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Master's thesis in Industrial Economics and Technology Management
Supervisor: Stein-Erik Fleten
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Preface

This master's thesis constitutes the final part of achieving the Master of Science degree in Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU), Trondheim.

First and foremost, we would like to express our sincere gratitude to our supervisor, Professor Stein-Erik Fleten, for lending us his expertise, guidance and constructive discussions throughout the process. We are also grateful to our contact person working at the Norwegian biorefinery for his time and valuable insights into their operations and the opportunity to analyze the biorefinery's cost base in detail. Lastly, we thank Morten Hegna at Montel for granting us access to the Montel XLF datastream.

We take full responsibility for any remaining errors.

Trondheim, June 2022.

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Abstract

In recent years, the coronavirus pandemic and rising global political uncertainty have led to increased volatility and price risk in the commodity markets. The commodity-intensive and growing biorefinery industry plays a crucial role in the ongoing green shift, highlighting the need for effective risk management of such production facilities going forward. This paper investigates procurement risk hedging of a Norwegian biorefinery considering its joint exposure to commodity price and foreign exchange rate risk. We propose a scenario optimization framework to determine the optimal hedging strategy where the objective is to minimize the biorefinery's Conditional Value-at-Risk. To capture potential dependencies between the risk factors, we use a multivariate vector error correction model as the basis for our scenario generation procedure. Our results show significant risk-reducing potential using the proposed hedging framework. However, the derived hedge positions only yield modest risk reduction compared to the simple naïve hedging strategy. Although oil is a fundamental energy-economic indicator, additional cross-hedging through oil forward contracts is not economically significant.

Sammendrag

I løpet av de siste årene har koronapandemien og økende global politisk usikkerhet ført til høyere volatilitet og prisrisiko i råvaremarkedene. Den råvareintensive og voksende bioraffineriindustrien spiller en avgjørende rolle i det pågående grønne skiftet, og fremhever behovet for effektiv risikostyring av slike produksjonsanlegg i tiden fremover. Denne oppgaven undersøker sikring av innkjøpsrisiko for et norsk bioraffineri og hensyntar dets felles eksponering mot råvarepris- og valutarisiko. Vi foreslår et scenariooptimerings-rammeverk til å bestemme den optimale sikringsstrategien der målet er å minimere bioraffineriets *Conditional Value-at-Risk*. For å fange opp potensielle avhengigheter mellom risikofaktorene benytter vi oss av en multivariat *vector error correction model* som grunnlag for å generere våre scenarier. Resultatene våre viser signifikant risikoreduserende potensial ved bruk av det foreslåtte sikringsrammeverket. De beregnede sikringsposisjonene gir imidlertid kun en beskjeden risikoreduksjon sammenlignet med den enkle naive sikringsstrategien. Selv om olje er en fundamental energi-økonomisk indikator, er ytterligere kryssikring ved bruk av terminkontrakter for olje ikke økonomisk signifikant.

Contents

1. Introduction

Effective risk management practices are critical elements to fostering growth and sustaining financial viability for industry firms exposed to multiple types of risk. Over the last decade or two, more extreme fluctuations in commodity prices and foreign exchange rates highlight the need for risk management to avoid exogenous risks from causing adverse consequences to the profitability of production facilities (Tevelson et al., 2007). The relevance and importance of this topic have particularly increased after the onset of the global coronavirus pandemic in early 2020, increasing the market volatility, followed by the energy price crunch starting in 2021. Moreover, Yin and Han (2014) find empirical evidence of rising prices and volatility in commodity markets as the volatility of economic policy uncertainty increases. In recent months, the global political turmoil as a consequence of the Russian invasion of Ukraine has introduced further complexity to the commodity markets and made the market dynamics even more unpredictable. Given Russia's historical role as one of the world's major energy-exporting countries, new political sanctions have the potential to cause instant changes in the general market conditions and can thus result in adverse changes in commodity prices.

This paper examines how a specific Norwegian biorefinery should reduce risks associated with its cost base. We choose to keep the identity of the particular biorefinery anonymous at the behest of our contact person working there. Biorefineries are industrial facilities manufacturing output products based on biomass as a sustainable alternative to petrochemical-based production. The world's immediate need to reduce the total greenhouse gas emissions and globally increasing environmental concerns puts the biorefinery industry in a central role in contributing to the green shift towards net zero. Increasing commodity price and exchange rate volatility introduces additional uncertainty and puts pressure on profit margins. Slight changes in market prices have the potential to heavily impact the profitability of low-margin operations (Geraili et al., 2014), highlighting their vulnerability to changing market dynamics. Thus, risk management is of more importance for firms with inherently lower operating margins since structural changes that may alter and potentially overthrow the whole business model can occur more easily.

In particular, we investigate how the biorefinery should hedge the joint commodity price and foreign exchange rate risk related to procuring the input factors needed for its daily operations. Our analysis considers all input factors exposed to market uncertainty and price risk, including natural gas, carbon emission rights (EUA), power, chemicals and wood. Thus, we extend the current biorefinery risk management literature by considering more than just a subset of the input risk factors and contribute to the literature with a more comprehensive understanding of a biorefinery's exposure to input price risk. In contrast to the biorefinery literature, we also account for currency risk by including euro and US dollar as part of the analysis to reflect the additional risk exposure when several input factors are traded in a foreign currency. Thus, the total procurement cost is the product of two uncertainties. With some modifications, we follow the portfolio construction of Haigh and Holt (2002) to account for all risk factors inherent in the biorefinery's procurement problem simultaneously. In this way, our analysis also serves as a helpful contribution to the current biorefinery literature by filling the gap regarding simultaneous hedging of multi-commodity price and currency risk.

We consider a procurement horizon of six months where we aim to reduce the biorefinery's exposure to price fluctuations in the spot market by taking offsetting positions in forward contracts. To identify the optimal hedging strategy, we propose a single-period scenario optimization framework with Conditional Value-at-Risk (CVaR) as our selected risk measure. While geometric Brownian motion is the most prominent method to simulate possible future price trajectories of commodities in the biorefinery risk management literature (see e.g. Yun et al., 2009; Cheng and Anderson, 2016), we base our scenario generation procedure on a vector error correction model (VECM). Extending the bivariate VECM of Cheng and Anderson (2017) into a multivariate time series model lets us capture potential dependencies between all risk factors considered in our analysis, which is crucial when determining appropriate hedging decisions. Scenarios based on an underlying vector autoregressive model (VAR) serve as a benchmark to the scenario set originating from the VECM model. Further, we calibrate the resulting scenario sets to ensure that the expectation of the simulated future price scenarios matches the observable forward prices in the market in order to obtain a risk-neutral valuation of the upcoming procurement costs.

In our analysis, we iteratively consider four consecutive procurement horizons with the first period starting at year-end 2019. The underlying multivariate empirical models forming the basis of our scenario generation procedure are estimated using time series data of all risk factors in monthly resolution, spanning from January 2009 until the hedge setup for the respective procurement horizon. Thus, in the fourth procurement period, the data span January 2009 through June 2021.

The resulting scenario sets highlight the unhedged procurement risks of our biorefinery, indicating extremely high total costs in the worst-case scenarios. Our results show significant risk-reducing potential using our proposed scenario optimization framework, with the hedge ratios of natural gas and EUA being consistently higher than the other risk factors. Further, the simple naïve hedging strategy performs almost as good as our derived hedge ratios in reducing the expected shortfall of our biorefinery's procurement costs. This finding suggests that accounting for potential dependencies between all risk factors does not yield substantial additional risk reduction, especially since the biorefinery's exposure to chemicals and wood is not directly hedgeable through forward contracts. Thus, due to its simplicity, the naïve approach appears as a highly reasonable alternative for our biorefinery when hedging its procurement risks. Nonetheless, our backtesting results indicate that our scenario optimization framework may provide additional value when the risk factors evolve very adversely. Given that oil is a fundamental energy-economic indicator, we further examine whether including oil forward contracts in the set of hedging instruments yields improved risk reduction for our biorefinery. Our results show a statistically significant decrease in expected shortfall, but we do not find the additional cross-hedging through oil forwards economically significant.

The remainder of this paper is structured as follows: Section 2 discusses the relevant biorefinery and hedging literature, which puts our research into further context. Next, Section 3 presents the problem under investigation together with our assumptions, followed by a description of our scenario optimization approach. Section 4 presents the data and simulates scenarios based on the estimated empirical models. Section 5 presents and discusses our results before providing some additional thoughts for further research. Finally, Section 6 concludes the paper.

2. Literature review

In this section, we review the relevant biorefinery literature and supplement this field of research with other relevant studies of particular interest to our analysis in cases where the biorefinery literature is considered deficient. We emphasize that the biorefinery hedging and risk management literature is at a nascent stage despite the increasing relevance of the topic in the last decade.

A large proportion of academia's attention towards the biorefinery industry focuses on the production process configuration, strategic planning or optimal design of the facilities to improve performance and profitability (e.g. Franceschin et al., 2008; Geraili et al., 2014; Sharma et al., 2013), while only some of these explicitly incorporate market uncertainty in the decision-making process (e.g. Geraili and Romagnoli, 2015). In contrast, our research does not consider operational aspects of the biorefinery. Instead, we focus solely on procurement risk management to mitigate financial risks due to price fluctuations of input factors. According to Franceschin et al. (2008), despite that technological improvement has the potential to reduce total production costs, the critical factors for profitability are price fluctuations of raw materials and products. This indicates that our research is highly relevant to the biorefinery industry nonetheless.

Another stream of research in the biorefinery literature actively engages in financial risk management to mitigate exposure to price fluctuations by entering the derivatives markets besides examining optimal production planning. Additionally, the shared focus between hedging and operational planning in these papers explains why most of them consider two-staged frameworks in contrast to our single-period approach. A variety of derivatives are used for hedging purposes to reduce price risk exposure. Examples are futures or forward contracts (e.g. Yun et al., 2009; Cheng and Anderson, 2016, respectively), and swaps (e.g. Cheng et al., 2016; Cheng and Anderson, 2017). These papers consistently suggest that actively mitigating price risks through derivatives successfully reduces the sensitivity of profitability towards market uncertainty. While Yun et al. (2009) derive variance-minimizing or risk-return maximizing optimal hedge ratios, Cheng and Anderson (2016) focus on reducing downside risk using CVaR as the risk measure. In this respect, we consider the latter research to be closest to our own regarding the objective behind determining the optimal forward contract positions.

A common tendency in the biorefinery hedging literature is its focus on a limited subset of the variables exposed to price risks. Yun et al. (2009) only consider price risks related to procuring the main input commodities (corn and wheat), Cheng et al. (2016) and Cheng and Anderson (2016) restrict their focus to mitigating price risks of the main output product (ethanol), whereas Awudu et al. (2016) and Cheng and Anderson (2017) take this one step further and examine hedging decisions for both feedstock (corn) and product (ethanol). Similarly, Ji et al. (2015) limit their attention to crude oil when examining the procurement problem of an oil refinery. Less attention has been given to several risk factors such as the energy required in the production, costs of carbon emissions and potential chemicals as part of the production process. As these input factors also face price uncertainties, ignoring these only results in suboptimal hedging decisions where parts of the risk exposure remain unhedged. However, Cheng and Anderson (2016) take a step in the right direction as they are the first to explicitly account for the effect of greenhouse gas emissions on risk management through carbon tax constraints, followed by Cheng et al. (2016) which consider a longer decision-horizon. In contrast to the literature, one of the characteristics of our analysis is that we include all input factors exposed to market price uncertainty and aim to reduce the aggregated procurement risk through available forward contracts with these risk factors as the underlying. We also emphasize that the biorefinery under consideration in this paper is utterly more complex than the simplified refinery processes in the literature, producing hundreds of niche products without observable historical prices covering multiple markets. Thus, we do not include product price uncertainty in our analysis.

The biorefinery literature commonly uses a scenario-based approach to find optimal solutions to the hedging problems under uncertainty. Geometric Brownian motion (GBM) is most frequently used to model the stochastic price behavior of commodities and to discretize the range of possible future price trajectories in the scenario generation process (see e.g. Yun et al., 2009; Geraili and Romagnoli, 2015; Ji et al., 2015; Cheng and Anderson, 2016). Cheng et al. (2016), on the other hand, argue that a Schwartz-Smith two-factor model (Schwartz and Smith, 2000) is more appropriate than GBM to simulate price trajectories for their longer-term model. However, it is important to account for the dependencies between the relevant price processes to obtain appropriate hedging decisions instead of simulating future price trajectories of each risk factor in isolation (Awudu et al., 2016; Cheng and Anderson, 2017). This is consistent with the research of Haarstad et al. (2022) who apply multivariate copula models in the Atlantic salmon farming industry, and find that exploiting dependencies between different commodities is beneficial compared to considering the commodities separately. Thus, Cheng and Anderson (2017) base their scenario generation procedure on a vector error correction model, which captures the inherent dynamics between the two risk factors. The bivariate vector error correction model of Cheng and Anderson (2017) naturally extends to our multivariate context with multiple input factors and forms the basis of our analysis.

None of the aforementioned studies consider risks associated with fluctuating foreign exchange rates, highlighting a gap in the biorefinery risk management literature since accounting for all sources of risk is critical when assessing the hedging potential of a specific derivative (Haigh and Holt, 2002). The research of Børsum and Ødegaard (2005) shows that many Norwegian firms are sensitive to exchange rate fluctuations, which also applies to the biorefinery under consideration in this paper. Moreover, the foreign exchange markets are essential for companies involved in cross-border trade and accurate measurements of market risks are critical for hedging strategy designs (Chang et al., 2013). Since most of the biorefinery's input factors are traded in foreign currencies, currency risk represents another uncertain risk dimension to our procurement problem. The finance literature focusing on optimal currency hedging has grown extensively. Among others, Chang et al. (2013) show that futures contract hedging has the potential to reduce risk effectively, and Albuquerque (2007) concludes that hedging using forward contracts exclusively outperforms options as hedging instruments in several economic models of downside risk.

Several papers in the risk management literature consider joint commodity price and foreign exchange rate risk. Husodo and Vidiapratama (2011) emphasize the importance of not considering risks associated with foreign exchange rates and commodity price exposure separately. Similar to Awudu et al. (2016) and Cheng and Anderson (2017), who advocate for the importance of jointly considering the commodities exposed to price risks, commodity and currency risks should also be considered simultaneously to explicitly account for potential dependencies between all risk factors (Husodo and Vidiapratama, 2011). Benninga et al. (1985) investigate the case of an export-driven company facing both foreign commodity price and currency uncertainty and come up with optimal hedging rules dependent on different properties of the forward markets. They conclude that optimal currency hedges depend on the commodity hedge and the properties of the commodity forward market, but not the other way around. In contrast, Zhang et al. (2007) consider hedging decisions of an importing firm exposed to simultaneous commodity price, foreign exchange rate and freight cost risk, which better aligns with the procurement problem under investigation in this paper. Although we do not consider freight costs and associated risks, they find that joint hedging of commodity price and exchange rate can reduce more risk than hedging the commodity price risk alone, further highlighting the importance of considering all market uncertainties and risks. Likewise, Haigh and Holt (2002) conclude that hedgers can further reduce risks by directly accounting for co-dependencies between prices in a similar research. Interestingly, their results suggest that omitting the currency hedging instrument from the hedging paradigm is undoubtedly the most detrimental to risk management. Based on these insights, we particularly follow the portfolio construction of Haigh and Holt (2002) with some modifications to make it fit our problem description and assumptions, thus bridging the gap in the literature.

3. Methodology

This section introduces the methodology that forms the basis for analyzing how the biorefinery can hedge its procurement risks. Subsection 3.1 presents some background and an introductory description of our problem of interest together with the main underlying assumptions of our research. Next, we describe the empirical method used to capture the dynamics between the biorefinery's individual risk factors in Subsection 3.2. We end this section with Subsection 3.3 where we formulate the scenario optimization framework.

3.1. Problem description and assumptions

The biorefinery under consideration produces a wide range of specialized biochemicals based on pulpwood covering multiple niche markets. Both electricity and natural gas serve as energy sources. In the energy-intensive and value-creating production process, several chemicals such as caustic soda and salt get added to create the desired properties of the products. Most of these input factors are traded globally and denoted in foreign currencies. Thus, fluctuations in commodity prices and foreign exchange rates represent joint financial risks to the biorefinery's operations, which we aim to reduce.

We view the problem from the perspective of a risk manager who wants to hedge against unfavorable movements in the relevant input factors and spot exchange rates. To at least partly hedge the risk, the risk manager can decide to enter the derivatives markets. Hedging refers to the action of taking opposite positions in the spot and derivatives market such that favorable movements in the latter can offset adverse movements in the former or vice versa. In our analysis, we will examine the use of forward contracts for hedging purposes.

We iteratively consider a procurement horizon of six months, assuming that each six-month period starts with full inventories of all the necessary input factors and that the biorefinery has enough storage capacity for the whole time horizon. Moreover, we assume no form of credit risk from either party and that the biorefinery has enough liquidity to procure everything needed to cover the period's production at the same time. The inventories get gradually used throughout the production process, resulting in no carryover inventory for the subsequent period. Our objective is to reduce the biorefinery's joint exposure to commodity price and currency risk when they need to procure the necessary input factors in six months to refill their empty inventories in order to cover the next period's operations.[1] However, replenishing the inventories with electric power, hereafter just power, is not feasible since we cannot store the commodity in its traditional form. Instead, we aim to hedge the power needed during the upcoming six months to accommodate this difficulty. This semi-annual procurement policy is a simplification, but it resembles the nature of the procurement problem of our biorefinery reasonably well and reflects the horizon of some existing rolling hedges.

Greenhouse gas emissions are natural consequences of the biorefinery's operations. As a Norwegian industry company, the *European Economic Area* (EEA) agreement requires the biorefinery to cover their direct greenhouse gas emissions within the EU ETS system with carbon emission rights.[2] The only requirement is that the biorefinery must cover all of its emissions with sufficient allowances at year-end, which does not directly fit into our proposed

[1] For clarity, these input factors will be used in the production process seven to twelve months after the hedge setup.

[2] The EU Emission Trading System (EU ETS) is the world's largest carbon market and follows a *cap-and-trade* system to i) ensure that the allowances have value and ii) reduce total greenhouse gas emissions over time.

six-month procurement framework. However, it fits perfectly if we assume that the biorefinery procures just enough allowances to cover its emissions on a semi-annual basis. Then the price risk related to climate allowances can be hedged in the same way as the direct input factors, which further allows the biorefinery to start the next six-month period at the status quo: with full inventories without lacking allowances to cover past emissions. For simplicity, we will regard carbon emission rights as both a commodity and an input factor to our biorefinery throughout this paper.

Hedging decisions are inherently sequential over the lifetime of a firm that has exposure to several types of market risks. As time goes by, inflexible static hedges cannot capture changes in the dynamics between the risk factors and can thus partly begin to work against their purpose. This advocates the use of a multi-staged optimization framework when analyzing how the biorefinery optimally should hedge its joint commodity and currency exposure. However, we approach the problem from a single-period context and we base the motivation behind our choice on several arguments. First, incorporating the possibility to make recourse decisions based on new market information in a multi-staged setting greatly complicates the optimization problem. This additional complexity reduces the transparency and interpretability of the model, which neither we nor our cooperating biorefinery desire. Second, a short time horizon of six months provides reasonable flexibility to capture changes in market dynamics from one period to another while focusing solely on the depicted procurement problem within each period. In this way, we preserve the possibility of (partly) dynamically adjusting the hedge positions between periods, even in a single-period context. Lastly, Brown and Smith (2011) study a dynamic portfolio optimization problem where they consider several heuristics based on models with less complexity. They find that heuristics that align well with our proposed formulation, such as one-step and rolling buy-and-hold strategies, perform nearly optimal.

3.2. Empirical method

To get a thorough understanding of the aggregated risk exposure and facilitate appropriate hedging decisions, we must understand how the relevant variables influence each other. Today, commodity and financial markets are closely linked, highlighting the importance of modeling multivariate systems compared to considering variables in isolation. Vector autoregressive models (VARs) are often used to examine empirical relationships in a system of endogenous variables. They offer a rich and flexible structure that enables the model to capture dependencies across variables by allowing variables to depend on their own lags in addition to lags from the other variables in the system (Brooks, 2019).

Let $\boldsymbol{y}_t$ denote the vector of time series data of the variables at time t. Following the notation of Pfaff (2008), a general formulation of a VAR model of order p is as follows:

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \boldsymbol{A}_1\,\boldsymbol{y}_{t-1} + \,...\, + \boldsymbol{A}_p\,\boldsymbol{y}_{t-p} + \boldsymbol{\Phi}\,\boldsymbol{D}_t + \boldsymbol{\varepsilon}_t\ , \quad \text{for } t = 1, ..., T\,. \tag{1}$$

Here, $\boldsymbol{\mu}$ is a vector of intercept terms and $\boldsymbol{D}_t$ is a vector of centered seasonal dummies which account for seasonal effects in the variables. The matrix $\boldsymbol{A}_i$, where $i \in \{1, ..., p\}$, represent the coefficient matrix for the variables at lag i. $\boldsymbol{\varepsilon}_t$ is the vector of disturbance terms, which we assume to be independent and identically distributed (i.i.d.) as $\boldsymbol{\varepsilon}_t \sim \mathcal{N}_K(\mathbf{0}, \boldsymbol{\Sigma})$, where K is the number of variables in the system.

Vector autoregressive models do not capture long-term equilibrium relationships between variables if present. The concept of *cointegration* was first introduced by Granger (1981) and refers to situations where a linear combination of integrated (i.e. non-stationary) variables is stationary (Alexander, 2008). Hereafter, we will refer to such linear combinations of the variables as the *cointegrating vectors*. Among other classic papers, cointegration was further formalized by Engle and Granger (1987) before new procedures were introduced to test for the presence of several cointegrated vectors in multivariate systems (Johansen, 1988, 1991; Johansen and Juselius, 1990).

Given that at least one cointegrated relationship exists between the variables, we can formulate a vector error correction model (VECM) to capture more of the inherent dynamics in the system by extending the concepts in (1). A generalized VECM specification is formulated as (Pfaff, 2008),[3]

$$\boldsymbol{\Delta y}_t = \boldsymbol{\mu} + \boldsymbol{\Gamma}_1 \, \boldsymbol{\Delta y}_{t-1} + ... + \boldsymbol{\Gamma}_{p-1} \, \boldsymbol{\Delta y}_{t-p+1} + \boldsymbol{\Pi} \, \boldsymbol{y}_{t-1} + \boldsymbol{\Phi} \, \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t \ , \tag{2}$$

where,

$$\boldsymbol{\Gamma}_i = - \, (\, \boldsymbol{\Pi}_{i+1} + \ ... \ + \boldsymbol{\Pi}_p \,), \ \text{ for } i = 1, ..., \, p-1 \, , \tag{2a}$$

$$\boldsymbol{\Pi} = - \, (\, \boldsymbol{I} - \boldsymbol{\Pi}_1 - \ ... \ - \boldsymbol{\Pi}_p \,) \ . \tag{2b}$$

In this model specification, the $\boldsymbol{\Gamma}_i$ matrices contain coefficients that measure the transitory effects (Pfaff, 2008). On the contrary, the $\boldsymbol{\Pi}$ matrix represents the error-correcting effect of the model based on the cointegrating relationship(s) between the variables in the system. It acts like a glue pulling the variables towards their long-term association(s) in response to variables beginning to drift away from their equilibrium relationship(s).[4]

3.3. Optimization framework

Continuous modeling of the distribution consisting of the uncertainty related to future spot prices of the biorefinery's input factors and fluctuating foreign exchange rates is analytically intractable. The multidimensional and aggregated risk faced by the biorefinery arises due to these uncertainties. An optimal hedge can be determined through an optimization framework based on a finite set of scenarios (Zenios, 2007; Blomvall and Ekblom, 2018). Given an empirical method based on historical data that captures the dynamics inherent in the multivariate system, we can generate sample trajectories of the uncertainties through Monte Carlo simulation. Bradley and Crane (1972) consider scenario generation techniques as applicable means to support financial decision-making and risk management purposes, and these techniques have become increasingly prominent in the literature (see e.g. Yun et al., 2009; Cheng et al., 2016; Blomvall and Ekblom, 2018 for different applications related to hedging).

The six-month forward prices observed in the market, denoted F_0, represent the market's current perception of the price evolutions over the next six months. We calibrate the set of scenarios such that the expected simulated value of each variable w six months into the future, $\bar{P}_6^w$, matches the observed and corresponding forward price:

[3] In contrast to the vector error correction models presented in seminal cointegration papers (see e.g. Johansen, 1988; Johansen and Juselius, 1990), equation (2) is the transitory version of the VECM specification. Although the transitory specification is the most frequent choice in the modern cointegration literature since it yields a clear interpretation of the estimated $\boldsymbol{\Gamma}$-matrices, both VECM specifications have the same explanatory power and the $\boldsymbol{\Pi}$ matrices will be identical (Pfaff, 2008).

[4] Johansen and Juselius (1990), and Pfaff (2008) describe the underlying mathematics behind the vector error correction formulation in extensive detail.

$$\bar{P}_6^w = \mathbb{E}\left[P_6^w\right] = F_0^w \ , \tag{3}$$

where w refers to a variable in the set W consisting of variables where forward contracts are available. In this way, the set of generated scenarios becomes consistent with the forward prices prevailing in the market. Market-consistent scenarios provide us with a risk-neutral valuation of the upcoming procurement costs. In a given scenario s in the set of all scenarios S, the payoff of a forward contract with variable w as the underlying is given by $P_{s,6}^w - F_0^w$. For the variables v whose forward contracts and associated prices are not available in the open market, $v \notin W$, we keep the simulated scenario values without performing any adjustments.

To optimize our biorefinery's procurement and hedging decisions, we need a suitable risk measure. We select Conditional Value-at-Risk (CVaR) for four reasons.[5] First, minimizing CVaR fits the economic situation and objectives of our biorefinery. In the context of risk management, firm managers usually associate risk with those outcomes that are unfavorable and with negative consequences (March and Shapira, 1987). As opposed to Value-at-Risk (VaR), which is just a quantile of the losses at some probability level α, CVaR is the expected shortfall conditioned on the losses that exceed VaR. Zenios (2007) emphasizes that optimizing Value-at-Risk hides the magnitude of the losses being worse than the prespecified probability level α. Our selected risk measure circumvents this issue and thus avoids the possibly severe consequences of not explicitly controlling losses in excess of VaR when optimizing. Second, CVaR is regarded as a *coherent* risk measure which implies that it satisfies some desired properties for decision making from a risk management perspective: translation invariance, sub-additivity, positive homogeneity and monotonicity.[6] Third, usage of CVaR is appropriate in single period contexts like the procurement problem we are examining. Lastly, we can solve the minimization problem of CVaR using linear programming methods. To obtain a linear formulation of our problem, we follow Zenios (2007) and introduce an auxiliary variable, y_s^+, which we define as (Zenios, 2007, p. 126):

$$y_s^+ = \max\left[\text{Loss}_s - \zeta, 0\right] \ . \tag{4}$$

Here, Loss_s is the loss function in scenario s whereas ζ denotes the VaR at a specified probability level α. From (4), we observe that the auxiliary variable is strictly positive when the loss function exceeds the Value-at-Risk and equals zero otherwise. Similar to Ji et al. (2015), we define our loss function as the total cost since we only focus on the costs related to procuring the necessary input factors in this study. Hence, we seek to minimize the expected total procurement cost in the worst $100(1-\alpha)\%$ of the scenarios. In practice, this implies that we focus on the right tail of the discretized total cost distribution formed by the scenarios. This constitutes a contrast to the general CVaR-literature which we often associate with the examination of the left tail of distributions and downside risk (e.g. minimizing portfolio value losses). We present our proposed optimization model in (5) and the model is consistent with the CVaR definition of Pflug (2000):

[5] In this paper, we will use Conditional Value-at-Risk (CVaR) and expected shortfall interchangeably when referring to the risk measure.

[6] See the seminal paper of Artzner et al. (1999) to obtain a thorough understanding of the four axioms and their consequences.

Minimizing Conditional Value-at-Risk in excess of the 100α% probability level

$$\text{minimize} \quad \zeta + \frac{\frac{1}{N}\sum_{s\in S} y_s^+}{1-\alpha} \tag{5a}$$

$$\text{subject to} \quad y_s^+ \geq C_{s,6} - \zeta, \quad \text{for all scenarios } s \in S, \tag{5b}$$

$$y_s^+ \geq 0, \quad \text{for all scenarios } s \in S. \tag{5c}$$

In the objective function (5a), N is the prespecified number of generated scenarios included in the optimization problem. We assign equal probabilities to all scenarios s, $\frac{1}{N}$, and the fraction in the objective function becomes the expected total procurement cost in excess of ζ in the worst $100(1-\alpha)$% of the scenarios. The constraints (5b) and (5c) force the model into a linear specification through the use of an auxiliary variable with the desired behavior as presented in (4). Finally, $C_{s,6}$ denotes the scenario-specific cost function in which the interesting decision variables (i.e. the hedge ratios) appear. We present the cost function in extensive detail in the upcoming section. Figure 1 illustrates our scenario optimization framework.

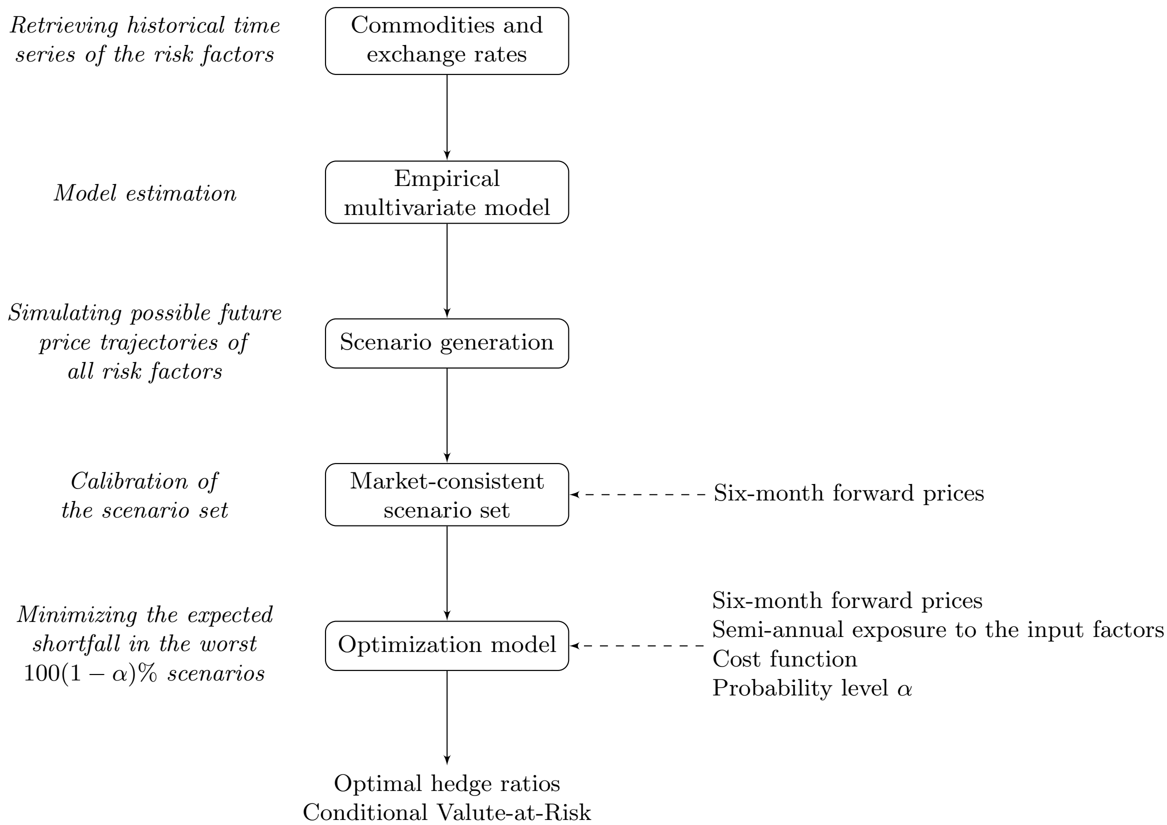


Figure 1: Illustration of the steps in our proposed single-period scenario optimization framework.

We provide the complete formulation of the optimization model in Appendix A. Note that we do not include any short-selling constraints in our model specification, but rather examine the results to see if any speculative effects appear. However, since our objective is to reduce the expected shortfall in the worst outcomes and thus reduce the aggregated risk, we do not expect any resulting speculative positions. Moreover, we do not impose any integer restrictions on the optimal number of contracts the biorefinery should buy (or sell) when calculating the optimal solution.[7] Thus, we implicitly assume that our biorefinery can obtain the desired, and in some cases fractional, amount of contracts with the same terms through a bank or other financial institutions.

To benchmark the expected shortfall-minimizing hedging decisions from the scenario optimization procedure, we employ the naïve hedge. The naïve approach involves entering offsetting forward positions in equal magnitude to the biorefinery's spot exposure. Thus, this strategy builds on the inherent assumption of high co-movement between the spot and forward prices. The naïve hedging strategy will be optimal and entirely eliminate price risk if proportionate changes in the spot and forward prices exactly match each other (Butterworth and Holmes, 2001).

[7]The futures contracts available on the market typically trade with contract sizes being multiples of thousand.

4. Estimation

This section presents the data in our analysis and estimates the empirical models we use to generate scenario sets. Subsection 4.1 introduces the time series of the risk factors and the biorefinery's risk exposure, before we present the function representing the total hedged procurement cost in a six-month procurement period. Next, Subsection 4.2 further focuses on the characteristics inherent in the data and presents the model estimating procedure. Finally, Subsection 4.3 describes how we generate scenarios based on the estimated empirical models.

4.1. Time series and data

The biorefinery under consideration sources most of its wood from the Norwegian market, and we retrieve monthly time series data of Norwegian spruce pulpwood prices [NOK/m^3] from Statistics Norway (SSB). We use front-month futures contracts as a proxy for the daily spot prices of natural gas [€/MWh] from the Dutch Title Transfer Facility (TTF) and carbon emission rights [€/tCO_2e], EU Allowances (EUA), to avoid potential problems due to low liquidity.[8] The former time series originates from the Refinitiv Eikon datastream and the latter from TradingView. Using front-month futures instead of spot prices is frequent practice in the financial literature (see e.g. Bailey and Chan, 1993; Bessembinder et al., 1995). We assume that the Nordic system price is representative of the power used by our biorefinery, and we obtain monthly data calculated as the average of daily prices [€/MWh] within each respective month from NordPool. To get a reasonable time series proxy covering a typical basket of relevant chemicals, we retrieve monthly data from TradingView[9] of the *Producer Price Index by Commodity: Chemicals and Allied Products (Alkalies and Chlorine)* [$ per index unit]. For simplicity, we will continue to use *chemicals* when referring to this index.

Further, we choose to measure total procurement cost in Norwegian kroner (NOK) since it is the reporting currency used in the financial statements of our biorefinery. To facilitate cost conversion into Norwegian kroner, we retrieve daily spot exchange rates of euro to Norwegian krone (EURNOK) and US dollar to Norwegian krone (USDNOK) from Refinitiv Eikon.

Although oil is not a direct input factor to our biorefinery's production, we include it as a variable in our analysis. This aligns with Junttila et al. (2018) who emphasize that oil is a major strategic commodity that financial economists follow closely as its price highly depends on the state of the global economy. Additionally, several studies in the literature provide indications that some linkages exist between oil and the risk factors we consider in our analysis (see e.g. Lutz et al. (2013), Chevallier et al. (2019) for its relation to some input factors and Papadamou and Markopoulos (2012) for exchange rate impact). Thus, the inclusion of oil can provide an additional explanation of the dynamics in the multivariate system and possibly act as a means to hedge some of the biorefinery's joint commodity and currency risks. We use the front-month contract of Brent Crude oil [$/barrel] obtained from Montel XLF as a proxy for the oil spot price.

We convert the daily time series into monthly resolution by using prices from the last day in each month where all variables were traded. In this way, we avoid temporal deviation between the prices, ensuring that the prices reflect the same market information. Our resulting

[8] tCO_2e is the common unit of measurement for greenhouse gas emissions and denotes a metric ton (t) of carbon dioxide (CO_2) equivalent (e).

[9] The Federal Reserve Economic Data (FRED) is the underlying database source for this particular index retrieved through the TradingView platform.

spot price data set in monthly granularity span January 2009 to June 2021 and Figure 5 in Appendix B.1 displays all the included variables in their levels. The figure reveals fluctuating prices, especially in recent years when the market dynamics have changed dramatically. Table 1 presents descriptive statistics of the data. Especially the high maximum values highlight the need for effective risk management of our biorefinery under such circumstances.

Table 1: The table shows summary statistics of our full data set of spot prices spanning January 2009 to June 2021 (150 observations). We include the mean, median, minimum, maximum, standard deviation, skewness and excess kurtosis.

	Mean	Median	Minimum	Maximum	St. Dev.	Skew	E. Kurt.
USDNOK	7.31	7.72	5.25	10.40	1.36	0.08	-1.44
EURNOK	8.89	8.90	7.29	11.48	1.00	0.30	-0.80
Natural Gas	18.67	19.23	3.63	33.58	5.85	-0.25	-0.63
EUA	13.31	9.64	3.12	55.38	9.73	1.74	3.66
Power	33.66	33.19	2.35	81.65	13.52	0.29	0.77
Wood	251.90	247.00	204.00	352.00	42.24	0.72	-0.54
Chemicals	307.00	306.40	254.10	412.60	24.85	0.80	2.38
Oil	75.31	69.31	22.74	125.89	25.92	0.27	-1.16

In our analysis, we consider four consecutive procurement horizons as described in Subsection 3.1 with the first hedge setup occurring at year-end 2019. The four vertical dotted lines in Figure 5 illustrate the start of each hedge setup, a period covering a significant degree of financial turmoil after the onset of the coronavirus pandemic. The 132 observations from January 2009 through December 2019 are used for model estimation for the first procurement period, with six additional observations for each subsequent hedge setup.

For each procurement horizon, we need hedge instruments to be able to (partly) hedge the risks inherent in the procurement problem. As a simplification in our research, we ignore marking-to-market and do not account for uncertainties related to interest rates which cause the theoretical difference between futures and forward contract prices. McDonald (2014) emphasizes that only minor deviations in prices exist between the two for short-lived contracts. Thus, we consider the difference between futures and forwards to be negligible, and we will consistently use the latter term throughout this paper when referring to fixed-price agreements on an underlying asset at a particular future date. We do not include the possibility to hedge risk(s) through forward contracts with wood and chemicals as the underlying since prices of such agreements are not available, reflecting that efficient markets for these raw materials are yet to be developed. Table 2 presents the six-month commodity forward prices retrieved from Montel XLF and the currency forward outrights obtained from Refinitiv Eikon. We assume that all forward contracts can be settled financially instead of actual delivery of the underlying.

Table 2: The table presents the forward prices used in each of the four hedge setups and their date of measurement in parentheses. These match the dates of the spot prices from the same months to reflect the same market information. The number of decimals differs across the variables due to different degrees of detail in each forward contract time series, and we use accurate prices in our analysis to fully reflect the market's perceptions.

	June 2020 (30.12.2019)	December 2020 (29.06.2020)	June 2021 (30.12.2020)	December 2021 (29.06.2021)
USDNOK	8.81	9.66	8.55	8.55
EURNOK	9.98	10.91	10.55	10.23
Natural Gas	11.71	12.23	15.90	33.61
EUA	25.00	26.62	32.11	55.64
Power	28.65	20.90	21.40	42.45
Wood	N/A	N/A	N/A	N/A
Chemicals	N/A	N/A	N/A	N/A
Oil	64.78	42.31	51.58	72.25

Note: The chosen power forward is a quarterly contract reflecting the price during the second nearest quarter (Q2 when hedge setup takes place at year-end and Q4 when it takes place mid-year). In the absence of a forward contract covering all six months, we assume that the relationship between the selected forward price and the last three months of the simulated six-month power price trajectories is representative of the whole horizon.

We compare information from several annual reports and other publicly available resources to approximate the biorefinery's total exposure to each input factor during six months of production. Moreover, we assume constant production volumes per time unit, which further implies that the quantities presented remain constant across hedging periods. The biorefinery uses one million cubic meters of wood a year, resulting in a need for 500 000 m^3 in our procurement horizon. In the biomass conversion process, the biorefinery needs 265 000 megawatt hours (MWh) of power to cover the base load and 200 000 MWh of equivalent heat energy from natural gas. We tune the quantity of chemicals such that the cost of chemicals (including currency conversion to Norwegian kroner) matches its reported fraction of the total cost base to accommodate the use of an index to represent the chemical basket. The semi-annual exposure to chemicals equals approximately 112 500 index units. In six months, the biorefinery under consideration typically emits 62 500 tonnes of CO_2 equivalent greenhouse gases within the EU ETS system.[10]

Equation (6) presents the scenario-specific cost function of procuring the input factors with currency conversion to Norwegian kroner (NOK) in accordance with the data presented as well as our problem description and assumptions outlined in Subsection 3.1. We ignore additional transaction costs in excess of what the forward prices already incorporate. In (6), we also include the possibility to cross-hedge some of the risks through oil forwards. Our specification is consistent with, although more complex, similar research examining the aggregated foreign exchange rate and commodity price risk in the literature, including the works of Liu et al. (2001) and Haigh and Holt (2002). In particular, we follow the hedged portfolio construction of Haigh and Holt (2002) and provide an *a priori* indication of the total number of each currency needed for the upcoming commodity procurement.[11] The formulation considers the interactions among the risk factors, and the resulting hedge ratios capture multivariate dynamics as opposed to if we have considered each risk factor in isolation. At the end of the six-month procurement horizon, the costs of procuring from the spot market get partially offset by the calculated payoffs from the financially settled forward contracts. Our resulting

[10] In our research, we disregard the free allocation of carbon emission rights to industrial installations and assume that the biorefinery must buy allowances to cover all their emissions themselves.

[11] In the absence of forward prices for the *chemicals* variable, we use the expectation of the scenario generated prices, $\bar{P}_6^{Chemicals}$, as an indication instead.

cost function is given by:[12]

$$
\begin{aligned}
C_{s,6} = {} & \overbrace{Q^{NG}\, P^{NG}_{s,6}\, P^{EUR}_{s,6}}^{\substack{\text{Procurement cost} \\ \text{in the spot market}}} - h^{NG}\, Q^{NG}\, \overbrace{(P^{NG}_{s,6} - F^{NG}_{0})}^{\substack{\text{Payoff from one} \\ \text{forward contract}}}\, P^{EUR}_{s,6} \\
& + Q^{EUA}\, P^{EUA}_{s,6}\, P^{EUR}_{s,6} - h^{EUA}\, Q^{EUA} (P^{EUA}_{s,6} - F^{EUA}_{0}) P^{EUR}_{s,6} \\
& + Q^{Power}\, P^{Power}_{s,6}\, P^{EUR}_{s,6} - h^{Power}\, Q^{Power} (P^{Power}_{s,6} - F^{Power}_{0}) P^{EUR}_{s,6} \\
& + Q^{Chemicals}\, P^{Chemicals}_{s,6}\, P^{USD}_{s,6} \\
& + Q^{Wood}\, P^{Wood}_{s,6} \\
& - x\, (P^{Oil}_{s,6} - F^{Oil}_{0})\, P^{USD}_{s,6} \\
& - h^{USD}\, (P^{USD}_{s,6} - F^{USD}_{0}) (Q^{Chemicals}\, \bar{P}^{Chemicals}_{6}) \\
& - h^{EUR}\, (P^{EUR}_{s,6} - F^{EUR}_{0}) \underbrace{(Q^{NG}\, F^{NG}_{0} + Q^{EUA}\, F^{EUA}_{0} + Q^{Power}\, F^{Power}_{0})}_{\text{Indicating the total number of euros needed in 6 months}} \quad ,
\end{aligned}
\tag{6}
$$

where $\boldsymbol{h} = (h^{NG}, h^{EUA}, h^{Power}, h^{USD}, h^{EUR})$ is the vector containing the optimal hedge ratios and x is the optimal number of oil forward contracts. The magnitude and sign of a hedge ratio indicate the size of the forward position per unit of spot exposure and whether it is long or short, respectively. Here, a positive hedge ratio implies that the biorefinery should go long (i.e. buy) in the respective forward contract. Q^v denotes the quantity needed of input factor v to cover six months of the biorefinery's operations. The subscripts indicate whether we can observe the price when making the hedging decision at time 0 or if the price is a scenario-specific value that we simulate six months into the future. Finally, the superscripts NG, EUR and USD denote abbreviations of natural gas, euro to Norwegian krone and US dollar to Norwegian krone, respectively.

4.2. Empirical model estimation

In this subsection, we complement Subsection 3.2 by presenting and justifying how we estimate the empirical models that form the basis of our scenario optimization framework. Since we consider four consecutive procurement periods, each of which we empirically estimate a model based on the same procedure, we only present the procedure for the first period in detail. Statistical and empirical tests as part of the model estimation in the other three procurement periods can be found in Appendix B.2 unless otherwise specified.

4.2.1. The order of integration

From Figure 5, it is evident that the variables enter the multivariate system with different scales in their levels. We log-transform the variables to mitigate potential scale issues in our time series model. The literature concerning cointegration regards log-transformation of variables as standard practice.[13] Prior to conducting cointegration analysis and constructing a vector error correction model, we must examine the variables' order of integration.

[12] $P^{Power}_{s,6}$ denotes the average of the simulated power prices in months four to six after the hedge setup in scenario s to match the forward price covering the whole second quarter of the six-month horizon.

[13] As Alexander (2008) argues, performing cointegration analysis using log-transformed prices is standard because cointegrated relations between variables usually appear both in levels and when log-transformed.

We use three different tests to determine the order of integration of our log-transformed time series. First, we perform an augmented version of the Dickey and Fuller (1979) test (Dickey and Fuller, 1981) to absorb any dynamic structure that might cause serial correlation in the residuals of the test regression. We use the information criterion presented by Schwarz (1978) to select the appropriate lag length with the additional restriction of including a maximum of 12 lags. Phillips and Perron (1988) propose a nonparametric alternative to the augmented Dickey-Fuller test based on asymptotic theory. Both these tests have a unit root under the null hypothesis, i.e. indicating non-stationarity, and in most cases, they provide uniform conclusions. However, they both suffer from low statistical power in small sample sizes. Lastly, we perform the stationarity test proposed by Kwiatkowski et al. (1992), which in contrast, has stationarity under the null hypothesis. To obtain robust and consistent conclusions across the tests, we should reject the null hypothesis for the augmented Dickey-Fuller and Phillips-Perron tests when the null under the Kwiatkowski-Phillips-Schmidt-Shin test does not get rejected, or vice versa. Thus, although our sample size can be considered limited, the latter test helps us circumvent the possible problem of drawing unit root conclusions too often. Brooks (2019) emphasizes that combining unit root and stationarity tests is an example of *confirmatory data analysis*.

Table 3 presents test statistics for the unit root and stationarity tests. As can be seen from the left-hand panel, the tests yield consistent conclusions indicating non-stationarity for most of the log-transformed variables. However, the results are inconsistent for natural gas, power and chemicals. Conflicting results are not sufficient to exclude non-stationary behavior robustly. Thus, we conclude that none of the log-transformed variables are stationary. To test for higher orders of integration, we apply the same tests on the first differenced version of the log-transformed variables. These test statistics are reported in the right-hand panel of Table 3 and demonstrate nonconflicting results suggesting that the log-transformed variables are stationary in their first differences. Thus, we can be confident that the log-transformed variables are integrated of order *one*, denoted I(1), since each variable only needs to be differenced once to induce stationarity.[14]

Table 3: Unit root and stationarity tests to determine the order of integration for each included variable. We present the test statistics from the augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for the log-transformed variables (left-hand panel) and their first differences (right-hand panel). The data span 2009M01 to 2019M12, providing 132 observations (131 in first differences).

	ADF	PP	KPSS
USDNOK	-0.60	-0.52	2.22***
EURNOK	-0.52	-0.51	1.96***
Natural Gas	-2.01	-2.42	0.37
EUA	-0.49	-0.80	0.52**
Power	-3.01**	-3.15**	0.55**
Wood	-0.27	-0.64	0.46**
Chemicals	-2.21	-3.85***	0.47**
Oil	-1.59	-1.92	0.94***

	ADF	PP	KPSS
ΔUSDNOK	-8.08***	-12.62***	0.25
ΔEURNOK	-8.52***	-11.75***	0.35
ΔNatural Gas	-7.48***	-11.25***	0.06
ΔEUA	-8.44***	-14.65***	0.36
ΔPower	-8.68***	-11.55***	0.04
ΔWood	-6.13***	-8.33***	0.43
ΔChemicals	-4.98***	-8.97***	0.33
ΔOil	-6.99***	-9.00***	0.23

Note: ** and *** denote statistical significance at the 5% or 1% level, respectively. The critical values are -2.88 and -3.46 for the ADF test, -2.88 and -3.48 for the PP test, whereas the critical values for the KPSS test are 0.46 and 0.74, respectively.

[14] The stationarity and unit root tests performed on the underlying data in the subsequent procurement periods are consistent with the conclusions drawn from Table 3.

4.2.2. Determining the optimal lag length

To test for cointegration and the number of cointegrating vectors, we must first select the optimal number of lags to include in our proposed vector error correction model. The order p of the VECM will be one less than the corresponding VAR$(p+1)$ model. We use the multivariate version of three different information criteria to trade off the additional fit of the model against the cost of losing degrees of freedom when including additional parameters. Table 4 reports the test results, and we choose the lag order that minimizes the information criteria.

Table 4: Determining the optimal lag length of the corresponding vector autoregressive model with the maximum lag order set to ten. We present values for the Akaike (1974) information criterion (AIC), the Schwarz (1978) information criterion (SIC) and the information criterion (HQIC) of Hannan and Quinn (1979) (extended to multivariate autoregressions by Quinn (1980)). The optimal number of lags according to each criterion is highlighted in bold. The data span 2009M01 to 2019M12.

Lags	AIC	SIC	HQIC
1	-48.50	**-44.82**	**-47.01**
2	-48.09	-42.94	-45.99
3	-47.54	-40.93	-44.86
4	-47.33	-39.24	-44.04
5	-47.20	-37.64	-43.32
6	-47.16	-36.12	-42.68
7	-47.37	-34.87	-42.29
8	-47.61	-33.63	-41.93
9	-48.18	-32.74	-41.91
10	**-49.34**	-32.42	-42.47

As can be seen, the tests yield contradictory conclusions. Both SIC and HQIC suggest one lag as the optimal choice, whereas the AIC criterion concludes with ten.[15] Including ten lags does not yield a parsimonious model and will substantially reduce the degrees of freedom. Given our sample size, we follow the recommendation by Liew (2004) and favor the lag order selection provided by the Hannan-Quinn information criterion. However, this further implies that the optimal order of the corresponding VECM is zero, which does not make any practical sense. Hence, to be as consistent with the results from Table 4 as possible, we choose the minimum non-zero lag length for our proposed vector error correction model, namely *one*. This leaves us with the following candidate vector error correction model:

$$\boldsymbol{\Delta y}_t = \boldsymbol{\mu} + \boldsymbol{\Gamma}_1\, \boldsymbol{\Delta y}_{t-1} + \boldsymbol{\Pi}\, \boldsymbol{y}_{t-1} + \boldsymbol{\Phi}\, \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t\,. \tag{7}$$

4.2.3. Specifying the cointegration rank of the model

We employ the Johansen test (Johansen, 1988, 1991; Johansen and Juselius, 1990) to investigate whether cointegration is present in our multivariate I(1) system. The number of statistically significant eigenvalues, r, determines the rank of the $\boldsymbol{\Pi}$ matrix in (7) which further indicates the number of cointegrating vectors in the system. From the trace test statistics reported in Table 5a, we observe that $r \leq 3$ is the first non-rejected null hypothesis at the 5% level. Thus, the trace test indicates that three cointegrated vectors are present between our variables. In

[15] The information criteria yield the exact same conclusions for the three subsequent procurement periods.

contrast, the results from the maximum eigenvalue test presented in Table 5b suggest the presence of only one cointegrated relationship. In this case, when the trace test and maximal eigenvalue test imply conflicting conclusions, we proceed with the results of the trace test, which is consistent with the recommendation by Alexander (2008). Hence, using our proposed vector error correction model in (7) as the basis for simulating future spot price trajectories seems adequate.

Table 5: Determining the cointegration rank r of the vector error correction model by performing the Johansen methodology. Given that we include eight variables in our analysis, the number of cointegrated vectors cannot exceed seven. Due to the high dimension of our proposed model, we use the critical values presented by Osterwald-Lenum (1992). Bold test statistics indicate a rejection of the null hypothesis at the 5% level of significance. The testing procedure is sequential with the alternative hypothesis of more than r cointegrated vectors for the trace test (5a) and $r+1$ for the maximum eigenvalue test (5b). The underlying data for the tests span 2009M01 to 2019M12.

(a) Trace test

H_0	Test statistic	5% level	1% level
$r \leq 7$	2.12	9.24	12.97
$r \leq 6$	5.41	19.96	24.60
$r \leq 5$	18.02	34.91	41.07
$r \leq 4$	35.64	53.12	60.16
$r \leq 3$	65.07	76.07	84.45
$r \leq 2$	**102.37**	102.14	111.01
$r \leq 1$	**144.66**	131.70	143.09
$r = 0$	**206.14**	165.58	177.20

(b) Maximum eigenvalue test

H_0	H_A	Test statistic	5% level	1% level
$r = 7$	$r = 8$	2.12	9.24	12.97
$r = 6$	$r = 7$	3.29	15.67	20.20
$r = 5$	$r = 6$	12.61	22.00	26.81
$r = 4$	$r = 5$	17.63	28.14	33.24
$r = 3$	$r = 4$	29.43	34.40	39.79
$r = 2$	$r = 3$	37.29	40.30	46.82
$r = 1$	$r = 2$	42.30	46.45	51.91
$r = 0$	$r = 1$	**61.48**	52.00	57.95

With three cointegrated vectors, we implicitly hypothesize that the $\mathbf{\Pi}$ matrix from (7) can be expressed by $\mathbf{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta}'$, where both $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $K \times r$ matrices (Johansen and Juselius, 1990). Here, $\boldsymbol{\beta}$ contains the cointegrated vectors whereas $\boldsymbol{\alpha}$ describes the speed of adjustment toward the long-run equilibrium between the variables. Visual inspection of the non-stationary series in Figure 5 indicates that linear trends do not exist in our variables.[16] Following the pioneering work of Johansen and Juselius (1990), we estimate model (7) with the restriction that $\boldsymbol{\mu} = \boldsymbol{\alpha}\boldsymbol{\beta}_0'$ to exclude any linear trends when modeling the dynamics of the system. Introducing a constant term in the cointegrating vectors has the additional advantage of setting the expectation of each long term relationship between the variables to zero (Alexander, 2008).

4.2.4. Empirical model and diagnostic tests

The primary motivation behind estimating a vector error correction model is to flexibly capture empirical relationships between the variables in the short and long term. The dynamics inherent in these relationships will further guide the subsequent scenario-generating process. We estimate our proposed vector error correction model using standard procedures (see e.g. Pfaff, 2008), and the estimated vector error correction models for the four procurement periods are presented in Appendix B.3. As can be seen, many of the coefficient estimates are not statistically significant. A relatively small sample size combined with a highly parameterized model reduces the degrees of freedom, implying higher standard errors of the estimated coefficients. Thus, the size of our data set can be considered a limitation of our analysis.

We employ two diagnostic tests to further evaluate the estimated VECM. First, we conduct a

[16] According to Alexander (2008), the variables in levels often have a unit root when the log-transformed variables have a unit root, and vice versa. Although we only present the results from the unit root tests of the log-transformed variables, we can confirm that the variables are non-stationary also in their levels.

multivariate version of the Breusch (1978) and Godfrey (1978) test to examine whether any auto- or cross-correlation is present between the lagged error terms in the system. Second, we test the model specification for potential ARCH effects (see Appendix B.3). Table 6 presents the resulting test statistics and associated p-values after conducting the Breusch-Godfrey test for the first procurement period.[17] The multivariate test results indicate that there is sufficient evidence to conclude that serially correlated errors are present in the system. Ignoring autocorrelation and heteroscedasticity due to ARCH effects does not affect the unbiasedness of the estimated coefficients but reduces the efficiency of the coefficient estimates, potentially distorting their standard errors (Brooks, 2019).

Table 6: Testing for auto- and cross-correlation in the residuals from the estimated vector error correction model for the first procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively.

Lags (m)	Test statistic (χ^2)	df	p-value
1	74.81	64	$p = 0.167$
2	165.27	128	$p = 0.015^{**}$
3	266.49	192	$p < 0.001^{***}$
4	347.11	256	$p < 0.001^{***}$
5	436.73	320	$p < 0.001^{***}$

4.2.5. Benchmark

In addition to a vector error correction model, we also estimate a vector autoregressive model in each of the four procurement periods. In this way, we are able to generate a comparable scenario set that is based on a less complex multivariate model. According to the results presented in Table 4, the selected lag order for the VAR models is one:

$$\boldsymbol{y}_t = \boldsymbol{\mu} + \boldsymbol{A}_1\, \boldsymbol{y}_{t-1} + \boldsymbol{\Phi}\, \boldsymbol{D}_t + \boldsymbol{\varepsilon}_t\,. \tag{8}$$

Further, we validate that the resulting VAR models satisfy the stability condition by verifying that all eigenvalues have a modulus less than one (i.e. they lie inside the unit circle). The estimated models can be found in Appendix B.3 together with their respective diagnostic tests. In short, the benchmarking VAR models also suffer from serially correlated error terms, and ARCH effects at lower lag orders are generally more present than in the corresponding VECM.

4.3. Scenario generation

To be able to analyze the procurement problem of our biorefinery with associated hedging decisions, we simulate the dynamics of our estimated multivariate systems represented by (7) and (8) six months into the future in a Monte Carlo fashion. Simulated monthly realizations replace the lagged values on the right-hand side of the equations as they become available in the iterative process. Each monthly error term vector gets randomly drawn from a multivariate

[17] The test results for the model specification of the three other procurement periods yield the same conclusions. Alternative VECM specifications with different lag structures also suffer from the same problems.

Gaussian distribution parameterized by mean vector zero and the empirical covariance matrix, $\varepsilon_t \sim \mathcal{N}_8(\mathbf{0}, \mathbf{\Sigma})$, since we assume that the vector of disturbance terms is independent and identically distributed as a multivariate normal distribution. In this way, we discretize the distribution of possible outcomes of the multivariate uncertainty through stochastic simulation. The scenario-specific prices get exponentiated back to their respective levels after simulation. Then, the scenario set from each of the two empirical models is adjusted to make the expected values consistent with the observed six-month forward prices in the market before serving as input to our optimization model. The scenario-specific price of power is the average of the last three monthly prices in the respective price trajectory to match the time aspect of the quarterly forward contract used in our analysis.

To ensure stability, we simulate 50 000 realizations of our empirical models to obtain extensive scenario sets consisting of possible future price trajectories. Table 7 presents some descriptive statistics of the generated scenarios for the first hedging period considered. The statistics illustrate the fan-shaped distribution of the scenario prices for each variable. We present the same descriptive statistics for the scenario sets forming the basis for the three other hedge setups in Table 28 through 30 in Appendix B.4.

Table 7: Descriptive statistics of the two simulated June 2020 scenario sets based on monthly time series data from early 2009 up until December 2019. We present the minimum, mean and maximum scenario values for each variable. To further illustrate the spread of the prices, we include the lower quartile (Q1), the median and the upper quartile (Q3).

	Minimum		Q1		Median (Q2)		Mean		Q3		Maximum	
	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR
USDNOK	6.49	6.37	8.41	8.33	8.79	8.78	8.81	8.81	9.19	9.25	11.56	12.04
EURNOK	8.55	8.36	9.73	9.71	9.97	9.97	9.98	9.98	10.22	10.24	11.69	11.60
Natural Gas	4.93	5.45	9.87	10.12	11.45	11.50	11.71	11.71	13.26	13.08	28.99	24.67
EUA	6.57	6.27	19.41	19.52	23.83	23.92	25.00	25.00	29.30	29.25	85.04	87.14
Power	9.33	9.51	23.25	23.37	27.70	27.76	28.65	28.65	32.99	32.96	81.16	76.31
Wood	246.82	258.52	319.04	325.67	332.68	339.92	333.33	340.60	346.89	354.67	423.56	436.54
Chemicals	268.06	260.03	313.93	313.64	322.59	322.57	322.89	322.78	331.58	331.60	383.11	388.49
Oil	27.10	30.82	54.87	57.23	63.38	63.98	64.78	64.78	73.11	71.42	148.62	132.01

Note: For all variables except wood and chemicals, which do not have available forward contracts, the mean value of the 50 000 simulated scenarios exactly equals the respective forward price presented in the second column of Table 2.

5. Results

This section presents and discusses the results of our proposed scenario optimization framework. Subsection 5.1 presents the resulting optimal hedge ratios and examines their characteristics. In Subsection 5.2, we compare these hedge setups with the naïve hedging strategy in terms of their ability to reduce expected shortfall. Moreover, we examine whether the additional flexibility of including oil forward contracts in the set of hedging instruments has a substantial risk-reducing effect on our biorefinery. Subsection 5.3 investigates the sensitivity of the optimal hedge ratios to the biorefinery's choice of probability level when minimizing Conditional Value-at-Risk. We backtest the different hedging strategies using realized spot prices in Subsection 5.4 to examine the performance of the various hedge setups if they were implemented by the biorefinery. Subsection 5.5 discusses our results in a holistic business economic context. Lastly, Subsection 5.6 reevaluates aspects of our proposed optimization procedure from a critical perspective and provides suggestions for further research.

We generate the market-consistent scenario sets with code written in R. The optimization model is implemented in Mosel and solved as a linear program using Xpress Workbench. We run the model on a computer with a 2 GHz Quad-Core Intel Core i5 processor and 16 GB RAM. The Mosel model runs for approximately 56 seconds before reaching the optimal hedge ratios when we include the possibility to hedge through oil forward contracts, while it runs for about 52 seconds without this additional cross-hedging opportunity.

5.1. Optimal hedge ratios

To run our optimization model and obtain optimal hedge ratios, we need to select an appropriate value of α (see (5) and Appendix A for its definition) which reflects the risk preferences of our biorefinery. After dialogue with our contact person, we choose to minimize the expected shortfall in the 15% worst outcomes (i.e. $\alpha = 0.85$) as a basis for our analysis.

Table 8 presents the results from the outlined scenario optimization procedure compared to the naïve hedging strategy and the unhedged case with zero positions in the derivatives market.[18] We emphasize that the mean total cost and Conditional Value-at-Risk are not directly comparable sizes across the two empirical models used in the scenario generation procedure. This is due to underlying differences in how each model captures dynamic relationships between the variables, resulting in simulated scenario sets consisting of somewhat different price trajectories and six-month ahead spot prices. Additionally, we should note that the mean total cost of the strategies slightly differs within each scenario set, implying a nonzero expected cost of hedging. We emphasize that the expected cost of hedging equals zero for all hedging instruments in their respective currencies. However, currency conversion using scenario-specific exchange rates (see (6)) causes this discrepancy.

We observe from Table 8 that all hedge ratios are positive. Given the formulation of our cost function (6), a positive hedge ratio implies going long in the respective forward contract. As expected, our results do not indicate any speculative positions despite allowing the decision variables to be negative by not imposing any non-negativity constraints in our optimization model. The biorefinery's spot exposure to all risk factors in our procurement problem is net short since a price increase of an input factor, or increasing exchange rates, implies increasing procurement costs. In the worst scenarios, i.e. those with the most unfavorable prices and

[18] The results from the scenario optimization procedure are stable across different random seeds.

Table 8: The resulting hedge setups from the scenario optimization procedure compared to the naïve hedging strategy and the unhedged position. The hedge ratios are relative sizes dependent on the biorefinery's exposure to each respective risk factor, whereas the position in oil forwards (rounded to nearest thousand) indicates the optimal number of contracts. We present the mean total cost (MNOK), the expected shortfall (MNOK) in the worst 15% outcomes ($\mathrm{CVaR}_{0.85}$) and the total cost standard deviation (MNOK) of applying the different hedging strategies to the cost function (6) to all 50 000 scenarios in each scenario set. In parenthesis, we present the percentage reduction in total procurement cost standard deviation compared to the unhedged strategy. The optimization results are presented for both the VECM-based and the VAR-based scenario sets.

	VECM-based scenario set				VAR-based scenario set			
First period	Unhedged	Optimal (with oil)	Optimal	Naïve hedge	Unhedged	Optimal (with oil)	Optimal	Naïve hedge
Hedge ratios								
Natural Gas	N/A	2.662	3.252	1	N/A	2.359	2.667	1
EUA	N/A	1.551	1.765	1	N/A	1.824	1.789	1
Power	N/A	1.233	1.145	1	N/A	1.190	1.202	1
USDNOK	N/A	1.246	0.994	1	N/A	1.139	1.030	1
EURNOK	N/A	1.622	1.862	1	N/A	2.247	2.386	1
Forward contract								
Oil	N/A	61	N/A	N/A	N/A	40	N/A	N/A
Scenario set								
Mean total cost	601	602	602	601	605	605	605	605
$\mathrm{CVaR}_{0.85}$	675	626	627	634	678	632	632	638
Total cost SD	45	15	16	21	45	17	17	21
		(-66.10%)	(-63.88%)	(-54.54%)		(-62.48%)	(-61.85%)	(-54.37%)
Second period								
Hedge ratios								
Natural Gas	N/A	1.256	2.032	1	N/A	1.990	2.212	1
EUA	N/A	1.592	1.678	1	N/A	1.512	1.496	1
Power	N/A	0.964	0.975	1	N/A	1.020	1.025	1
USDNOK	N/A	1.314	1.008	1	N/A	1.083	0.994	1
EURNOK	N/A	0.938	1.243	1	N/A	2.208	2.272	1
Forward contract								
Oil	N/A	136	N/A	N/A	N/A	41	N/A	N/A
Scenario set								
Mean total cost	593	594	594	594	525	525	525	525
$\mathrm{CVaR}_{0.85}$	667	628	630	633	597	549	549	553
Total cost SD	45	21	23	24	44	15	15	17
		(-52.57%)	(-49.64%)	(-46.09%)		(-66.01%)	(-65.48%)	(-60.61%)
Third period								
Hedge ratios								
Natural Gas	N/A	0.844	1.291	1	N/A	1.638	1.860	1
EUA	N/A	1.687	1.737	1	N/A	1.538	1.525	1
Power	N/A	0.927	0.951	1	N/A	1.075	1.100	1
USDNOK	N/A	1.500	1.096	1	N/A	1.151	1.032	1
EURNOK	N/A	0.434	0.316	1	N/A	1.855	1.853	1
Forward contract								
Oil	N/A	155	N/A	N/A	N/A	58	N/A	N/A
Scenario set								
Mean total cost	545	546	546	546	568	569	568	568
$\mathrm{CVaR}_{0.85}$	624	576	579	581	646	594	595	598
Total cost SD	47	19	21	22	47	16	17	19
		(-60.19%)	(-55.36%)	(-53.55%)		(-65.79%)	(-64.86%)	(-60.03%)
Fourth period								
Hedge ratios								
Natural Gas	N/A	1.360	1.379	1	N/A	1.206	1.309	1
EUA	N/A	1.189	1.302	1	N/A	1.130	1.136	1
Power	N/A	0.952	0.960	1	N/A	1.044	1.054	1
USDNOK	N/A	1.150	1.047	1	N/A	1.141	1.037	1
EURNOK	N/A	1.278	1.095	1	N/A	1.392	1.402	1
Forward contract								
Oil	N/A	30	N/A	N/A	N/A	39	N/A	N/A
Scenario set								
Mean total cost	663	664	664	664	703	704	703	703
$\mathrm{CVaR}_{0.85}$	814	692	693	696	831	731	732	735
Total cost SD	86	18	18	20	76	17	18	20
		(-79.47%)	(-78.85%)	(-76.56%)		(-76.90%)	(-76.40%)	(-74.05%)

exchange rates, long positions in forward contracts will incur positive payoffs offsetting at least parts of the additional costs caused by adverse movements in prices. Thus, from a risk-reducing perspective, positive hedge ratios make intuitive sense when our objective is to minimize the expected shortfall of the biorefinery.

Next, we will examine the magnitude of the optimal hedge ratios and compare these to the naïve hedging strategy. Our focus is mainly on the optimal hedge ratios without including oil forwards in the set of hedging instruments until otherwise specified. As can be seen, most of the hedge ratios reported in Table 8 are large in magnitude and exceed the naïve hedge of one. This applies to the results from both the VECM-based and the VAR-based scenario sets. In this respect, it is important to recall that we do not have available forward contracts with chemicals and wood as the underlying, which are the two most significant contributors to the cost base under consideration. Thus, the total procurement cost is not fully hedged despite most optimal hedge ratios exceeding one. Although the hedge ratios are static for each procurement period, they change across periods indicating that they are dynamic in nature and capable of responding to evolving dynamics between the risk factors going forward. This observation is consistent with several studies in the literature who find that optimal hedge ratios vary over time due to time-varying volatility and correlation between risk factors (see e.g. Haigh and Holt, 2002; Xu and Lien, 2020; Haarstad et al., 2022).

The optimal hedge ratios for natural gas and EUA stand out as being consistently high compared to the other hedge ratios in all periods across both scenario sets.[19] Higher hedge ratios indicate that the respective forward contracts are able to, relative to the biorefinery's spot exposure to the underlying, offset the aggregated procurement risk in the worst scenarios to a greater extent than the other hedging instruments considered. To examine whether natural gas and EUA forward contracts can partly offset some of the risks related to fluctuating chemical and wood prices, we further investigate the relationships between these variables. Pairwise cointegration tests only reveal statistically significant relationships at the 5% level towards chemical prices for natural gas and EUA. These results are not that surprising given the energy-intensive production of chemicals where both natural gas prices and costs associated with greenhouse gas emissions are related factors. Thus, we find statistically sufficient evidence to conclude that long-term linkages exist between some of these variables, potentially indicating the presence of cross-hedging effects on top of reducing price risks associated with the underlying variable itself. The VAR-based results also show larger hedge ratios for natural gas and EUA, indicating that the potential cross-hedging effects may also stem from other dependencies than cointegrated relationships. By examining the estimated VAR models in Appendix B.3 we observe that lagged EUA prices have a statistically significant impact on chemicals prices, whereas natural gas impacts both wood and chemicals.

Simonsen (2005) finds that Nordic power exhibit substantially higher volatility compared to what is typical for most other financial markets. This is also evident based on Table 1 where power yields the second-highest relative standard deviation in our data set, despite being the only variable calculated as the average of daily prices. Given this characteristic, we observe that the optimal CVaR-minimizing hedge ratio for power in the VECM- and VAR-based scenario sets is relatively stable and approximately equal to the naïve hedge, where it is generally slightly lower in the former and somewhat higher in the latter. Similarly, Byström (2003) finds that the naïve hedge performs well compared to more sophisticated models in terms of variance reduction when hedging exposure to the Nordic Power Exchange using futures contracts in a shorter time horizon. Thus, although we consider a multivariate setting

[19] In the VAR-based scenario sets, the optimal hedge ratios of EURNOK are at least as high.

accounting for dependencies between risk factors, the optimal hedge ratios of power turn out approximately equal to the naïve approach.

The actual size of the biorefinery's currency exposure is inherently uncertain and depends on the commodity prices traded in the respective currencies (Benninga et al., 1985). Thus, we refer to the cost function (6) and emphasize that the resulting sizes of the optimal currency hedge ratios are relative to an a priori indication of the total currency amount needed in each respective procurement period. Given that we minimize the expected shortfall in the 15% worst procurement cost outcomes, the currency exposure in these scenarios is likely greater than initially indicated. Interestingly, we observe a distinct difference between the optimal hedge ratios for the two currencies. The USDNOK results are similar to what we discover for power, with ratios close to the naïve hedge across both scenario sets in all periods. In contrast, the hedge ratios for EURNOK vary greatly. They range from 0.316 (1.402) to 1.862 (2.386) in the VECM-based (VAR-based) scenario sets, implying significant periodical differences in the risk-reducing effect of EURNOK forward contracts. A closer examination of the scenario sets and the dynamics between the variables does not provide clear explanations supporting the observed differences between the derived hedge ratios for the currencies and why the VECM-based EURNOK ratios are substantially lower than the VAR-based.

We observe some adjustments in the optimal hedge ratios after expanding the set of possible hedging instruments with oil forward contracts. However, the optimal hedge ratios of power are almost unaffected, whereas we cannot observe any consistent impact on the EURNOK forward positions. The results for natural gas, whose optimal hedge ratios consequently decrease after the inclusion of oil, are worth a closer look in this respect. This observation indicates that oil forwards capture parts of the CVaR reducing effect that natural gas forwards initially had on the total procurement cost. The decreasing tendency of natural gas hedge ratios is also consistently present in the VAR-based results, further strengthening our observation. Lin and Li (2015) discover a unidirectional price spillover effect from Brent Crude oil to European natural gas, which may help explain why a decreasing hedge ratio for natural gas follows from taking long positions in oil forward contracts. However, they base their results on a statistically significant cointegration relationship between the two variables, for which we cannot find sufficient statistical evidence in our data set. A weaker connection between Brent Crude oil and European natural gas in recent years can be explained by both commodities being priced based on their respective fundamentals after the liberalization of the European gas market, making it more mature (Perifanis and Dagoumas, 2020). Nonetheless, a strong positive correlation between the oil and natural gas prices suggests that long positions in their corresponding forward contracts partially offset the same types of risks.[20]

Both Ji et al. (2018) and Wang and Guo (2018) identify that the oil price greatly affects EUA price changes, and the latter research concludes that oil commodities can be useful in hedging price risks in the carbon market. However, we only observe slight decreases in the VECM-based EUA hedge ratios when we include oil forwards in the hedging portfolio, indicating weaker dynamics than evident in the decreasing natural gas hedge ratios. This further suggests that oil forwards are not a particularly useful supplement when it comes to hedging risks that were initially captured by EUA forwards. Additionally, the VAR-based results show that the EUA hedge ratios are almost unaffected after the inclusion of oil forwards, with minor increases in three periods. Further, a statistically significant pairwise cointegration relationship is not present between the two variables and the lagged oil coefficients in the EUA equation are insignificant for all model specifications (see Appendix B.3). Thus, our

[20] The correlation coefficient is 0.662 in the last five years of the sample period.

results do not support the strong relationship found in the papers of Ji et al. (2018) and Wang and Guo (2018). Gong et al. (2021), on the other hand, find that the spillover effect of Brent crude oil futures on the carbon market is time-varying where both the size and direction of the impact depend on the sample period. This finding may explain why we do not observe the same empirical dependence in our analysis.

Moreover, the currency hedge ratio of USDNOK consistently increases in all periods across both scenario sets after including oil forwards. Benninga et al. (1985) conclude that optimal foreign exchange rate hedges are dependent on the commodity hedge sizes. Consequently, since oil forwards are quoted in US dollars, the total currency amount to be converted into Norwegian kroner is affected by the position's optimal size. Additionally, the magnitude of the hedge ratio increases with the optimal number of oil forward contracts to enter. These dynamics become particularly interesting given that the oil price and USDNOK exchange rate exhibit a highly negative correlation.[21] Increasing (decreasing) oil prices are associated with a relative appreciation (depreciation) of Norwegian kroner to US dollars (Reboredo, 2012; ter Ellen, 2016). Negatively correlated variables usually act as natural means to (partly) reduce risks associated with a portfolio. Thus, it would be tempting to assume that the introduction of oil as a hedging instrument should naturally offset parts of the currency risk and reduce the hedge ratio of USDNOK. In contrast, long forward positions in oil combined with a short spot exposure to USDNOK both impact the total procurement cost in the same direction rather than having an offsetting effect on each other. Hence, oil forwards' increasing effect on the hedge ratio size of USDNOK should come from the additional dollar amount involved.

5.2. Conditional Value-at-Risk

In this subsection, we compare the expected shortfall from the different hedging strategies and examine to what extent they are able to reduce total procurement cost in the 15% worst outcomes. From Table 8, we observe that the naïve approach and the optimal hedge ratios reduce the expected shortfall substantially compared to the unhedged case. This is further substantiated by the massive reduction in total procurement cost standard deviation, which decreases by more than 50% in most cases for both hedging strategies. Figure 2a illustrates that the magnitude of the most unfavorable total procurement cost scenarios becomes largely restricted when applying the optimal hedging strategy.[22] In the worst scenarios, extremely high unhedged costs highlight the biorefinery's motivation to engage in hedging. However, reducing the total procurement cost in the worst outcomes by minimizing Conditional Value-at-Risk comes at a cost: we sacrifice the low procurement cost scenarios as evident when comparing the left tails in Figure 2a. Thus, minimizing the expected shortfall (the right tail) implies forgoing the most favorable scenarios resulting in a more concentrated total procurement distribution. Hence, as emphasized by Tevelson et al. (2007) and Stulz (2013), we fully expect applied hedges to incur additional costs if the hedged exposures evolve in a favorable direction for the biorefinery.

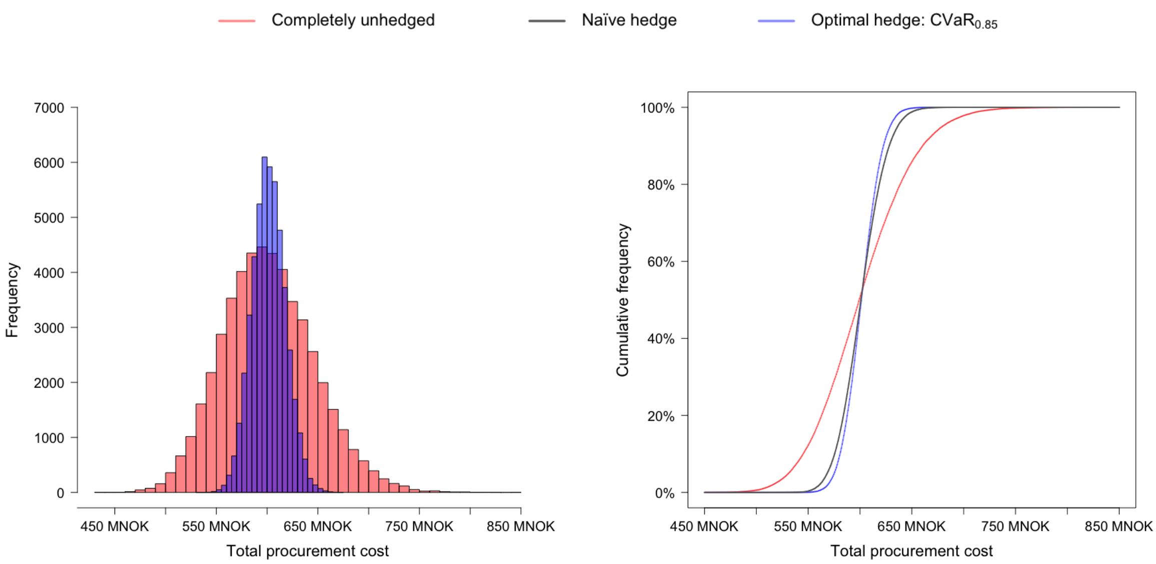
The optimal hedge ratios yield lower CVaR than the naïve hedging strategy in all periods and across both scenario sets. The expected shortfall further declines when we include the

[21] The correlation coefficient is -0.82 in our data spanning from January 2009 to December 2019 and slightly increases in absolute terms after the onset of the coronavirus pandemic.

[22] Although some individual differences exist across periods, the tendencies illustrated in Figure 2 are representative of both the VECM-based and VAR-based scenario sets for the other procurement periods. However, we emphasize that the largest difference between the naïve approach and the optimal strategy occurred in the first period, which is the one we use to illustrate the overall tendencies.

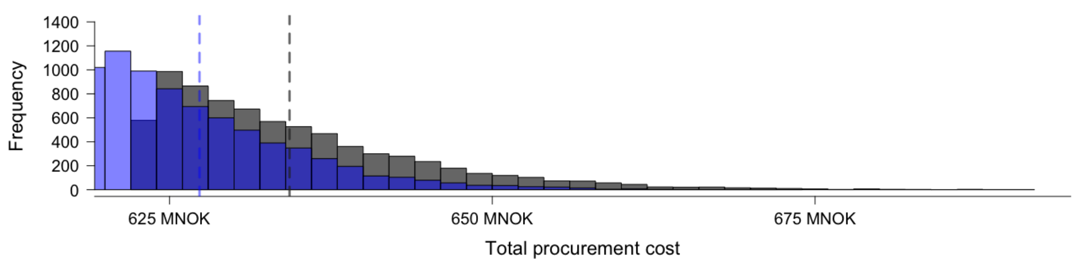
possibility of hedging risks using oil forward contracts. These observations are trivial in-sample since we optimize with the intention to minimize CVaR, and every additional flexibility introduced in the model implies a (weak) improvement of the objective function value. Hence, the hedging outcomes from the optimization model can never yield a scenario set-specific CVaR that is inferior to those produced by the naïve hedging strategy.

Interestingly, despite several optimal hedge ratios being considerably higher than one, our results indicate that the additional CVaR reduction from applying the optimal hedge is small compared to the naïve approach. At most, the optimally derived hedge ratios reduce the expected shortfall under the naïve hedging strategy with 1.10% (0.91%) in the VECM-based (VAR-based) scenario sets. This implies that the naïve approach only performs slightly worse than the optimal hedging strategy when reducing our biorefinery's procurement risks. The naïve approach does not consider the two most significant contributors to the total procurement cost, chemicals and wood, since they are not directly hedgeable through forward contracts. Thus, these results indicate that considering dependencies between all risk factors does not yield substantial cross-hedging effects. Therefore, due to its simplicity without the



(a) Distributional plot showing the total procurement cost in all 50 000 scenarios in the scenario set.

(b) Cumulative distribution plot of the three strategies across the whole scenario set.



(c) Right tail distribution (worst 15%) of the total procurement cost outcomes. The dotted vertical lines represent the respective CVaR value for the two hedging strategies.

Figure 2: Several distributional plots illustrating the differences between the optimal hedging strategy without including oil forwards as a hedging instrument (blue), the naïve hedge (grey) and being unhedged (red). The scenario set is based on the vector error correction model from the first period we consider (ending in June 2020).

need to allocate resources to follow the time-varying dynamics between the risk factors, the naïve hedging strategy appears as a highly reasonable alternative for our biorefinery.

Figure 2b shows the cumulative version of the distributional plot (Figure 2a), with the addition of the cumulative procurement cost distribution originating from applying the naïve strategy. Here, steeper slopes indicate less variance in the scenario-specific procurement costs. We observe that the naïve hedge follows the outcomes of the optimal hedging strategy quite closely, where the latter exhibit the lowest variance. While Figure 2c illustrates how the optimal strategy shifts the worst outcomes towards lower total costs compared to the naïve hedge, Figure 2b shows that the naïve strategy manages to keep slightly more favorable outcomes located in the left tail. These observations are supported by the total cost standard deviations reported in Table 8. Thus, our results indicate that a decrease in total procurement cost standard deviation, or variance equivalently, is closely linked to the reduction of expected shortfall. This finding is consistent with other studies in the risk management literature (see e.g Krokhmal et al., 2001; Haarstad et al., 2022). The tradeoff between the gains of reducing CVaR against the additional costs of sacrificing favorable outcomes depends on the utility function of the biorefinery and how they value saving additional costs in an unfavorable state compared to a favorable one (i.e. its level of risk aversion).

Next, we examine the CVaR-reducing impact of the additional flexibility to hedge parts of the procurement risk with oil forward contracts. We have already observed that whether oil forwards should be included or not greatly affects some of the resulting hedge ratios. Including oil forwards as a hedging instrument reduces the expected shortfall within the range of 0.08% to 0.54% in the four VECM-based scenario sets, whereas the CVaR reduction in the VAR-based scenario sets does not exceed 0.08%. Thus, the additional decrease in the expected shortfall in the worst 15% total procurement cost outcomes is relatively marginal and amounts to an approximate CVaR reduction in the range of 0.55 to 3.1 million Norwegian kroner over six months in the VECM-based scenarios. Further, we examine the absolute worst outcomes in each scenario set to investigate whether these can be avoided if our biorefinery includes oil forwards in its hedging portfolio. A closer examination reveals that this additional flexibility only offers some cost reductions without showing any clear tendency towards effective avoidance of the most extreme scenarios, indicating that oil forwards do not capture new aspects of the biorefinery's procurement risk.

Given these observations, we want to test whether the inclusion of oil forwards statistically significantly reduces the expected shortfall of our biorefinery. However, a standard two-sample t-test cannot be validly conducted due to a violation of its underlying assumptions since the right tail of the hedged total procurement cost distribution is not normally distributed. We accommodate this issue by conducting a hypothesis test using a bootstrapping procedure.[23] The results in Table 32 show uniform rejection of the null hypothesis of no difference in the expected shortfall between the two strategies at the 5% level in all scenario sets. Hence, we can conclude that including oil forward contracts statistically significantly reduces the CVaR.[24]

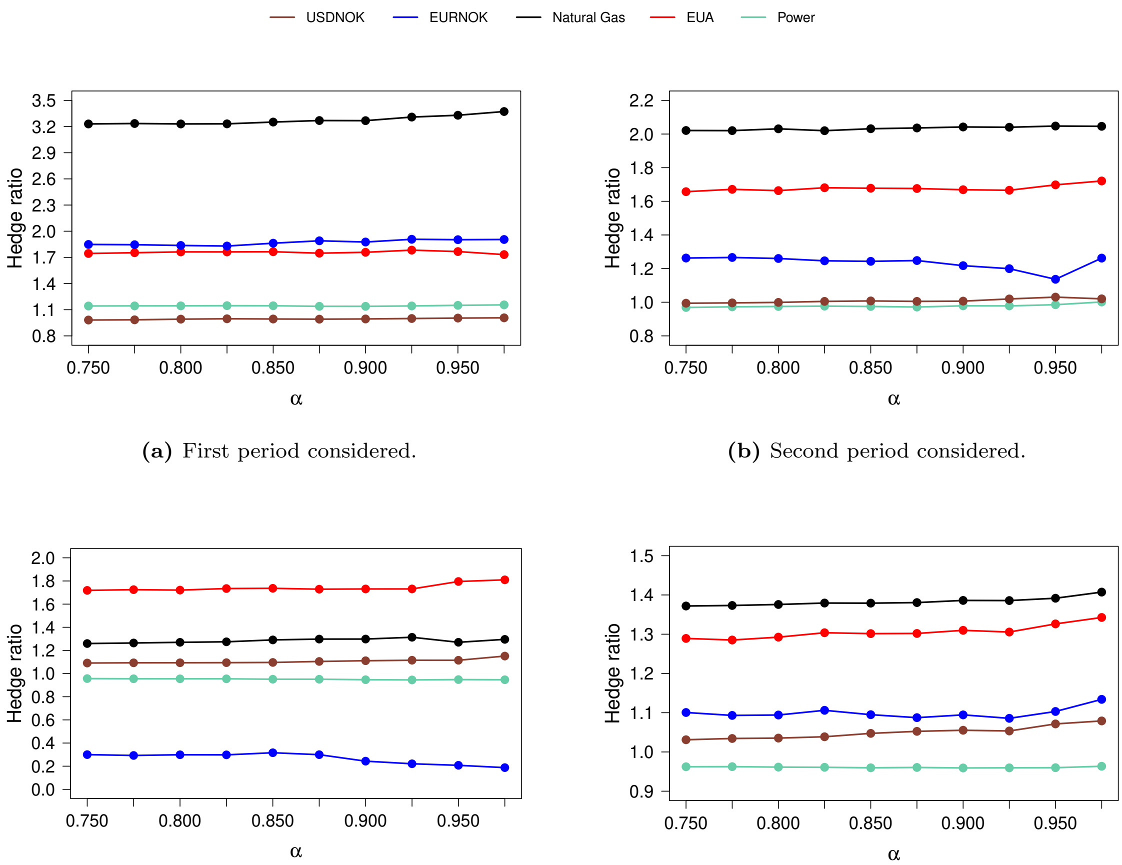
[23]Further details of the bootstrapping procedure and its associated results are provided in Appendix D.

[24]We also obtain consistent conclusions showing statistically significant CVaR reductions when testing the hedging strategy without including oil forwards against the naïve approach.

5.3. Sensitivity with respect to choice of probability level α

From Table 8, we have seen that the hedge ratios and the optimal number of oil forward contracts can vary across periods. However, it is also in our interest to investigate the sensitivity of our results with respect to α, which reflects the biorefinery's preferences towards risk. Ideally, the hedging outcomes should not vary to a great extent when changing the probability level for CVaR. Relatively stable results across different values of α imply that the optimal hedging outcomes for one specific probability level are close to optimal for another. On the contrary, unstable results indicate that the hedging outcomes are highly dependent on the choice of a single parameter in the model, which in turn weakens the confidence of our results.

We observe in Figure 3 that the optimal hedge ratios for the strategy without including oil forwards are relatively stable irrespective of the choice of alpha within the chosen interval, especially when $\alpha \in [0.75, 0.925]$. As can be observed, some individual deviations begin to occur for higher alphas. However, even the largest deviations in absolute value are relatively modest. This further indicates that optimal hedge ratios for one probability level in the range covered in Figure 3 are near-optimal for alternative risk preferences within the same range. Thus, this insensitivity provides confidence to our biorefinery. The hedge ratios' sensitivity



(a) First period considered.

(b) Second period considered.

(c) Third period considered.

(d) Fourth period considered.

Figure 3: The four panels 3a through 3d illustrate how the optimal hedge ratios, without including the possibility to (partly) hedge risks with oil forward contracts, changes with respect to α in the VECM-based scenario sets. All panels consider probability levels (α) in the interval [0.75, 0.975] with 0.025 as the increment in the given range between each re-optimization. The hedge ratios in all panels for $\alpha = 0.85$ match those presented in Table 8 in each respective period. We note that the y-axis range differs across the four panels to better fit each period's hedge ratio sensitivities.

to the chosen probability level increases when we expand the set of hedging instruments to include oil forward contracts, as shown in Figure 6. Increased sensitivity after including oil forwards is also evident in the VAR-based results (see Figure 7 and 8 for the case without and with oil forwards, respectively).

A closer examination of the sensitivity plots reveals some tendencies. Interestingly, we observe from both Figure 6 and 8 that the optimal long position in oil forward contracts (yellow dotted line) increases with the probability level α. This implies that our biorefinery should buy more oil forward contracts if they choose to minimize the expected shortfall in a smaller fraction of scenarios in the right tail of the total procurement cost distribution. Slight increases in the optimal hedge ratios of USDNOK (brown line) as a function of α follow the increasing number of oil forward contracts, which is consistent with our findings in Subsection 5.1. Additionally, we observe that the optimal hedge ratios of power (green line) are almost constant across all probability levels in all figures, further emphasizing the stable nature of the optimal power hedge.

5.4. Backtesting

From the biorefinery's perspective, the performance of the different hedging strategies if they actually were applied is of more importance. We backtest our results against the realized spot prices to examine the hedging outcomes if the proposed hedge setups were put into place.

Figure 4 presents the unhedged total procurement cost of the biorefinery in accordance with our assumptions primarily outlined in Subsection 3.1 to provide some context to our backtesting results. Before the first hedging horizon that we have considered (to the left of the vertical dotted line), we observe that the six-month total procurement cost was quite stable at approximately 450 MNOK in the period up until 2017 before an increasing trend started to appear. Given that the biorefinery's cost base is net short its input factors and the foreign exchange rates, most of the time series plots in Figure 5 help explain this development of the historical unhedged cost.

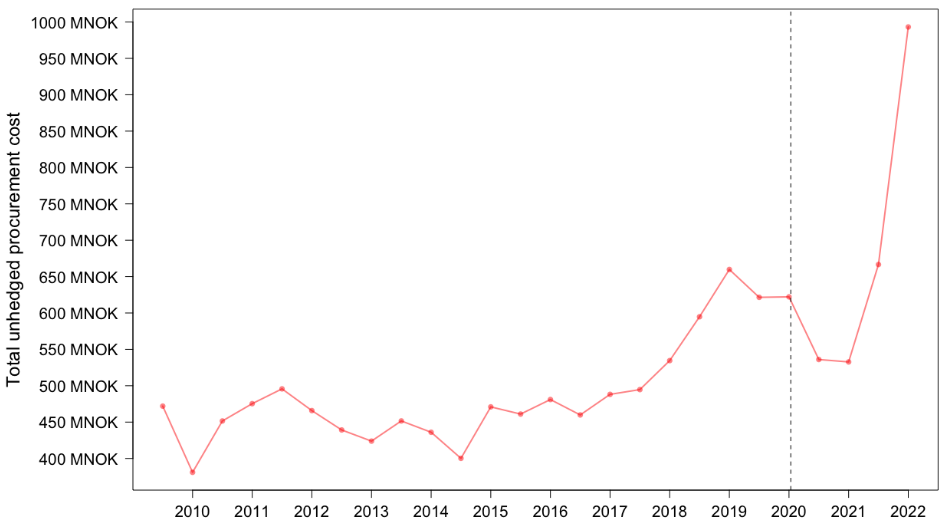


Figure 4: The historical unhedged total procurement cost (MNOK) in the period June 2009 through December 2021 under our assumptions. The vertical dotted line illustrates the time of our first hedge setup, and the four unhedged costs to the right of this line are directly comparable to our hedging outcomes.

Table 9 presents the total procurement costs after applying the different hedging strategies to the cost function (6) in each of the four procurement horizons we have considered in our analysis.[25] These four periods cover two years characterized by financial turmoil after the global onset of the coronavirus pandemic in early 2020. In the first procurement period considered, the coronavirus outbreak caused the foreign exchange rates to increase substantially, whereas the commodity prices generally experienced a decline. A substantial price decrease in most input factors is positive from the buyer's perspective with inherent short positions and explains the decrease in the total procurement cost. Under these circumstances, the unhedged strategy performs the best since it retains the benefits of favorable price developments without incurring additional costs caused by losses from forward positions. Likewise, the naïve approach performed much better than the optimal hedge ratios stemming from the VECM-based and VAR-based scenario sets. Lower hedge ratios for the naïve strategy in this period limited the losses incurred on the hedge instruments. The unhedged strategy outperformed the others in the second period as well. Interestingly, the optimal hedge ratios with and without oil for both VECM-based and VAR-based scenario sets performed better than the naïve hedge in the second period despite total procurement costs remaining at approximately the same level as the first.

Significant price increases characterized the development of most of the biorefinery's input factors in the last two procurement horizons, but hedging provides the biorefinery with protection from directly facing commodity price and currency risks in the spot market. Here, the naïve approach and all optimal hedge setups substantially reduced the total costs compared to the unhedged strategy, where the naïve strategy provided the smallest cost reduction out of these. This is particularly evident in the fourth period, where the unhedged total procurement costs reached astronomical heights.

Table 9: The total costs (MNOK) in each of the four procurement horizons after applying the different hedge setups presented in Table 8. Below each hedging strategy with non-zero hedging positions, we present the percentage total cost increase (positive) or reduction (negative) compared to the unhedged approach after accounting for the net payoffs from the financially settled forward contracts.

			VECM-based		VAR-based	
	Unhedged	Naïve hedge	Optimal (with oil)	Optimal	Optimal (with oil)	Optimal
First period	536	573	608	602	593	591
(2020M01 - 2020M06)		6.82%	13.49%	12.24%	10.70%	10.32%
Second period	533	579	575	563	564	562
(2020M07 - 2020M012)		8.72%	7.85%	5.70%	5.94%	5.43%
Third period	667	564	530	542	520	523
(2021M01 - 2021M06)		-15.44%	-20.52%	-18.66%	-21.95%	-21.59%
Fourth period	993	759	736	734	734	729
(2021M07 - 2021M12)		-23.54%	-25.88%	-26.15%	-26.06%	-26.64%

Note: When calculating the total cost of applying the naïve hedge, we use the $\bar{P}_6^{Chemicals}$ from the respective VECM-based scenario set to calculate the payoff from the USDNOK forward contracts in (6).

To summarize, our backtesting results highlight the need for effective risk management in periods of adverse changes in commodity prices and exchange rates where an unhedged position can incur immensely high costs. All hedge setups from our optimization procedure outperformed the naïve hedge in the last three periods, whereas the inclusion of oil as a hedging

[25] The realized spot prices at the end of each respective procurement horizon are listed in Table 31 in Appendix B.5.

instrument only resulted in lower total procurement cost in the third period. Additionally, we observe from Table 9 that the optimal VAR-based hedge setups without including oil forwards consequently performed better than those based on the VECM in all four periods. Since we do not have enough data observations in our analysis to perform extensive backtesting of the hedging outcomes, we should note that four periods are insufficient to conclude whether one strategy is superior to another. However, these backtesting results indicate that our hedging framework based on a multivariate empirical model can yield improved risk-reduction of our biorefinery's joint multi-commodity and exchange rate exposure when the prices develop in an unfavorable direction, at the cost of additional expenses when the prices turn out favorably.

5.5. Business economic context

Due to sensitivity considerations connected with detailed information about the biorefinery's revenues, we have only focused on the procurement risks associated with the cost base in our analysis. Thus, it is essential to put our results into a broader business economic context, in which they are suboptimal in a holistic sense. The reason why is two-fold.

First, isolating our focus on procurement costs without considering revenues does not capture potential relations between the prices of raw materials and produced products. If these prices naturally move together to some extent, this dynamic will automatically act as a natural hedge reducing the necessity of particular hedging instruments (Haigh and Holt, 2002). Additionally, the revenue streams of our biorefinery are highly export-driven and mainly denoted in euros and US dollars. These incoming foreign currency cash flows offset the biorefinery's currency exposure from procuring raw materials as currency matching of costs and revenues may cancel each other out (Bartram, 2008). Considering that the biorefinery's costs besides input factor procurement primarily are in the local currency (NOK), the total net currency exposures towards EURNOK and USDNOK turn out to be net long instead of net short as they are under our procurement assumptions.

Second, the ability to partially pass along cost increases of input factors to the customers through higher prices should be taken into account. The extent to which procurement costs are associated with increases in the biorefinery's revenues determines its commodity exposure (Titman, 2021). Chemical enterprises and industrial goods manufacturers are typical examples of raw material-intensive companies experiencing difficulties incorporating cost increases in their product prices in the short to medium term (Tevelson et al., 2007). However, the biorefinery under consideration produces specialized products in global niche markets with substantial market shares, suggesting that they at least have some pricing flexibility in their product mix. Abbas and Lan (2020) find that energy commodities are the most important drivers of price appreciation across countries, indicating opportunities to partially pass through the additional costs of the energy-intensive production following rising energy prices to the customers without sacrificing market positions. The possibility of charging higher prices for their products in response to cost increases reduces the biorefinery's net exposure to its related commodity price risks.

Thus, the biorefinery is likely to *overhedge* their total risk exposure if they base their hedging decisions solely on the dynamics inherent in the cost base. These aspects further indicate that our general findings are of higher importance to the biorefinery than the actual sizes of the optimal hedge ratios.

5.6. Critical reflections and possible future research

In the extension of the business economic aspects not incorporated in our analysis, we also provide some critical thoughts on our proposed scenario optimization framework and suggestions for possible future research.

Parameter estimation greatly impacts the quality of the subsequent scenario generation process. For example, Blomvall and Ekblom (2018) emphasize that the properties and dynamics reflected in the generated scenarios are of crucial importance for the quality of the derived hedge ratios from our optimization model in the subsequent step. In this respect, the hedging outcomes from our proposed scenario optimization model highly depend on the estimated multivariate models. We have based our analysis on a data set with a limited number of observations and associated diagnostic tests of our estimated models show that the residuals do not satisfy all the assumptions inherent in the model (see Subsection 4.2.4). This further indicates that our highly parameterized models do not capture all the dynamics between the risk factors, which negatively influences our confidence associated with the precision of the derived hedge ratios.

Selecting the appropriate lag order in the model and which parameters to include is fundamental to the scenario optimization framework since it indirectly affects the resulting hedging positions. The ultimate aim of our cooperating biorefinery is to improve its financial risk management and obtain a hedge setup that provides the best possible performance in practice. We have based our decisions regarding model structure on statistical information criteria to handle the tradeoff between model fit and losing degrees of freedom. However, the underlying criterion of our biorefinery involves other preferences than just the tradeoff considered by the different statistical information criteria used in our model estimation procedure. Instead, it would be beneficial to determine the most appropriate specification of the underlying empirical models based on initial hedging outcomes by conducting an extensive out-of-sample analysis. In this way, we would accommodate the biorefinery's risk-reducing preferences by capturing the essential features in the data, thus tailoring the whole optimization framework toward yielding the best hedging performance in practice. However, such an analytical approach requires substantially more data than we have available. Hence, we leave the work of incorporating a tailored model specification that focuses on selecting the most relevant parameters to accommodate the biorefinery's objective for further research.

Another aspect worth highlighting is that historical time series and past associations between risk factors are not always representative of how the future may evolve. To counteract this fact and complement our scenarios solely based on historical data, we suggest that future work should attempt to include qualitative and custom-made scenarios to increase the range of possible future states taken into account by the optimization model. Incorporating additional scenarios that do not originate from historical tendencies between the risk factors may increase the robustness of the biorefinery's hedging strategy in the face of something unexpected having the potential to turn historical market dynamics upside down.

For further research on the outlined procurement problem and potentially improving the risk-reducing strategy, we propose three additional directions for our biorefinery going forward. First, consistently higher hedge ratios for natural gas and EUA trigger a new question: can we develop intuitive decision rules providing the biorefinery with guidance on reducing the procurement risk using fewer hedging instruments without noticeably sacrificing the ability of CVaR reduction? Due to limited time series observations, we do not have sufficient data to investigate this question in an empirical context. Hence, we leave this as an interesting question for further research as more detailed and comprehensive data are required.

Second, given that the biorefinery has detailed data on its output products, a natural extension of our current optimization framework would be to explicitly account for the revenue streams to make it fit the holistic business economic context. Constructing company-specific indices representing the revenue streams in the main currencies allows for exploring potential connections between the procurement risk factors and output products. In this way, the biorefinery would facilitate more appropriate hedging decisions, which may improve risk reduction. Lastly, it would be useful to investigate the sensitivity of the optimal hedge ratios with respect to different procurement horizons and examine whether the choice of time horizon affects hedging performance.

6. Conclusion

This paper addresses the procurement problem of a Norwegian biorefinery, considering its joint exposure to multi-commodity price and currency risks. We propose a scenario optimization framework to determine the optimal hedge positions in forward contracts to reduce financial risk when the biorefinery procures the necessary input factors to cover its production.

Our results show that the biorefinery can greatly reduce its procurement risk in the 15% worst outcomes by applying our scenario optimization procedure based on an underlying vector error correction model that captures the dynamics between the risk factors. Entering forward contracts to minimize expected shortfall affects both tails of the total procurement cost distribution, implying that applied hedges induce additional expenses in low-cost scenarios. A sensitivity analysis shows that the optimal hedge ratios do not highly depend on the biorefinery's risk preferences as they are relatively insensitive to the choice of probability level in our CVaR-minimizing model.

The results from our scenario optimization approach further reveal that the naïve hedging strategy performs almost as good as our optimally derived hedge positions, with small deviations in the expected shortfall between the two approaches. This is particularly interesting given the fact that chemicals and wood are not directly hedgeable through forward contracts. Thus, although we explicitly account for potential dependencies between all risk factors in a multivariate context, our scenario optimization procedure does not yield substantial additional risk reduction. Moreover, the great risk-reducing performance of the naïve approach is further substantiated by the optimally derived hedge ratios of power and USDNOK, whose values are approximately equal to one across several procurement periods. Based on our analysis, the naïve hedging strategy appears as a highly reasonable alternative to our biorefinery due to its simplicity. Nonetheless, the backtesting results indicate that the proposed scenario optimization procedure based on a multivariate empirical model may provide additional value in terms of cost reduction when extremely adverse changes in commodity prices and exchange rates occur.

Additionally, we find that including oil forwards in the set of hedging instruments statistically significantly reduces the biorefinery's expected shortfall. However, statistical significance does not necessarily imply economic significance. Our results indicate that this additional flexibility only results in a modest reduction in expected shortfall without noticeably avoiding the most extreme and adverse scenarios, further supported by our backtesting results. Moreover, including oil forward contracts in the hedging portfolio somewhat increases the hedge ratios' sensitivity to the choice of probability level when minimizing CVaR. Hence, despite yielding a statistically significant CVaR reduction, we do not regard additional cross-hedging through oil forward contracts as economically significant enough to recommend our biorefinery to pursue this strategy.

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Appendix

A. Formulation of the CVaR_α optimization model

Sets

I	set of input factors to the biorefinery
S	set of scenarios
V	set of variables
W	set of variables with available forward contracts (subset of V)

Subscripts and superscripts

i	input factor i,	where $i \in$ {NG, EUA, Power, Chemicals, Wood}
s	scenario s,	where $s \in$ {1, ..., N}
v	variable v,	where $v \in$ {NG, EUA, Power, Chemicals, Wood, USDNOK, EURNOK, Oil}
w	variable w,	where $w \in$ {NG, EUA, Power, USDNOK, EURNOK, Oil}

0	time of the hedge setup
6	six months after the hedge setup (the horizon of the procurement problem)

Parameters

α		probability level (percentile) for CVaR
F_0^w	$w \in W$	forward price observed in the market for variable w at time 0
N		number of scenarios
$P_{s,6}^v$	$v \in V,\ s \in S$	price of variable v in scenario s at time 6
Q^i	$i \in I$	quantity of exposure to input factor i during the six-month horizon

Decision variables

ζ		Value-at-Risk at the 100α% probability level
h^w	$w \in W \backslash \{\text{Oil}\}$	optimal hedge ratio of variable w
x		optimal number of oil forward contracts

Auxiliary variables

y_s^+	$s \in S$	total procurement cost in excess of the Value-at-Risk (ζ) in scenario s

Objective

$$\text{minimize} \quad \zeta + \frac{\frac{1}{N}\sum_{s \in S}\ y_s^+}{1-\alpha} \tag{A.1}$$

Constraints

$$y_s^+ \geq C_{s,6} - \zeta \qquad \forall s \in S, \text{ where } C_{s,6} \text{ is given by (6)} \tag{A.2}$$

$$y_s^+ \geq 0 \qquad \forall s \in S \tag{A.3}$$

B. Data

B.1. Time series plot

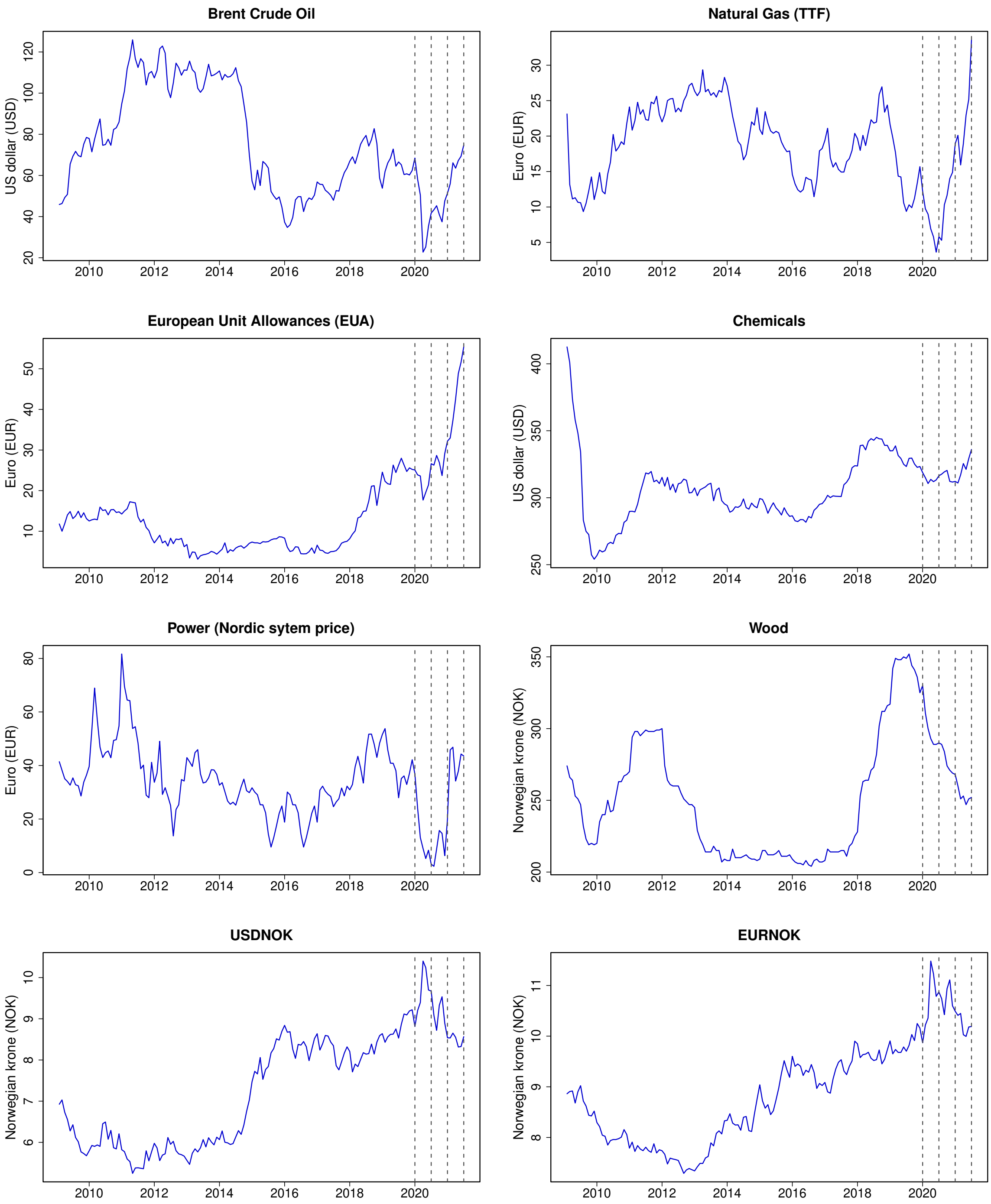


Figure 5: The figure depicts the monthly time series of all variables in our analysis, with spot prices spanning from January 2009 to June 2021. The vertical dotted lines illustrate the starting point of each of our four hedge setups.

B.2. Model estimation tests for the last three periods

Second procurement period considered

Table 10: Determining the cointegration rank r of the vector error correction model by performing the Johansen methodology. Given that we include eight variables in our analysis, the number of cointegrated vectors cannot exceed seven. Due to the high dimension of our proposed model, we use the critical values presented by Osterwald-Lenum (1992). Bold test statistics indicate a rejection of the null hypothesis at the 5% level of significance. The testing procedure is sequential with the alternative hypothesis of more than r cointegrated vectors for the trace test (10a) and $r + 1$ for the maximum eigenvalue test (10b). The underlying data for the tests span 2009M01 to 2020M06. We observe that the results of the two tests differ and we proceed with the results provided by the trace test: two cointegrated vectors are present.

(a) Trace test

H_0	Test statistic	5% level	1% level
$r \leq 7$	2.57	9.24	12.97
$r \leq 6$	8.46	19.96	24.60
$r \leq 5$	20.31	34.91	41.07
$r \leq 4$	34.07	53.12	60.16
$r \leq 3$	52.44	76.07	84.45
$r \leq 2$	93.64	102.14	111.01
$r \leq 1$	**145.47**	131.70	143.09
$r = 0$	**208.45**	165.58	177.20

(b) Maximum eigenvalue test

H_0	H_A	Test statistic	5% level	1% level
$r = 7$	$r = 8$	2.57	9.24	12.97
$r = 6$	$r = 7$	5.89	15.67	20.20
$r = 5$	$r = 6$	11.85	22.00	26.81
$r = 4$	$r = 5$	13.76	28.14	33.24
$r = 3$	$r = 4$	18.37	34.40	39.79
$r = 2$	$r = 3$	**41.20**	40.30	46.82
$r = 1$	$r = 2$	**51.83**	46.45	51.91
$r = 0$	$r = 1$	**62.98**	52.00	57.95

Third procurement period considered

Table 11: Determining the cointegration rank r of the vector error correction model by performing the Johansen methodology. Given that we include eight variables in our analysis, the number of cointegrated vectors cannot exceed seven. Due to the high dimension of our proposed model, we use the critical values presented by Osterwald-Lenum (1992). Bold test statistics indicate a rejection of the null hypothesis at the 5% level of significance. The testing procedure is sequential with the alternative hypothesis of more than r cointegrated vectors for the trace test (11a) and $r + 1$ for the maximum eigenvalue test (11b). The underlying data for the tests span 2009M01 to 2020M12. Here, we observe that the two tests provide consistent conclusions: two cointegrated vectors are present.

(a) Trace test

H_0	Test statistic	5% level	1% level
$r \leq 7$	3.02	9.24	12.97
$r \leq 6$	6.61	19.96	24.60
$r \leq 5$	17.53	34.91	41.07
$r \leq 4$	32.22	53.12	60.16
$r \leq 3$	50.22	76.07	84.45
$r \leq 2$	84.89	102.14	111.01
$r \leq 1$	**135.39**	131.70	143.09
$r = 0$	**197.72**	165.58	177.20

(b) Maximum eigenvalue test

H_0	H_A	Test statistic	5% level	1% level
$r = 7$	$r = 8$	3.02	9.24	12.97
$r = 6$	$r = 7$	3.59	15.67	20.20
$r = 5$	$r = 6$	10.92	22.00	26.81
$r = 4$	$r = 5$	14.69	28.14	33.24
$r = 3$	$r = 4$	18.00	34.40	39.79
$r = 2$	$r = 3$	34.66	40.30	46.82
$r = 1$	$r = 2$	**50.50**	46.45	51.91
$r = 0$	$r = 1$	**62.33**	52.00	57.95

Fourth procurement period considered

Table 12: Determining the cointegration rank r of the vector error correction model by performing the Johansen methodology. Given that we include eight variables in our analysis, the number of cointegrated vectors cannot exceed seven. Due to the high dimension of our proposed model, we use the critical values presented by Osterwald-Lenum (1992). Bold test statistics indicate a rejection of the null hypothesis at the 5% level of significance. The testing procedure is sequential with the alternative hypothesis of more than r cointegrated vectors for the trace test (12a) and $r+1$ for the maximum eigenvalue test (12b). The underlying data for the tests span 2009M01 to 2021M06. We observe that the results of the two tests differ and we proceed with the results provided by the trace test: one cointegrated vector is present, indicating that one linear combination of the variables will be stationary.

(a) Trace test

H_0	Test statistic	5% level	1% level
$r \leq 7$	2.44	9.24	12.97
$r \leq 6$	6.21	19.96	24.60
$r \leq 5$	13.96	34.91	41.07
$r \leq 4$	29.98	53.12	60.16
$r \leq 3$	49.55	76.07	84.45
$r \leq 2$	77.92	102.14	111.01
$r \leq 1$	130.25	131.70	143.09
$r = 0$	**190.79**	165.58	177.20

(b) Maximum eigenvalue test

H_0	H_A	Test statistic	5% level	1% level
$r = 7$	$r = 8$	2.44	9.24	12.97
$r = 6$	$r = 7$	3.77	15.67	20.20
$r = 5$	$r = 6$	7.75	22.00	26.81
$r = 4$	$r = 5$	16.02	28.14	33.24
$r = 3$	$r = 4$	19.56	34.40	39.79
$r = 2$	$r = 3$	28.37	40.30	46.82
$r = 1$	$r = 2$	**52.33**	46.45	51.91
$r = 0$	$r = 1$	**60.54**	52.00	57.95

B.3. Estimated models and diagnostic tests

In this part of the Appendix, we present the estimated empirical models and their associated diagnostic tests to examine whether autocorrelation in the residuals and ARCH effects are present.

First procurement period considered - VECM

Table 13: Normalized cointegrating vectors ($\boldsymbol{\beta}$) and the coefficient estimates of the first-period vector error correction model based on (7). To impose econometric identification restrictions, we follow Johansen (1995) by restricting the first part of $\boldsymbol{\beta}$ to equal the identity matrix. To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Variable	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK	Constant
Cointegrating vectors (β)									
First (ECT 1)	1.0000	0.0000	0.0000	1.0306	-1.4105***	-1.9244***	4.5460	-3.5518**	9.6542**
Second (ECT 2)	0.0000	1.0000	0.0000	-0.0659***	0.7457***	-3.21	-0.4891**	3.5891	4.7757
Third (ECT 3)	0.0000	0.0000	1.0000	0.2738***	-4.0361	4.0254	-0.1821***	-0.0269***	-3.5038

Vector error correction model (r = 3)

Variable (Δy_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Loading matrix (α)								
ECT 1	-0.0422	0.0934***	0.0405	-0.1521**	0.0074	0.0110*	0.0054	0.0146**
ECT 2	-0.0221	-0.1793***	-0.0236	0.0448	0.0405***	0.0333***	-0.0009	-0.0125
ECT 3	0.0007	-0.0108	0.0612	-0.0162	0.0280***	-0.0196***	0.0016	0.0019
Lagged differences (Δy_{t-1})								
USDNOK	0.3293	0.4734	0.4354	1.0737	0.0363	-0.0483	-0.1712	-0.1539**
EURNOK	-0.0965	-0.8352	0.1782	-0.3893	-0.1526	-0.1424	-0.0140	0.0343
Natural Gas	0.0368	-0.0295	-0.1591	0.0317	-0.0367*	-0.0162	0.0043	0.0156
EUA	0.0429	0.1025	-0.2171**	0.1666	-0.0119	0.0217	-0.0085	-0.0073
Power	0.0373	-0.1664***	-0.1214	-0.0203	-0.0002	-0.0087	0.0008	-0.0113
Wood	0.0250	-0.3996	-0.1132	-0.4953	0.0654	-0.0656	0.0648	0.0016
Chemicals	-0.0773	0.8167*	-0.0232	0.8049	0.1920**	0.1350	0.2724*	0.0454
Oil	0.2384**	0.1913	0.1304	0.1769	0.0292	0.0108	-0.0368	-0.0415
Seasonal dummies (Φ)								
January	0.0160	-0.0169	-0.1361*	0.1288	0.0176*	-0.0093	-0.0155	-0.0134
February	0.0633*	0.0086	0.0104	0.0996	0.0017	-0.0054	-0.0112	-0.0127
March	0.0143	-0.0836*	-0.0881	-0.0802	-0.0078	-0.0140	-0.0002	0.0024
April	0.0583	-0.0210	-0.0316	-0.0167	0.0026	0.0030	-0.0146	-0.0098
May	-0.0275	-0.0543	-0.0444	-0.0746	0.0047	-0.0042	0.0183	0.0000
June	0.0041	-0.0415	-0.0826	-0.1236	0.0061	0.0030	0.0036	0.0070
July	-0.0144	-0.0210	-0.0619	-0.1136	0.0098	-0.0138	-0.0086	-0.0056
August	0.0061	0.0554	0.0248	0.1134	0.0105	0.0019	0.0050	0.0003
September	-0.0115	0.0880**	-0.0214	0.0188	0.0083	-0.0001	-0.0055	-0.0005
October	-0.0021	0.0810*	-0.0240	0.0621	-0.0001	-0.0103	0.0040	0.0050
November	-0.0293	0.0790*	-0.0925	0.0999	0.0025	-0.0060	0.0241*	0.0094

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

We test for potential heteroscedasticity in the residuals of the VECM by conducting a multivariate ARCH-LM test across a wide range of lags (see e.g. Lütkepohl, 2005). All test results yield consistent conclusions and do not find sufficient evidence to reject the null hypothesis of no ARCH effects at the 5% level. The lowest p-value obtained is 0.441 ($\chi^2 = 3\ 900.50$, df $= 3\ 888$) with three lags.

First procurement period considered - benchmarking VAR model

Table 14: Coefficient estimates of the first-period benchmarking VAR model based on (8). To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Vector autoregressive model

Variable (y_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Constant	-0.1707	1.2154	-2.2415**	0.2931	0.2008	0.3847***	-0.0371	0.0017
Lagged variables (y_{t-1})								
USDNOK	-0.3353**	0.5482**	-0.1502	-0.1319	-0.0137	0.0144	1.0366***	0.0840**
EURNOK	0.2505	-0.6601*	0.8030	0.1394	0.1667**	0.0891	0.0019	0.8647***
Natural Gas	0.0063	0.7545***	-0.0685	-0.0404	0.0407***	0.0345***	0.0023	-0.0004
EUA	-0.0512	-0.0191	0.8568***	0.0853	0.0130	-0.0191**	0.0046	0.0037
Power	0.0320	0.0653	0.0612	0.7753***	0.0193**	0.0034	-0.0016	0.0092
Wood	0.2068	-0.1586	0.2297	-0.0875	0.9578***	0.0901***	-0.0343	-0.0403
Chemicals	-0.0259	-0.0914	-0.0690	0.0852	-0.0868**	0.7959***	0.0021	0.0475
Oil	0.8325***	0.2468***	0.0564	0.0862	-0.0044	-0.0011	0.0300	0.0089
Seasonal dummies (Φ)								
January	0.0128	0.0258	-0.1343**	0.1383*	0.0220**	-0.0021	-0.0108	-0.0115
February	0.0345	-0.0155	-0.0210	0.0717	0.0049	-0.0002	0.0014	-0.0085
March	0.0163	-0.0205	-0.0817	-0.0587	-0.0009	-0.0056	0.0034	0.0019
April	0.0564	0.0232	-0.0101	-0.0238	0.0046	0.0081	-0.0144	-0.0069
May	-0.0073	-0.0009	-0.0457	-0.0827	0.0108	0.0058	0.0224	0.0036
June	0.0211	-0.0007	-0.0546	-0.1336*	0.0111	0.0077	0.0025	0.0077
July	0.0068	0.0095	-0.0417	-0.1459*	0.0149	-0.0082	-0.0078	-0.0024
August	0.0266	0.0652	0.0271	0.0597	0.0131	0.0070	0.0038	0.0040
September	0.0236	0.0934**	-0.0428	0.0019	0.0123	0.0054	-0.0046	-0.0004
October	0.0187	0.0924**	-0.0289	0.0352	0.0030	-0.0061	0.0071	0.0077
November	-0.0114	0.0821*	-0.0948	0.0847	0.0022	-0.0039	0.0222	0.0099

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 15: Testing for auto- and cross-correlation in the residuals from the benchmarking VAR model for the first procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	86.99	64	$p = 0.030$**
2	155.23	128	$p = 0.051$
3	237.22	192	$p = 0.015$**
4	317.91	256	$p = 0.005$***
5	392.21	320	$p = 0.004$***

All test results across a wide range of lags yield consistent conclusions and do not find sufficient evidence to reject the null hypothesis of no ARCH effects at the 5% level, also for the benchmarking VAR model in the first period. The lowest p-value obtained is 0.275 ($\chi^2 = 3\,940.40$, df $= 3\,888$) with three lags.

Second procurement period considered - VECM

Table 16: Normalized cointegrating vectors ($\boldsymbol{\beta}$) and the coefficient estimates of the second-period vector error correction model based on (7). To impose econometric identification restrictions, we follow Johansen (1995) by restricting the first part of $\boldsymbol{\beta}$ to equal the identity matrix. To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Variable	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK	Constant
Cointegrating vectors ($\boldsymbol{\beta}$)									
First (ECT 1)	1.0000	0.0000	-0.1610***	-0.1171**	0.8135***	-2.9047***	2.1632***	-0.5303***	5.5025*
Second (ECT 2)	0.0000	1.0000	-0.6574*	-0.3071	3.5962***	-6.1814	-0.7037***	4.4936***	6.8102

Vector error correction model (r = 2)

Variable ($\boldsymbol{\Delta y_t}$)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Loading matrix ($\boldsymbol{\alpha}$)								
ECT 1	-0.4142***	0.1563**	-0.0856	-0.2892**	-0.0263	0.0063	0.0750***	0.0523***
ECT 2	0.2247***	-0.1456**	0.0193	0.1547	0.0173	0.0312***	-0.0450***	-0.0341***
Lagged differences ($\boldsymbol{\Delta y_{t-1}}$)								
USDNOK	1.1255***	0.4918	0.7923	1.3975	0.0882	-0.0356	-0.3320**	-0.2254***
EURNOK	-0.8794	-0.5665	-0.0818	-0.9706	-0.0392	-0.1246	0.1348	0.0825
Natural Gas	-0.0622	-0.0574	-0.1913	0.3048*	0.0030	-0.0046	0.0094	0.0174
EUA	0.0898	0.0188	-0.1879*	0.1272	0.0087	0.0201	-0.0172	-0.0132
Power	0.1198**	0.0084	-0.0196	-0.1061	0.0137	0.0008	-0.0131	-0.0165*
Wood	-0.4628	-0.3485	0.1277	-0.2882	0.2147**	-0.0482	0.1504	0.0440
Chemicals	0.2224	1.1170**	-0.0154	0.3053	0.1538	0.1576*	0.2223	0.0297
Oil	0.4313***	0.2268*	0.2520	0.3875	0.0225	0.0079	-0.0840**	-0.0554**
Seasonal dummies ($\boldsymbol{\Phi}$)								
January	0.0173	-0.0155	-0.1249*	0.1141	0.0143	-0.0087	-0.0142	-0.0115
February	0.0658	0.0161	-0.0065	0.0416	-0.0016	-0.0044	-0.0113	-0.0118
March	-0.0303	-0.0583	-0.1059	-0.0932	-0.0070	-0.0086	0.0048	0.0088
April	0.1174***	0.0386	-0.0058	-0.0310	0.0016	0.0062	-0.0236*	-0.0149*
May	0.0457	-0.0525	-0.0256	-0.0200	0.0041	-0.0031	0.0056	-0.0076
June	0.0739*	0.0171	-0.0519	-0.1420	0.0031	0.0046	-0.0081	0.0009
July	0.0683	0.0038	-0.0415	-0.0532	0.0066	-0.0144	-0.0231	-0.0154*
August	0.0855*	0.0822	0.0343	0.1787*	0.0046	-0.0001	-0.0087	-0.0101
September	0.0339	0.0767	-0.0283	0.0782	0.0020	-0.0030	-0.0128	-0.0072
October	0.0438	0.0819	-0.0204	0.0905	-0.0037	-0.0123	-0.0032	-0.0012
November	-0.0060	0.0796	-0.0898	0.1157	0.0015	-0.0069	0.0206	0.0060

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 17: Testing for auto- and cross-correlation in the residuals from the estimated vector error correction model for the second procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	82.03	64	$p = 0.064$
2	175.35	128	$p = 0.003$***
3	265.93	192	$p < 0.001$***
4	361.72	256	$p < 0.001$***
5	454.26	320	$p < 0.001$***

For the second period VECM, all test results across a wide range of lags yield consistent conclusions and do not find sufficient evidence to reject the null hypothesis of no ARCH effects at the 5% level. The lowest p-value obtained is 0.372 (χ^2 = 3 916.30, df = 3 888) with three lags.

Second procurement period considered - benchmarking VAR model

Table 18: Coefficient estimates of the second-period benchmarking VAR model based on (8). To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Vector autoregressive model

Variable (y_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Constant	-0.1528	1.2696	-2.2936**	1.0480	0.2236	0.3801***	-0.0648	-0.0269
Lagged variables (y_{t-1})								
USDNOK	-0.5438***	0.6153***	-0.2050	-0.3423	-0.0485	0.0142	1.0733***	0.1135***
EURNOK	0.3887	-0.8454**	0.8257*	0.2245	0.1978**	0.0871	-0.0252	0.8470***
Natural Gas	0.0335	0.7133***	-0.0800	0.1825*	0.0431***	0.0289***	-0.0071	-0.0112
EUA	-0.0991**	-0.0268	0.8419***	0.0350	0.0113	-0.0172**	0.0110	0.0113
Power	0.0565*	0.0976***	0.0607	0.9296***	0.0130*	-0.0028	-0.0057	-0.0008
Wood	0.3397**	-0.2244	0.2770	-0.1080	0.9696***	0.0896***	-0.0510	-0.0530*
Chemicals	-0.0625	0.0090	-0.0643	-0.0112	-0.0910**	0.8007***	0.0108	0.0545
Oil	0.7179***	0.2526***	0.0311	-0.1365	-0.0147	0.0032	0.0499**	0.0298**
Seasonal dummies (Φ)								
January	0.0030	-0.0008	-0.1336**	0.0988	0.0151	-0.0032	-0.0065	-0.0079
February	0.0128	-0.0298	-0.0303	-0.0001	0.0023	-0.0005	0.0043	-0.0045
March	-0.0493	-0.0486	-0.1054*	-0.0802	-0.0006	-0.0039	0.0112	0.0109
April	0.0505	0.0154	-0.0137	-0.0422	0.0042	0.0064	-0.01305	-0.0071
May	0.0249	-0.0325	-0.0418	0.0030	0.0125	0.0051	0.0155	-0.0011
June	0.0470	0.0253	-0.0421	-0.1362	0.0149	0.0086	-0.0005	0.0043
July	0.0186	0.0063	-0.0440	-0.0678	0.0139	-0.0108	-0.0107	-0.0069
August	0.0377	0.0665	0.0239	0.1505	0.0112	0.0038	0.0010	-0.0011
September	0.0354	0.0923*	-0.0442	0.0713	0.0113	0.0030	-0.0073	-0.0046
October	0.0265	0.0927*	-0.0299	0.0829	0.0021	-0.0079	0.0054	0.0048
November	-0.0055	0.0837*	-0.0947	0.1122	0.0016	-0.0049	0.0211	0.0081

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 19: Testing for auto- and cross-correlation in the residuals from the benchmarking VAR model for the second procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	94.01	64	$p = 0.009$***
2	166.22	128	$p = 0.013$**
3	261.71	192	$p < 0.001$***
4	343.77	256	$p < 0.001$***
5	421.82	320	$p < 0.001$***

The null hypothesis of no ARCH effects is rejected at the 5% level for the multivariate ARCH-LM test only in the case where we include two lags, in which we obtain a p-value of 0.028 (χ^2 = 2 731.80, df = 2 592). Thus, we find sufficient statistical evidence to conclude that some autoregressive conditional heteroscedasticity is present in the second period benchmarking VAR model.

Third procurement period considered - VECM

Table 20: Normalized cointegrating vectors ($\boldsymbol{\beta}$) and the coefficient estimates of the third-period vector error correction model based on (7). To impose econometric identification restrictions, we follow Johansen (1995) by restricting the first part of $\boldsymbol{\beta}$ to equal the identity matrix. To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Variable	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK	Constant
Cointegrating vectors ($\boldsymbol{\beta}$)									
First (ECT 1)	1.0000	0.0000	-0.1758***	-0.1310**	0.9103***	-3.0391***	2.1304	-0.4868**	5.7855*
Second (ECT 2)	0.0000	1.0000	-1.3075***	-0.3513	6.0938***	-8.9838	-0.4202***	4.6613***	9.7402

Vector error correction model (r = 2)

Variable ($\Delta \boldsymbol{y}_t$)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Loading matrix ($\boldsymbol{\alpha}$)								
ECT 1	-0.4323***	0.1061	-0.1045	-0.1746	-0.0043	0.0086	0.0756***	0.0485***
ECT 2	0.1643***	-0.0751*	0.0177	0.0482	-0.0012	0.0190***	-0.0300***	-0.0207***
Lagged differences ($\Delta \boldsymbol{y}_{t-1}$)								
USDNOK	0.9470**	0.2535	0.6304	0.1348	0.0664	-0.0425	-0.2663**	-0.1782**
EURNOK	-0.8708	-0.6996	-0.1869	-1.6839	-0.0210	-0.0778	0.1198	0.0685
Natural Gas	-0.0491	-0.0857	-0.1275	0.2041	-0.0056	0.0041	0.0058	0.0185
EUA	0.1352**	0.0200	-0.1957*	0.2180	0.0045	0.0218*	-0.0261	-0.0177
Power	0.0274	-0.0016	-0.0469	-0.1655*	0.0034	0.0003	0.0191	0.0027
Wood	-0.1633	-0.7753	0.1919	-0.6830	0.2700***	-0.0042	0.0895	-0.0090
Chemicals	0.1335	1.4130**	-0.0954	1.3425	0.1781	0.1382	0.2122	0.0258
Oil	0.4056***	0.2555*	0.2274	0.2310	0.0105	0.0019	-0.0810**	-0.0485**
Seasonal dummies ($\boldsymbol{\Phi}$)								
January	-0.0020	-0.0411	-0.1296**	-0.0235	0.0111	-0.0070	-0.0071	-0.0071
February	0.0433	0.0017	-0.0146	-0.0794	-0.0043	-0.0044	-0.0051	-0.0075
March	-0.0627	-0.0748	-0.1114*	-0.2353**	-0.0117	-0.0084	0.0149	0.0153*
April	0.0801*	0.0248	-0.0140	-0.1479	-0.0033	0.0054	-0.0119	-0.0073
May	0.0103	-0.0763	-0.0372	-0.1851	-0.0008	-0.0029	0.0178	-0.0001
June	0.0454	0.0122	-0.0548	-0.2703**	-0.0040	0.0037	0.0013	0.0074
July	0.0413	-0.0185	-0.0477	-0.2301**	-0.0005	-0.0143*	-0.0142	-0.0086
August	0.0604	0.1152**	0.0241	0.1400	-0.0016	-0.0003	-0.0026	-0.0063
September	0.0137	0.0677	-0.0253	-0.0021	-0.0034	-0.0028	-0.0053	-0.0021
October	0.0196	0.0752	-0.0431	-0.0304	-0.0065	-0.0118	0.0039	0.0033
November	0.0067	0.0698	-0.0772	-0.0522	0.0008	-0.0051	0.0175	0.0033

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 21: Testing for auto- and cross-correlation in the residuals from the estimated vector error correction model for the third procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	89.11	64	$p = 0.021^{**}$
2	195.52	128	$p < 0.001^{***}$
3	295.53	192	$p < 0.001^{***}$
4	385.86	256	$p < 0.001^{***}$
5	476.73	320	$p < 0.001^{***}$

For the third period VECM, all test results across a wide range of lags yield consistent conclusions and do not find sufficient evidence to reject the null hypothesis of no ARCH effects at the 5% level. The lowest p-value obtained is 0.058 (χ^2 = 2 705.80, df = 2 592) where two lags are included.

Third procurement period considered - benchmarking VAR model

Table 22: Coefficient estimates of the third-period benchmarking VAR model based on (8). To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Vector autoregressive model

Variable (y_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Constant	-0.1336	1.2625	-2.2656**	1.2499	0.2210	0.3790***	-0.0643	-0.0205
Lagged variables (y_{t-1})								
USDNOK	-0.6175***	0.4146*	-0.2934	-0.2048	-0.0278	0.0171	1.0902***	0.1182***
EURNOK	0.5169	-0.5124	0.9787**	-0.1575	0.1595**	0.0799	-0.0577	0.8369***
Natural Gas	0.0561	0.7699***	-0.0482	0.1413	0.0349***	0.0267***	-0.0115	-0.0116
EUA	-0.0768*	0.0544	0.8561***	0.1561	0.0104	-0.0152**	0.0062	0.0116
Power	0.0158	-0.0149	0.0341	0.7876***	0.0126**	-0.0067	0.0051	0.0016
Wood	0.3188**	-0.3534*	0.2750	-0.4195	0.9673***	0.0857***	-0.0478	-0.0558*
Chemicals	-0.0694	0.0653	-0.0928	0.2985	-0.0816**	0.8062***	0.0139	0.0575*
Oil	0.7246***	0.2796***	0.0210	0.0126	-0.0076	0.0070	0.0468**	0.0289**
Seasonal dummies (Φ)								
January	-0.0070	-0.0282	-0.1430**	0.0230	0.0153	-0.0030	-0.0040	-0.0075
February	0.0093	-0.0383	-0.0354	-0.0518	0.0024	0.0003	0.0051	0.0045
March	-0.0529	-0.0584	-0.1084*	-0.1501	-0.0015	-0.0036	0.0122	0.0109
April	0.0433	-0.0031	-0.0193	-0.1163	0.0034	0.0064	-0.0111	-0.0067
May	0.0125	-0.0680	-0.0499	-0.1019	0.0113	0.0044	0.0188	-0.0005
June	0.0350	-0.0096	-0.0484	-0.2526**	0.0129	0.0075	0.0029	0.0049
July	0.0122	-0.0524	-0.0535	-0.2263**	0.0146	-0.0100	-0.0104	-0.0067
August	0.0255	0.0547	0.0140	0.0950	0.0116	0.0035	0.0034	-0.0023
September	0.0103	0.0515	-0.0577	-0.0183	0.0075	0.0027	0.0041	0.0008
October	0.0017	0.0630	-0.0540	-0.0426	0.0000	-0.0094	0.0116	0.0069
November	-0.0024	0.0531	-0.0873	-0.0683	-0.0003	-0.0054	0.0186	0.0052

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 23: Testing for auto- and cross-correlation in the residuals from the benchmarking VAR model for the third procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	92.39	64	p = 0.012**
2	173.34	128	p = 0.005***
3	278.17	192	p < 0.001***
4	355.01	256	p < 0.001***
5	440.02	320	p < 0.001***

The null hypothesis of no ARCH effects is rejected at the 5% level for the multivariate ARCH-LM test in the cases where we include one and two lags. The resulting p-values are 0.019 (χ^2 = 1 403.80, df = 1 296) and 0.001 (χ^2 = 2 830.00, df = 2 592), respectively. Thus, we find sufficient statistical evidence to conclude that some autoregressive conditional heteroscedasticity is present at lower lag orders.

Fourth procurement period considered - VECM

Table 24: Normalized cointegrating vector (β) and the coefficient estimates of the fourth-period vector error correction model based on (7). To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Variable	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK	Constant
Cointegrating vectors (β)									
First (ECT 1)	1.0000	2.6982***	-1.2010***	-0.4460	7.3431***	-17.5589***	1.2577	9.6807**	28.6030***

Vector error correction model (r = 1)

Variable (Δy_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Loading matrix (α)								
ECT 1	-0.0166	-0.0228*	-0.0139	-0.0133	0.0022	0.0116***	0.0022	0.0006
Lagged differences (Δy_{t-1})								
USDNOK	0.2842	0.3076	0.5136	-0.4491	0.0532	-0.0440	-0.1552	-0.1161
EURNOK	-0.1716	-0.6887	0.0217	-0.8920	0.0109	-0.0454	0.0348	-0.0108
Natural Gas	-0.0170	-0.0263	-0.0936	0.3221*	-0.0155	-0.0061	0.0021	0.0213
EUA	0.0240	0.0522	-0.1898**	0.1650	0.0081	0.0172	-0.0070	-0.0061
Power	0.0366	-0.0063	-0.0144	-0.0723	0.0005	0.0003	0.0197*	0.0026
Wood	0.3151	-0.6980	0.1469	-0.3712	0.2592***	-0.0936	0.0092	-0.0395
Chemicals	0.0216	1.5625***	-0.0272	0.9093	0.1280	0.1791**	0.2232	0.0024
Oil	0.2090*	0.2844**	0.2102	0.1376	0.0153	0.0151	-0.0442	-0.0333
Seasonal dummies (Φ)								
January	-0.0073	-0.0298	-0.1163*	0.0442	0.0079	-0.0075	-0.0063	-0.0063
February	0.0374	-0.0215	-0.0065	-0.0845	-0.0056	0.0003	-0.0017	-0.0056
March	-0.0706	-0.0694	-0.1013	-0.2347**	-0.0088	-0.0036	0.0151	0.0131
April	0.0635	0.0271	-0.0027	-0.1421	-0.0042	0.0077	-0.0102	-0.0058
May	-0.0074	-0.0719	-0.0371	-0.1685	0.0033	0.0025	0.0205	0.0033
June	-0.0006	0.0332	-0.0597	-0.2639**	-0.0018	0.0092	0.0115	0.0125
July	-0.0154	-0.0208	-0.0592	-0.2381**	0.0010	-0.0103	-0.0043	-0.0023
August	0.0115	0.1163**	0.0162	0.1279	-0.0014	0.0054	0.0062	-0.0017
September	-0.0232	0.0633	-0.0464	-0.0391	-0.0003	0.0003	0.0007	0.0015
October	-0.0113	0.0721	-0.0543	-0.0540	-0.0041	-0.0100	0.0091	0.0063
November	-0.0034	0.0688	-0.0819	-0.0675	0.0012	-0.0047	0.0189	0.0040

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 25: Testing for auto- and cross-correlation in the residuals from the estimated vector error correction model for the fourth procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	89.55	64	$p = 0.019^{**}$
2	200.85	128	$p < 0.001^{***}$
3	294.82	192	$p < 0.001^{***}$
4	388.88	256	$p < 0.001^{***}$
5	474.45	320	$p < 0.001^{***}$

For the fourth period VECM, we only reject the null hypothesis of no ARCH effects at the 5% level for the multivariate ARCH-LM test in the case where we include two lags, in which we obtain a p-value of

0.015 (χ^2 = 2 751.30, df = 2 592). Thus, we find sufficient statistical evidence to conclude that some autoregressive conditional heteroscedasticity is present in this model.

Fourth procurement period considered - benchmarking VAR model

Table 26: Coefficient estimates of the fourth-period benchmarking VAR model based on (8). To avoid the dummy variable trap, we do not include the twelfth month (i.e. December) for the centered seasonal dummies.

Vector autoregressive model

Variable (y_t)	Oil	Natural Gas	EUA	Power	Wood	Chemicals	USDNOK	EURNOK
Constant	0.0896	1.4817	-1.9609*	1.2273	0.1514	0.4145***	-0.0853	-0.0301
Lagged variables (y_{t-1})								
USDNOK	-0.5861***	0.4721**	-0.2274	-0.3673	-0.0244	0.0274	1.0715***	0.1053***
EURNOK	0.5332	-0.5612	0.9613**	0.0617	0.1338*	0.0779	-0.0328	0.8455***
Natural Gas	0.0804	0.7930***	-0.0209	0.1894	0.0232**	0.0290***	-0.0084	-0.0098
EUA	-0.0254	0.1151***	0.9305***	0.1436*	-0.0052	-0.0063	0.0010	0.0061
Power	0.0142	-0.0192	0.0313	0.7702***	0.0143***	-0.0062	0.0045	0.0008
Wood	0.1558	-0.5494***	0.0329	-0.3197	1.0123***	0.0547**	-0.0266	-0.0334
Chemicals	-0.0157	0.1620	0.0022	0.2091	-0.0909**	0.8177***	-0.0002	0.0456
Oil	0.7461***	0.3062***	0.0582	-0.0394	-0.0107	0.0127	0.0402**	0.0221*
Seasonal dummies (Φ)								
January	-0.0009	-0.0164	-0.1328**	0.0716	0.0098	-0.0037	-0.0024	-0.0066
February	0.0286	-0.0429	-0.0175	-0.0503	-0.0053	0.0027	0.0058	-0.0040
March	-0.0395	-0.0426	-0.0866	-0.1591	-0.0052	0.0001	0.0102	0.0065
April	0.0596	0.0146	0.0053	-0.1092	-0.0032	0.0071	-0.0127	-0.0076
May	0.0243	-0.0576	-0.0351	-0.0931	0.0079	0.0071	0.0178	0.0005
June	0.0476	0.0123	-0.0347	-0.2404**	0.0077	0.0095	0.0056	0.0046
July	0.0184	-0.0482	-0.0470	-0.2174*	0.0118	-0.0092	-0.0096	-0.0064
August	0.0334	0.0611	0.0231	0.0997	0.0086	0.0048	0.0038	-0.0025
September	0.0121	0.0515	-0.0567	-0.0118	0.0063	0.0029	0.0048	0.0012
October	0.0026	0.0626	-0.0538	-0.0386	-0.0006	-0.0094	0.0121	0.0071
November	-0.0031	0.0520	-0.0885	-0.0675	-0.0001	-0.0055	0.0187	0.0053

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 27: Testing for auto- and cross-correlation in the residuals from the benchmarking VAR model for the fourth procurement period. Following the notation of Tsay (2005), we test the null hypothesis of no serial correlation, $H_0 : \boldsymbol{\rho}_1 = \cdots = \boldsymbol{\rho}_m = \mathbf{0}$, against the alternative of $H_a : \boldsymbol{\rho}_i \neq \mathbf{0}$ for some i $\in \{1, ..., m\}$. The table presents the test statistics, the degrees of freedom (df) and the associated p-values. We only include test statistics up to and including $m = 5$. ** and *** denote statistical significance at the 5% and 1% level, respectively. The test results clearly show that the residuals are serially correlated.

Lags (m)	Test statistic (χ^2)	df	p-value
1	105.11	64	p < 0.001***
2	184.09	128	p < 0.001***
3	296.47	192	p < 0.001***
4	366.11	256	p < 0.001***
5	452.95	320	p < 0.001***

Similar to the third period benchmarking VAR model, we find sufficient statistical evidence to conclude that some autoregressive conditional heteroscedasticity is present at lower lag orders in this model specification. We only reject the null hypothesis of no ARCH effects at the 5% level for the multivariate ARCH-LM test in the cases where we include one and two lags. The resulting p-values are 0.002 (χ^2 = 1 452.20, df = 1 296) and 0.001 (χ^2 = 2 831.60, df = 2 592), respectively.

B.4. Descriptive statistics of the scenario sets

Table 28: Descriptive statistics of the simulated December 2020 scenario sets based on monthly time series data from early 2009 up until June 2020. We present the minimum, mean and maximum scenario values for each variable. To further illustrate the spread of the prices, we include the lower quartile (Q1), the median and the upper quartile (Q3).

	Minimum		Q1		Median (Q2)		Mean		Q3		Maximum	
	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR
USDNOK	7.26	6.85	9.23	9.13	9.65	9.64	9.66	9.66	10.08	10.16	12.60	13.77
EURNOK	9.30	8.94	10.63	10.59	10.91	10.90	10.91	10.91	11.19	11.23	13.11	12.94
Natural Gas	3.47	4.27	9.73	10.14	11.75	11.90	12.23	12.23	14.19	13.95	34.44	32.88
EUA	6.62	6.56	21.07	20.98	25.56	25.50	26.62	26.62	31.00	31.00	83.74	92.78
Power	3.65	3.41	14.92	14.59	19.40	19.23	20.90	20.90	25.14	25.32	94.65	102.65
Wood	199.73	170.75	274.86	215.41	289.85	225.10	290.60	225.60	305.33	235.24	398.20	290.44
Chemicals	262.01	235.87	305.81	274.36	315.37	282.05	315.67	282.26	325.15	289.85	377.34	334.83
Oil	16.63	17.12	36.12	36.18	41.46	41.42	42.31	42.31	47.53	47.52	98.14	105.95

Note: For all variables except wood and chemicals, which do not have available forward contracts, the mean value of the 50 000 simulated scenarios exactly equals the respective forward price presented in the third column of Table 2.

Table 29: Descriptive statistics of the simulated June 2021 scenario sets based on monthly time series data from early 2009 up until December 2020. We present the minimum, mean and maximum scenario values for each variable. To further illustrate the spread of the prices, we include the lower quartile (Q1), the median and the upper quartile (Q3).

	Minimum		Q1		Median (Q2)		Mean		Q3		Maximum	
	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR
USDNOK	6.35	6.04	8.14	8.06	8.52	8.52	8.55	8.55	8.93	9.00	11.16	12.18
EURNOK	8.98	8.76	10.26	10.23	10.54	10.54	10.55	10.55	10.83	10.86	12.33	12.49
Natural Gas	4.33	6.22	12.37	13.15	15.20	15.47	15.90	15.90	18.62	18.17	60.25	42.57
EUA	8.07	8.28	25.53	25.30	30.86	30.76	32.11	32.11	37.34	37.46	91.84	102.61
Power	2.61	3.69	13.67	15.24	18.97	19.85	21.40	21.40	26.37	25.77	150.31	103.14
Wood	195.11	229.70	254.67	289.06	268.65	301.97	269.54	302.70	283.37	315.70	369.20	399.52
Chemicals	257.50	268.69	298.93	305.65	308.15	314.17	308.38	314.38	317.52	322.81	377.51	370.69
Oil	19.83	23.19	44.17	44.27	50.61	50.62	51.58	51.58	57.90	57.73	116.31	113.63

Note: For all variables except wood and chemicals, which do not have available forward contracts, the mean value of the 50 000 simulated scenarios exactly equals the respective forward price presented in the fourth column of Table 2.

Table 30: Descriptive statistics of the simulated December 2021 scenario sets based on monthly time series data from early 2009 up until June 2021. We present the minimum, mean and maximum scenario values for each variable. To further illustrate the spread of the prices, we include the lower quartile (Q1), the median and the upper quartile (Q3).

	Minimum		Q1		Median (Q2)		Mean		Q3		Maximum	
	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR	VECM	VAR
USDNOK	6.07	6.14	8.12	8.07	8.53	8.52	8.55	8.55	8.96	9.00	12.06	11.89
EURNOK	8.43	8.35	9.90	9.92	10.23	10.22	10.23	10.23	10.56	10.54	12.32	12.32
Natural Gas	9.19	8.02	25.73	26.50	31.90	32.22	33.61	33.61	39.73	39.22	115.60	108.96
EUA	15.99	11.45	43.61	42.45	53.26	52.83	55.64	55.64	65.13	65.69	187.21	207.96
Power	3.17	6.76	25.06	30.10	36.28	39.30	42.45	42.45	52.87	51.19	352.71	208.50
Wood	178.80	219.71	238.85	277.73	251.47	289.95	252.24	290.50	264.95	302.61	357.90	384.96
Chemicals	272.63	290.76	320.81	341.78	330.51	351.52	330.77	351.80	340.37	361.51	404.17	414.43
Oil	18.39	31.45	55.44	61.70	68.81	70.81	72.25	72.25	85.26	81.33	268.44	161.88

Note: For all variables except wood and chemicals, which do not have available forward contracts, the mean value of the 50 000 simulated scenarios exactly equals the respective forward price presented in the fifth column of Table 2.

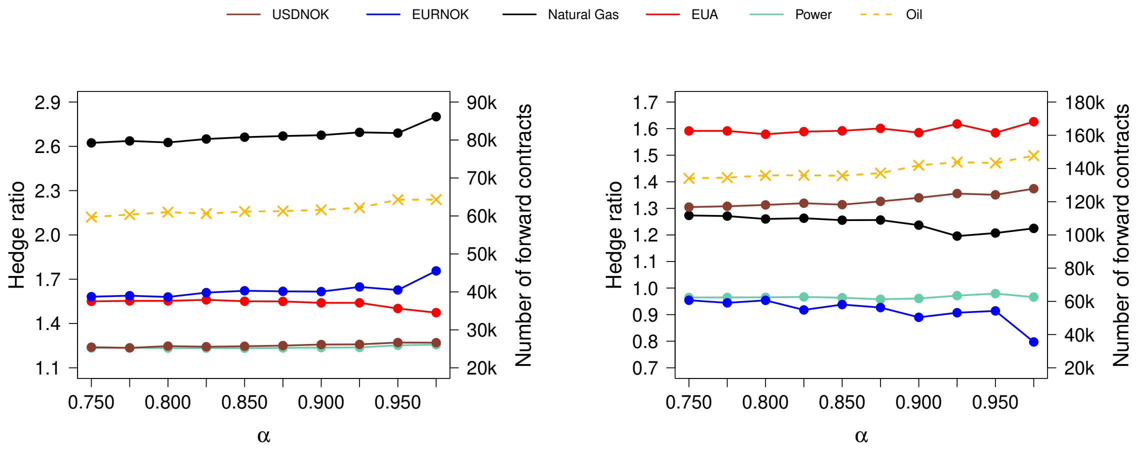
B.5. Realized spot prices

Table 31: The realized spot prices at the end of each procurement horizon, with their exact measurement date in parenthesis. We emphasize that some prices and exchange rates are rounded to two decimals.

	June 2020 (29.06)	December 2020 (30.12)	June 2021 (30.06)	December 2021 (31.12)
USDNOK	9.67	8.54	8.56	8.81
EURNOK	10.87	10.49	10.19	10.01
Natural Gas	5.80	18.90	33.58	69.00
EUA	26.63	32.19	55.38	80.90
Power	5.58	13.68	41.89	96.11
Wood	290.00	268.00	252.00	263.00
Chemicals	316.40	312.20	336.03	421.77
Oil	41.71	51.34	74.76	77.78

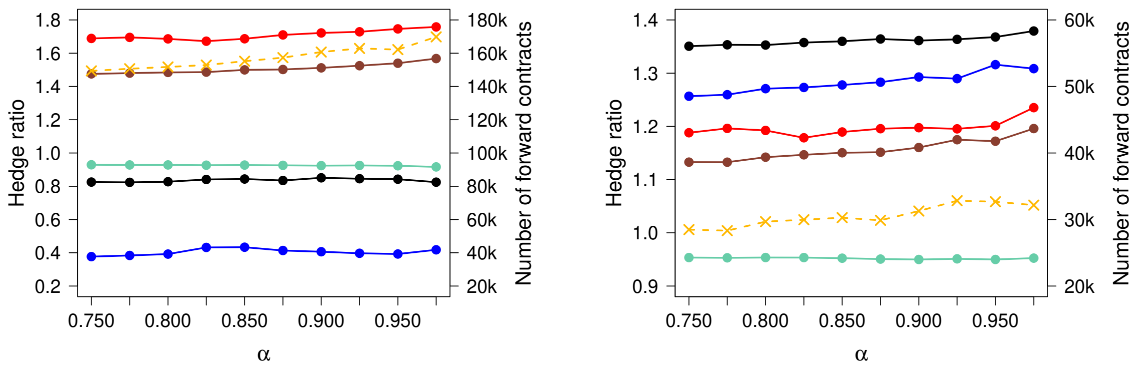
Note: The realized spot prices for power are calculated as the average spot price from the last three months in each procurement horizon to match the time aspect of the quarterly forward contract.

C. Supplementary results



(a) First period considered.

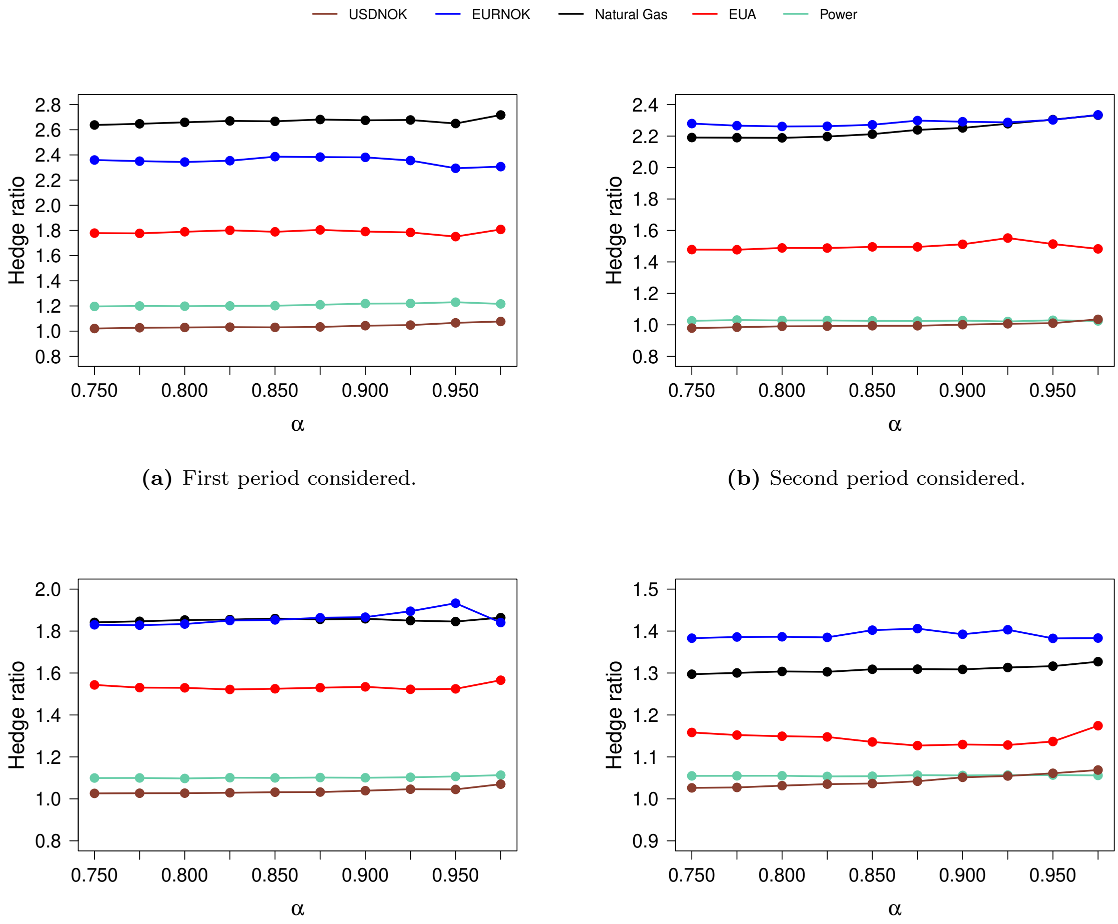
(b) Second period considered.



(c) Third period considered.

(d) Fourth period considered.

Figure 6: The four panels 6a through 6d illustrate how the optimal hedge ratios changes with respect to α in the VECM-based scenario sets when we include the possibility to (partly) hedge risks with oil forward contracts. All panels consider probability levels (α) in the interval [0.75, 0.975] with 0.025 as the increment in the given range between each re-optimization. The hedge ratios in all panels for $\alpha = 0.85$ match those presented in Table 8 in each respective period. We note that the y-axis range differs across the four panels to better fit each period's hedge ratio sensitivities. Additionally, the secondary y-axis (to the right) belongs to the optimal position in oil forwards (yellow dotted line).



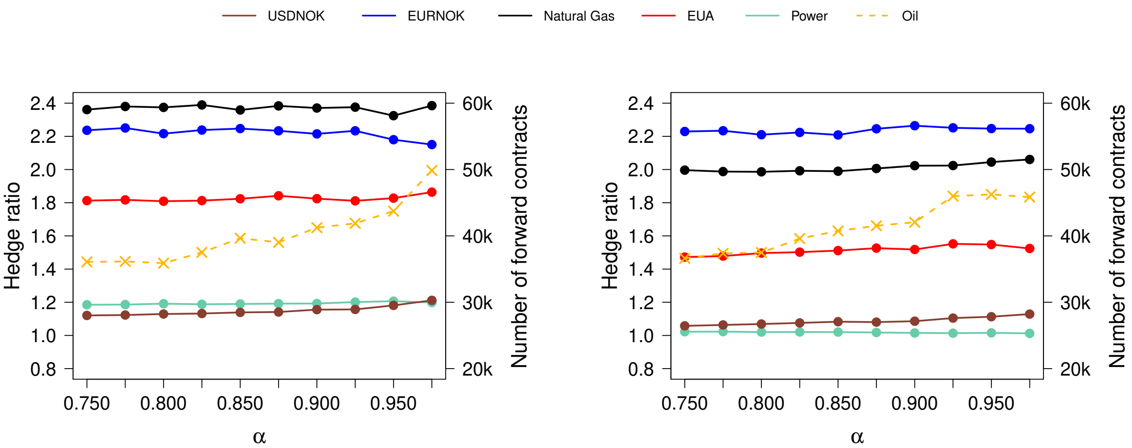
(a) First period considered.

(b) Second period considered.

(c) Third period considered.

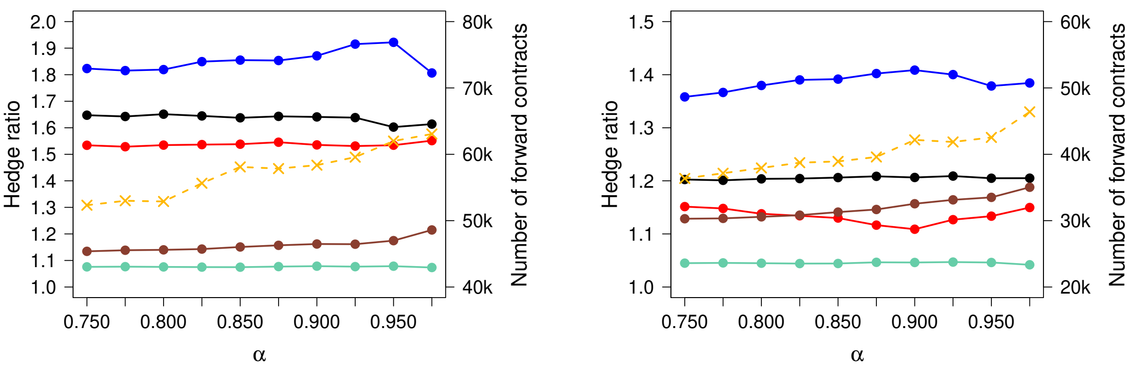
(d) Fourth period considered.

Figure 7: The four panels 7a through 7d illustrate how the optimal hedge ratios, without including the possibility to (partly) hedge risks with oil forward contracts, changes with respect to α in the VAR-based scenario sets. All panels consider probability levels (α) in the interval [0.75, 0.975] with 0.025 as the increment in the given range between each re-optimization. The hedge ratios in all panels for $\alpha = 0.85$ match those presented in Table 8 in each respective period. We note that the y-axis range differs across the four panels to better fit each period's hedge ratio sensitivities.



(a) First period considered.

(b) Second period considered.



(c) Third period considered.

(d) Fourth period considered.

Figure 8: The four panels 8a through 8d illustrate how the optimal hedge ratios changes with respect to α in the VAR-based scenario sets when we include the possibility to (partly) hedge risks with oil forward contracts. All panels consider probability levels (α) in the interval [0.75, 0.975] with 0.025 as the increment in the given range between each re-optimization. The hedge ratios in all panels for $\alpha = 0.85$ match those presented in Table 8 in each respective period. We note that the y-axis range differs across the four panels to better fit each period's hedge ratio sensitivities. Additionally, the secondary y-axis (to the right) belongs to the optimal position in oil forwards (yellow dotted line).

D. The bootstrapping procedure

As an alternative to the two-sample t-test, we tailor a bootstrapping procedure to empirically examine whether the inclusion of oil forward contracts in the set of hedging instruments statistically significantly reduces the expected shortfall of our biorefinery. We define the worst 15% total procurement costs, the 7 500 scenarios in the right tail, after applying the two hedging strategies as members of the respective populations under examination.

Under the assumption of no difference in the expected shortfall between the two strategies where the observations originate from the same distribution, the null hypothesis, we pool the observations into one group. Then, 15 000 (i.e. two times 15% of the scenario set size) observations are sampled repeatedly with replacement from the pooled total procurement costs. Due to high computational complexity, we limit the number of bootstrap resamples to 25 000, which results in a 15 000 x 25 000 bootstrap sample matrix.

We further define our test statistic to equal the absolute difference between the means (i.e. CVaR) of the two strategies in each bootstrapped sample. From optimization theory, the expected shortfall with oil forwards can never exceed the CVaR without oil due to additional flexibility in the optimization problem. Under the assumption of no improved risk-reducing effect after including oil forwards, we can validly bisect each column of the bootstrap matrix and assign the lowest mean value out of these two lists to the hedging strategy where oil forwards are included.

The null hypothesis,

$$H_0 : \mu_{\text{without oil}} = \mu_{\text{with oil}} \qquad (\text{i.e. } \mu_{\text{without oil}} - \mu_{\text{with oil}} = 0) \ , \tag{A.4}$$

is then tested against the alternative hypothesis of

$$H_A : \mu_{\text{without oil}} > \mu_{\text{with oil}} \ . \tag{A.5}$$

We check for statistical significance by calculating the associated p-value of our bootstrapping procedure by comparing the bootstrapped differences in means (μ) with the observed CVaR reduction obtained from our optimization procedure (see results in Table 8):

$$p\text{-value} = \frac{\text{Number of bootstrap test statistics exceeding the CVaR reduction from our optimization results}}{\text{Total number of bootstrap resamples (25 000)}} \ . \tag{A.6}$$

The p-value indicates the proportion of outcomes that yield a test statistic at least as extreme as the CVaR reduction observed in our results when assuming that the null hypothesis is true. We present the results of the bootstrapping procedure in Table 32.

Table 32: Results from applying the bootstrapping procedure to examine whether including oil forwards statistically significantly reduces the biorefinery's CVaR. The table shows the observed CVaR reduction (in NOK) calculated from results in Table 8 together with the corresponding p-value from the bootstrapping procedure. We find sufficient evidence to reject the null hypothesis in all tests at the 5% level of significance.

	VECM-based		VAR-based	
	Observed CVaR reduction	p-value	Observed CVaR reduction	p-value
First period (2020M01 - 2020M06)	1 350 679	$p < 0.001^{***}$	288 879	$p = 0.030^{**}$
Second period (2020M07 - 2020M012)	1 794 941	$p < 0.001^{***}$	233 557	$p = 0.043^{**}$
Third period (2021M01 - 2021M06)	3 115 389	$p < 0.001^{***}$	475 810	$p < 0.001^{***}$
Fourth period (2021M07 - 2021M12)	552 680	$p < 0.001^{***}$	404 318	$p = 0.003^{***}$

Note: ** and *** denote statistical significance at the 5% and 1% level, respectively.

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