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Exploring the futures hedging possibilities for the Norwegian lumber market, using the U.S. market as a proxy

Testing the effectiveness of different minimum variance hedge ratio approaches

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Abstract

This paper explores the possibility for a cabin producer to manage lumber price volatility by hedging with futures contracts. Our intention is to explore if the introduction of a futures market for lumber will provide Norwegian (and European) producers with a viable way to handle said volatility. With a set of simplifying assumptions, a minimum variance strategy is tested on an artificially constructed cabin producer to estimate the effectiveness of such a strategy. Estimating the minimum variance hedge position is done using two advanced autoregressive models, in addition to a simpler, unconditional model. The three approaches are compared in a segmented time-series to isolate the effectiveness prior to and after the price shock that came with the Covid-19 pandemic.

The findings indicate that the hedging strategy has great potential of reducing the variance of the cash flows. Prior to the Covid-19 outbreak, the variance of the cash flows could have been reduced by almost 50 percent. In that period, all three estimation models achieved almost identical effectiveness, with all three being within three percentage points of each other. Following the Covid-19 outbreak, there is a greater spread between the approaches, with the surprise being that the simpler, unconditional model outperforms the autoregressive models. The inferior performance of the conditional models indicates a weakness in the models' ability to estimate the optimal hedge position in times of sustained increased volatility.

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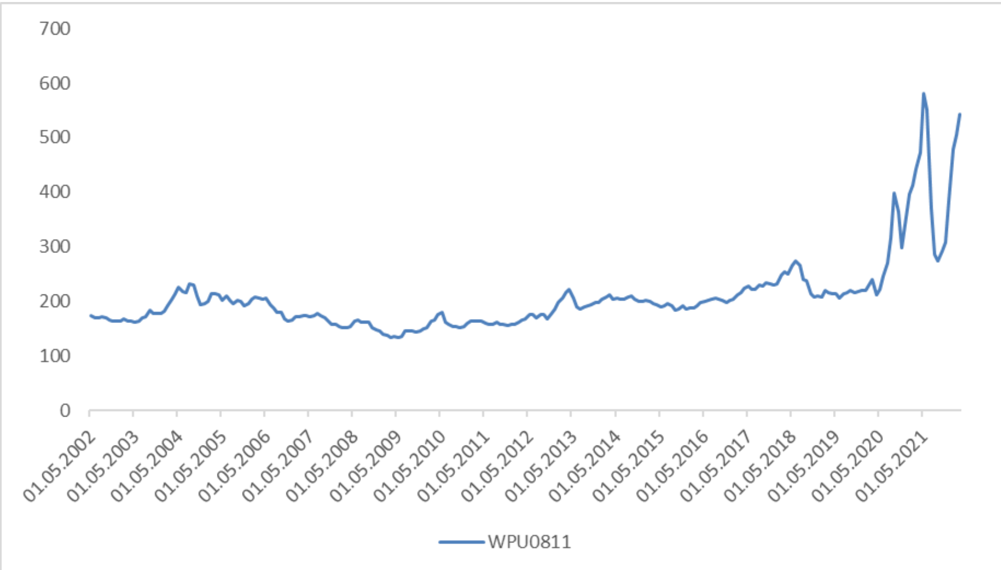
1 Introduction

The construction industry is characterized by lengthy project timelines, complex supply chains and sensitivity to external factors. Factors such as extreme weather, changes in laws- and regulations, and humanitarian crises like the Covid-19 outbreak and the invasion of Ukraine. Events like these can have, and have had, a big impact on production and prices in the industry.

Following the Covid-19 outbreak, labor shortage and an unexpected increase in demand caused US lumber prices to rise by more than 300% (van Kooten & Schmitz, 2022). The increase in demand came at a time where the inventory in the US lumber industry was already suffering due to forest fires and beetle infestations (Lambert, 2021). Subsequently, this led to an increase in import from Europe, which caused the European prices to rise. Just like that, the global lumber industry experienced a price shock, seemingly out of nowhere. Price shocks of that magnitude are few and far between, but the sudden increase in volatility has great damage potential.



Graph 1: Softwood lumber producer price index (BLS, 2022)

Commodity price volatility (CPV) is a major source of risk in the construction industry because contracts are usually signed long before materials are acquired. The severity of CPV in the industry is illustrated by the rise in lumber prices during the Covid-19 outbreak. A price increase of that magnitude is enough to financially ruin a firm without a strategy in place to manage that particular risk.

In the Norwegian cabin industry, the most common way to manage CPV has been with an escalation clause. The clause usually states that prices can be adjusted from the time of signing until the time of delivery (or production). The adjustment is based on a third-party index that aims to mirror the price changes in the marked (SSB, 2022). Because the index represents an average cabin model, the effectiveness of this risk management strategy will vary among producers and models. Nevertheless, a quick search reveals that many of the major cabin production firms in Norway use this strategy ((Telemarkhytter (2021), Familiehytta (2021), Nordlyshytter (2021), RanaHytter (n.a.), Saltdalshytta (2021)). After exploring other possible strategies, it becomes apparent why.

Gaudenzi et al. (2018) categorize different CPV management strategies into three main groups. First group is *sourcing strategies*, which include capital intensive strategies like vertical integration and store keeping. Second group is *contracting strategies*, in which, among other things, the escalation clause used in Norway falls. The final group is *financial strategies*, which means hedging. When looking at the preferences of producers and customers, it is revealed that the choice of CPV management strategy is somewhat constrained.

Considering the probable requirements of the sourcing strategies, it becomes apparent why it might be a less preferred strategy. Vertical integration, purchase timing (which would require store keeping), and commodity substitution are all examples of sourcing strategies. For the average firm, they all require substantial investments and/or significant changes in the supply chain. For that reason, firms might not prefer it as a CPV management strategy, which leaves *contracting strategies* and *financial strategies*.

Of the contracting strategies mentioned by Gaudenzi et al. (2018), the interesting ones are the escalation clause and a closely related strategy, which involves directly passing on the price increase to the customer without the use of a third-party index. While the price increase seen during the Covid-19 outbreak has caused turmoil among producers, the customers are also heavily affected by it. Customers who signed contracts with escalation clauses would have seen the price of their cabin projects increase tremendously, and news coverage of the situation has led to great uncertainty among potential customers who are considering buying. The recent price increase alone has led to a decrease in the average cabin customer’s relative purchasing power, which has resulted in a decrease in the realistic number of potential customers. On top of that comes the risk of even further price increases, which has scared a great portion of the remaining potential customers. This uncertainty has resulted in a severe reduction in sales industrywide (Boligprodusentene, 2022b), which has sparked an interest in the producers to explore the only remaining group of strategies, the *financial strategies*. Exploring the possibility and effectiveness of a hedging strategy is the underlying aim of this thesis, and will be done using different estimation techniques. A hedging strategy can be combined with the escalation clauses, giving the customer a more stable price outlook, which is precisely what is being called for.

A detached house or cabin is made out of many different types of material, and hedging the entirety of the house would therefore require a whole bundle of different futures contracts. When taking into consideration the varying amounts needed of the different types of material, a complete hedging strategy would undoubtedly appear excessive. Of all the materials used to build an average Norwegian detached house, or cabin, wood accounts for approximately 50 percent (SSB, 2019). The remaining 50 percent consists of smaller amounts of metal, pipes, electrical components and more. Consequently, the exposure to lumber price volatility is significantly greater than the exposure to price volatility from other commodities. For that reason, this thesis will exclusively look at the management of lumber price volatility.

An immediate issue with a lumber hedging strategy in the Norwegian housing -and cabin industry, is the lack of a lumber futures market in Europe. The only real lumber futures market that exists is on the Chicago Mercantile Exchange (CME), where contracts on American lumber are traded. Meanwhile, most of the lumber used in the Norwegian industry is of domestic origin, or comes from other European producers (Treindustrien, 2022). One could try to use CME lumber futures contracts to hedge against lumber price volatility in Norway, but the lack of covariation between Norwegian lumber prices and CME lumber futures contracts would make it ineffective (appendix 1). For that reason, this thesis will look at a lumber hedging strategy from an artificially constructed American cabin producer's perspective. Even though the hedging is done from the perspective of a cabin producer, the hedging itself will be possible for a multitude of industries that are exposed to lumber price volatility. Therefore, the results can be useful to numerous industry parties, and potentially be used as support for the creation of a European lumber futures market.

The primary aim of this thesis is to answer the following two research questions:

i. To what extent can a cabin producer reduce lumber price volatility by hedging with futures contracts?

ii. How do advanced, autoregressive hedge ratio estimation models perform compared to a simple, unconditional estimation model?

2 Literature review

2.1 Optimal hedge ratio

One of the main objectives when using derivative instruments for hedging purposes is determining the optimal hedge ratio (Chen et al., 2003; Harris & Shen, 2003; Myers & Thompson, 1989). That is, the amount of spot positions to be covered by opposite positions in the futures market (Myers & Thompson, 1989). The optimal hedge ratio depends on the objective function to be optimized (Chen et al., 2003), but one of the most common hedging strategies is based on minimizing the variance of the hedged portfolio. The minimum variance (MV) hedge ratio is popular due to its simplicity and effectiveness, but it is important to point out one of its shortcomings.

The only task of the MV hedge ratio is to minimize the variance of the hedged portfolio. For that reason it completely ignores the expected return, which is not in accordance with the mean-variance framework introduced by Markowitz (1952). In the mean-variance framework, risk and reward are weighted against each other, which means both variance *and* expected return are included in the investment decision. The exclusion of expected return in the MV strategy implicitly assumes that investors are infinitely risk averse or that the expected return is equal to zero, which would be the case if expected returns follow a stochastic process. The point is that the MV hedge ratio is optimal only under certain conditions.

As mentioned earlier, the MV hedge ratio is only optimal when the objective function is to minimize the variance of the hedged portfolio. When the objective function is different, the optimal hedge ratio is also different. There has been done extensive research on the topic of optimal hedge ratios, and many different objective functions have been studied (Chen et al., 2003). However, in accordance with the purpose of this thesis, which is to explore the possibility of hedging against lumber price volatility, utility functions in the industry, and the effectiveness of other hedging strategies are not included. Therefore, the only hedge ratio to be included in this thesis is the MV hedge ratio.

2.2 Stochastic process of commodities

The mean reverting nature of commodity prices has been studied previously. Schwartz (1997) notes how fundamental microeconomic reasoning suggests that periods of high prices would cause more producers to contribute to the supply which drives the prices back down, and vice versa. Faustmann's formula further backs this reasoning, where the optimal time for cutting down a forest is pushed back if the price of timber falls causing the added growth to be less valuable compared to the potential returns of holding on longer. This causes the supply to fall and will eventually cause the price to rise. The opposite is true for when the prices are higher than normal.

Similar findings are made by Insley (2002) where the real option valuation within forestry management is compared between models using geometric Brownian motion versus mean reversion as assumptions for the underlying stochastic process of lumber prices. She notes how the characteristics of a GBM model will have an effect on the option value at lower prices, thereby "… implying option value estimates will be inaccurate for low prices" (Insley, 2002). The production of timber globally has previously shifted from cutting old growth over to more industrial plantation-grown wood and second-growth wood (Sedjo, 1997). Such a shift in operations toward industrial plantations implies that the prices will follow a mean reverting process with the long-run marginal cost as its mean (Insley, 2002). Using models that assume a long run mean reversion, like the ARMA-GARCH models, is therefore appropriate.

2.3 ARMA-GARCH

The ARMA(p,q)-GARCH(p,q) model specifies both the *conditional mean* and the *conditional variance* of a time-series in the same model. ARMA-GARCH models' forecasting ability have been extensively tested and applied. Liu et. Al (2011) tested the forecasting ability of several ARMA-GARCH models in modelling the mean of wind speed data. Even though this is not a financial time series, it still showcases the models' ability to model nonlinearity. Using ARMA-GARCH models has become commonplace in modelling return time series due to its accuracy and ability to accommodate for heteroscedasticity (Shi et. Al, 2013).

2.4 Hedging effectiveness

The effectiveness of the hedging strategy is measured by comparing the variance of the hedged portfolio with the unhedged portfolio, using the following formula from Ederington (1979):

$$HE = 1 - \frac{Var(CF^{H})}{Var(CF^{UH})}$$

The interpretation is straightforward. A hedging effectiveness (HE) below 0 means the variance of the hedged portfolio is greater than the unhedged. A HE between 0 and 1 means the variance is decreased, and a HE of 1 means all the variance is eliminated (i.e., a perfect

3 Data

3.1 Futures prices

Unlike stocks, futures contracts have an expiration date. When the current front-month contract expires, the contract that previously was the two-period contract, is then the new front-month contract. For that reason, futures prices need to be manipulated to be used in historical data analysis. This is done by rolling the contracts over, and combining them into, so called, continuation contracts. The continuation contracts used in this thesis is collected from Refinitiv’s Datastream. The one-period and three-period contracts are the primary contracts being used in this thesis. The four-period contract is also utilized, but in a supplementary fashion.

In Datastream, the continuation contracts are limited to 20 years of historical data. Therefore, the time-series used in this thesis is a 20-year long, monthly series starting from April 2002.

3.2 Producer price index

To simulate how the price of lumber develops in the spot market, the Producer Price Index (PPI) published by the U.S. Bureau of Labor Statistics is used. Specifically, the PPI for softwood lumber (code WPU0811). The PPI’s aim is to measure the average change in selling prices over time received by U.S. producers of goods and services (*Producer Price Indexes*, 2018). To match the length of all the time-series’, and because of the 20-year limitation in the futures contracts, the data from the PPI is also 20 years, starting from April 2002.

4 Method

To test the hedging strategy, this thesis uses an artificially constructed cash flow. The cash flow is created with the purpose of replicating that of an actual cabin production firm, while keeping it as simple as possible. For simplicity, a set of assumptions is placed on the cash flow.

4.1 General assumptions

The purpose of the thesis is to test the possibility for a cabin production firm to hedge against lumber price volatility, and the potential effectiveness of such a hedge. For that reason, the constructed cash flow includes only wood related costs and revenues. Further, the cash flow is designed to replicate that of a firm which sells pre-cut cabin kits, and it excludes everything that is not related to cabin kit sales or the acquirement of wood related materials. A cabin kit would naturally include other components than wood, and a firm selling them would have other costs than those associated with procurement of wood, but for the purpose of this thesis, all such factors are excluded.

Following this trend of simplicity, the cost estimates used in the cash flow time series is assumed to follow the movement of the softwood lumber PPI. For testing purposes, all values have to be the same unit of measure. The transformation of the PPI into U.S. Dollars is done by assuming the first periods cost is equal to the front-month futures price in the same period plus a markup. This assumption is made because firms that sell pre-cut cabin kits are usually outsourcing the actual preparation of the lumber. These producers are assumed to buy lumber from their local sawmill at the prevailing market price. A market price which, if the law of one price holds, will be relatively close to the front-month futures contract price. With a cost timeseries in U.S. Dollars, a similar assumption is made about the price at which the firm sells the cabin kits.

One could assume that the firm takes into account the expected future price of lumber in their pricing strategy by looking at the longer period futures contracts. To maximize the effect of hedging, however, it is assumed that the firm does not include information from the futures market in their pricing strategy. They simply use the prevailing price offered by the cabin kit manufacturer and add a markup to cover costs and profits.

To calculate the total cash flow, as well as the hedge position, a specific number of sold cabins must be determined. Using information about the number of construction-starts in 2021 from the top five biggest cabin firms in Norway, and assuming a steady stream of construction-starts and sales throughout the year, an average of 30 cabins a month is acquired (Boligprodusentene, 2022a). In addition to a number of cabins sold, an estimate of lumber consumption per cabin is needed. The estimate used is an average of 30 cubic meters of lumber per cabin and comes from a conversation with an employee at one of the biggest cabin firms in Norway. 30 cubic meters is approximately equal to 12,7 thousand board feet (mbf).

Another feature of the cabin industry which require an assumption is the lengthy sales process, which is also the primary reason a CPV management strategy is necessary. In Norway, the local government is responsible for issuing building permits, which results in geographical variation in processing time. Considering all the other factors that are distinctive to each project, there will be considerable variation in processing time between the projects. However, for testing purposes the assumption is that the sales process is six months for each project. This also leads to the assumption that the firm always closes out its position before settlement. That is, the firm holds the futures contract for approximately six months and then cancels the long futures position by taking an equal sized short position.

The six months-assumption, in combination with the fact that the futures contracts are only traded with settlement every other month, causes a minor issue that needs to be addressed. A three-period contract entered into on either of the "off-months" (the months without settlement) will have five months to settlement, not six. For the purpose of this thesis, the "issue" is ignored on account that the three-period and four-period contracts are very closely correlated (appendix 2). The increased validity from implementing a model that considers four-period contracts for the off-months, is judged to be of less value than the associated increase in complexity and chance of more severe, statistical issues. For that reason, the three-period continuation contracts are used to estimate the six months hedge payoff.

4.2 Cash flow formula

Because the futures contracts are quoted in U.S. Dollars per thousand board feet (mbf), all other elements in the cash flow are also built on the same quotation.

Unhedged cash flow per mbf (later referred to as CF1)*:*

$$CF\ per\ mbf_t = P_{t-6}^C - C_t^C \quad (1)$$

Cash flow per mbf at time *t* is simply the price at which the lumber portion of the cabin is sold minus the associated lumber costs. The only caveat is, again, that the price is set six months prior to the cost being observable.

Unhedged cash flow per cabin:

$$CF\ per\ cabin_t = \lambda P_{t-6}^C - \lambda C_t^C = \lambda(P_{t-6}^C - C_t^C) \quad (2)$$

Cash flow per cabin is equal to the cash flow per mbf multiplied by the amount of lumber used per cabin, denoted with the Greek letter lambda. Then, to get the total unhedged cash flow, the unhedged cash flow per cabin is multiplied with the amount of cabins sold.

Total unhedged cash flow:

$$CF_t = N\lambda P_{t-6}^C - N\lambda C_t^C = N\lambda(P_{t-6}^C - C_t^C) \quad (3)$$

In accordance with the assumption that the firm always closes out its position before the settlement date, the profit from the hedge is the following.

Hedge profit per mbf (later referred to as CF2)*:*

$$\Pi_t^H = (F_t^1 - F_{t-6}^3) \quad (4)$$

Where F^1 is the front month futures contract, and F^3 is the three-period contract. To acquire the total hedge profit, the per mbf profit formula is multiplied by the hedge position and the ratio of the contract unit and price quotation. The hedge position is denoted by *H* and the ratio by *q*.

Total hedge profit:

$$Total\ hedge\ profit = Hq\Pi_t^H \tag{5}$$

Adding the total hedge profit to the total unhedged cash flow yields the total hedged cash flow.

Total hedged cash flow:

$$CF_t^H = N\lambda(P_{t-6}^C - C_t^C) + Hq(F_t^1 - F_{t-6}^3) = CF_t^H = N\lambda CF\ per\ mbf_t + Hq\Pi_t^H \tag{6}$$

4.2.1 Deriving the minimum variance hedge position

Deriving the variance of the total hedged cash flow formula, yields:

Variance of total hedged cash flow:

$$\begin{aligned} Var(CF_t^H) = N^2\lambda^2 Var\left(CF_{t_{per\ mbf}}\right) + H^2q^2Var(\Pi_t^H) \\ + 2N\lambda HqCov\left(CF_{t_{per\ mbf}}, \Pi_t^H\right) \end{aligned} \tag{7}$$

Applying the first order condition for minimum variance and solving for *H* yields the optimal MV hedge position.

$$\frac{\partial Var(CF_t^H)}{\partial H} = 2Hq^2Var(\Pi_t^H) + 2N\lambda qCov\left(CF_{t_{per\ mbf}}, \Pi_t^H\right) = 0 \tag{8}$$

Minimum variance hedge position:

$$H^* = -\frac{N\lambda Cov\left(CF_{t_{per\ mbf}}, \Pi_t^H\right)}{Var(\Pi_t^H)q} \tag{9}$$

4.3 Hedge position estimation

Estimating the hedge position is done by using three different variance -and covariance estimation models. Two of which are ARMA-GARCH/mGARCH DCC models where one uses the six months ahead forecast, while the other uses the on-date estimate to calculate the hedge ratios, and the last is an unconditional expanding window estimation.

4.3.1 Conditional model

4.3.1.1 ARMA (p,q)

The ARMA model was first introduced in Peter Whittle's thesis *"Hypothesis testing in time series analysis"* in 1951. The ARMA model contains an autoregressive (AR) process introduced by G.U. Yule and moving average (MA) process introduced by E. Slutsky. The ARMA(p,q) model can be specified as:

$$y_t = \alpha_0 + \mu_t + \epsilon_t \tag{10}$$

Where μ_t is the *conditional mean* of the process, and is estimated as:

$$\mu_t | I_t = \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{k=1}^{q} \beta_k \epsilon_{t-k} \tag{11}$$

Where:

- I_t is the available information at time t and can be defined as $I_t = (y_{t-1}, y_{t-2}, y_{t-3}, \dots)$,
- p is the order of autocorrelations (how many lags back in time the model uses),
- q is the order of the moving average (how many lags back in time the model uses),
- α_0 is a constant,
- $\alpha_i, \dots, \alpha_p$ are the parameters for the autocorrelation process,
- $\beta_k, \dots, \beta_q$ are the parameters for the moving average process,
- ϵ_t is a white noise term, meaning $E(\epsilon_t) = 0$.

The ARMA model assumes constant volatility, meaning $E(\sigma_t^2) = \sigma^2$.

Wold's representation theorem is the underlying assumption of the ARMA model. The ARMA method models the return of a *stationary* stochastic process to its equilibrium after a shock (a significant deviation from said equilibrium). The process needs to be stationary because the coefficients (and therefore the equilibrium) in an ARMA model do not change over time. A non-stationary component (such as a trend) will necessitate the parameters to change over time which in turn makes predictions impossible to model. One of the constraints placed on the model is therefore that the time series needs to be stationary.

4.3.1.2 GARCH (p,q)

The ARMA model assumes a constant variance throughout the time series, however this is usually not the case. Most time series, including commodities are usually characterized as having periods of elevated volatility where the price deviates substantially from the mean and periods of relatively low volatility where the price fluctuates closer to the mean. An alternative variance error model was presented by Engle in 1982 that allows for "… mean zero, serially uncorrelated processes with nonconstant variances conditional on the past, but constant unconditional variances" (Engle, 1982). Essentially, it allowed the conditional variance to be estimated using lagged squared error terms and their corresponding parameters. An extension of the ARCH model was proposed in 1986 by Tim Bollerslev titled Generalized autoregressive conditional heteroscedasticity" (GARCH). The GARCH model added the previous conditional variances to the estimation of the current conditional variance, thereby making it an ARMA equivalent of the ARCH process (Bollerslev, 1986).

The GARCH process is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \sigma_{t-i}^2 \tag{12}$$

Where:

- ω is a non-negative and non-zero constant,
- ε_t^2 is the squared error term at time t,
- $\varepsilon_t^2 | I_{t-1} \sim N(0, \sigma^2)$,
- σ_t^2 is the conditional variance at time t,
- α_t and β_t are non-negative parameters for the previous squared errors and previous conditional variances respectively,
- $\frac{\omega}{1-\alpha-\beta}$ is the *long run average variance*,
- q and p are the orders of lags for squared residuals and conditional respectively,

GARCH(1,1) models assume that $\alpha + \beta < 1$, if not, the time series may not be stationary.

Stationarity is, like ARMA, a necessary assumption for the GARCH model.

Note that if $\beta_t = 0$, then the GARCH model is reduced to the ARCH (q) model. Also, if $q = p = 0$, then the squared error terms (ε_t) is reduced to a white noise term.

Benoit Mandelbrot (1963) showed that price changes in financial time series are usually followed by price changes of similar magnitude, a phenomenon known as volatility clustering. Due to the GARCH model specifying the autocorrelative nature of conditional volatility, it can handle these periods of volatility clustering and provide more accurate volatility estimates. The ubiquity of volatility clustering in financial data and its possible explanations is explored further by Lux et. al (2000).

4.3.1.3 mGARCH DCC

mGARCH (short for Multivariate Generalized AutoRegressive Heteroscedasticity) is a model used to specify the conditional covariance matrix of two or more time series as following a dynamic structure using past conditional covariance matrixes.

Several mGARCH models exists, such as the constant conditional correlation (CCC), dynamic conditional correlation (DCC, the one used in this thesis, introduced by Engle and Sheppard in 2001), and varying conditional correlation (VCC).

The general mGARCH model can be written as:

$$y_t = Cx_t + \epsilon_t \tag{13}$$

$$\epsilon_t = H_t^{1/2} v_t \tag{14}$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{15}$$

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{16}$$

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1 \varepsilon'_{t-1} \varepsilon^*_{t-1} + \lambda_2 Q_{t-1} \tag{17}$$

Where:

- y_t is an m vector of dependent variables,
- C is an $M * k$ matrix of parameters,
- x_t is a k-vector of independent variables,
- $H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t,
- v_t is an m vector of normal, independent, and identically distributed errors,
- D_t is a diagonal matrix of conditional variances,

- ε'_{t-1} and ε^*_{t-1} are immediate disturbances.

The conditional variance in the diagonal matrix D_t is specified according to a univariate GARCH model. The CCC differs from the DCC in its calculation of H_t, where $R_t = R$, meaning that the CCC keeps the conditional correlation constant over time regardless of previous realisations of the Q_t matrix. The R_t matrix are known as conditional quasicorrelations (Aielli, 2009).

Also note that if $\lambda_1 = \lambda_2 = 0$, then the DCC is reduced to a CCC model.

4.3.1.4 Forecasting

Suppose we have an AR (1) process where the variance follows a GARCH process. We get:

$$y_{t+1} = C + \rho y_t + \varepsilon_{t+1}$$

Then it follows that:

$$y_{t+2} = C + \rho y_{t+1} + \varepsilon_{t+2}$$

$$\rightarrow = C + \rho\ (C + \rho y_t + \varepsilon_{t+1}) + \varepsilon_{t+2}$$

So:

$$y_{t+n} = \sum_{i=1}^{n} \rho^{n-i} C + \rho^{n-1} y_t + \sum_{i=1}^{n} \rho^{n-i} \varepsilon_{t+i}$$

Where:

- $\varepsilon_{t+1} \sim N(0, \sigma^2)$, σ^2 follows a GARCH process,
- ρ is the AR-coefficient.

The variance forecast becomes:

$$Var(y_{t+n}) = Var_t(\underbrace{\sum_{i=1}^{n} \rho^{n-i} C + \rho^{n-i} y_t}_{\text{Constants}} + \sum_{i=1}^{n} \rho^{n-i}\ \varepsilon_{t+i})$$

$$= Var_t(\sum_{i=1}^{n} \rho^{n-i}\ \ \varepsilon_{t+i})$$

$$= \sum_{i=1}^{n} (\rho^{n-i})^2\ \ \sigma_{t+i}^2 \qquad (18)$$

The GARCH forecast for σ_{t+i}^2 is given in Hull (2018, p. 236) as:

$$E[\sigma_{n+t}^2] = V_L + (\alpha + \beta)^t(\sigma_t^2 - V_L) \tag{19}$$

Where:

- V_L is the long run variance
- α and β is the ARCH and GARCH coefficients respectively.

Note how the GARCH forecasts pulls the variance forecasts towards the long run variance if $\alpha + \beta < 1$, and the last term of the equation becomes smaller the further ahead one forecasts. If $\alpha + \beta > 1$, then the "long-term average variance is negative and the process is mean fleeing rather than mean reverting" (Hull, 2018, p. 236).

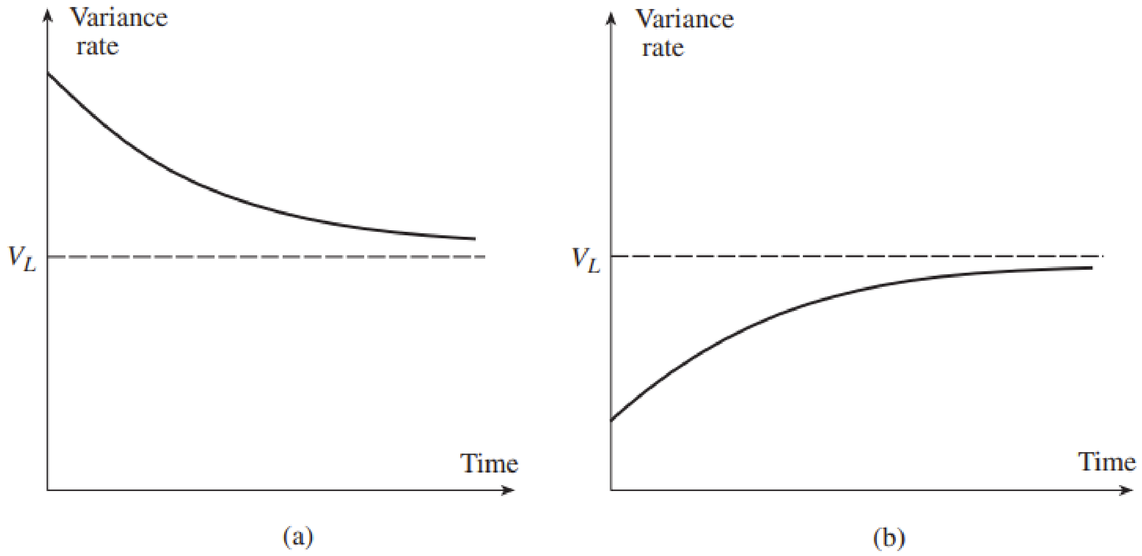


Figure 1: Visualization of the mean reverting nature of the variance forecasts. Graph (a) shows the forecast when current conditional variance is above the long run variance, and (b) shows when the variance is below. (Taken from Hull, 2018, p. 236)

The Q_{t+n} is forecasted the same way as the univariate GARCH model, which means our correlation forecasts can be written as:

$$Corr(\varepsilon_{1,t+n}, \varepsilon_{2,t+n}) = diag(Q_{t+n})^{-1/2} Q_{t+n} diag(Q_{t+n})^{-1/2} \tag{20}$$

The covariance forecast then becomes the product of the forecasted correlation and the forecasted standard deviations:

$$Cov_t(\varepsilon_{1,t+i}, \varepsilon_{2,t+i}) = Corr_t(\varepsilon_{1,t+n}, \varepsilon_{2,t+n}) * \sqrt{Var_{t+n}(\varepsilon_1)} * \sqrt{Var_{t+n}(\varepsilon_2)} \qquad (21)$$

4.3.1.5 Parameter estimation

The parameter estimation method used in STATA for all models is the maximum likelihood estimation (MLE) with a Gaussian distribution, where coefficients is determined by the iteration of the model producing the highest log-likelihood estimate. Using the maximum likelihood estimation technique will enable us to use the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) to find optimal orders of p and q in the ARMA/GARCH model.

4.3.1.6 AIC and BIC

The Akaike information criterion and the Bayesian information criterion are both model selection methods utilizing the maximum likelihood estimate as its main criteria. While both are used for the same purpose, they do have their differences that will need to be considered:

The Akaike information criterion developed by Hirotsugu Akaike in 1973 can be written as:

$$AIC = -2\ln(L) + 2k$$

Where:

- L is the maximum likelihood estimate from the model,
- k is the number of parameters in the model.

The Bayesian information criterion developed by Gideon E. Schwartz can be written as:

$$BIC = -2\ln(L) + k\ln(\mathrm{n})$$

Where:

- n is the sample size.

Note that the lowest AIC and BIC is considered the best model. With this in mind, we see both criterions punish an increase in parameters without a corresponding increase to the log-likelihood of the model. The difference between the two is that the BIC punishes the parameters more severely compared to the AIC (if the sample size surpasses 8). The “danger” of using the two are therefore the complete opposite; where the AIC may overfit the optimal model, the BIC may underfit.

Weakliem (1999) and Burnham et. al (2004) argue that the selection of a selection method should be based on the philosophy toward whether one of the models is the “true” representation or an approximation. If the one of the models is a “true” representation of reality, then the elimination of models containing extra parameters providing minor effects is desirable, thereby justifying the strictness of the BIC. We can, however, not make any such assertions about our models. Therefore, should the two selection models disagree on the optimal model specification, then the AIC will take precedence.

4.3.1.7 Testing for stationarity

As mentioned previously, both time series need to be stationary if the ARMA-GARCH model is to be applied. To test for this, we use the augmented Dickey-Fuller unit-root test. If both time series follow a unit-root process, meaning they are non-stationary, then the Johansen test (1995) for cointegration will be used.

4.3.2 Unconditional model

In addition to the conditional variance -and covariance estimation models, a model using unconditional estimates is also employed. The model uses expanding window (see discussion), standard variance -and covariance estimations. The unconditional model requires far less effort than the conditional models. Comparing them might give insight as to whether a simple model yield satisfying results, or if an advanced model should be employed.

The first 12 hedge positions used in the unconditional time-series is static, and is acquired using the variance and covariance from the period prior to the pandemic outbreak.

4.4 Time-series segmentation

The increased volatility following the Covid-19 outbreak is a big reason for the interest in hedging. However, the severity of the increase could also be an issue when attempting to estimate the hedge position. The sudden increase in volatility could result in less ideal estimates for the conditional variance- and covariance model. For that reason, it is interesting to divide the time-series into pre- and post-pandemic, to explore how the strategy performs in the event of sudden and severe changes in volatility. The strategy is therefore evaluated for three time periods, the full period, pre-pandemic outbreak, and post-pandemic outbreak.

5 Results

5.1 Model specification

5.1.1 Autocorrelation (AC) and partial autocorrelation (PAC) plots

The AC an PAC plots from STATA gives us the following:

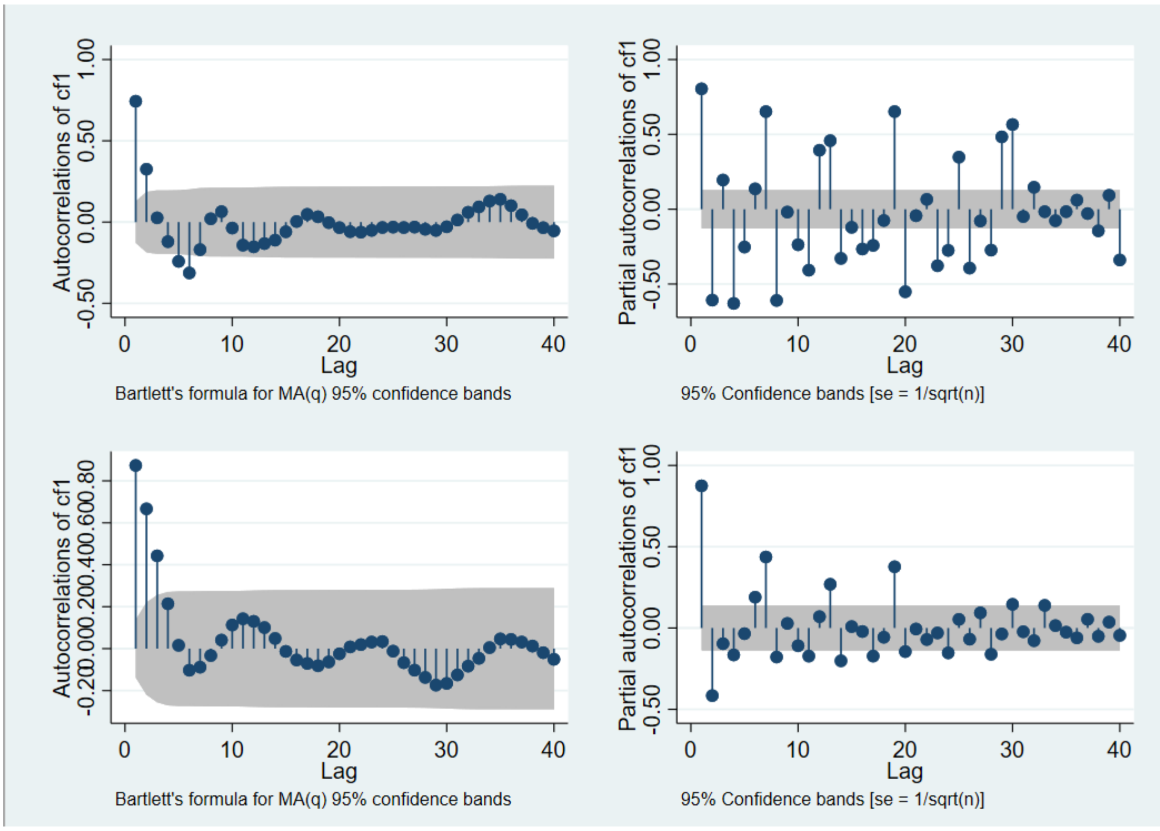


Figure 2: AC and PAC plots for CF1. Top are unrestricted, bottom are time restricted

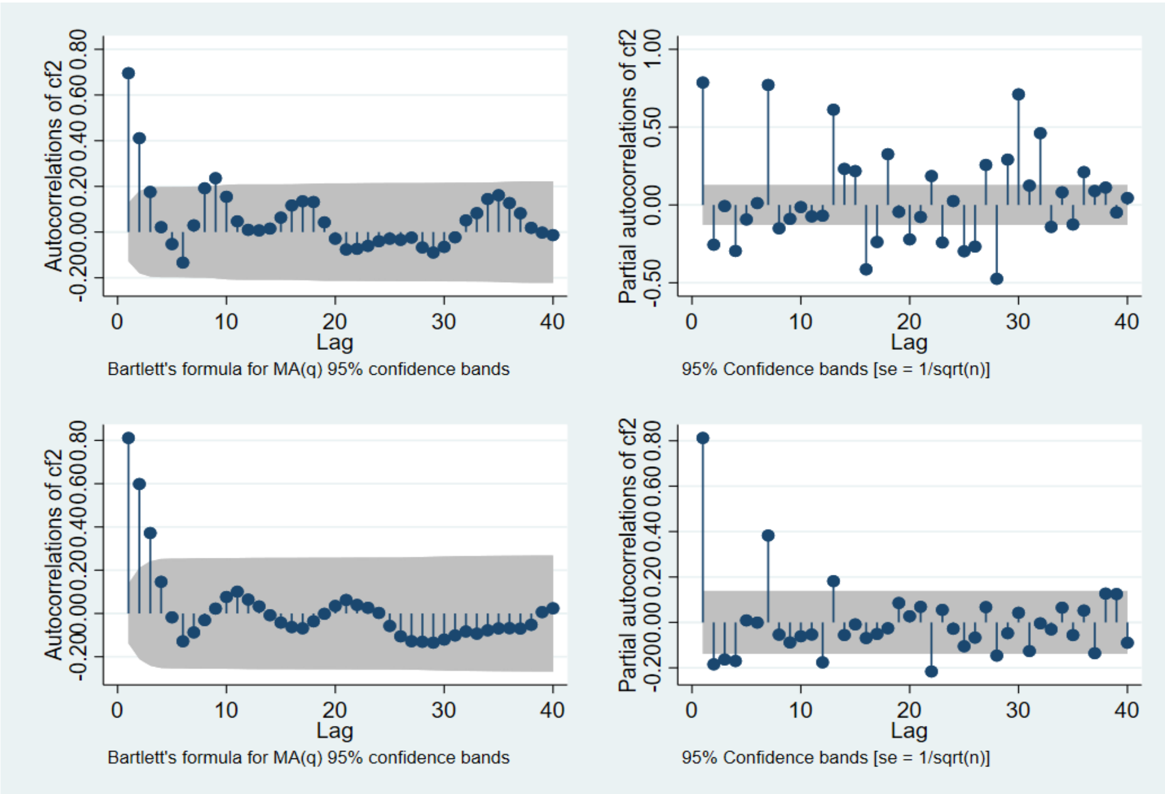


Figure 3: AC and PAC plot for CF2. Top are unrestricted, bottom are time restricted

The top AC and PAC plots includes the entirety of the time series. The PAC plot is quite erratic and hard to interpret. ARMA-GARCH models gives $\alpha + \beta > 1$ (Appendix 5), which makes forecasting impossible. The most probable reason for this is the extreme volatile period post-covid, where the price fluctuations and sustained elevated prices is hard to properly model together with the pre-covid period. The bottom AC and PAC plots restricts the time-series to pre-covid only. For both time-series the restrictions cause better behaved coefficient estimates ($\alpha + \beta < 1$) and a far less erratic PAC plot. The ARMA-GARCH models will therefore need be constrained to the more stable pre-covid period. All forecasts will be made using coefficients from the constrained models. The PAC plots show some significant lags of higher order; however, they are small. The plots together seem to indicate an AR(1) process.

5.1.2 Dickey-Fuller test

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.495	-3.466	-2.881	-2.571

MacKinnon approximate p-value for Z(t) = 0.0002

Figure 4: Dickey-Fuller test for CF1

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.529	-3.466	-2.881	-2.571

MacKinnon approximate p-value for Z(t) = 0.0002

Figure 5: Dickey-Fuller test for CF2

Where:

$$H_0\text{: The time series contains a unit-root}$$

$$H_a\text{: No unit-root is present}$$

Both Dickey-Fuller tests are rejected at a 1% level. We do not find evidence of non-stationarity in either time-series and assume them to be stationary.

5.1.3 AIC and BIC

	c1	c2
r1	2676.1283	2686.4814
r2	2540.7452	2554.5493
r3	2581.8598	2595.6639
r4	2541.9894	2559.2446

Figure 6: AIC and BIC for ARMA CF1

	c1	c2
r1	2812.8154	2823.1685
r2	2800.3064	2814.1106
r3	2801.4258	2815.23
r4	2801.7169	2818.9721

Figure 7: AIC and BIC for ARMA CF2

c1 and c2 are AIC and BIC respectively. r1 is ARMA (1,0), r2 is ARMA (1,1), r3 is ARMA (2,0), r4 is ARMA (2,1).

The AIC and BIC agree as to the optimal ARMA specification, the ARMA (1,1). Next will be to find the optimal ARMA (1,1)-GARCH (p,q) specification.

	c1	c2
r1	1996.4187	2016.2086
r2	1999.2829	2025.6694

Figure 8: AIC and BIC for GARCH for CF2

r1 is ARMA (1,1)-GARCH (1,1), r2 is ARMA (1,1)-GARCH (2,2). The ARMA (1,1)-GARCH (2,2) did not converge for the first time series. The ARMA (1,1)-GARCH (1,1) seem to be the best fit and is used for the rest of the thesis.

5.1.4 mGARCH

The problem with running the mGARCH DCC is that STATA is unable to run it using an ARMA-GARCH specification. The solution can be found in Francq and Zakoïan's paper "Estimating multivariate volatility models equation by equation" (2015). The papers original intent was reducing the computational burden experienced when running multivariate volatility models known as the *dimensionality curse*. In step one, a GARCH model is estimated for the time-series and the residuals are extracted from it. In step two, the conditional correlation matrix (R_t) is estimated using the residuals. Conveniently, this approach will enable the specification of an ARMA-GARCH model. For us, this means extracting the residuals from the ARMA(1,1)-GARCH(1,1) for both time-series and inserting them into the mGARCH DCC model. Note here that the residuals from the GARCH models will be non-autocorrelative, have no moving-average and are mean-zero due to the ARMA specification. The mGARCH model will therefore have to be specified without constants and independent variables.

The mGARCH gives us the following:

corr(cf1_resid,cf2_resid)	-.6888696	.0464224	-14.84	0.000	-.7798558	-.5978835
/Adjustment						
lambda1	.0525632	.0552484	0.95	0.341	-.0557215	.160848
lambda2	.7477024	.262352	2.85	0.004	.2335019	1.261903

Figure 9: Quasi-correlation, Lambda1 and Lambda2

```
. test _b[/Adjustment:lambda1] = _b[/Adjustment:lambda2] = 0

 ( 1)  [/Adjustment]lambda1 - [/Adjustment]lambda2 = 0
 ( 2)  [/Adjustment]lambda1 = 0

           chi2(  2) =   23.27
         Prob > chi2 =    0.0000
```

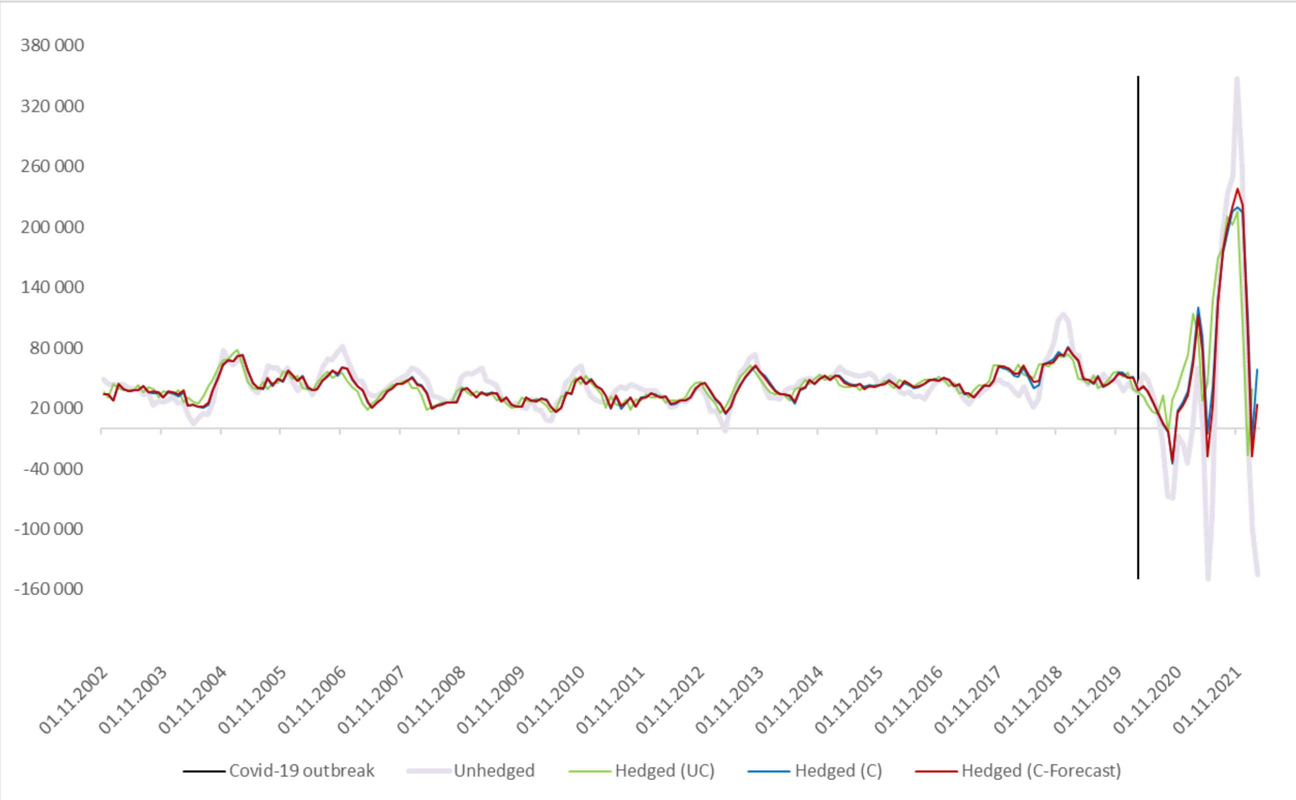
Figure 10: Wald test for Lambda 1 and Lambda 2

Lambda 2 is significant at the 99% level, however Lambda 1 is very weakly significant. The Wald test show that both lambdas collectively are significant and that the time-invariant correlation imposed by the CCC is too restrictive for our time-series.

The quasi-correlation and lambdas are used in forecasting and is teamed with the conditional variance estimates from the GARCH models in estimating the conditional covariance matrix (H_t) manually.

5.2 Hedging strategy

Results from the backtesting show that the variances of the hedged cash flows, using the three different hedge position estimation models, are all lower than that of an unhedged cash flow. From the graph below it is clearly visible that the hedging strategy does reduce the spread in the cash flow, especially in periods of increased volatility.



Graph 2: Cash flows from the different estimation models and the unhedged cash flow. The outbreak of the Covid-19 pandemic is illustrated with the vertical, black line.

The difference between the three estimation models, however, does not appear that significant on the graph. Nevertheless, it is quite visible when putting the variance and hedging effectiveness up against each other, which can be seen in the table below. The estimates are presented for all three variance -and covariance estimation models, as well as for the three time periods. For all estimation models and time periods, the HE is above 0, which indicates that the hedging strategy reduces the variance compared to an unhedged cash flow.

		Variance	HE	CF
Full period	Unhedged	1 994 312 438	-	9 828 266
	Unconditional	770 971 067	0,61	10 449 926
	Conditional	866 923 713	0,57	10 400 195
	Conditional (F)	923 037 973	0,54	10 323 058
Pre covid-19	Unhedged	294 382 308	-	8 876 753
	Unconditional	156 844 392	0,47	8 561 998
	Conditional	161 567 560	0,45	8 576 545
	Conditional (F)	159 832 624	0,46	8 606 919
Post covid-19	Unhedged	16 118 708 431	-	951 513
	Unconditional	4 815 092 920	0,70	1 887 929
	Conditional	5 837 703 747	0,64	1 823 650
	Conditional (F)	6 609 232 727	0,59	1 716 139

Figure 11: Variance, HE and CF for all estimation models, and time periods.

Results from the time-series segmentation show that the HE is greatest in the period after the pandemic outbreak. In this period the hedged cash flows are also notably higher than the unhedged cash flow. Prior to the pandemic outbreak, the HE is reasonably lower, but still convincing. Opposite to the post-outbreak period, the hedged cash flows in the pre-outbreak period is slightly lower than the unhedged cash flow, however much more volatile.

6 Discussion

6.1 Estimation models

The main weakness of this model is how it deviates from the real-life approach that would be taken. The conditional variance estimates and forecasts are all using coefficients estimated from a model using information they would not have access to until after the fact. Two likely approaches would be the *rolling window estimation* and *expanding window estimation* methods.

For the rolling window estimation, the number of periods used in estimating the coefficients are kept constant, however the sample shifts as new observations are added. Usually, the smaller of the two estimation methods, it will help with avoiding “lookback-bias” where older observations that are no longer relevant exerts influence over the coefficient estimates because as the “window rolls” the oldest observation is excluded. This will in turn cause the model and its forecasts to be more reactive to new observations. It will also help avoid overfitting the model because factors that will interfere with the estimation of the coefficients such as various forms of price shocks over time (especially if the AIC is used as a criterion). Choosing the correct window size would be the main challenge of such an approach. If the window is too large then lookback-bias will be a threat, but a window too small may give coefficients that are too biased toward recent observations. In instances such as sustained price shocks, the long run mean and variance will most likely be too high and the model will be unable to give accurate predictions when the price falls back down to the “true” long run mean.

For the expanding window estimation, the number of periods used in the coefficient estimation is, as the name implies, expanding as new observations are added. This method will likely be more reliable in handling price shocks that are sustained for longer periods compared to the rolling window method because the stochastic process from more stable periods is given more weight. The big downside to this approach is its vulnerability to giving weight to obsolete data in the past. New innovations within the industry that changes the long run mean and volatility in the market that is relevant for the future will not be given the influence it is due. It should be noted that the expanding window approach will also at some point face the problem of $\alpha + \beta > 1$.

There are two reasons these approaches were excluded as ARMA-GARCH methods. Firstly, the data available is too scarce. The data available for the various future prices only stretches back 20 years and preliminary data is needed to forecast from 2002. Secondly, the computational load. The “true” approaches would have a new ARMA-GARCH and mGARCH model be made as new observations came in. For backtesting, this means estimating a new model for each observation and getting the appropriate forecasts using equally as many unique coefficients. The first observations would need to be used as preliminary data for estimating the first models.

6.2 Hedging performance

Results from the backtesting are promising, and it shows that the hedging strategy has potential to significantly reduce the volatility of the cash flows. Of all the variance -and covariance estimation models used, in addition to the time-series segmentation, the lowest HE in the backtesting was 0,45.

The forecasting model is marginally stronger than the non-forecasting dynamic model pre-covid, however it suffers post-covid. All coefficients are, as mentioned previously, fitted for the pre-covid period and hints therefore at the model's ability to accurately forecast both conditional variances and covariances for this period. The ability to accurately forecast the mean reverting nature of prices and volatility gives marginally better, but ultimately negligible results pre-covid.

It is very important to note that the hedging effectiveness of the forecasting models post-covid does NOT equate forecasting accuracy. The coefficients and the long-run variance and mean are all calculated from a stable, pre-covid period. This means that periods of sustained price shocks and volatility will always be predicted to fall in the forecasts. This is further shown when considering that the only period it outperforms the other models is in the sharp price drop in 2021. Appendix 3 shows how the post-covid period substantially deviates from pre-covid. The poorer performance of the forecasting model post-covid is reflected in it causing a higher variance and lower cash flow compared to the non-forecasting dynamic model.

The most notable observation in the results is the effectiveness of the unconditional expanding window approach. There are negligible differences in hedging effectiveness between the three approaches pre-covid, but more significant ones post-covid. The unconditional approach provides both a larger reduction in volatility and a larger increase in cash flow compared to the conditional approaches. This is more of an indication of the weakness of complex models under extraordinary circumstances, than it is to the strength of a more simplistic approach. The extreme and sustained differences between the pre-, and post-covid period makes it difficult to accurately model the full period, and the compromises made makes the model suffer during prolonged aberrative periods.

An assumption made related to the hedge position, is the ability to purchase fractions of a futures contract. In reality, that is not possible with the CME lumber futures contracts. The assumption is made for testing purposes, and more importantly, comparing the different estimation models. A real-world hedging strategy would have to account for that, and it would likely be an obstacle for smaller consumers. The reason being that the contract size of 110.000 board feet, which equals nearly five truckloads, is quite large and the exposure that smaller agents experience might not be large enough to cover that amount. In the case of the Norwegian cabin industry, using the average monthly sale and the average amount of lumber needed per cabin, the hedge positions throughout the time-series range from 0,8 to 2,6. Which means, the average Norwegian cabin production firm will have a hard time hedging with contracts of that size. Therefore, the average Norwegian cabin producer will have to employ a strategy that accounts for that issue. The handling of said issue is beyond the scope of this paper, and is therefore excluded, but it should be pointed out.

As a final point of discussion, it should be reiterated that the assumptions and simplifications made in the thesis are all factors that can, and almost certainly will, result in the strategy deviating from a real-world approach. Each individual firm will have distinctive features that will affect the effectiveness and practical implementation of the strategy. Also important to recognize, is the possible lack of applicability of the strategy in a potential European market. There are multiple factors in the separate markets that are dissimilar, and the applicability of the strategy will therefore be hard to predict.

6.3 Further research

It should be noted that this thesis only tested the standard ARMA-GARCH model. Testing the applicability of a wider spectrum of models could possibly give further insight as to the nature of the underlying process of the lumber prices. Examples could be the exponential weighted moving average (EWMA), the NAGARCH (Nonlinear Asymmetric GARCH) in case of leverage effect, and QGARCH (Quadratic GARCH) if there are asymmetric effects of negative and positive shocks.

7 Concluding remarks

After exploring a minimum variance lumber hedging strategy for a cabin production firm, the results are promising and show great potential of reducing lumber price volatility with the use of futures contracts. With the assumptions that were made, and the strategy described, a cabin producer would have been able to reduce its lumber price volatility by up to 70 percent in the wake of the Covid-19 outbreak. Prior to the outbreak, in the longer, more stable period, the strategy would have yielded a variance reduction of almost 50 percent. Overall, the results show that the strategy has significant effectiveness, but that choice of estimation model does have a slight influence on the hedging effectiveness.

For the entire time-series, the performance of the conditional models was inferior to the simpler, unconditional estimation model. Splitting the time-series into pre -and post-outbreak showed that the unconditional model performed marginally better pre-outbreak, and post-outbreak it performed quite a lot better. Those results suggest that the conditional models are unable to effectively handle a sustained price shock of the magnitude that was seen during the Covid-19 outbreak. Further, it suggests that the unconditional model matches, if not surpasses, the performance of the conditional models. This is an interesting discovery, and it implies that a more advanced estimation model might not only be unnecessary, but also less effective. That information would especially be of interest to parties interested in hedging, but who are intimidated by the modeling requirements of such a strategy.

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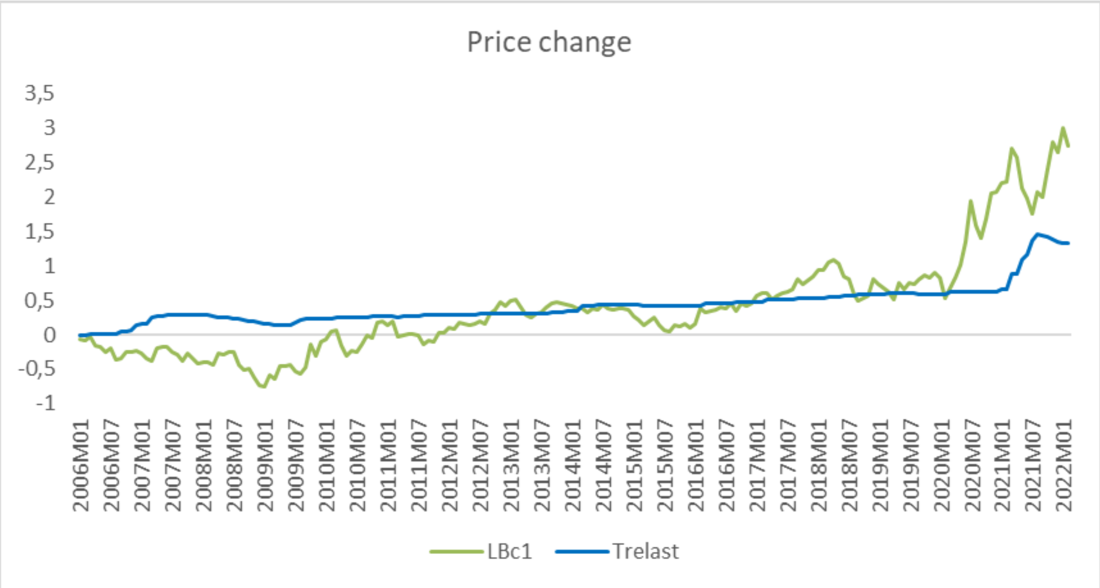
9 Appendices

9.1 Appendix 1

Correlation between the price change on the Norwegian lumber index and the one-period lumber continuation futures contract:

σ	Norwegian lumber index
LBc1	-0,07135

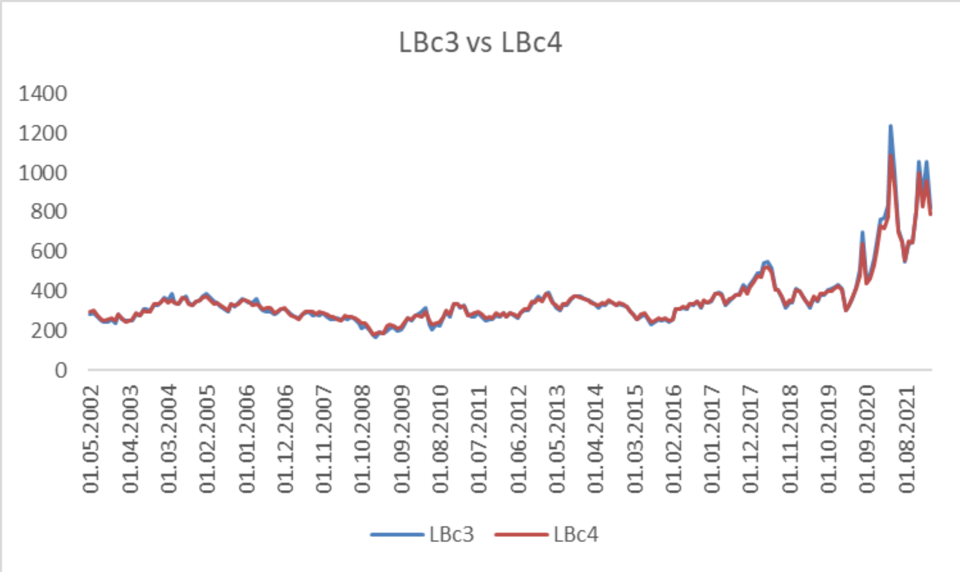
Plotted accumulated prices changes:



9.2 Appendix 2

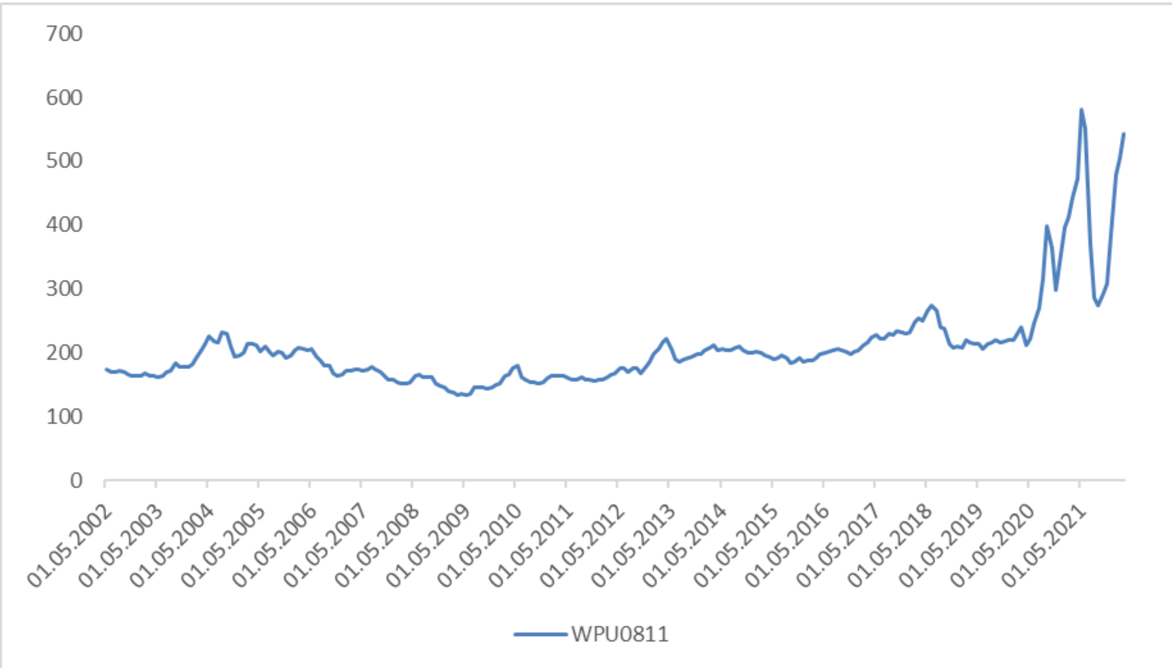
Correlation between three-period and four-period lumber continuation futures contracts.

σ	LBc3
LBc4	0,997



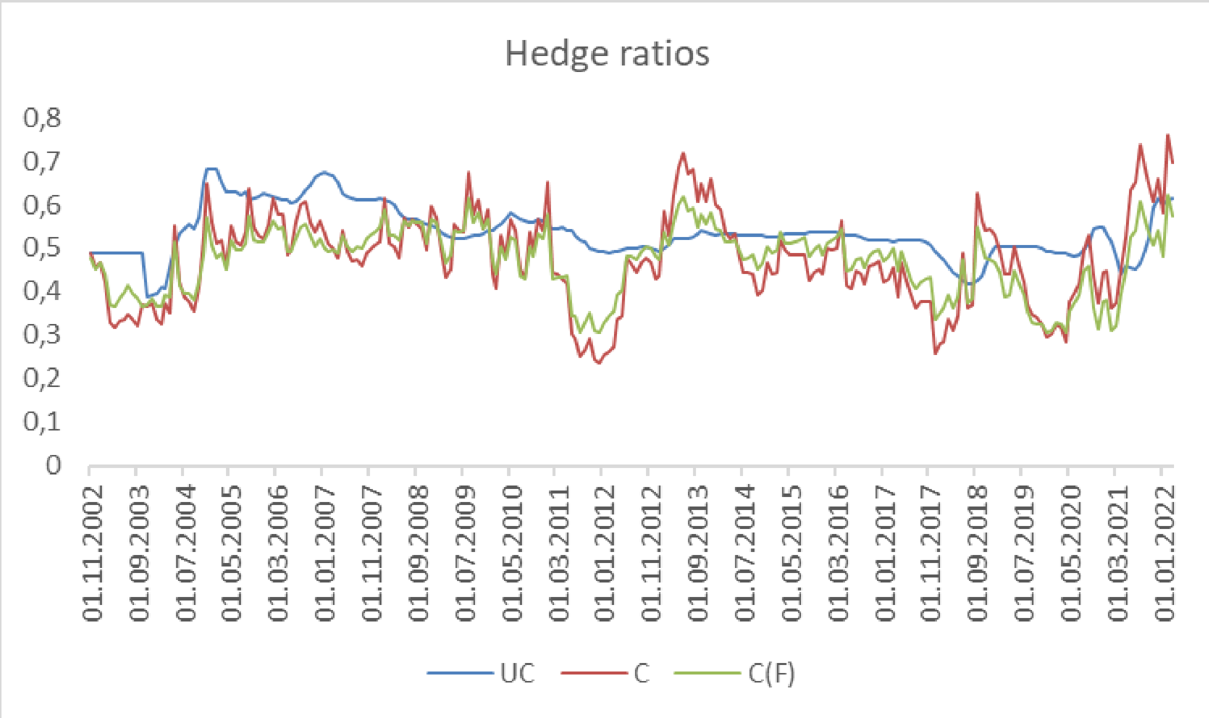
9.3 Appendix 3

WPU0811 softwood lumber producer price index.



9.4 Appendix 4

Hedge ratios from the different estimation models.



9.5 Appendix 5

ARMA-GARCH estimates

ARMA						
ar L1.	.7877113	.0495128	15.91	0.000	.6906681	.8847546
ma L1.	.3881861	.0769672	5.04	0.000	.2373331	.539039
ARCH						
arch L1.	.4478194	.1091851	4.10	0.000	.2338205	.6618183
garch L1.	.5714331	.0979114	5.84	0.000	.3795303	.763336
_cons	50.39119	27.62059	1.82	0.068	-3.744164	104.5265

Figure 12: Cf1 ARMA-GARCH unrestricted

ARMA						
ar						
L1.	.7675056	.0524892	14.62	0.000	.6646286	.8703826
ma						
L1.	.1823191	.0942569	1.93	0.053	-.002421	.3670592
ARCH						
arch						
L1.	.2667376	.0619695	4.30	0.000	.1452796	.3881955
garch						
L1.	.7834614	.0632896	12.38	0.000	.659416	.9075068
_cons	25.05018	36.68537	0.68	0.495	-46.85181	96.95218

Figure 13: Cf2 ARMA-GARCH unrestricted

ARMA						
ar						
L1.	.7916465	.0495443	15.98	0.000	.6945414	.8887516
ma						
L1.	.3552197	.0915715	3.88	0.000	.1757428	.5346965
ARCH						
arch						
L1.	.2194768	.1111704	1.97	0.048	.0015869	.4373667
garch						
L1.	.6851496	.1738888	3.94	0.000	.3443339	1.025965
_cons	47.76449	37.42319	1.28	0.202	-25.58361	121.1126

Figure 14: CF1 ARMA-GARCH restricted

ARMA						
ar						
L1.	.7491402	.0522592	14.34	0.000	.6467141	.8515662
ma						
L1.	.1612522	.0980182	1.65	0.100	-.03086	.3533645
ARCH						
arch						
L1.	.1399541	.078778	1.78	0.076	-.0144479	.2943561
garch						
L1.	.8293917	.1128881	7.35	0.000	.6081351	1.050648
_cons	53.39572	67.78102	0.79	0.431	-79.45263	186.2441

Figure 15: CF2 ARMA-GARCH restricted

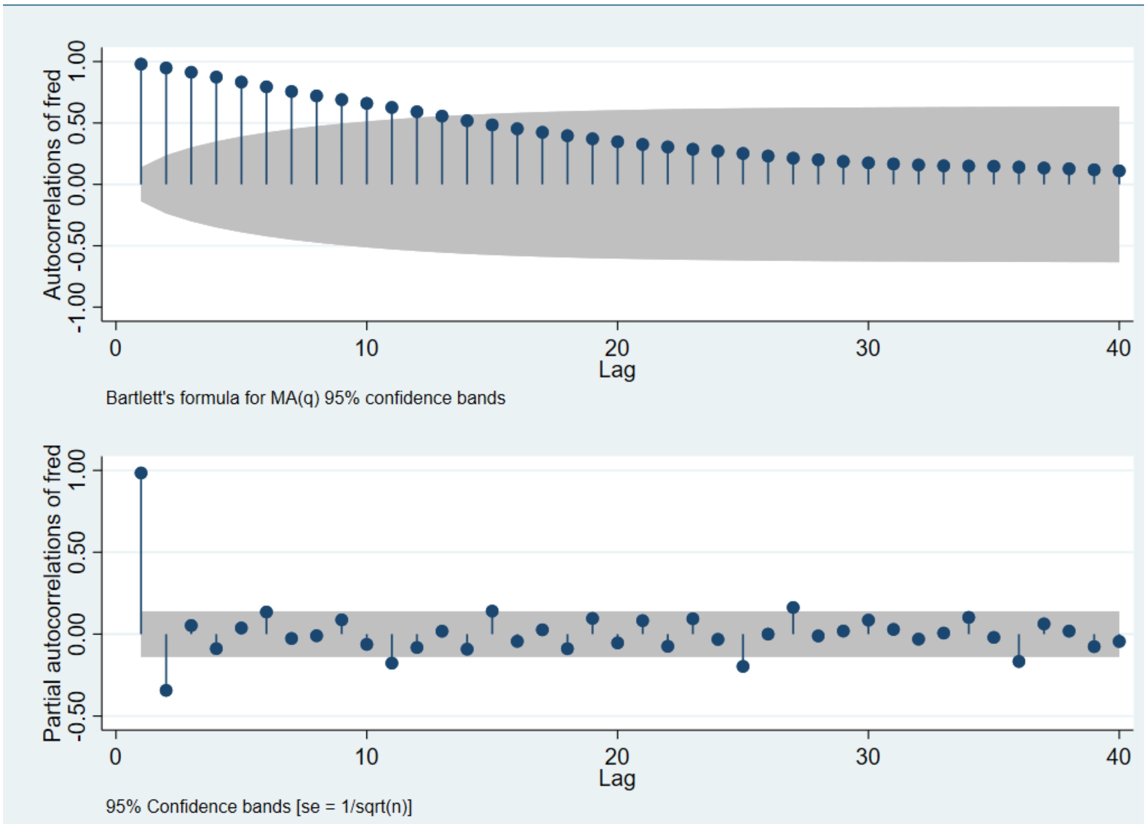


Figure 16: AC and PAC for the FRED index, pre-covid

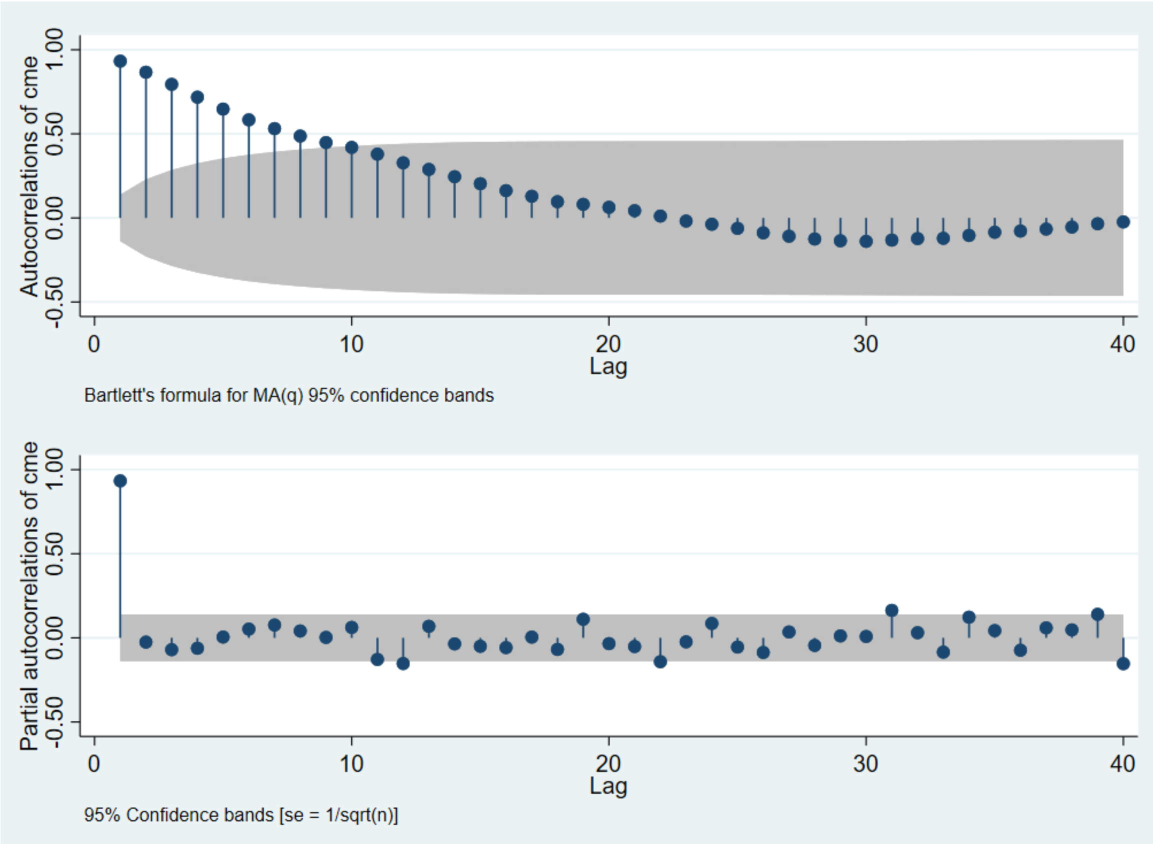


Figure 17: AC and PAC for CME prices, pre-covid