0191	0.5667
Petroleum	0.2758	0.0360	0.7085	0.7365	-0.0300	0.5815
Grains	0.2963	-0.0901	0.6516	0.7902	-0.0961	0.6862
Gasoil	0.1582	0.0000	0.6711	0.7177	-0.0610	0.6230
Aluminium	0.3055	-0.1554	0.7005	0.8829	-0.0634	0.6078
Nickel	0.2775	-0.0492	0.6733	0.8724	0.2143	0.4867
Zinc	0.2635	-0.0979	0.6900	0.8698	0.0439	0.5268
Brent Crude	0.2592	0.0651	0.6692	0.7299	-0.0156	0.5825
Precious Metals	0.0747	0.0022	0.7294	0.8011	-0.0098	0.6380

The table presents estimated parameter for selected commodities using GPD. $T_{\hat{u}_L}/T$ and $T_{\hat{u}_R}/T$ are, respectively, the left and the right tail portions, obtained applying the ForwardStop rule by Bader et al. (2018). $\hat{\xi}_L$ and $\hat{\xi}_R$ are, respectively, the left and the right shape parameters, obtained by ML. $\hat{\sigma}_L$ and $\hat{\sigma}_R$ are, respectively, the left and the right scale parameters, obtained by ML.

Table 5: Matrix of correlation parameters for t copula.

	TTFGas	*Energy*	*Petroleum*	*Grains*	*Gasoil*	*Aluminum*	*Nickel*	*Zinc*	*Brent Crude*	*Precious Metals*
ARMA(1,1)-GARCH(1,1)										
TTFGas	1.0000	0.1797	0.1729	0.0338	0.2167	0.0512	0.0577	0.0589	0.1705	-0.0422
Energy	0.1797	1.0000	0.9944	0.1889	0.7705	0.2464	0.2465	0.2225	0.9783	0.1058
Petroleum	0.1729	0.9944	1.0000	0.1864	0.7742	0.2457	0.2439	0.2246	0.9841	0.1086
Grains	0.0338	0.1889	0.1864	1.0000	0.1485	0.1224	0.1409	0.1087	0.1802	0.0968
Gasoil	0.2167	0.7705	0.7742	0.1485	1.0000	0.2464	0.2350	0.2516	0.7464	0.0998
Aluminium	0.0512	0.2464	0.2457	0.1224	0.2464	1.0000	0.4139	0.4740	0.2415	0.1524
Nickel	0.0577	0.2465	0.2439	0.1409	0.2350	0.4139	1.0000	0.4940	0.2393	0.1921
Zinc	0.0589	0.2225	0.2246	0.1087	0.2516	0.4740	0.4940	1.0000	0.2185	0.1491
Brent Crude	0.1705	0.9783	0.9841	0.1802	0.7464	0.2415	0.2393	0.2185	1.0000	0.1058
Precious Metals	-0.0422	0.1058	0.1086	0.0968	0.0998	0.1524	0.1921	0.1491	0.1058	1.0000
ARMA(1,1)-EGARCH(1,1)										
TTFGas	1.0000	0.1817	0.1750	0.0340	0.2147	0.0502	0.0545	0.0572	0.1720	-0.0435
Energy	0.1817	1.0000	0.9944	0.1918	0.7713	0.2472	0.2477	0.2233	0.9783	0.1074
Petroleum	0.1750	0.9944	1.0000	0.1891	0.7754	0.2457	0.2447	0.2252	0.9842	0.1100
Grains	0.0340	0.1918	0.1891	1.0000	0.1526	0.1205	0.1412	0.1109	0.1827	0.0976
Gasoil	0.2147	0.7713	0.7754	0.1526	1.0000	0.2469	0.2376	0.2510	0.7461	0.1049
Aluminium	0.0502	0.2472	0.2457	0.1205	0.2469	1.0000	0.4097	0.4726	0.2410	0.1494
Nickel	0.0545	0.2477	0.2447	0.1412	0.2376	0.4097	1.0000	0.4932	0.2399	0.1919
Zinc	0.0572	0.2233	0.2252	0.1109	0.2510	0.4726	0.4932	1.0000	0.2201	0.1505
Brent Crude	0.1720	0.9783	0.9842	0.1827	0.7461	0.2410	0.2399	0.2201	1.0000	0.1067
Precious Metals	-0.0435	0.1074	0.1100	0.0976	0.1049	0.1494	0.1919	0.1505	0.1067	1.0000
ARMA(1,1)-GJR(1,1)										
TTFGas	1.0000	0.1784	0.1718	0.0350	0.2152	0.0512	0.0579	0.0574	0.1694	-0.0418
Energy	0.1784	1.0000	0.9941	0.1901	0.7711	0.2477	0.2465	0.2213	0.9793	0.1076
Petroleum	0.1718	0.9941	1.0000	0.1879	0.7740	0.2465	0.2443	0.2238	0.9844	0.1096
Grains	0.0350	0.1901	0.1879	1.0000	0.1485	0.1236	0.1408	0.1092	0.1812	0.0983
Gasoil	0.2152	0.7711	0.7740	0.1485	1.0000	0.2452	0.2352	0.2486	0.7439	0.1023
Aluminium	0.0512	0.2477	0.2465	0.1236	0.2452	1.0000	0.4128	0.4748	0.2412	0.1520
Nickel	0.0579	0.2465	0.2443	0.1408	0.2352	0.4128	1.0000	0.4922	0.2388	0.1940
Zinc	0.0574	0.2213	0.2238	0.1092	0.2486	0.4748	0.4922	1.0000	0.2164	0.1488
Brent Crude	0.1694	0.9793	0.9844	0.1812	0.7439	0.2412	0.2388	0.2164	1.0000	0.1066
Precious Metals	-0.0418	0.1076	0.1096	0.0983	0.1023	0.1520	0.1940	0.1488	0.1066	1.0000

The table represents correlation matrix for the t copula. *ARMA(1,1)-GARCH(1,1)* refers to the correlation matrix computed over standardized residuals estimated from ARMA(1,1)-GARCH(1,1). *ARMA(1,1)-EGARCH(1,1)* refers to the correlation matrix computed over standardized residuals estimated from ARMA(1,1)-EGARCH(1,1). *ARMA(1,1)-GJR(1,1)* refers to the correlation matrix computed over standardized residuals estimated from ARMA(1,1)-GJR(1,1).

Table 6: TTF Natural Gas Forecasts.

	Days	**Baseline Scenario**		**Fixed Price Cap**		**Dynamic Price Cap**	
	Ahead	**FHS**	**EVT**	**FHS**	**EVT**	**FHS**	**EVT**
Mean	*1*	0.0383	0.0347	-0.4096	-0.4027	-0.0280	-0.0353
	3	0.1041	0.0995	-0.5803	-0.5785	-0.0673	-0.0725
	6	0.1817	0.1892	-0.6981	-0.6919	-0.0885	-0.0990
	9	0.2472	0.2531	-0.7431	-0.7318	-0.1088	-0.1034
	12	0.3062	0.3187	-0.7520	-0.7564	-0.0999	-0.0908
TrimMean	*1*	0.0284	0.0240	-0.3897	-0.3843	-0.0237	-0.0315
	3	0.0728	0.0723	-0.5455	-0.5488	-0.0505	-0.0550
	6	0.1265	0.1345	-0.6541	-0.6430	-0.0533	-0.0723
	9	0.1720	0.1850	-0.6949	-0.6816	-0.0670	-0.0758
	12	0.2117	0.2301	-0.6994	-0.7056	-0.0548	-0.0578
Q1	*1*	-0.1672	-0.1684	-0.5271	-0.5163	-0.1923	-0.2007
	3	-0.2396	-0.2369	-0.7129	-0.7568	-0.2965	-0.3050
	6	-0.2833	-0.2630	-0.9011	-0.8461	-0.3575	-0.3547
	9	-0.3062	-0.2896	-0.9466	-0.9255	-0.3954	-0.4081
	12	-0.3257	-0.3026	-0.9682	-0.9489	-0.4262	-0.4208
Median	*1*	0.0162	0.0150	-0.3565	-0.3640	-0.0265	-0.0301
	3	0.0438	0.0462	-0.4981	-0.5077	-0.0396	-0.0373
	6	0.0857	0.0828	-0.5853	-0.5859	-0.0358	-0.0603
	9	0.1193	0.1284	-0.6361	-0.6302	-0.0389	-0.0556
	12	0.1526	0.1694	-0.6453	-0.6437	-0.0197	-0.0357
Q3	*1*	0.2186	0.2103	-0.2466	-0.2363	0.1490	0.1426
	3	0.3649	0.3565	-0.3531	-0.3159	0.2136	0.1949
	6	0.5037	0.4980	-0.3966	-0.3861	0.2689	0.2319
	9	0.6016	0.6178	-0.4189	-0.4173	0.3019	0.2745
	12	0.6982	0.7114	-0.3947	-0.4168	0.3405	0.3346
Range	*1*	0.3858	0.3787	0.2805	0.2800	0.3413	0.3434
	3	0.6045	0.5934	0.3598	0.4409	0.5101	0.4999
	6	0.7870	0.7610	0.5045	0.4600	0.6264	0.5866
	9	0.9079	0.9074	0.5277	0.5082	0.6974	0.6826
	12	1.0239	1.0140	0.5735	0.5320	0.7667	0.7555

The table represents descriptive statistic for the compounded simulated returns over 1,3,6,9 and 12 months (results from different models have been merged). *Mean* is sample average. *TrimMean* is sample average removing 5% lower and 5% upper outliers. *Q1* is first quartile. *Median* is the second quantile. *Q3* is the third quantile. *Range* is the interquartile range, difference between *Q3* and *Q1*.

Table 7: Energy Forecasts.

	Days Ahead	Baseline Scenario FHS	Baseline Scenario EVT	Fixed Price Cap FHS	Fixed Price Cap EVT	Dynamic Price Cap FHS	Dynamic Price Cap EVT
Mean	*20*	-0.0052	-0.0058	-0.0228	-0.0305	-0.0080	-0.0087
	60	-0.0177	-0.0195	-0.0447	-0.0527	-0.0244	-0.0262
	125	-0.0408	-0.0434	-0.0810	-0.0877	-0.0468	-0.0577
	190	-0.0649	-0.0704	-0.1138	-0.1302	-0.0842	-0.0800
	250	-0.0885	-0.0961	-0.1457	-0.1534	-0.1035	-0.1000
TrimMean	*20*	-0.0019	-0.0028	-0.0178	-0.0262	-0.0050	-0.0058
	60	-0.0083	-0.0098	-0.0342	-0.0411	-0.0153	-0.0169
	125	-0.0219	-0.0251	-0.0633	-0.0697	-0.0297	-0.0363
	190	-0.0364	-0.0434	-0.0914	-0.0989	-0.0532	-0.0508
	250	-0.0532	-0.0607	-0.1156	-0.1134	-0.0673	-0.0623
Q1	*20*	-0.0538	-0.0555	-0.0748	-0.0834	-0.0545	-0.0586
	60	-0.0987	-0.1022	-0.1217	-0.1464	-0.1057	-0.1076
	125	-0.1605	-0.1636	-0.1991	-0.2192	-0.1713	-0.1695
	190	-0.2098	-0.2197	-0.2807	-0.2890	-0.2272	-0.2159
	250	-0.2654	-0.2712	-0.3208	-0.3358	-0.2762	-0.2614
Median	*20*	0.0023	0.0006	-0.0176	-0.0225	-0.0012	-0.0023
	60	0.0020	0.0015	-0.0269	-0.0293	-0.0062	-0.0048
	125	-0.0017	-0.0036	-0.0382	-0.0457	-0.0131	-0.0172
	190	-0.0110	-0.0161	-0.0504	-0.0652	-0.0266	-0.0306
	250	-0.0200	-0.0262	-0.0771	-0.0619	-0.0331	-0.0272
Q3	*20*	0.0528	0.0527	0.0404	0.0346	0.0513	0.0474
	60	0.0897	0.0891	0.0655	0.0727	0.0857	0.0787
	125	0.1308	0.1282	0.1059	0.1005	0.1264	0.1127
	190	0.1581	0.1576	0.1206	0.1186	0.1424	0.1468
	250	0.1788	0.1752	0.1384	0.1186	0.1717	0.1618
Range	*20*	0.1065	0.1082	0.1152	0.1179	0.1057	0.1059
	60	0.1884	0.1914	0.1872	0.2191	0.1914	0.1862
	125	0.2913	0.2918	0.3050	0.3197	0.2977	0.2822
	190	0.3679	0.3773	0.4013	0.4076	0.3695	0.3627
	250	0.4443	0.4463	0.4592	0.4545	0.4480	0.4232

Table 8: Petroleum Forecasts.

	Days Ahead	Baseline Scenario FHS	Baseline Scenario EVT	Fixed Price Cap FHS	Fixed Price Cap EVT	Dynamic Price Cap FHS	Dynamic Price Cap EVT
Mean	*20*	-0.0054	-0.0060	-0.0229	-0.0306	-0.0083	-0.0086
	60	-0.0189	-0.0208	-0.0455	-0.0539	-0.0258	-0.0275
	125	-0.0451	-0.0477	-0.0854	-0.0907	-0.0515	-0.0628
	190	-0.0727	-0.0783	-0.1199	-0.1355	-0.0936	-0.0887
	250	-0.0993	-0.1078	-0.1559	-0.1621	-0.1168	-0.1130
TrimMean	*20*	-0.0019	-0.0029	-0.0176	-0.0262	-0.0052	-0.0056
	60	-0.0088	-0.0107	-0.0344	-0.0418	-0.0161	-0.0176
	125	-0.0242	-0.0282	-0.0654	-0.0712	-0.0327	-0.0396
	190	-0.0413	-0.0496	-0.0966	-0.1038	-0.0592	-0.0571
	250	-0.0607	-0.0693	-0.1232	-0.1224	-0.0757	-0.0708
Q1	*20*	-0.0546	-0.0568	-0.0738	-0.0857	-0.0560	-0.0578
	60	-0.1005	-0.1064	-0.1261	-0.1517	-0.1092	-0.1102
	125	-0.1682	-0.1736	-0.2111	-0.2294	-0.1833	-0.1802
	190	-0.2227	-0.2328	-0.2867	-0.3206	-0.2423	-0.2297
	250	-0.2795	-0.2905	-0.3413	-0.3442	-0.2874	-0.2855
Median	*20*	0.0023	0.0009	-0.0163	-0.0201	-0.0013	-0.0018
	60	0.0023	0.0009	-0.0264	-0.0274	-0.0051	-0.0041
	125	-0.0019	-0.0065	-0.0397	-0.0451	-0.0128	-0.0197
	190	-0.0128	-0.0207	-0.0527	-0.0639	-0.0256	-0.0331
	250	-0.0251	-0.0297	-0.0820	-0.0702	-0.0403	-0.0319
Q3	*20*	0.0534	0.0539	0.0418	0.0364	0.0511	0.0487
	60	0.0917	0.0918	0.0692	0.0714	0.0858	0.0838
	125	0.1341	0.1315	0.1152	0.1040	0.1282	0.1180
	190	0.1607	0.1607	0.1215	0.1235	0.1463	0.1483
	250	0.1822	0.1765	0.1357	0.1226	0.1721	0.1701
Range	*20*	0.1081	0.1107	0.1157	0.1220	0.1071	0.1065
	60	0.1922	0.1982	0.1954	0.2231	0.1951	0.1940
	125	0.3023	0.3051	0.3264	0.3334	0.3115	0.2982
	190	0.3834	0.3935	0.4082	0.4440	0.3886	0.3780
	250	0.4617	0.4670	0.4769	0.4667	0.4595	0.4557

Table 9: Grains Forecasts.

	Days Ahead	**Baseline Scenario FHS**	**Baseline Scenario EVT**	**Fixed Price Cap FHS**	**Fixed Price Cap EVT**	**Dynamic Price Cap FHS**	**Dynamic Price Cap EVT**
Mean	*20*	0.0039	0.0041	-0.0008	0.0026	0.0023	0.0044
	60	0.0106	0.0102	0.0012	0.0122	0.0064	0.0098
	125	0.0223	0.0224	0.0048	0.0280	0.0154	0.0214
	190	0.0329	0.0326	0.0179	0.0401	0.0250	0.0329
	250	0.0429	0.0424	0.0238	0.0439	0.0334	0.0434
TrimMean	*20*	0.0033	0.0038	-0.0011	0.0018	0.0016	0.0038
	60	0.0094	0.0093	0.0002	0.0114	0.0044	0.0085
	125	0.0202	0.0208	0.0043	0.0255	0.0133	0.0204
	190	0.0306	0.0302	0.0175	0.0376	0.0228	0.0306
	250	0.0399	0.0399	0.0206	0.0409	0.0293	0.0417
Q1	*20*	-0.0364	-0.0368	-0.0397	-0.0373	-0.0373	-0.0368
	60	-0.0590	-0.0588	-0.0655	-0.0565	-0.0641	-0.0591
	125	-0.0763	-0.0766	-0.0929	-0.0595	-0.0847	-0.0738
	190	-0.0886	-0.0889	-0.0982	-0.0768	-0.1026	-0.0858
	250	-0.0988	-0.0980	-0.1116	-0.0828	-0.1125	-0.0936
Median	*20*	0.0026	0.0030	-0.0014	0.0021	0.0001	0.0035
	60	0.0076	0.0076	0.0008	0.0099	0.0029	0.0067
	125	0.0173	0.0189	0.0063	0.0247	0.0114	0.0192
	190	0.0253	0.0278	0.0124	0.0348	0.0164	0.0313
	250	0.0353	0.0369	0.0225	0.0371	0.0225	0.0410
Q3	*20*	0.0430	0.0437	0.0362	0.0406	0.0401	0.0438
	60	0.0757	0.0771	0.0636	0.0785	0.0679	0.0743
	125	0.1144	0.1159	0.0975	0.1194	0.1087	0.1161
	190	0.1508	0.1475	0.1397	0.1432	0.1469	0.1472
	250	0.1775	0.1756	0.1450	0.1683	0.1708	0.1750
Range	*20*	0.0793	0.0805	0.0758	0.0778	0.0773	0.0806
	60	0.1347	0.1359	0.1291	0.1350	0.1320	0.1334
	125	0.1907	0.1925	0.1904	0.1788	0.1933	0.1899
	190	0.2394	0.2364	0.2379	0.2199	0.2495	0.2330
	250	0.2763	0.2737	0.2566	0.2511	0.2833	0.2686

Table 10: Gasoil Forecasts.

	Days Ahead	**Baseline Scenario**		**Fixed Price Cap**		**Dynamic Price Cap**	
		FHS	**EVT**	**FHS**	**EVT**	**FHS**	**EVT**
Mean	*20*	-0.0050	-0.0046	-0.0356	-0.0408	-0.0117	-0.0103
	60	-0.0228	-0.0235	-0.0753	-0.0729	-0.0403	-0.0390
	125	-0.0538	-0.0533	-0.1319	-0.1262	-0.0681	-0.0725
	190	-0.0786	-0.0818	-0.1670	-0.1657	-0.1039	-0.1044
	250	-0.1040	-0.1071	-0.1884	-0.1993	-0.1222	-0.1254
TrimMean	*20*	-0.0018	-0.0016	-0.0318	-0.0377	-0.0083	-0.0070
	60	-0.0139	-0.0137	-0.0659	-0.0643	-0.0301	-0.0287
	125	-0.0351	-0.0342	-0.1097	-0.1062	-0.0497	-0.0515
	190	-0.0529	-0.0559	-0.1382	-0.1371	-0.0741	-0.0751
	250	-0.0724	-0.0756	-0.1513	-0.1627	-0.0870	-0.0932
Q1	*20*	-0.0790	-0.0793	-0.1077	-0.1221	-0.0837	-0.0837
	60	-0.1451	-0.1451	-0.2119	-0.2055	-0.1615	-0.1615
	125	-0.2193	-0.2185	-0.2959	-0.2875	-0.2280	-0.2311
	190	-0.2763	-0.2762	-0.3721	-0.3527	-0.2941	-0.2848
	250	-0.3264	-0.3273	-0.4137	-0.4115	-0.3329	-0.3371
Median	*20*	0.0030	0.0028	-0.0253	-0.0289	-0.0010	-0.0017
	60	-0.0035	-0.0022	-0.0500	-0.0444	-0.0213	-0.0146
	125	-0.0135	-0.0148	-0.0814	-0.0872	-0.0300	-0.0309
	190	-0.0240	-0.0302	-0.0981	-0.1048	-0.0417	-0.0518
	250	-0.0407	-0.0450	-0.1295	-0.1228	-0.0563	-0.0598
Q3	*20*	0.0763	0.0784	0.0446	0.0503	0.0687	0.0735
	60	0.1250	0.1255	0.0757	0.0824	0.1077	0.1154
	125	0.1619	0.1607	0.1026	0.1039	0.1447	0.1420
	190	0.1878	0.1869	0.1258	0.1219	0.1549	0.1516
	250	0.2021	0.2012	0.1319	0.1317	0.1730	0.1745
Range	*20*	0.1553	0.1577	0.1523	0.1725	0.1524	0.1572
	60	0.2701	0.2706	0.2877	0.2879	0.2692	0.2769
	125	0.3813	0.3792	0.3985	0.3914	0.3728	0.3732
	190	0.4641	0.4631	0.4979	0.4746	0.4490	0.4363
	250	0.5285	0.5285	0.5456	0.5432	0.5059	0.5115

Table 11: Aluminum Forecasts.

	Days Ahead	**Baseline Scenario FHS**	**Baseline Scenario EVT**	**Fixed Price Cap FHS**	**Fixed Price Cap EVT**	**Dynamic Price Cap FHS**	**Dynamic Price Cap EVT**
Mean	*20*	0.0050	0.0044	0.0003	0.0040	0.0049	0.0038
	60	0.0126	0.0115	0.0058	0.0102	0.0118	0.0086
	125	0.0241	0.0247	0.0208	0.0208	0.0235	0.0225
	190	0.0364	0.0371	0.0367	0.0285	0.0344	0.0318
	250	0.0467	0.0491	0.0434	0.0403	0.0450	0.0459
TrimMean	*20*	0.0040	0.0031	-0.0009	0.0023	0.0036	0.0027
	60	0.0107	0.0092	0.0061	0.0093	0.0106	0.0070
	125	0.0213	0.0214	0.0199	0.0189	0.0207	0.0203
	190	0.0336	0.0337	0.0348	0.0279	0.0314	0.0296
	250	0.0433	0.0457	0.0427	0.0398	0.0414	0.0427
Q1	*20*	-0.0550	-0.0564	-0.0552	-0.0599	-0.0565	-0.0583
	60	-0.0814	-0.0826	-0.0958	-0.0855	-0.0784	-0.0859
	125	-0.0984	-0.0970	-0.1119	-0.1108	-0.0991	-0.0934
	190	-0.1047	-0.1053	-0.1059	-0.1110	-0.1042	-0.1046
	250	-0.1080	-0.1074	-0.1112	-0.1164	-0.1061	-0.1080
Median	*20*	0.0016	0.0015	-0.0072	0.0009	0.0016	0.0036
	60	0.0069	0.0075	0.0035	0.0082	0.0051	0.0058
	125	0.0163	0.0178	0.0179	0.0137	0.0172	0.0160
	190	0.0282	0.0293	0.0244	0.0223	0.0227	0.0300
	250	0.0371	0.0416	0.0325	0.0445	0.0304	0.0394
Q3	*20*	0.0627	0.0613	0.0554	0.0603	0.0610	0.0603
	60	0.1012	0.0981	0.1025	0.1023	0.0985	0.0966
	125	0.1372	0.1379	0.1487	0.1501	0.1353	0.1308
	190	0.1684	0.1690	0.1756	0.1708	0.1661	0.1567
	250	0.1929	0.1963	0.1859	0.1997	0.1891	0.1900
Range	*20*	0.1178	0.1177	0.1106	0.1203	0.1175	0.1186
	60	0.1826	0.1808	0.1983	0.1878	0.1769	0.1825
	125	0.2356	0.2349	0.2606	0.2608	0.2343	0.2242
	190	0.2732	0.2743	0.2815	0.2817	0.2703	0.2613
	250	0.3008	0.3038	0.2971	0.3160	0.2952	0.2981

Table 12: Nickel Forecasts.

	Days Ahead	Baseline Scenario FHS	Baseline Scenario EVT	Fixed Price Cap FHS	Fixed Price Cap EVT	Dynamic Price Cap FHS	Dynamic Price Cap EVT
Mean	*20*	0.0053	0.0046	-0.0050	-0.0007	0.0037	0.0044
	60	0.0195	0.0156	0.0058	0.0065	0.0179	0.0130
	125	0.0417	0.0369	0.0221	0.0154	0.0355	0.0307
	190	0.0654	0.0560	0.0399	0.0341	0.0578	0.0473
	250	0.0846	0.0751	0.0524	0.0646	0.0735	0.0670
TrimMean	*20*	0.0035	0.0039	-0.0068	-0.0006	0.0019	0.0046
	60	0.0159	0.0145	0.0029	0.0055	0.0140	0.0125
	125	0.0366	0.0359	0.0191	0.0157	0.0303	0.0297
	190	0.0595	0.0551	0.0375	0.0345	0.0518	0.0472
	250	0.0781	0.0744	0.0448	0.0673	0.0676	0.0667
Q1	*20*	-0.0651	-0.0643	-0.0823	-0.0689	-0.0658	-0.0614
	60	-0.0943	-0.0944	-0.1156	-0.0952	-0.0973	-0.0914
	125	-0.1180	-0.1158	-0.1562	-0.1407	-0.1256	-0.1209
	190	-0.1278	-0.1278	-0.1563	-0.1465	-0.1405	-0.1385
	250	-0.1315	-0.1301	-0.1836	-0.1443	-0.1393	-0.1366
Median	*20*	0.0037	0.0031	-0.0087	-0.0009	0.0015	0.0055
	60	0.0152	0.0134	0.0055	0.0023	0.0128	0.0099
	125	0.0332	0.0341	0.0171	0.0101	0.0299	0.0300
	190	0.0543	0.0532	0.0479	0.0238	0.0505	0.0491
	250	0.0695	0.0735	0.0353	0.0673	0.0602	0.0674
Q3	*20*	0.0717	0.0720	0.0644	0.0671	0.0705	0.0722
	60	0.1220	0.1215	0.1152	0.1108	0.1218	0.1170
	125	0.1887	0.1895	0.1882	0.1647	0.1838	0.1809
	190	0.2415	0.2369	0.2254	0.2192	0.2419	0.2370
	250	0.2868	0.2783	0.2538	0.2785	0.2772	0.2718
Range	*20*	0.1368	0.1364	0.1467	0.1361	0.1362	0.1336
	60	0.2163	0.2158	0.2307	0.2060	0.2191	0.2084
	125	0.3068	0.3053	0.3444	0.3054	0.3094	0.3018
	190	0.3693	0.3647	0.3818	0.3658	0.3824	0.3755
	250	0.4183	0.4084	0.4374	0.4229	0.4164	0.4084

Table 13: Zinc Forecasts.

	Days Ahead	**Baseline Scenario** FHS	**Baseline Scenario** EVT	**Fixed Price Cap** FHS	**Fixed Price Cap** EVT	**Dynamic Price Cap** FHS	**Dynamic Price Cap** EVT
Mean	*20*	0.0036	0.0039	-0.0016	-0.0003	0.0013	0.0056
	60	0.0103	0.0123	0.0071	0.0026	0.0065	0.0123
	125	0.0244	0.0272	0.0191	0.0095	0.0220	0.0235
	190	0.0402	0.0416	0.0393	0.0216	0.0355	0.0403
	250	0.0537	0.0553	0.0477	0.0361	0.0473	0.0545
TrimMean	*20*	0.0038	0.0041	-0.0009	-0.0013	0.0019	0.0061
	60	0.0111	0.0132	0.0088	0.0023	0.0080	0.0127
	125	0.0258	0.0281	0.0210	0.0113	0.0249	0.0254
	190	0.0418	0.0426	0.0401	0.0214	0.0376	0.0430
	250	0.0550	0.0566	0.0494	0.0375	0.0502	0.0567
Q1	*20*	-0.0580	-0.0564	-0.0717	-0.0616	-0.0596	-0.0518
	60	-0.0904	-0.0871	-0.0951	-0.0966	-0.0936	-0.0888
	125	-0.1080	-0.1073	-0.1105	-0.1337	-0.1105	-0.1116
	190	-0.1176	-0.1178	-0.1236	-0.1486	-0.1241	-0.1182
	250	-0.1248	-0.1222	-0.1550	-0.1479	-0.1268	-0.1197
Median	*20*	0.0033	0.0042	-0.0003	-0.0032	0.0019	0.0072
	60	0.0128	0.0151	0.0144	0.0077	0.0131	0.0157
	125	0.0283	0.0297	0.0213	0.0144	0.0267	0.0278
	190	0.0420	0.0442	0.0424	0.0208	0.0419	0.0544
	250	0.0571	0.0608	0.0602	0.0390	0.0515	0.0650
Q3	*20*	0.0658	0.0655	0.0674	0.0600	0.0632	0.0674
	60	0.1129	0.1137	0.1181	0.1002	0.1075	0.1145
	125	0.1604	0.1665	0.1525	0.1496	0.1591	0.1688
	190	0.2022	0.2046	0.2065	0.1812	0.2022	0.2069
	250	0.2368	0.2387	0.2609	0.2219	0.2376	0.2364
Range	*20*	0.1238	0.1219	0.1392	0.1216	0.1228	0.1192
	60	0.2033	0.2008	0.2131	0.1968	0.2011	0.2033
	125	0.2685	0.2739	0.2630	0.2834	0.2696	0.2803
	190	0.3198	0.3224	0.3301	0.3298	0.3263	0.3251
	250	0.3616	0.3610	0.4159	0.3699	0.3644	0.3561

Table 14: Brent crude oil Forecasts.

	Days Ahead	**Baseline Scenario** FHS	**Baseline Scenario** EVT	**Fixed Price Cap** FHS	**Fixed Price Cap** EVT	**Dynamic Price Cap** FHS	**Dynamic Price Cap** EVT
Mean	*20*	-0.0070	-0.0075	-0.0252	-0.0319	-0.0097	-0.0099
	60	-0.0194	-0.0209	-0.0465	-0.0551	-0.0267	-0.0270
	125	-0.0426	-0.0451	-0.0823	-0.0905	-0.0488	-0.0592
	190	-0.0673	-0.0715	-0.1142	-0.1337	-0.0868	-0.0805
	250	-0.0909	-0.0974	-0.1484	-0.1576	-0.1097	-0.1013
TrimMean	*20*	-0.0036	-0.0046	-0.0201	-0.0280	-0.0068	-0.0071
	60	-0.0102	-0.0117	-0.0351	-0.0440	-0.0175	-0.0179
	125	-0.0235	-0.0272	-0.0628	-0.0721	-0.0321	-0.0376
	190	-0.0380	-0.0450	-0.0924	-0.1016	-0.0545	-0.0506
	250	-0.0552	-0.0624	-0.1160	-0.1173	-0.0705	-0.0626
Q1	*20*	-0.0570	-0.0596	-0.0790	-0.0878	-0.0600	-0.0620
	60	-0.1042	-0.1078	-0.1262	-0.1553	-0.1127	-0.1101
	125	-0.1670	-0.1713	-0.1936	-0.2313	-0.1791	-0.1745
	190	-0.2190	-0.2256	-0.2624	-0.3132	-0.2402	-0.2222
	250	-0.2729	-0.2808	-0.3456	-0.3360	-0.2847	-0.2688
Median	*20*	-0.0001	-0.0009	-0.0166	-0.0257	-0.0028	-0.0035
	60	0.0004	-0.0011	-0.0241	-0.0299	-0.0064	-0.0080
	125	-0.0034	-0.0063	-0.0410	-0.0493	-0.0144	-0.0166
	190	-0.0111	-0.0148	-0.0549	-0.0633	-0.0280	-0.0248
	250	-0.0200	-0.0263	-0.0710	-0.0740	-0.0378	-0.0266
Q3	*20*	0.0531	0.0531	0.0408	0.0382	0.0507	0.0461
	60	0.0919	0.0909	0.0652	0.0710	0.0842	0.0824
	125	0.1333	0.1335	0.1067	0.1043	0.1278	0.1171
	190	0.1618	0.1610	0.1171	0.1191	0.1447	0.1460
	250	0.1821	0.1797	0.1379	0.1313	0.1690	0.1683
Range	*20*	0.1101	0.1127	0.1198	0.1260	0.1108	0.1081
	60	0.1961	0.1987	0.1914	0.2263	0.1969	0.1925
	125	0.3003	0.3049	0.3004	0.3356	0.3069	0.2916
	190	0.3808	0.3866	0.3795	0.4323	0.3849	0.3682
	250	0.4549	0.4605	0.4835	0.4673	0.4537	0.4371

Table 15: Precious Metals Forecasts.

	Days Ahead	**Baseline Scenario** FHS	**Baseline Scenario** EVT	**Fixed Price Cap** FHS	**Fixed Price Cap** EVT	**Dynamic Price Cap** FHS	**Dynamic Price Cap** EVT
Mean	*20*	-0.0003	0.0004	0.0006	0.0035	0.0007	0.0022
	60	0.0028	0.0029	0.0103	0.0048	0.0054	0.0048
	125	0.0080	0.0077	0.0184	0.0112	0.0116	0.0120
	190	0.0120	0.0117	0.0224	0.0157	0.0143	0.0182
	250	0.0156	0.0156	0.0235	0.0222	0.0201	0.0259
TrimMean	*20*	-0.0002	0.0005	0.0005	0.0032	0.0008	0.0020
	60	0.0025	0.0027	0.0096	0.0055	0.0055	0.0043
	125	0.0076	0.0070	0.0176	0.0103	0.0112	0.0110
	190	0.0111	0.0108	0.0207	0.0148	0.0138	0.0173
	250	0.0147	0.0146	0.0218	0.0206	0.0195	0.0247
Q1	*20*	-0.0307	-0.0300	-0.0300	-0.0287	-0.0293	-0.0279
	60	-0.0495	-0.0496	-0.0441	-0.0485	-0.0472	-0.0476
	125	-0.0676	-0.0669	-0.0664	-0.0613	-0.0634	-0.0620
	190	-0.0808	-0.0809	-0.0782	-0.0795	-0.0767	-0.0704
	250	-0.0893	-0.0888	-0.0951	-0.0839	-0.0869	-0.0810
Median	*20*	-0.0002	0.0009	-0.0009	0.0014	0.0003	0.0026
	60	0.0017	0.0027	0.0100	0.0049	0.0056	0.0024
	125	0.0079	0.0062	0.0176	0.0054	0.0118	0.0081
	190	0.0093	0.0097	0.0174	0.0160	0.0125	0.0140
	250	0.0132	0.0146	0.0159	0.0236	0.0186	0.0246
Q3	*20*	0.0303	0.0306	0.0342	0.0361	0.0312	0.0305
	60	0.0553	0.0542	0.0654	0.0560	0.0595	0.0546
	125	0.0814	0.0804	0.1028	0.0831	0.0832	0.0840
	190	0.1019	0.1007	0.1184	0.0986	0.1038	0.1062
	250	0.1167	0.1161	0.1413	0.1174	0.1207	0.1262
Range	*20*	0.0609	0.0607	0.0642	0.0648	0.0605	0.0585
	60	0.1048	0.1038	0.1095	0.1045	0.1067	0.1022
	125	0.1490	0.1473	0.1692	0.1444	0.1466	0.1459
	190	0.1826	0.1816	0.1965	0.1781	0.1805	0.1766
	250	0.2060	0.2049	0.2364	0.2014	0.2076	0.2072

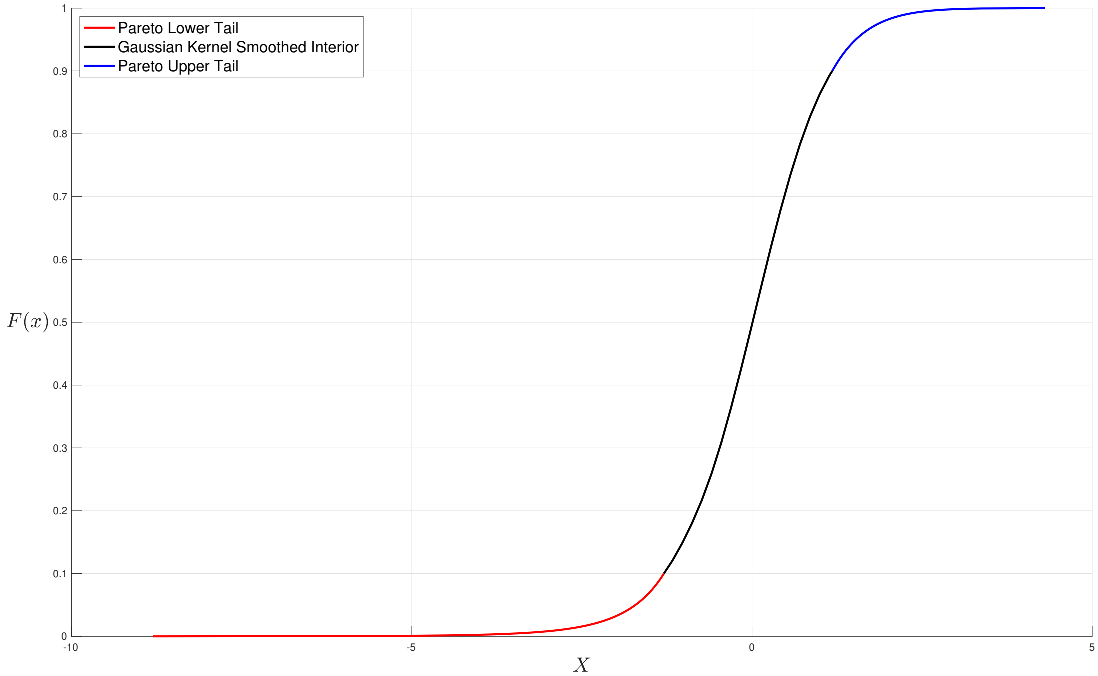
Table 16: Estimated and Forecasted Conditional Volatility.

	TTF	En	Pet	Gr	Gl	Al	Ni	Zi	Br	PM
historical										
Mean	0.0339	0.0213	0.0223	0.0126	0.0204	0.0119	0.0196	0.0150	0.0226	0.0100
TrimMean	0.0307	0.0197	0.0206	0.0123	0.0192	0.0115	0.0188	0.0148	0.0212	0.0098
Q1	0.0175	0.0143	0.0148	0.0104	0.0141	0.0099	0.0171	0.0130	0.0151	0.0083
Median	0.0251	0.0185	0.0192	0.0119	0.0178	0.0110	0.0183	0.0143	0.0199	0.0096
Q3	0.0405	0.0247	0.0258	0.0140	0.0231	0.0128	0.0200	0.0166	0.0267	0.0109
Range	0.0230	0.0104	0.0111	0.0037	0.0091	0.0029	0.0029	0.0036	0.0117	0.0026
baseline scenario FHS										
Mean	0.0499	0.0219	0.0228	0.0130	0.0244	0.0140	0.0202	0.0173	0.0237	0.0106
TrimMean	0.0418	0.0198	0.0206	0.0127	0.0227	0.0137	0.0197	0.0171	0.0214	0.0105
Q1	0.0220	0.0140	0.0145	0.0105	0.0158	0.0109	0.0174	0.0145	0.0150	0.0092
Median	0.0349	0.0181	0.0186	0.0123	0.0212	0.0130	0.0190	0.0168	0.0195	0.0104
Q3	0.0583	0.0243	0.0252	0.0145	0.0281	0.0164	0.0216	0.0196	0.0262	0.0116
Range	0.0363	0.0102	0.0108	0.0040	0.0123	0.0055	0.0043	0.0051	0.0111	0.0024
baseline scenario EVT										
Mean	0.0495	0.0222	0.0233	0.0130	0.0247	0.0141	0.0201	0.0173	0.0240	0.0106
TrimMean	0.0416	0.0202	0.0210	0.0127	0.0229	0.0138	0.0197	0.0171	0.0218	0.0105
Q1	0.0221	0.0142	0.0148	0.0106	0.0160	0.0109	0.0174	0.0145	0.0153	0.0093
Median	0.0349	0.0184	0.0191	0.0124	0.0215	0.0131	0.0190	0.0168	0.0199	0.0104
Q3	0.0579	0.0247	0.0259	0.0146	0.0284	0.0164	0.0217	0.0197	0.0267	0.0116
Range	0.0358	0.0105	0.0111	0.0040	0.0124	0.0055	0.0043	0.0051	0.0114	0.0024
Fixed Price Cap FHS										
Mean	0.0364	0.0224	0.0234	0.0128	0.0250	0.0141	0.0202	0.0173	0.0242	0.0106
TrimMean	0.0336	0.0203	0.0211	0.0125	0.0229	0.0138	0.0197	0.0171	0.0219	0.0105
Q1	0.0193	0.0142	0.0146	0.0104	0.0157	0.0109	0.0174	0.0145	0.0152	0.0092
Median	0.0287	0.0183	0.0189	0.0122	0.0213	0.0131	0.0190	0.0169	0.0197	0.0104
Q3	0.0457	0.0250	0.0260	0.0143	0.0286	0.0165	0.0217	0.0197	0.0268	0.0116
Range	0.0263	0.0108	0.0114	0.0039	0.0129	0.0056	0.0043	0.0051	0.0116	0.0024
Fixed Price Cap EVT										
Mean	0.0364	0.0226	0.0235	0.0129	0.0254	0.0141	0.0201	0.0173	0.0243	0.0106
TrimMean	0.0334	0.0205	0.0213	0.0126	0.0237	0.0138	0.0197	0.0171	0.0221	0.0105
Q1	0.0193	0.0144	0.0149	0.0106	0.0164	0.0109	0.0174	0.0146	0.0155	0.0092
Median	0.0283	0.0187	0.0193	0.0123	0.0223	0.0131	0.0190	0.0168	0.0202	0.0104
Q3	0.0454	0.0252	0.0263	0.0144	0.0295	0.0163	0.0216	0.0197	0.0274	0.0116
Range	0.0261	0.0109	0.0115	0.0039	0.0131	0.0054	0.0042	0.0051	0.0119	0.0024
Dynamic Price Cap FHS										
Mean	0.0269	0.0216	0.0226	0.0128	0.0242	0.0139	0.0201	0.0173	0.0235	0.0106
TrimMean	0.0251	0.0194	0.0202	0.0125	0.0222	0.0136	0.0195	0.0171	0.0210	0.0105
Q1	0.0163	0.0137	0.0141	0.0104	0.0154	0.0108	0.0173	0.0145	0.0147	0.0092
Median	0.0214	0.0177	0.0182	0.0122	0.0207	0.0129	0.0188	0.0168	0.0190	0.0104
Q3	0.0313	0.0237	0.0246	0.0143	0.0275	0.0161	0.0214	0.0197	0.0256	0.0116
Range	0.0150	0.0100	0.0105	0.0038	0.0121	0.0053	0.0040	0.0052	0.0109	0.0024
Dynamic Price Cap EVT										
Mean	0.0270	0.0217	0.0227	0.0129	0.0243	0.0138	0.0199	0.0173	0.0235	0.0105
TrimMean	0.0252	0.0199	0.0207	0.0126	0.0224	0.0135	0.0195	0.0171	0.0214	0.0104
Q1	0.0163	0.0140	0.0145	0.0105	0.0156	0.0107	0.0173	0.0145	0.0150	0.0092
Median	0.0214	0.0181	0.0188	0.0123	0.0209	0.0128	0.0188	0.0168	0.0195	0.0103
Q3	0.0315	0.0244	0.0255	0.0144	0.0277	0.0159	0.0213	0.0196	0.0263	0.0115
Range	0.0152	0.0104	0.0110	0.0039	0.0121	0.0052	0.0040	0.0052	0.0113	0.0024

The table represents statistics for estimated and forecasted conditional volatility (results from different models have been merged). *Mean* is sample daily average. *TrimMean* is sample daily average removing 5% lower and 5% upper outliers. *Q1* is first quartile. *Median* is the second quantile. *Q3* is the third quantile. *Range* is the interquartile range, difference between *Q3* and *Q1*. *TTF* is Dutch TTF Gas, *En* is *Energy*, *Gr* is *Grains*, *Gl* is *Gasoil*, *Al* is *Aluminum*, *Ni* is *Nickel*, *Zi* is *Zinc*, *Br* is *Brent crude oil* and *PM* are *Precious Metals*.

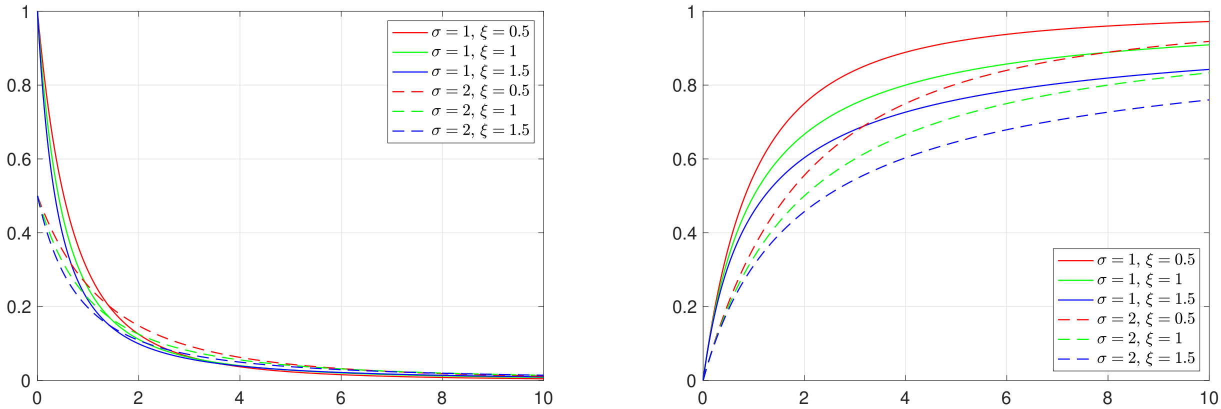
D Figures

Figure 1: Piece-wise CDF



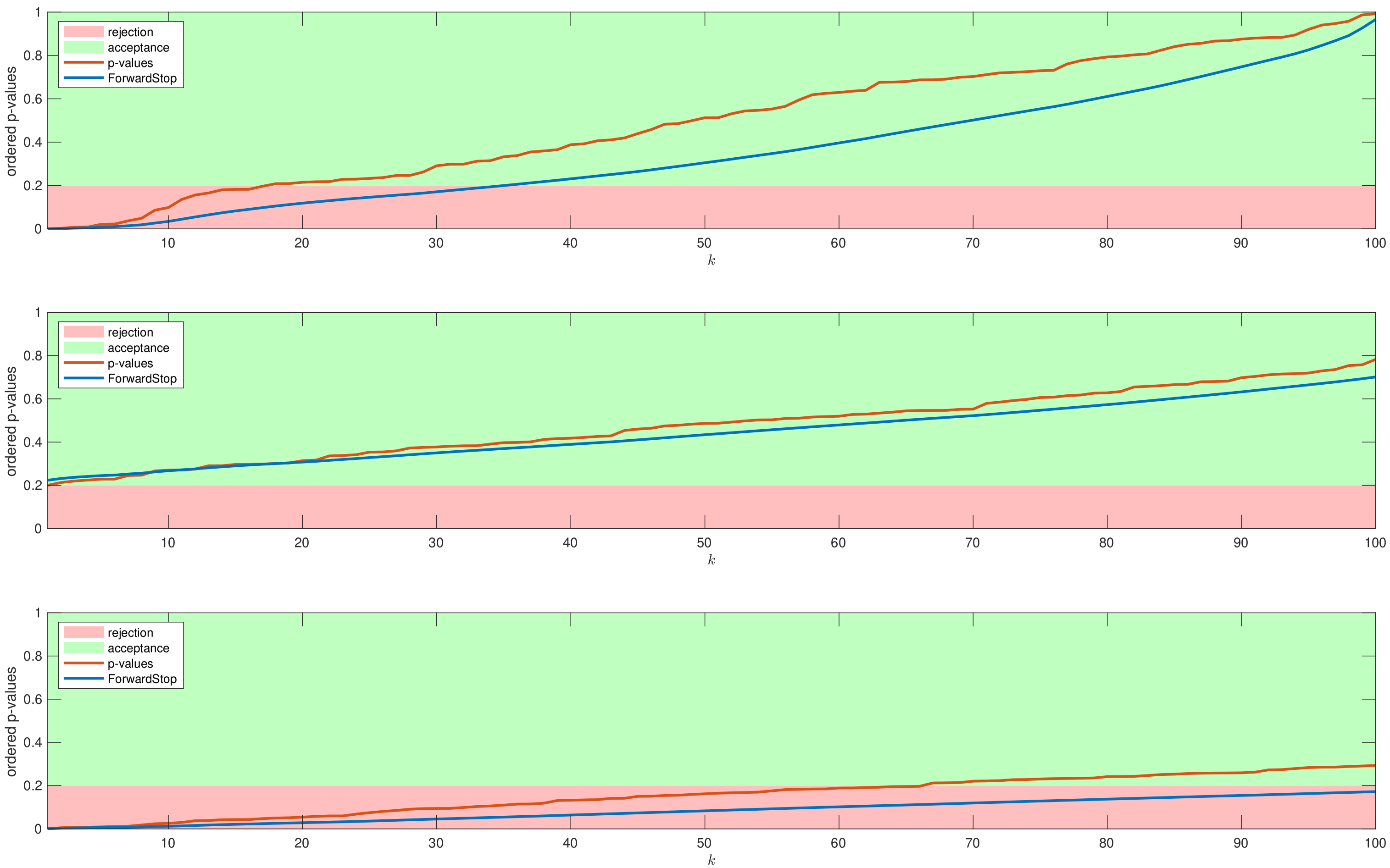
Sample CDF of a simulated Student-t random variable fitted using a Gaussian kernel estimate for the interior and a GPD estimate for the upper and lower tails. Threshold has been selected according to a fixed percentile rule.

Figure 2: GPD PDF and CDF



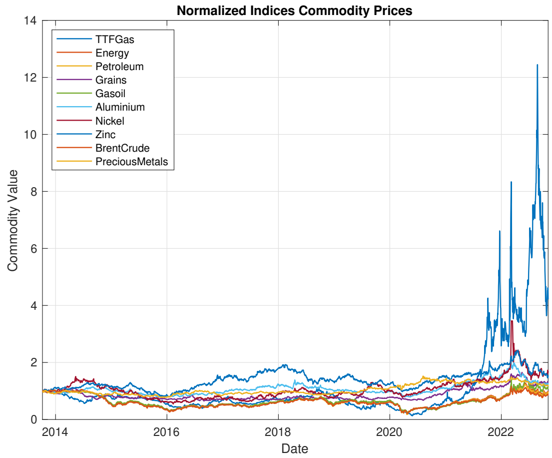
GPD probability density and CDFs for $u = 0$ and different values of σ and ξ.

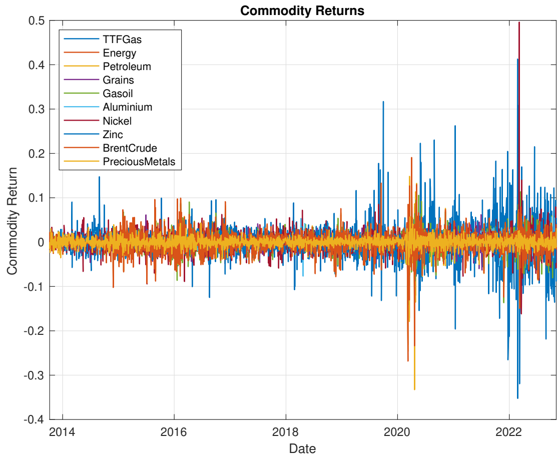
Figure 3: ForwardStop algorithm for simulated p-values.



x-axis = ordered statistics, y-axis = Anderson-Darling p-values. Orange line corresponds to the simulated ordered p-values. Blue line is ForwardStop accumulation formula. $\alpha = 0.20$. The first plot gives $\hat{k} \in (1, K)$: the null hypothesis is not rejected only for $K > k > \hat{k}$. The second plot displays the case of acceptance of the complete set of null hypotheses, i.e., the GPD fits all the data and the threshold is the minimum observation. The third plot displays the case of rejection of the complete set of null hypotheses, i.e the GPD does not fit the data at level α.

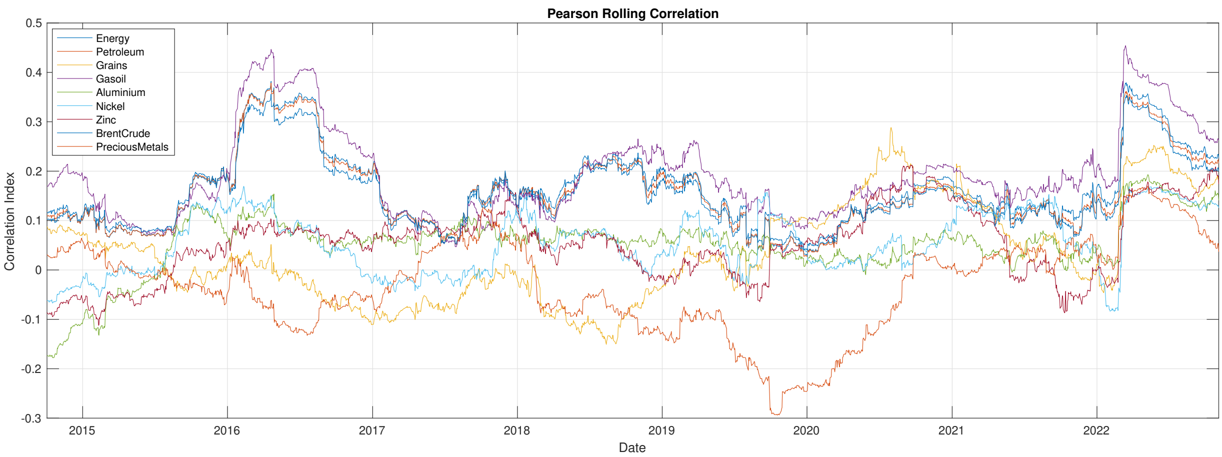
Figure 4: Relative price movements of each commodity and returns plot.





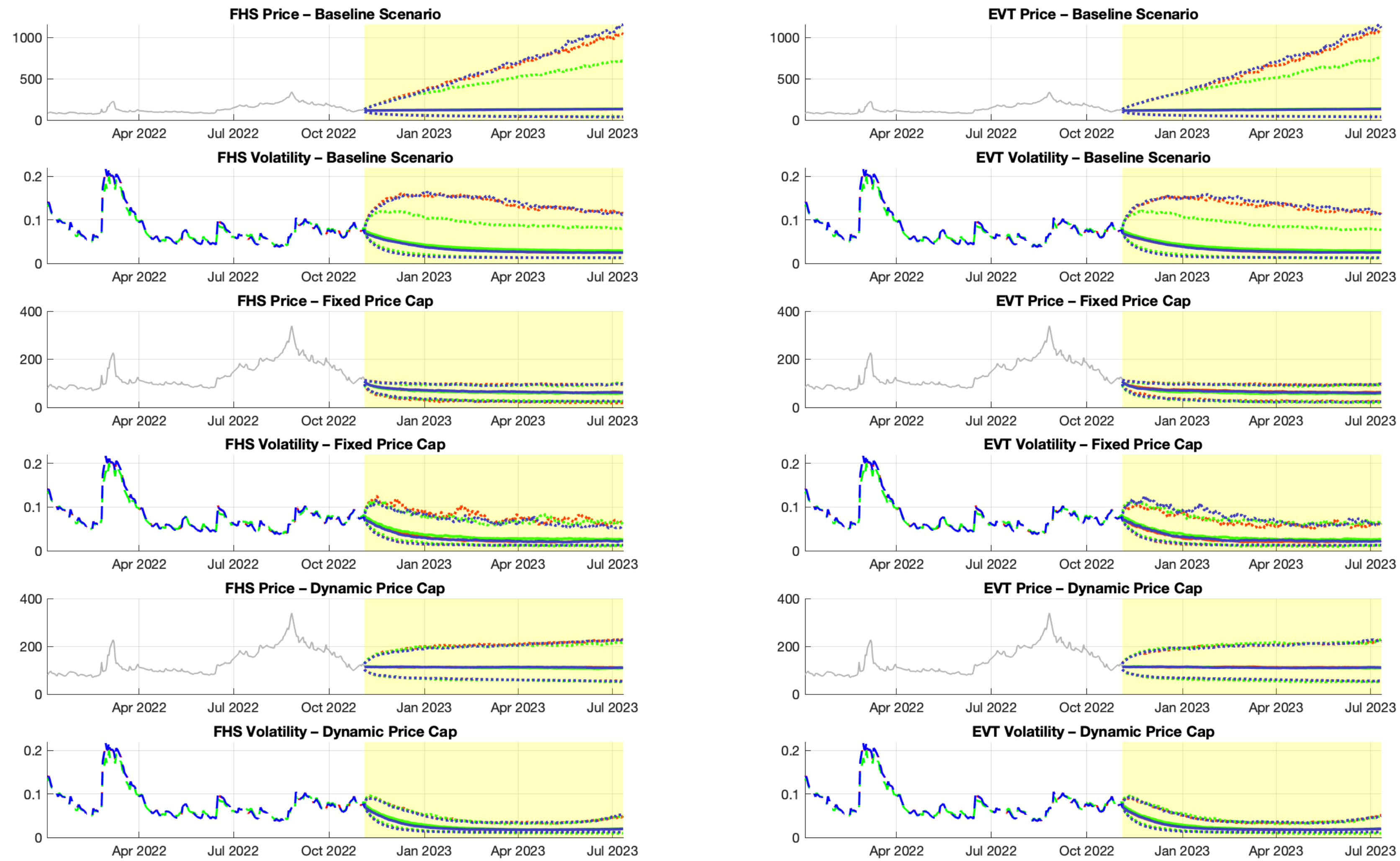
In the right plot the initial level of each commodity has been normalized to unity to facilitate the comparison of relative performance.

Figure 5: Rolling Pearson correlation.



The plot shows rolling Pearson correlation coefficient of *TTFGas* with other commodities: starting from day 250 each day a new observation is added and an old observation is dropped from the calculation.

Figure 6: TTF Natural Gas



The plots show forecasts for the selected commodity prices. The gray solid line correspond to historical observed returns. The yellow area correspond to the forecasting horizon. The red lines are for ARMA(1,1)-GARCH(1,1). The green lines are for ARMA(1,1)-EGARCH(1,1). The blue lines are for ARMA(1,1)-GJR(1,1). Dotted lines represent 0.05 and 0.95 percentiles. Colored solid lines represent the median.

Figure 7: Energy

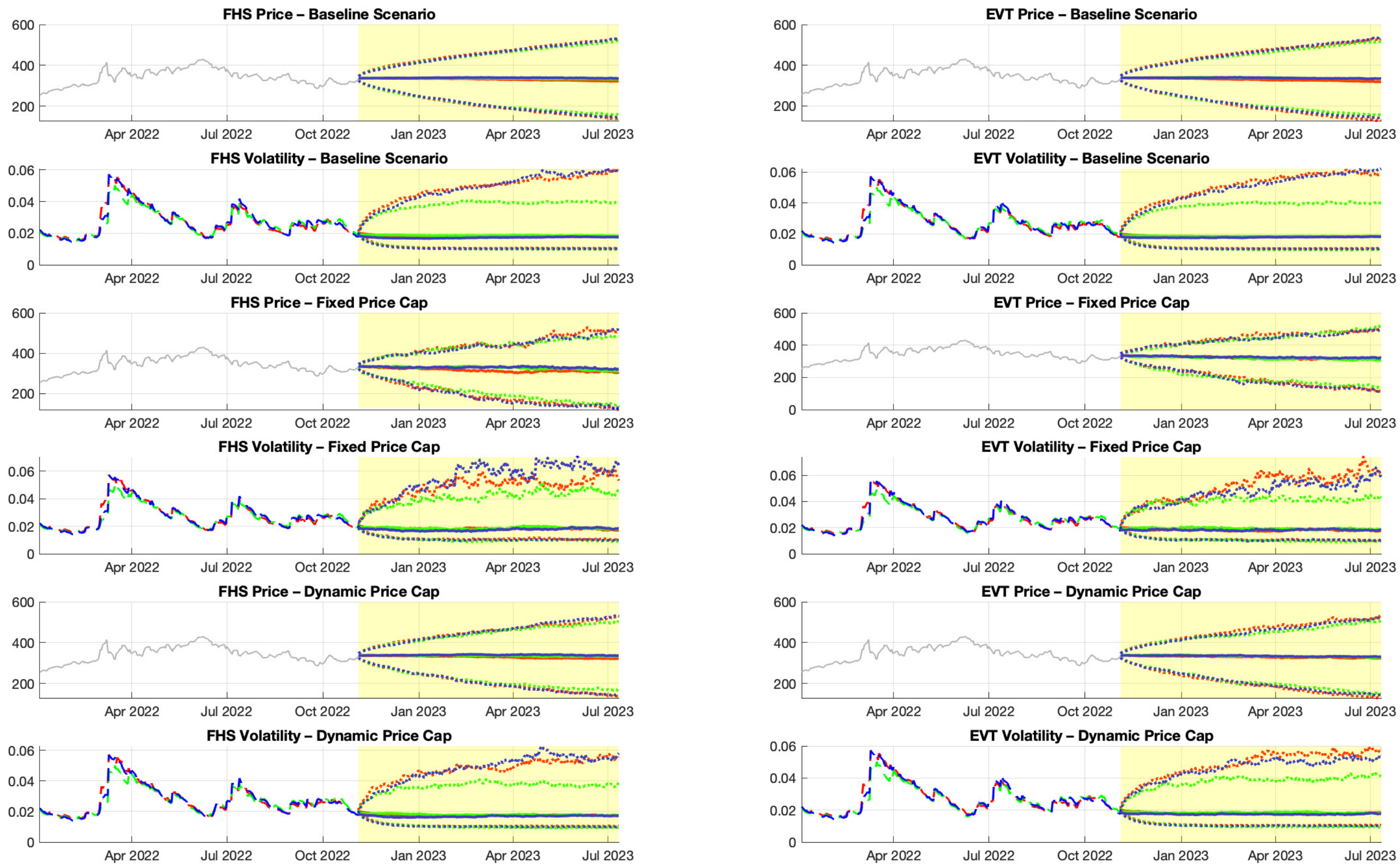


Figure 8: Petroleum

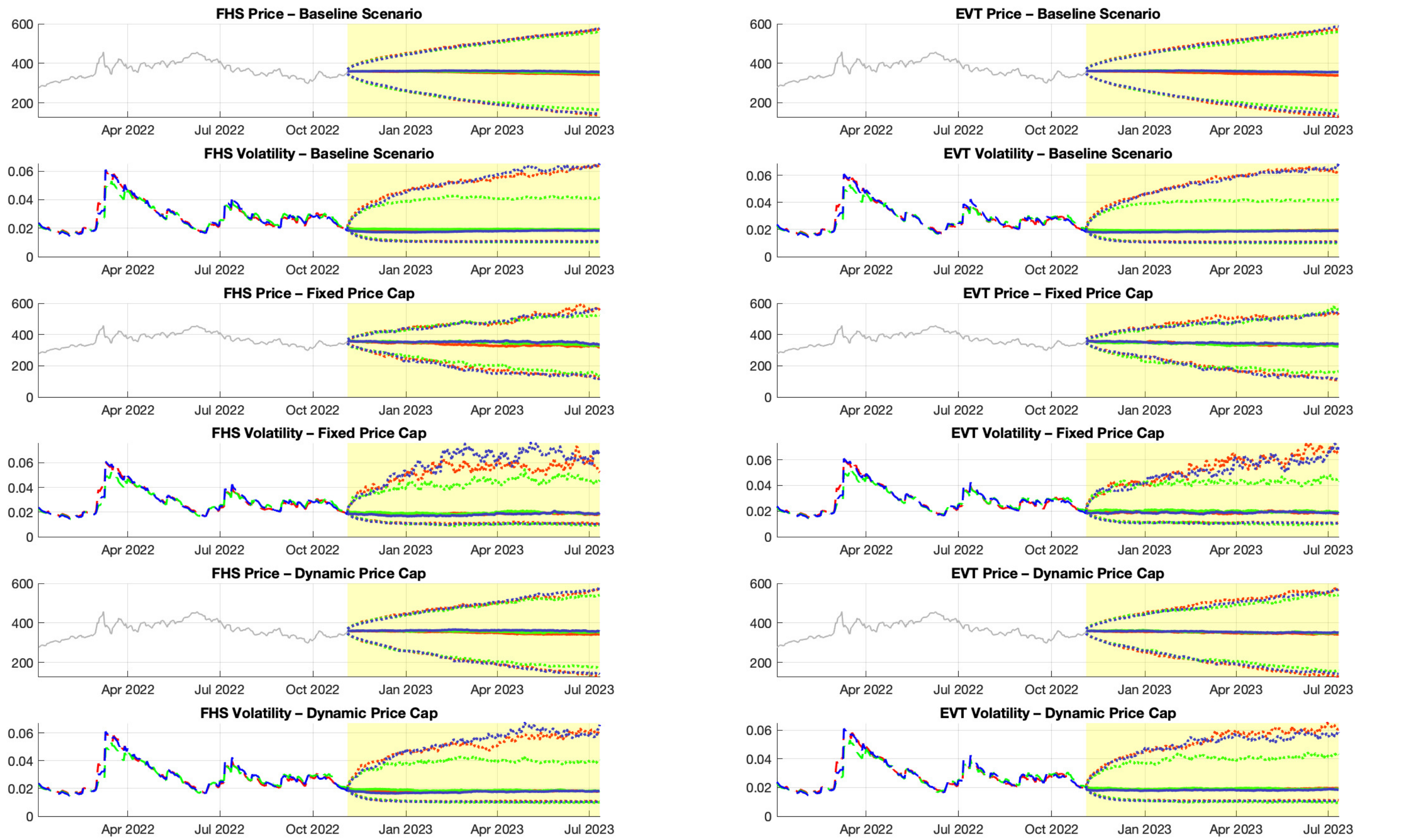


Figure 9: Grains

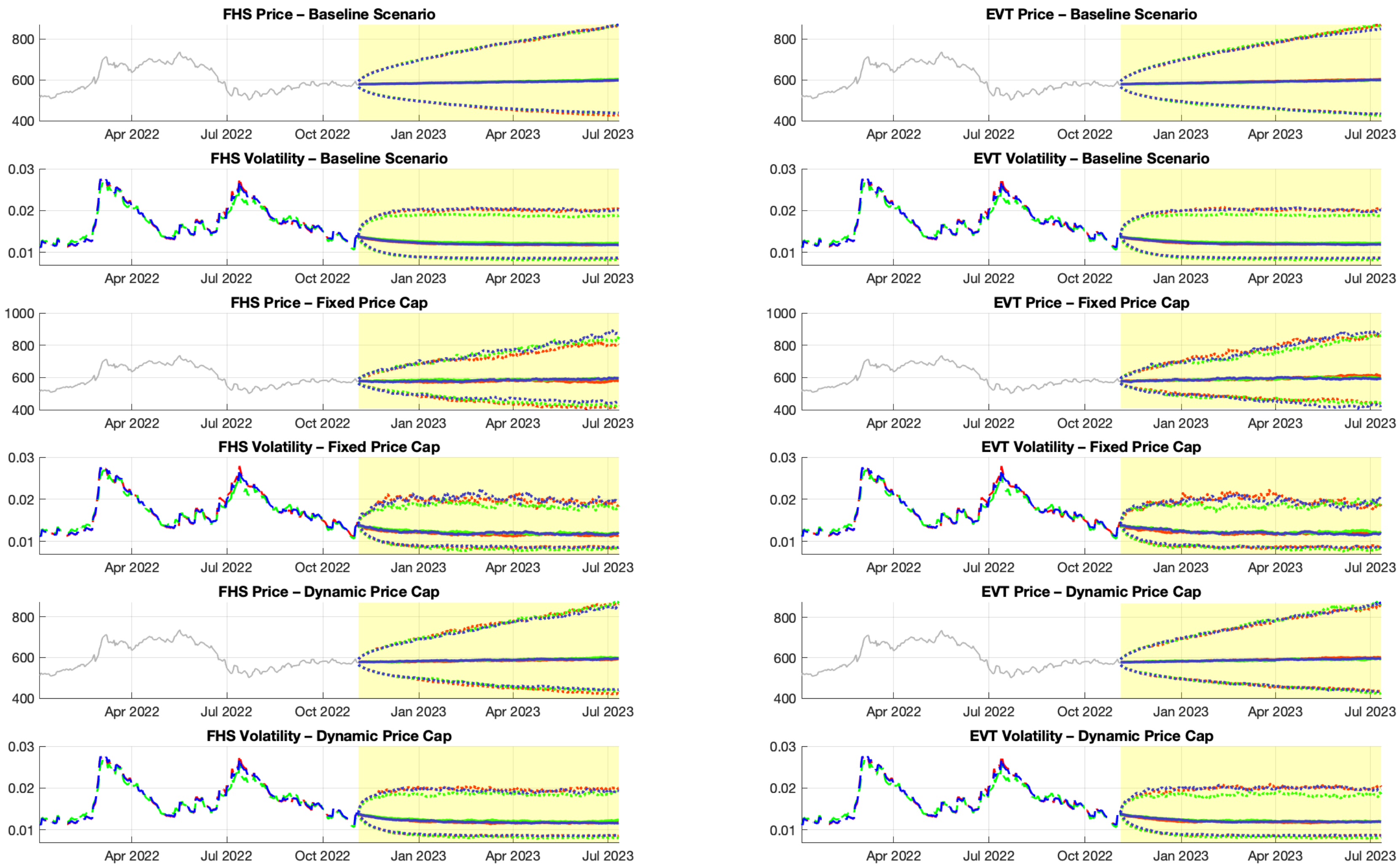


Figure 10: Gasoil

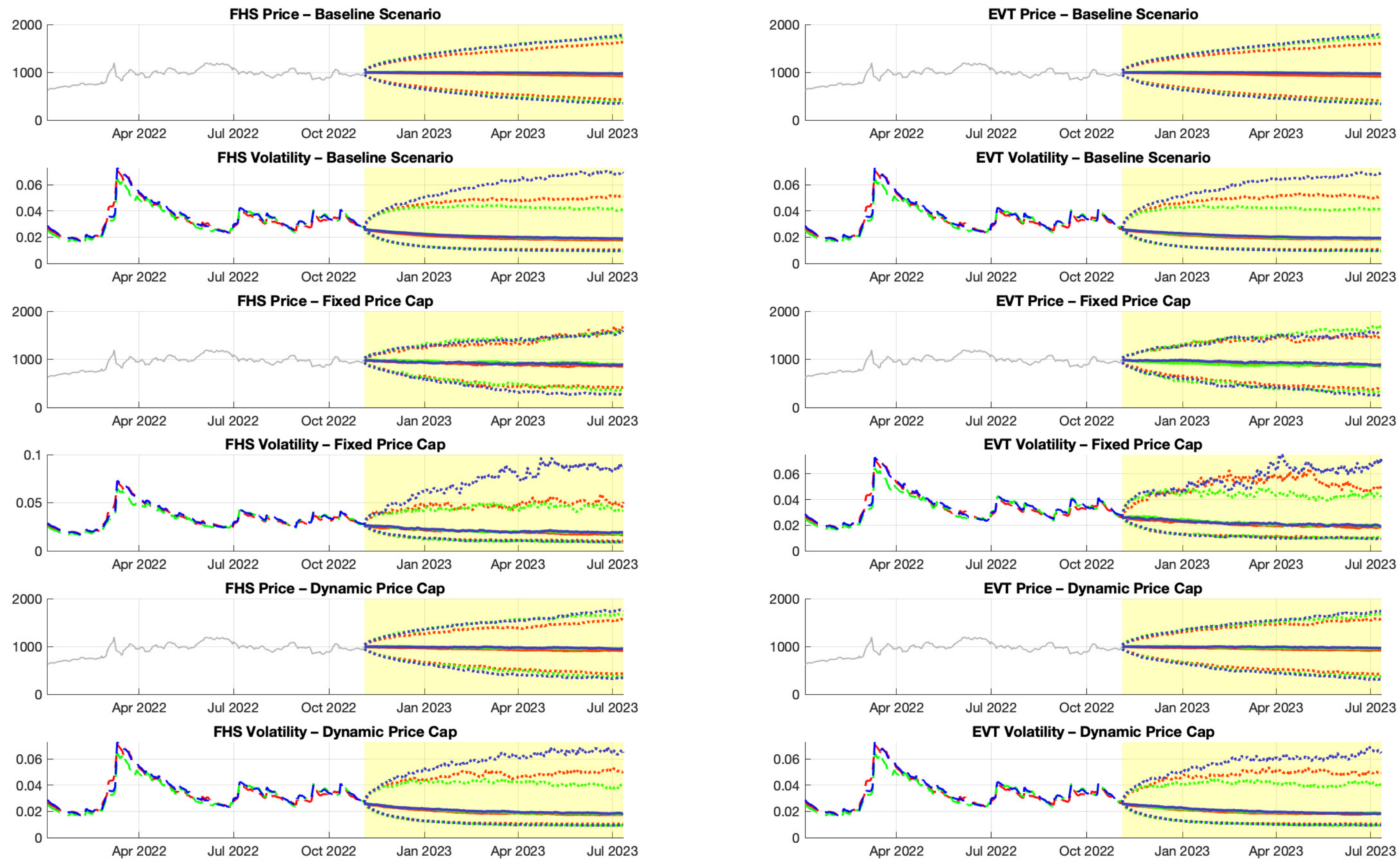


Figure 11: Aluminum

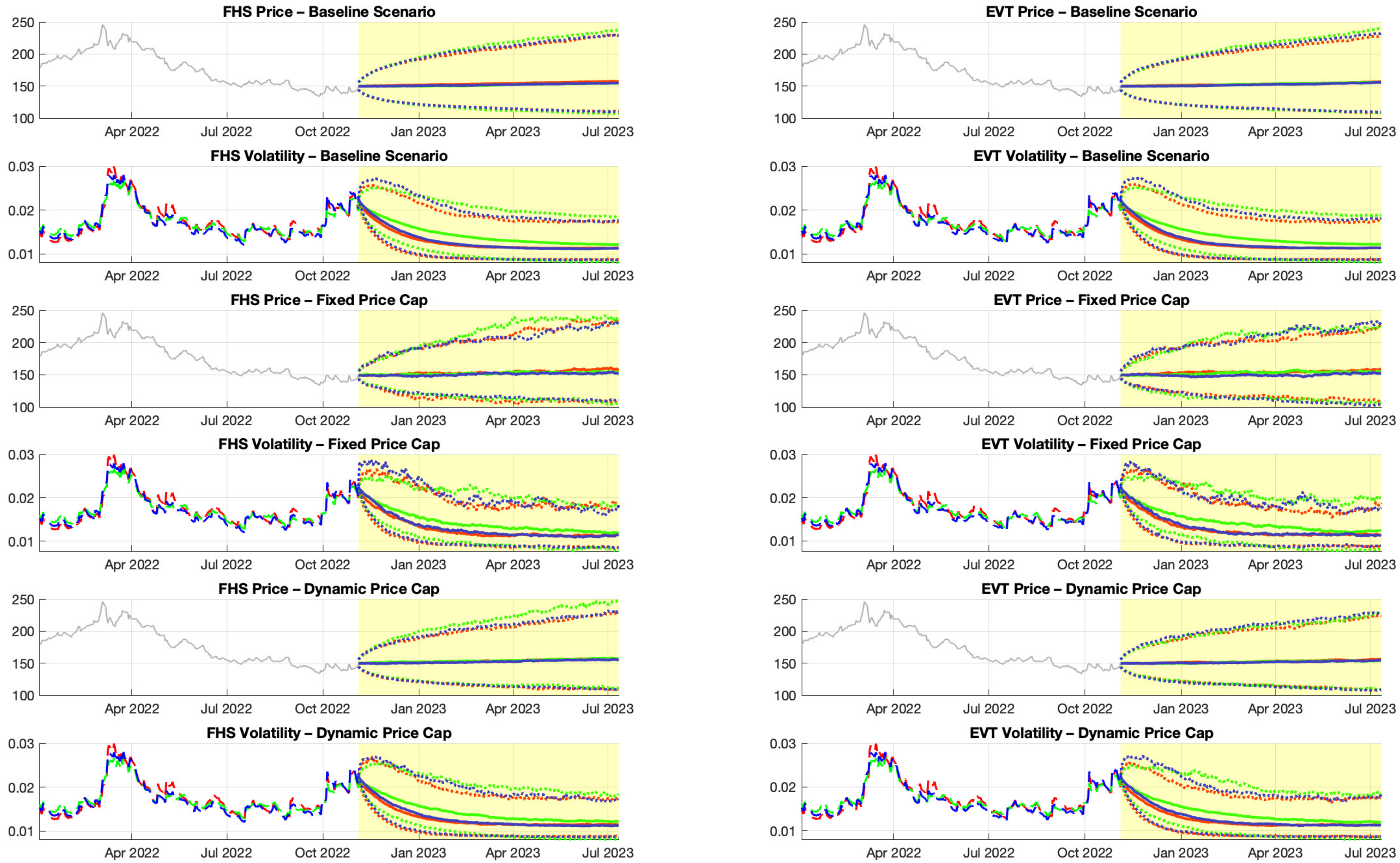


Figure 12: Nickel

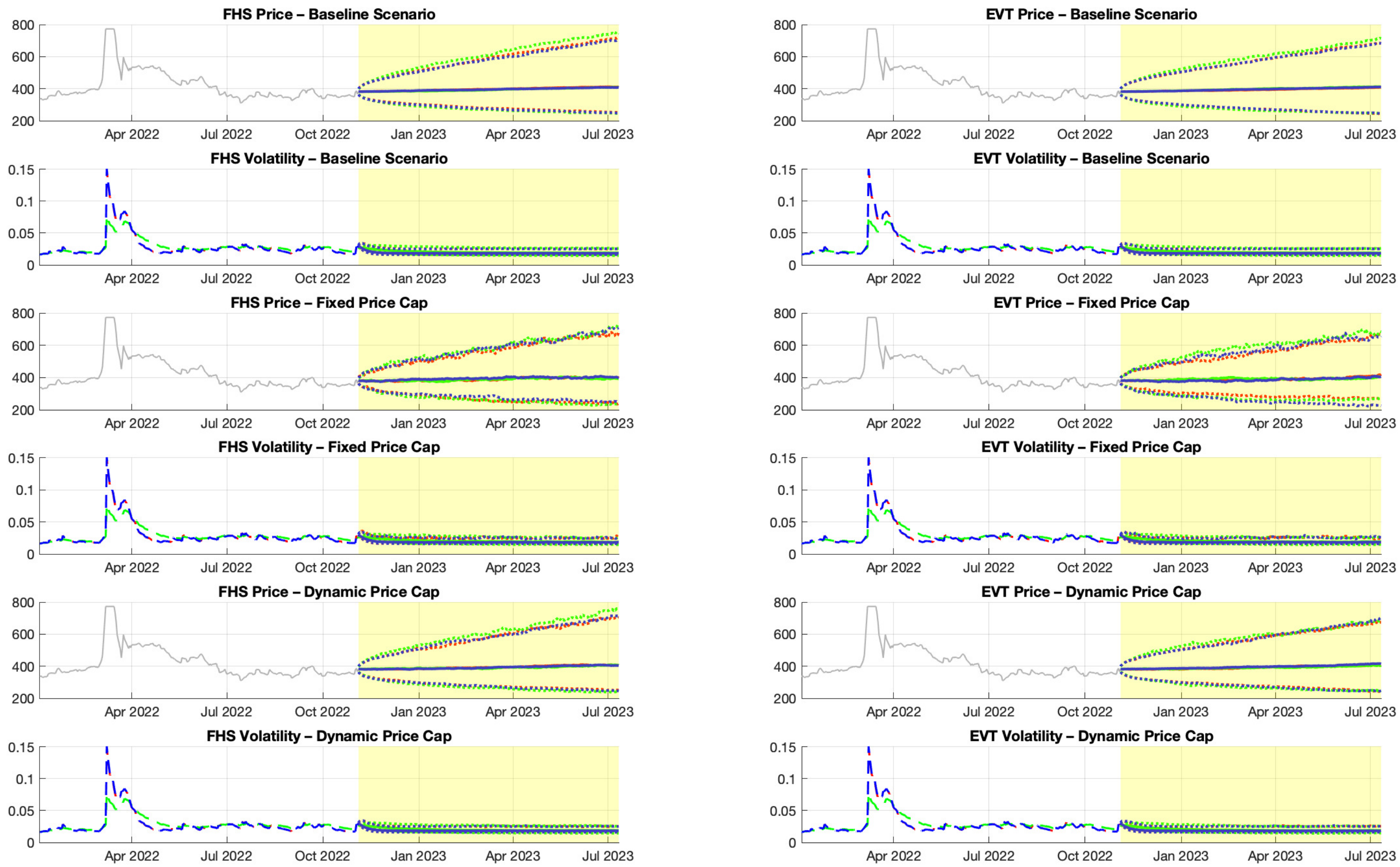


Figure 13: Zinc

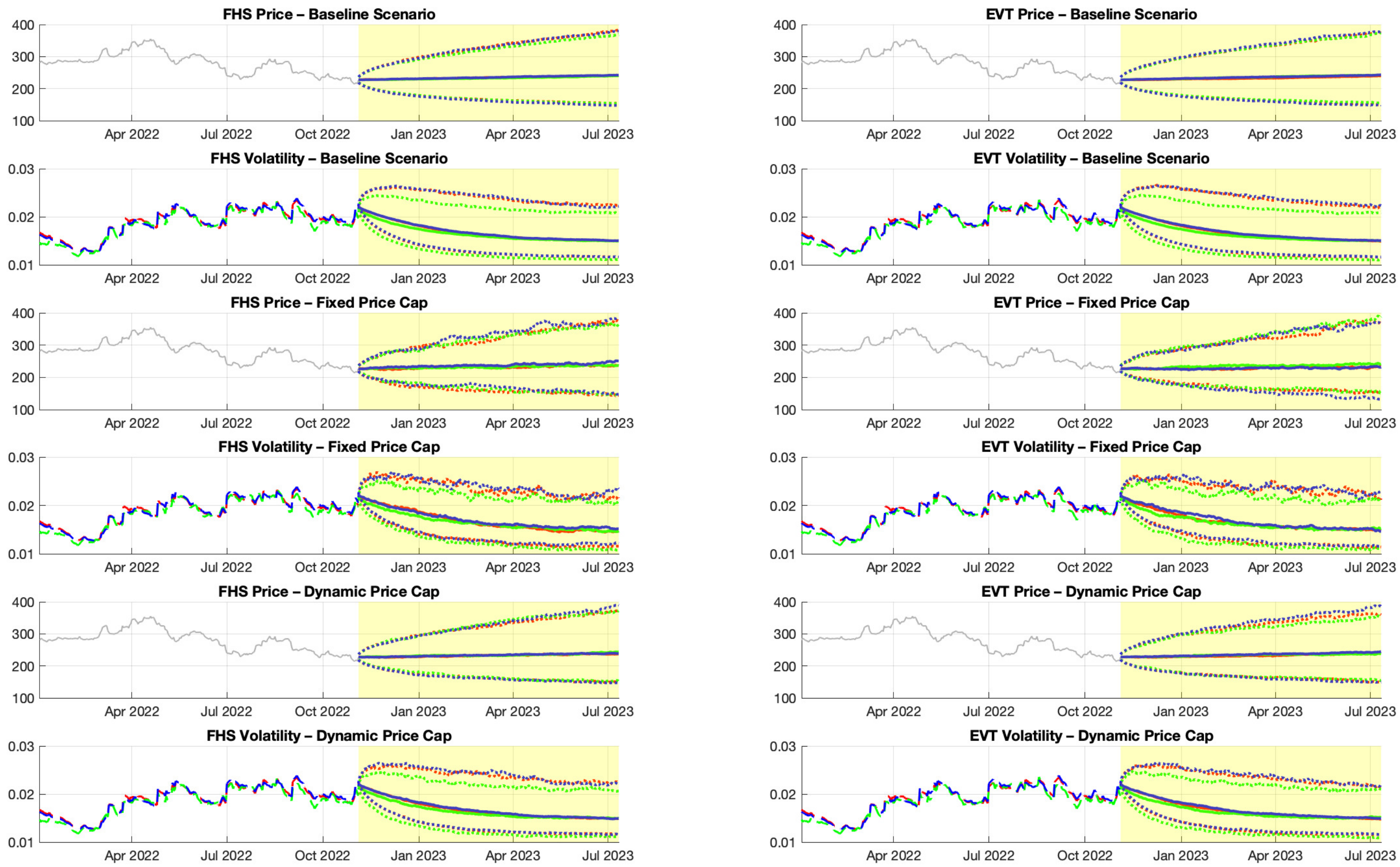


Figure 14: Brent Crude Oil

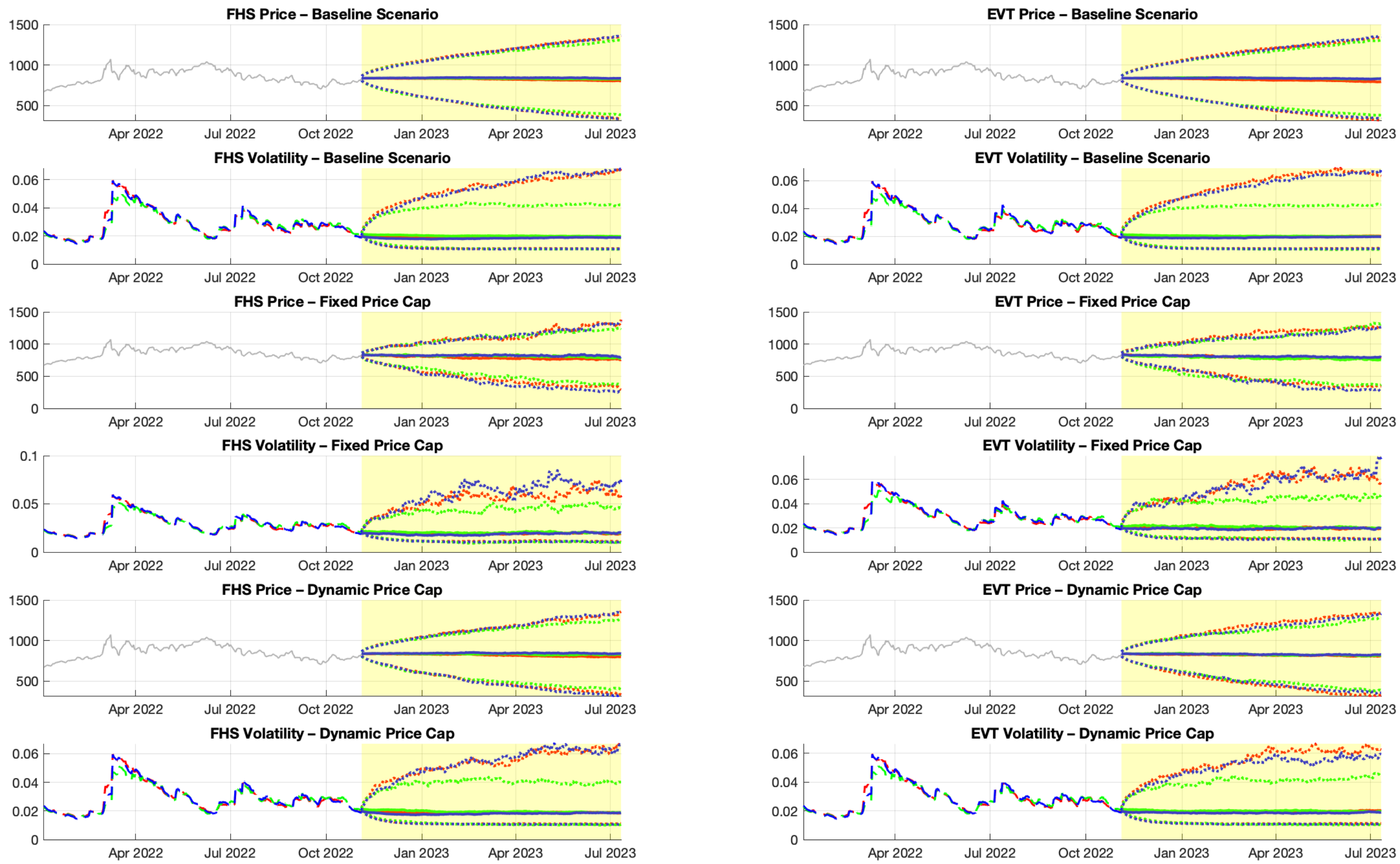


Figure 15: Precious Metals