J.P. MORGAN CENTER FOR COMMODITIES
UNIVERSITY OF COLORADO DENVER BUSINESS SCHOOL

GLOBAL COMMODITIES
APPLIED RESEARCH DIGEST

SUMMER 2021

INDUSTRY ANALYSES

"VOLATILITY IN DAIRY MARKETS: TOWARDS A DYNAMIC VALUE AT RISK MODEL FOR DAIRY COMMODITY TRADING"

BY VINCENT ALMERING, GROUP TREASURER, INTERFOOD HOLDING B.V., THE NETHERLANDS;

HERBERT RIJKEN, Ph.D., FULL PROFESSOR IN CORPORATE FINANCE, VRIJE UNIVERSITEIT AMSTERDAM, THE NETHERLANDS; and

FRANS CLETON, SENIOR MANAGER, KPMG ADVISORY, THE NETHERLANDS and PROGRAM MANAGER AND INSTRUCTOR, POSTGRADUATE PROGRAM, TREASURY AND CORPORATE FINANCE, VRIJE UNIVERSITEIT AMSTERDAM

Seeded by a generous grant from CME GROUP FOUNDATION

Business School
UNIVERSITY OF COLORADO DENVER

Volatility Modeling in Dairy Markets:
Towards a Dynamic Value at Risk Model for Dairy Commodity Trading

Vincent Almering
Group Treasurer, Interfood Holding B.V., The Netherlands

Herbert Rijken, Ph.D.
Full Professor in Corporate Finance, Vrije Universiteit Amsterdam, The Netherlands

Frans Cleton
Senior Manager, KPMG Advisory, The Netherlands; and Program Manager and Instructor, Postgraduate Program, Treasury and Corporate Finance, Vrije Universiteit Amsterdam

Commodity prices are subject to extreme price volatility and are a prominent source of risk for treasurers, as highlighted in Treasury Today (2020). The current geopolitical uncertainty is one of the main causes behind the recent uptick in volatility in many markets, complicating the ability of a treasurer to manage risk. Inevitably, the dairy sector is also affected by these developments and is on the lookout for more advanced market risk management tools. One promising tool is volatility modelling. This paper will focus on how volatility modelling can benefit commodity traders to dynamically manage price risk in the European Union (EU) dairy market with time series models.

Introduction

Commodity trading has shown significant growth over the last century due to trade liberalization, urbanization and the opening of new markets. Large trading firms have emerged with a strong foothold in multiple countries in order to span the entire supply chain. These firms are in the business of transforming commodities in space (logistics), in time (storage), and in form (processing). If the price of a material plus the transformation costs (e.g., processing, transportation, financing) is less than the price of the transformed product in a particular market, traders will be motivated to engage in this activity until the price differential nears zero (Pirrong, 2014).

Commodity trading firms keep a close eye on local market conditions since demand and supply imbalances or updated rules and regulations can suddenly close arbitrage windows. They are diverse and vary in size, product offerings, locations and asset strategy. Large > 10€ billion commodity trading firms that trade a vast variety of commodities invest heavily in fixed assets such as plantations, storage locations, and processing facilities while at the other end of the spectrum, smaller and highly specialized commodity trading firms operate in a niche segment of the market and carry almost no fixed assets on their books.

While engaging in these activities, commodity trading firms face a wide array of risks that can be managed by hedging, insurance and/or diversification. Risks typically translate into price swings which can be measured by the underlying volatility of an asset. Volatility is rarely seen as a positive signal because it increases uncertainty about returns, potentially preventing investors to enter a particular market. With margins generally being thin, large capital expenditures financed with debt (e.g., production facilities or storage centers) could bankrupt a company with an ill-timed investment or a disadvantaged unhedged position. Concerns about increased price volatility are usually voiced by producers and processors who, in the absence of risk management tools, are exposed to uncertainty associated with changing prices.

These parties could use some help in managing the risks and returns on their product portfolio especially when input costs are high and certain utilization rates have to be met (Soutter and Manuel, 2019).

Most commodity trading firms are willingly exposed to market risk because it allows them to arbitrage between markets and take positions. A firm's risk metrics compare its current risk exposure to the risk appetite of the firm. These metrics are typically reviewed at regular intervals as markets rarely operate in a steady state. This triggers the need for management to understand and, when possible, estimate the short-term "riskiness" of the markets in which they operate.

Research Methodology

Risk management is at the center of many commodity trading firms since they cannot control how asset prices will develop over time despite their extensive knowledge of commodity markets. This paper focuses on the open position of a trading firm which is the main source of (market) risk. Risk metrics at commodity traders are frequently based on historical data, rules of thumb and typically remain static over time. In practice, markets are rarely constant, and warrant a more dynamic approach towards risk management. The objective of this article is *to characterize the existence of price volatility in EU dairy markets and utilize historic time series analysis to predict future volatility to manage price risk*. This should lead to a more advanced and dynamic set of risk management tools.

Scope

The scope of this study is the EU Dairy Market. Despite being a mature market, it is highly volatile as regulatory changes, weather effects, and demand changes have significant implications on the prices of dairy products. The products of interest are Skim Milk Powder (SMP) and Butter. These two commodities represent the protein and fat content of milk and can be traded both physically as well as on the futures market. Weekly public price information for SMP and Butter published by the EU Agriculture and Rural Development board for the period 2001-2017 (European Commission, 2018) have been used as the input of this research.

Academic Relevance

The agricultural commodity sector has been an important subject of economic research, for example the effects of changes in local legislation or the impact of pricing mechanisms on the supply chain (Moyer and Josling, 2002). Johnson (1975) already described how the effect of agricultural price stabilization in one market amplifies the volatility in the markets of its trading partners. Mathematically modelling volatility has been a subject of many debates. Several authors concluded that modelling volatility is inherently difficult as it is rarely constant, asymmetric, and exhibits certain properties (e.g., autocorrelation) that do not easily fit into standard statistical models (Pagan and Schwert, 1990). Volatility however does encompass specific behaviors that can be captured by mathematical models; e.g., the Moving Average (MA) and Autoregressive (AR) models are used by economists to model time series of assets returns.

Value at Risk (VaR), defined as the value of a portfolio of assets that can be expected to be lost during adverse market conditions, became a popular concept in the mid '90s. VaR has been widely adopted by banks and other financial institutions to manage risk (Linsmeier and Pearson, 1996). Despite some criticism, regulatory frameworks such as Basel refer to the use of VaR models for capital requirement ratios and stress testing purposes. Volatility estimates are a critical input in VaR models. Several articles combine conditional volatility estimates from time series models with Value at Risk, but few turn it into a practical application (Engle, 2001).

Moledina *et al*. (2004) published an article on how to estimate the volatility of various soft commodities with the help of time series models. O'Connor *et al*. (2011) used the method described by Moledina *et al*. (2004) to measure the volatility in dairy markets for the period 1990 to 2007 to verify whether the EU's price policy had the desired dampening effect on EU dairy prices. This paper will investigate how time series models can describe the underlying volatility patterns in dairy prices and assess if the conditional volatility estimates are able to outperform traditional methods (e.g., a historic volatility assumption). In addition, we explain how these volatility metrics can be used in a trading environment to enhance the risk management practice of a commodity trading company.

Global Dairy Markets

Soft commodities, e.g., dairy, wheat, grain, and coffee, are typically grown rather than mined or extracted, lose their value over time and tend to be more volatile when compared to regular commodities. Many governments try to protect local agriculture markets by imposing import tariffs, offering private storage programs, set intervention prices or have other means to subsidize local farmers which can result in significant prices difference among regions.

Milk is produced by over 260 million cows worldwide and equals an annual milk volume of 600 million metric tons (MT's) of which 42% comes from Europe (FAO, 2016). The EU and the US are the two largest producers of dairy products and have well developed domestic demand markets which consume the majority of the dairy products they produce. The remainder is traded internationally, which accounts for 7% to 10% of the world's milk output. A small change in global milk production, e.g., due to severe weather conditions or diseases, has an amplified effect on the global supply of dairy products. In monetary terms, dairy is the largest soft commodity market in the world with an annual production value of 328 billion USD (FAO, 2016).

Three prominent factors that influence the volatility in dairy volumes/prices are as follows: (1) the impact of small changes in the quantities on internationally traded volumes, (2) the delayed response in the demand or supply of dairy products, and (3) the effect of government bodies that regulate agricultural policies. These factors make it difficult for farmers to predict in which direction the market is heading and whether they need to sell forward part of their production volumes. Stocking dairy commodities may help to reduce price fluctuations by balancing demand and supply. However, speculation by traders or government intervention programs could lead to the build-up of large stock reserves.

Agricultural derivatives markets allow farmers and cooperatives to hedge positions and trade in physical or cash-settled contracts. The development of dairy derivative markets has made it easier for participants to manage outright price risk. The presence of speculators is often seen as a necessary condition for functioning markets, but volatility can attract speculative activity, which may destabilize markets. The ramp-up of the EU dairy derivatives markets coincides with a period of increased volatility (2010-2017).

Dairy Data Analysis

Analyzing financial data is usually done using returns rather than prices or absolute returns. The benefit of using relative returns is the normalization of the data which gives the ability to compare datasets. Logarithmic returns provide the additional benefit of time-additivity, ease of calculation (e.g., log normality) and numerical stability. Market volatility can be defined as the degree to which prices fluctuate over time. Volatility is often regarded as an important measure of risk in financial markets and consequently has become the price of uncertainty. Let's denote S_t as the price of a financial asset, e.g., the price of a metric ton of Butter at time t, which should be a positive value at all times. The log return of holding such an asset during time period t is given by:

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right);\ S_t \geq 0 \tag{1}$$

The log return of an asset is considered to be a random variable and is characterized by an expected value µ and a volatility σ. Volatility measures to what extent a return fluctuates around its sample mean and is measured by the sample standard deviation of a return in a time period T:

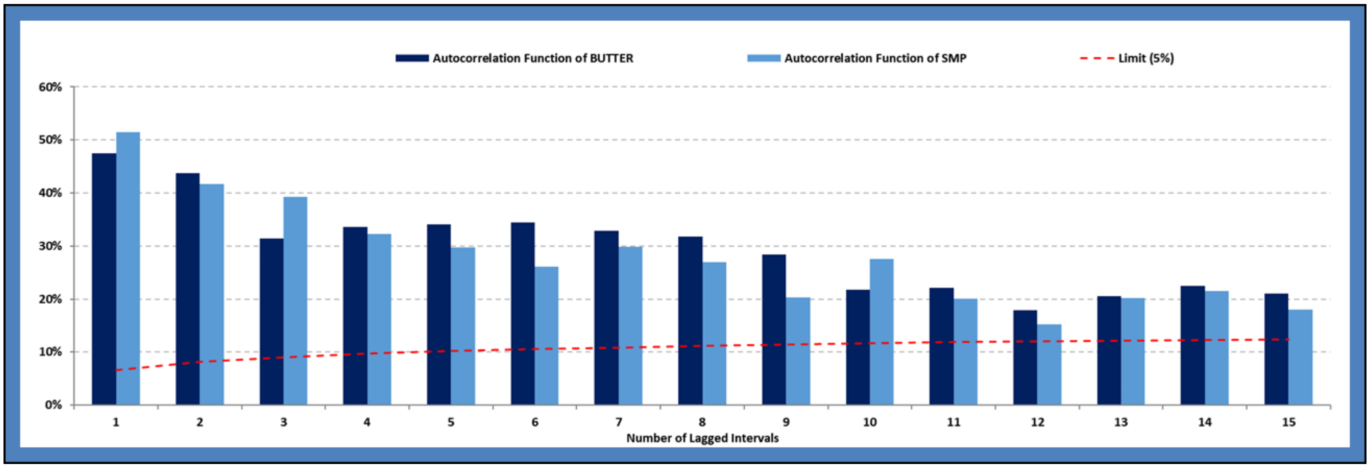
$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \hat{\mu})^2} \tag{2}$$

The volatility of an asset has interesting statistical properties which can be of use in forecasting it; e.g., volatility in commodity prices may cluster, are likely to persist or even may reverse to the mean in time. The next section visualizes these three important statistical properties in the Butter and SMP time series.

Positive autocorrelation signals volatility clustering (Piot-Lepetit and M'Barek, 2011). Autocorrelation can be measured between returns and historic returns for various numbers of lagged intervals. Figure 1 on the next page shows the autocorrelation for 1 to 15 lagged intervals in the absolute weekly returns for Butter and SMP prices. The one lag interval autocorrelation has the highest value after which the autocorrelation gradually decays for larger intervals.

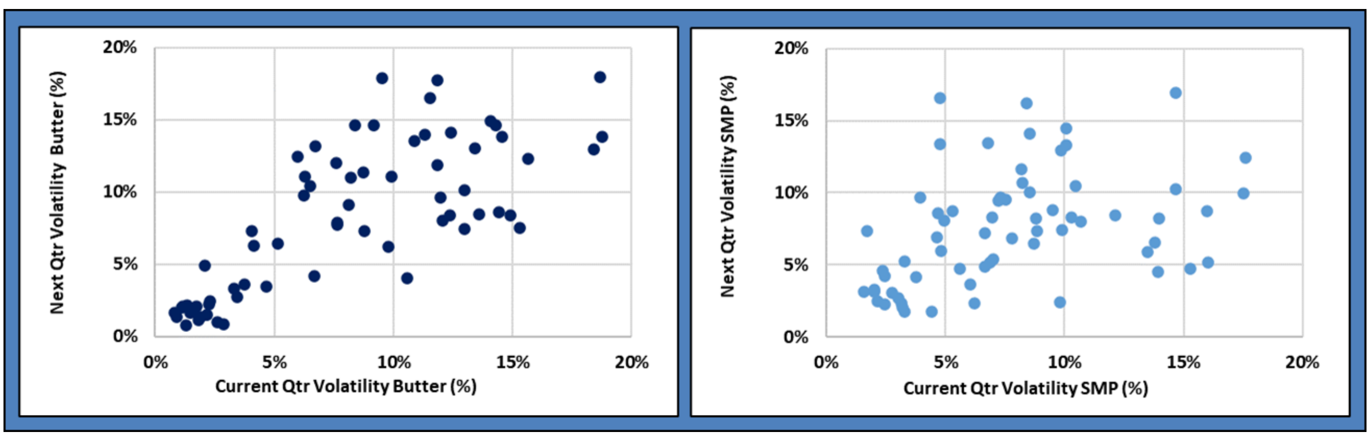
The volatility of an asset is rarely constant. When the *volatility* of a time series itself is fluctuating, the time series is referred to as "heteroskedastic" compared to "homoscedastic," which refers to a time series with constant volatility. Heteroskedastic properties challenge statisticians in time series regression as the error term is not time invariant, a standard condition for standard regressions. Error terms might be larger in some ranges of the dataset compared to others.

Figure 1
Autocorrelation of SMP & Butter Measured in Absolute Weekly Returns (2001-2017)



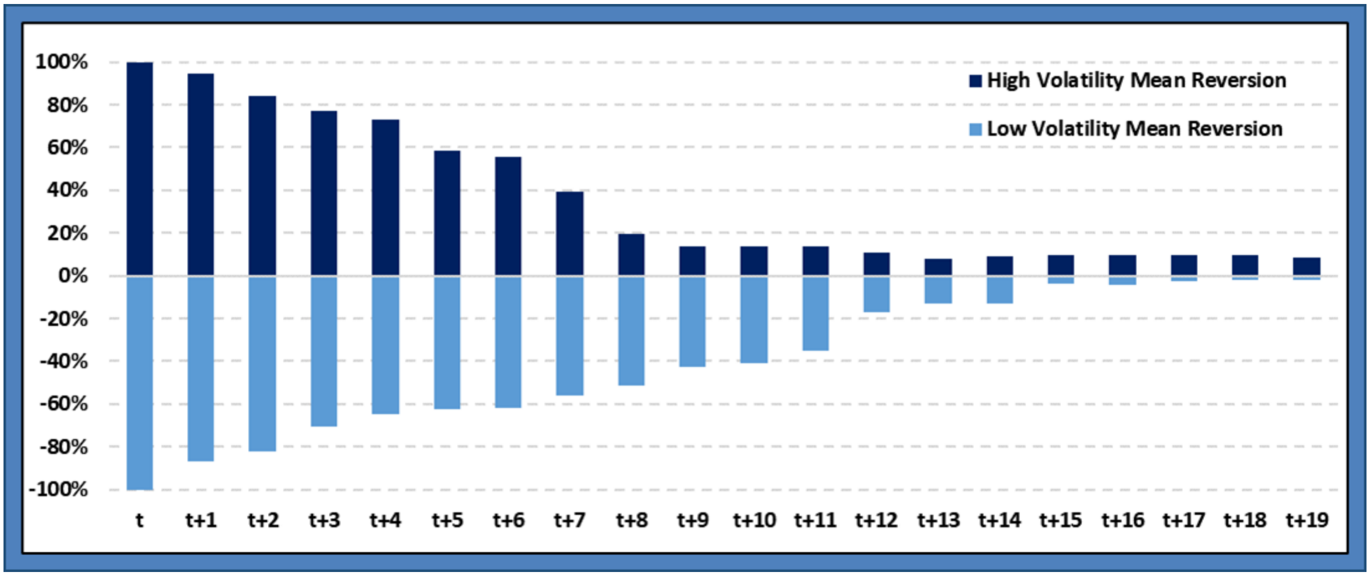
The volatility of Butter and SMP has been calculated for 16x4 quarterly periods in the past 16 years. The quarterly volatility figures ranged between 2% to 19% both for Butter and SMP. The volatility is far from constant but both times series do exhibit a certain level of volatility persistence (Figure 2). The R^2 value of the linear regression between the volatility of two consecutive quarters for Butter is (59%) and for SMP (17%). The correlations are positive and the standard deviation of the returns of the past quarter may predict to some extent the next quarter's volatility.

Figure 2
Annualized Volatility of Returns Qtr on Qtr for Butter and SMP (2001-2017)



Another common empirically observable feature for return volatility, as mentioned by Engle and Patton (2007), is its tendency to revert to the mean. In other words, the volatility gradually returns to its long-term average. From 2007 to 2017, eleven quarterly periods of high volatility ($1\sigma >$ the mean volatility) and eight quarterly periods of low volatility ($1\sigma <$ the mean volatility) were observed in the Butter time series. The delta between the average volatility and the extreme value in the high or low volatility period was noted for each consecutive week and converted into a percentage improvement to the long-term average.

Figure 3
Mean Reversion Effect of the Butter Dataset in Weeks (2007-2017)



Mean reversion is clearly observable in Figure 3. The time it takes for the volatility of Butter to move to halfway its long-term average (half-life), is about 7 to 8 weeks. After about 13 weeks the volatility levels are back to the long-term average. The effect is however not symmetric; periods of low volatility take a slightly longer time to revert to the mean in our sample. This analysis gives an idea how frequent volatility estimates have to be updated and reflects the short-term risk in the order book at a commodity trading firm.

These three typical properties of volatility in the EU dairy commodity dairy market can serve as inputs to model volatility. Additional statistical tests show that log returns of the Butter and SMP time series follow a stationary process with no trend, zero mean ($\hat{\mu}$) and are not normally distributed at the 95% significance level, warranting further research on the type of non-normality and possible correlations between individual data points.

Volatility Modelling

A prerequisite to modelling the dynamics of a time series is to determine whether the series behaves as a stationary or non-stationary process (Moledina *et al*., 2004). The Augmented Dickey-Fuller (ADF) test will help to verify this property. If there is no unit root, the data is considered stationary. The regular returns for Butter and SMP show signs of non-stationarity because the presence of a unit root (the null hypothesis, H_0) cannot be rejected. This is significant for the first two variants of the ADF test (p-value > 0.05). The first difference of the time series did completely remove the non-stationarity from both datasets.

The time series are also checked for the presence of higher order, non-linear, forms of autocorrelation with the help of the Autoregressive Conditional Heteroscedastic (ARCH) test, which can detect a time-varying phenomenon in the conditional volatility. The ARCH effect is present in both datasets and is significant at the 1% level for at least the first 3 lags. The next period's volatility is likely dependent upon both the past volatility and the past innovations of the same series.

In order to start forecasting, let's define the following standard equation for the log return of an asset in time series with a zero mean:

$$r_t = \sigma_t \, Z_t \tag{3}$$

where Z_t, the error term, is a sequence of $N(0,1)$. We will utilize four models to obtain an estimate for the future volatility $\hat{\sigma}_t$, based on certain properties of the time series.

Model 1: Historical average model (HIS): This model assumes that the future volatility is equal to the volatility over a fixed period (training period) and does not take any time conditional information into account.

$$\hat{\sigma}_t^2 = \sigma^2 \tag{4}$$

Model 2: Exponential Weighted Moving Average model (EWMA): The EWMA model computes $\hat{\sigma}_t^2$ based on historical values. The weighting decreases exponentially with each historic time period. The smoothing parameter λ is estimated by minimizing the Mean Square Error function on the training data.

$$\hat{\sigma}_t^2 = \lambda \, \sigma_{t-1}^2 \, + (1 - \lambda) \, r_{t-1}^2 \, with \, \lambda \sim \{0,1\} \tag{5}$$

Model 3: Autoregressive Moving Average model (ARMA): ARMA (p,q) models, popularized by Box and Jenkins in the 1970's, are moving average models that adjust the weights of historic observations to optimize the predictive power over the training period (Box *et al*., 1995). The conditional volatility is expressed as a function of its past values σ_{t-i} along with an error term ε_{t-j}.

$$\hat{\sigma}_t = c + \sum_{i=1}^{p} \varphi_i \sigma_{t-i} + \varepsilon_t \, + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{6}$$

Model 4: Generalized Autoregressive Heteroskedastic model (GARCH): Autoregressive conditionally heteroskedastic ARCH (q,p) models were introduced by Engle in 1982 and later extended by Bollerslev into a generalized version (Bollerslev, 1986). In a GARCH model the $\hat{\sigma}_t^2$ is calculated from a long-run average variance rate, as well as from the last squared return r_{t-i}^2 and the last period's forecast σ_{t-j}^2.

$$\hat{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, r_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \;\; with \;\; \alpha_i \geq 0 \; and \; \beta_j \geq 0 \tag{7}$$

The parameter estimation of these models is performed with the help of NumXL™, an advanced statistical plug-in for Excel which estimates the parameters by maximum likelihood methodology on the training data. NumXL™ also evaluates the statistical fit by the Akaike Information Criterion (AIC) which is used as a metric for model selection. Additionally, AIC penalizes models with many parameters (e.g. overfitting).

Testing and Validation

After estimating the model parameters on the training dataset (2001-2013), all four parameterized models are tested in the 2014-2017 period. The models have to forecast the conditional volatility for $t + 1$ week and the results are compared to the realized volatility. The realized volatility is calculated by averaging the past quarter's intraweek log returns and using it as a proxy for the realized weekly volatility. The Root Mean Square Error (RMSE) (8) and the Mean Heteroscedastic Square Error (MHSE) (9) error functions are used to compare the realized and the forecasted volatility, where $\hat{\sigma}_t$ is a forecast of the volatility, σ_t is the realized volatility in week t and T is the number of weeks in the test period.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t - \sigma_t)^2} \tag{8}$$

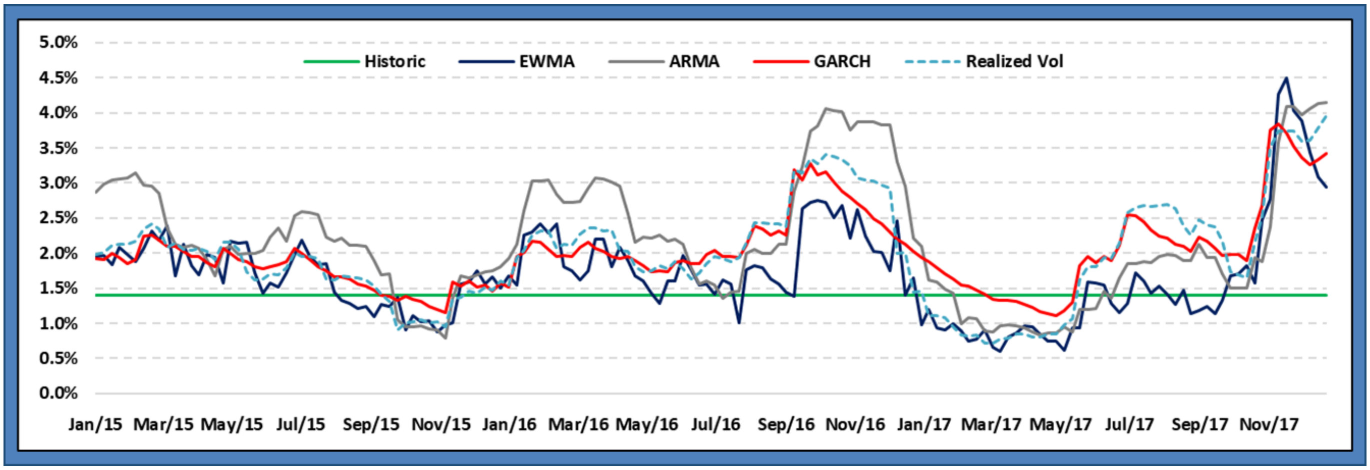
$$MHSE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\sigma_t}{\hat{\sigma}_t} - 1\right)^2 \tag{9}$$

The RMSE is commonly used among practitioners, but it has some drawbacks; e.g., the RMSE uses the absolute delta and does not proportionally relate estimates to each other (Bollerslev and Ghysels, 1996). MHSE addresses the issue of the RMSE by measuring the error in relation to its estimate. A lower number on each of the error functions indicates a better fit.

Volatility Modelling Results

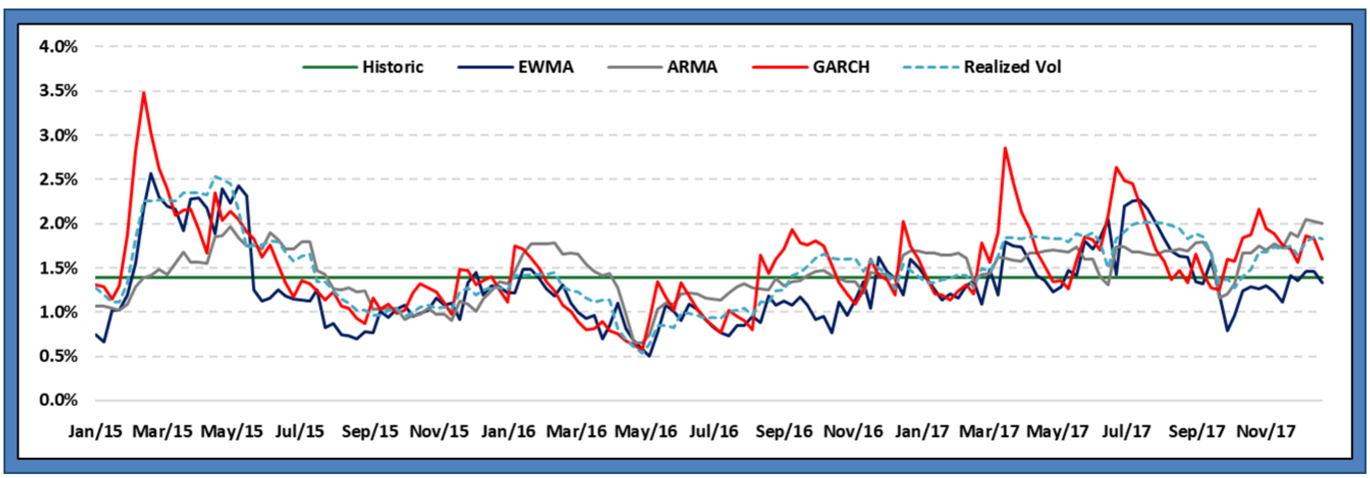
Figure 4 on the next page shows the result of the four volatility models versus the realized volatility (dotted blue line) for Butter for a period of 3 years. The realized weekly volatility of Butter in the period 2015-2017 clearly exceeds the historical average of the training dataset (dark green line). The GARCH and EWMA models track the realized volatility of Butter more accurately than the ARMA model which seems to overestimate the volatility in most periods.

Figure 4
Conditional Volatility Forecasting Result for Butter (2015-2017)



The weekly volatility of SMP, as seen in Figure 5, is more in line with its long-term average although periods of low volatility (2016) and increased levels of volatility (2017) can be observed. The ARMA and EWMA models seem to outperform the GARCH model as the latter reacts more strongly to changes in the realized log returns. This can be explained by the higher value of the estimated α parameter in the GARCH model of the SMP dataset compared to Butter (0.26 vs. 0.09).

Figure 5
Conditional Volatility Forecasting Result for SMP (2015-2017)



Comparing Results

The historical model (HIS), which acts as a proxy for a *static* risk approach, performed the worst for both Butter and SMP. The EWMA model did a better job and was able to reduce the MHSE by half for Butter compared to the historical average. The next class of models, ARMA and GARCH, further improved the result with GARCH scoring the highest on both error measures: RMSE (.28) and MHSE (16.6%) criteria for the Butter returns. The volatility of the SMP dataset was best predicted by the ARMA model, with an MHSE score of 19.4%, and the GARCH model at 19.8%.

Test Dataset	*Error Function*	*Historic*	*EWMA*	*ARMA (1,1)*	*GARCH (1,1)*
Butter	RMSE	0.96	0.54	0.51	**0.28**
(2014-2017)	MHSE	68.7%	36.9%	22.8%	**16.6%**
SMP	RMSE	0.43	0.32	**0.29**	0.32
(2014-2017)	MHSE	31.2%	29.8%	**19.4%**	19.8%

The standardized residuals analysis for both the GARCH and ARMA models have a mean of 0, standard derivation near 1, indicating that residuals were showing signs of randomness/white noise. Full normality could not be established (p value > 0.05), mainly due to excess kurtosis. The ARCH effects did largely disappear in the residuals, although still present in the ARMA case, which could warrant the search for a more complex ARMA-GARCH model for SMP.

We ran a few more simulations with more complex model variants, e.g., EGARCH, and higher order ARMA (X,X) and GARCH (X,X) models for both time series, but despite the additional parameters, no significant improvement was found. In general, we can conclude that in our datasets the basic ARMA (1,1) and GARCH (1,1) model fits the time series best. The next section explains how these volatility estimates facilitate the implementation of a dynamic risk management approach supported by the VaR.

Application in Practice

The Value at Risk (VaR) metric is a useful method to determine the (market) risk of carrying a position. Although it has received some criticism, it is still widely used by financial institutions, asset managers and trading houses. The VaR is essentially a function of three parameters: the time horizon, the confidence level (X%), and an estimate of the forward-looking volatility of a portfolio of assets which is usually the most difficult one to estimate.

We will use the volatility estimates made by the ARMA and GARCH models from the previous section to calculate a Value at Risk, based on the notion that the future volatility can be derived from past innovations of the same time series. In a second application the logic of the VaR model is reversed to define the maximum position limits at regular time intervals to ensure that the risk, expressed as the Value at Risk as % of equity, stays within the predefined limits.

1. Calculating a Dynamic VaR

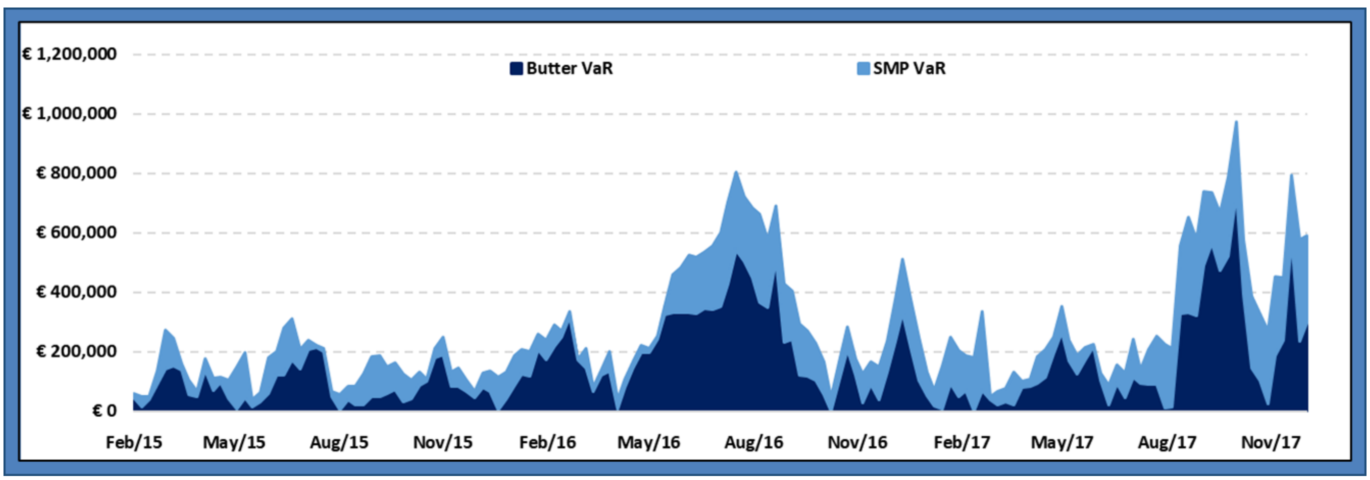
Let's set the maximum position limit for Butter at 5,000 MT's and SMP at 10,000 MT's and that traders are only allowed to trade outside these position limits with the consent of their management. The position limit is transformed into a one-day VaR (in EUR) with help of the following formula:

$$One\ day\ VaR_t \ = \frac{|O_t| \cdot p_t \cdot (e^{\hat{\sigma}_t \cdot P_{95\%}} - 1)}{\sqrt{5}} \tag{10}$$

with O_t the maximum product position in metric tons, p_t the weekly price of the commodity in EUR, $\hat{\sigma}_t$ the weekly conditional volatility estimate and $P_{95\%}$ as the 95th percentile of the standardized residuals of the error term. A histogram was used to determine the range in which 95% of the standardized residuals would fit. For a standard normal distribution this is 1.65x the standard deviation, but for the Butter and SMP errors the 5% quantile amounts to 1.99x and 2.14x respectively, which is caused by the non-normality of the returns (Engle, 2001). At each t the GARCH model was used to estimate the conditional volatility $\hat{\sigma}_t$ for Butter and the ARMA model for SMP.

Figure 6 sums the one-day VaR's of both products positions without correcting for the correlation between them. It shows that the overnight VaR ranges from less than 100kEUR to almost 1,000kEUR, which might be above the risk appetite of a firm. Although the Butter position was smaller compared to SMP, it represented on average, 60% of the total VaR due to the higher volatility levels.

Figure 6
The Overnight VaR for Butter and SMP Combined in EUR



Q3'16 and Q4'17 were two periods in which Butter prices were highly volatile; weekly price changes of >300 EUR/MT were no exception. This analysis illustrates that in times of high volatility the accompanying risk level increases significantly. Traders should be vigilant in times of increased volatility and consider hedging their open positions in order not to increase the exposure of the firm beyond predetermined risk levels.

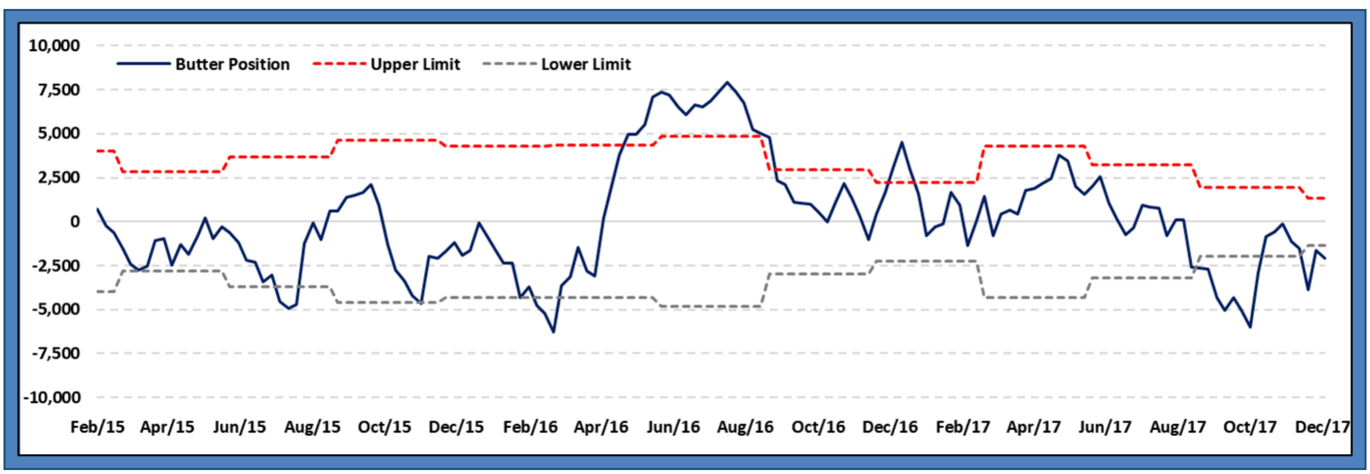
2. Calculating Dynamic Position Limits

The conditional volatility estimate could also be used to implement a strategy in which a firm employs *dynamic* position limits with the goal to stay within the agreed VaR as % of equity. Product positions consist of multiple products and traders can maximize one position at the expense of the other. Without correcting for the correlation of the returns of SMP and Butter and given the traders' intent to create a position in both products, what would have been the appropriate position limits for each product?

Assume that the traders are allowed to allocate 60% of the VaR on Butter and 40% on SMP, reflecting the average allocation of the VaR over the past three years. Position limits are recalculated quarterly with the help of formula (10) and the average limit of the past five weeks will set the limit for the quarter ahead. Position limits can be either long and short and the one-day 95% VaR is capped at 1% of equity. Maximum position limits should be reassessed periodically. The frequency depends on the nature of the business and the maturity of the commodity market in which the firm operates.

Figure 7 clearly illustrates the effect of the conditional volatility estimate; it narrows the boundaries (dotted lines) when the volatility increases and widens the position limits again in periods of relative calm. In most instances, the Butter position stayed within its precalculated limits. The same exercise was done for SMP, resulting in positions limits between 4,000 and 7,000 MT. When comparing these dynamic position limits to the static limits of 5,000 MT (Butter) and 10,000 MT (SMP) respectively, the static limits underestimate the actual volatility in the market and would not allow a company to maintain its 1% VaR over equity target.

Figure 7
The Butter Position and the Dynamic Position Limits in MT's



Dynamic limits may allow a company to anticipate volatility trends and to timely adjust positions before the associated position risk level increases. It is worth noting that the somewhat weak correlation between weekly Butter and SMP returns does reduce the overall risk of the portfolio. The positive correlation between Butter and SMP of 0.33 over the past three years gives an approximate 15% to 20%

reduction of the VaR of the combined portfolio. However, correlations are not constant and if the positions are managed independently, the offsetting effect of weak correlations can be limited in practice.

These two practical applications illustrate that the conditional volatility estimates are useful in the calculation of a weekly VaR metric and can also be used to dynamically set position limits for commodity traders to allow for better risk management.

Embedding a Dynamic VaR model in an Organization

One of the first questions that the shareholders of a company have to decide upon is: "*What is the level of risk we feel comfortable with*?" Once the risk appetite is defined (e.g., position limits, VaR as % of equity), the firm has to create a proper risk management framework within the organization. This section explains how commodity traders can embed dynamic risk management in their risk routine.

A middle office desk is typically concerned with daily risk management responsibilities and could calculate the dynamic product position and VaR limits based on the current volatility outlook. Conditional volatility estimates are derived with the help of a preselected volatility model, e.g., the GARCH or ARMA variants. Historical returns are usually publicly available, and with the help of a statistical software package, model parameters can be established with little effort. Care should be taken to ensure the data is stationary before modelling since financial time series are rarely independent. A supporting organization is essential in execution and maintenance of a dynamic risk management model.

- **Traders**: the traders are responsible for maintaining an accurate position and should get a basic understanding of volatility estimates and obtain training on the logic behind a VaR model.

- **Middle Office**: this is the center of risk management and is ideally positioned to reconcile trades, perform desk research, update volatility estimates and advise management on position limits.

- **Management**: the firm's management has to determine the risk appetite of the firm and needs to be fully aware of the VaR metric and is in charge of reviewing it on a regular basis.

- **Finance department**: this department serves as the reporting and accounting backbone of the organization and checks if limits are respected and/or if escalations are performed in accordance to internal guidelines.

- **Treasury**: the treasury department is typically interested in the results of the model as they need to ensure sufficient liquidity is available for margin calls or provide credit support.

The decision to reduce or increase a certain position should be carefully considered as other factors may be at play. The breach of a VaR or position limit serves as a trigger to investigate. The position accuracy has to be verified first, in addition to a review of the current market circumstances. If, for example, the recent uptick in volatility can be explained, and the traders are comfortable with the level of risk, they could be given the consent of the management's board to maintain their positions. Despite the popularity of VaR models, it remains just one measure in the toolkit of a risk manager. Stress tests and sensitivity analysis amongst others have to be run in parallel to ensure a proper assessment of the risk is made.

Summary and Conclusion

This paper studied the time series properties of price volatility in EU dairy markets and has tested models to forecast the price volatility. Second, it showed how to use these forecasted volatility estimates to manage price risk at a commodity trader.

Volatility in dairy is predominately driven by external factors far beyond the control of a typical commodity trading firm and are not easily captured in a model. On the positive side, time series of EU Butter and SMP commodities demonstrated significant positive autocorrelation, strong forms of volatility persistence and quantifiable levels of mean reversion. This heteroskedastic behavior combined with leptokurtosis and non-normality is modelled best with the help of an ARMA or GARCH time series model. These models provided a conditional estimate of the expected future volatility, which is a welcome input for Value at Risk models that are frequently used to assess the risk of the open positions at trading firms.

This paper discussed how product positions in combination with a volatility outlook can be translated into a dynamic VaR number. In addition, in times of high volatility, the accompanying risk level increases significantly, and could exceed the risk appetite of the firm. Another application was to use the conditional volatility estimates to dynamically set position limits. When the expected volatility increases, the model narrows the position limits and widens the boundaries again in periods of relative calm. We conclude that volatility modeling is an interesting field to further explore and offers multiple opportunities for commodity trading firms to enhance their risk management suite. A dynamic VaR model could replace some "static" tools or methods currently in place, but it cannot be a sole substitute for a prudent risk management practice at any firm.

Further Research

This research can be expanded by including dairy commodity prices from other geographical areas, or more advanced time series models to obtain a better volatility estimate. It would also be interesting to understand if the parameter estimation method can be improved with the help of semiparametric approaches since the assumptions about the underlying distributions are often violated. Lastly, the dairy futures market has grown rapidly in the past few years and has become a key platform to mitigate price risk. The volatility of futures could, for instance, help to estimate the forward-looking volatility of dairy products.

References

Bollerslev, T., 1986, "Generalized Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics,* Vol. 31, No. 3, April, pp. 307-327.

Bollerslev, T. and E. Ghysels, 1996, "Periodic Autoregressive Conditional Heteroscedasticity," *Journal of Business & Economic Statistics,* Vol. 14, No. 2, April, pp. 139-151.

Box, G., Jenkins, G. and G. Reinsel, 1995, "Time Series Analysis: Forecasting and Control," *Technometrics,* Vol. 32, No. 2, May, pp. 238-239.

Engle, R., 2001, "GARCH 101: An Introduction to the Use of ARCH/GARCH Models in Applied Econometrics," *Journal of Economic Perspectives,* Vol. 15, No. 4, Fall, pp. 157-168.

Engle, R. and A. Patton, 2007, "What Good is a Volatility Model?", in J. Knight, and S. Satchell (eds) Forecasting Volatility in the Financial Markets (Third Edition), Oxford: Butterworth-Heinemann, pp. 47-63.

European Commission, 2018, "European Commission's Agriculture and Rural Development Department: Milk and Milk Products." Accessed via website: https://ec.europa.eu/agriculture/milk_en on January 27, 2018.

[FAO] Food and Agriculture Organization of the United Nations, 2016, "Global Dairy Statistics."

Johnson, D., 1975, "World Agriculture, Commodity Policy, and Price Variability," *American Journal of Agricultural Economics*, Vol. 57, No. 5, December, pp. 823-828.

Linsmeier, T. and N. Pearson, 1996, "Risk Measurement: An Introduction to Value at Risk," ACE Reports 14796, University of Illinois at Urbana-Champaign, Department of Agricultural and Consumer Economics.

Moledina, A., Roe, T. and M. Shane, 2004, "Measuring Commodity Price Volatility and the Welfare Consequences of Eliminating Volatility," 2004 Annual meeting, August 1-4, Denver, CO 19963, American Agricultural Economics Association.

Moyer, W. and T. Josling, 2002, Agricultural Policy Reform: Politics and Process in the EU and US in the 1990s, Abingdon (U.K.): Routledge.

O'Connor D., Keane M., 2011, "Empirical Issues Relating to Dairy Commodity Price Volatility," in I. Piot-Lepetit and R. M'Barek (eds) Methods to Analyse Agricultural Commodity Price Volatility, New York: Springer, pp. 63-83.

Pagan, A. and G. Schwert, 1990, "Alternative Models for Conditional Stock Volatility," *Journal of Econometrics*, Vol. 45, No. 1-2, July-August, pp. 267-290.

Piot-Lepetit, I. and R. M'Barek, 2011, "Methods to Analyse Agricultural Commodity Price Volatility," in I. Piot-Lepetit and R. M'Barek (eds) Methods to Analyse Agricultural Commodity Price Volatility, New York: Springer, pp. 1-11.

Pirrong, C., 2014, "The Economics of Commodity Trading Firms," *Trafigura White Paper*, March. Accessed via website: https://www.trafigura.com/white-papers/the-economics-of-commodity-trading-firms/ on January 10, 2021.

Soutter, T. and I. Manuel, 2019, "A Mean-Variance Approach for Optimizing Physical Commodity Production Decisions," *Global Commodities Applied Research Digest,* Advisory Council Analyses, Vol. 4, No. 1, Summer, pp. 58-63.

Treasury Today, 2020, "Effective Commodity Risk Management in a Volatile Economic Climate," January. Accessed via website: https://treasurytoday.com/risk-management/market-risk/effective-commodity-risk-management-in-a-volatile-economic-climate-ttb2b on January 7, 2021.

Author Biographies

VINCENT ALMERING
Group Treasurer, Interfood Holding B.V., The Netherlands

Mr. Vincent Almering is the Group Treasurer of Interfood Holding B.V., a leading Dutch Dairy commodity trading firm with over 2€ billion in turnover. He is responsible for global treasury operations, bank relationships, risk management and works closely with commercial participants to structure commodity derivatives products and optimize the use of working capital. Mr.

Almering has a Master of Science degree in Industrial Engineering from the Technical University in Eindhoven and an Executive Master in Finance degree from TIAS Business School, both of which are in The Netherlands. Mr. Almering also holds both the Registered Controller and Registered Treasurer titles.

HERBERT RIJKEN, Ph.D.
Full Professor in Corporate Finance, Vrije Universiteit Amsterdam, The Netherlands

Dr. Herbert Rijken, Ph.D., is a Full Professor in Corporate Finance at the Vrije Universiteit (VU) Amsterdam. His current research interests are in equity and credit risk pricing models, and credit rating agencies. He is a program director of two executive post graduate programs: the VU program in Treasury Management & Corporate Finance and the VU/University of Groningen program in Mergers & Acquisitions and Valuation.

FRANS CLETON
Senior Manager, KPMG Advisory, The Netherlands; and Program Manager and Instructor, Postgraduate Program, Treasury and Corporate Finance, Vrije Universiteit Amsterdam

Mr. Frans Cleton completed his Master in Business Economics degree at the University of Groningen in 1990. He has worked as the Treasurer, Business Controller and Chief Financial Officer in various companies for 15 years. Since 2010 he has worked for KPMG as a management consultant with a specific focus on Financial and Risk Management. Since 2015 Mr. Cleton has worked as a program manager and teacher for the Postgraduate Program in Treasury Management and Corporate Finance at the Vrije Universiteit Amsterdam.

GLOBAL COMMODITIES
APPLIED RESEARCH DIGEST

The *Global Commodities Applied Research Digest (GCARD)* is produced by the J.P. Morgan Center for Commodities (JPMCC) at the University of Colorado Denver Business School.

The JPMCC is the first center of its kind focused on a broad range of commodities, including agriculture, energy, and mining. Established in 2012, this innovative center provides educational programs and supports research in commodities markets, regulation, trading, investing, and risk management. The JPMCC's Executive Director is Dr. Thomas Brady, Ph.D.

Subscriptions to the *Global Commodities Applied Research Digest* are complimentary at jpmcc-gcard.com/subscribe.

The *GCARD* is edited by Ms. Hilary Till, the JPMCC's Solich Scholar, jpmcc-gcard.com/hilary-till, whom can be contacted at till@jpmcc-gcard.com.

J.P. MORGAN CENTER FOR COMMODITIES
UNIVERSITY OF COLORADO DENVER BUSINESS SCHOOL

Physical Address

J.P. Morgan Center for Commodities

University of Colorado Denver Business School

1475 Lawrence Street
Denver, CO 80202

Mailing Address

J.P. Morgan Center for Commodities

University of Colorado Denver Business School

Campus Box 165
P.O. Box 173364
Denver, CO 80217

Web

business.ucdenver.edu/commodities

Contact

Erica Hyman

Program Manager

J.P. Morgan Center for Commodities

University of Colorado Denver Business School

erica.hyman@ucdenver.edu
1.303.315.8019

Business School
UNIVERSITY OF COLORADO DENVER