RISK EVALUATION OF LIVESTOCK COMMODITIES – VALUE-AT-RISK APPROACH

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ABSTRACT

This paper tries to assess the level of losses that investors in four livestock commodities might have. The analysis comprises live cattle, feeder cattle, lean hogs and milk class III, and for the risk calculation, we use parametric and historical VaR measures. Full sample is divided into pre-crisis and crisis subsamples. According to the results, lean hogs are the riskiest asset in the pre-crisis period, regarding both parametric and historical VaR. In the crisis period, milk is the riskiest asset in terms of parametric VaR in all probability levels. However, in terms of historical VaR, lean hogs have the highest potential of loses between 90-97% VaR, but at 99% VaR, milk takes upper hand. In the crisis period, the level of losses for lean hogs and milk exceeds 4% in one day at 99% probability, which means that these commodities should be hedged if investors want to avoid great losses. The results indicate that parametric VaR significantly deviates from historical VaR in both subsamples, which means that investors in livestock commodities should use historical VaR for downside risk measurement.

Introduction

It is well known among academics and practitioners that agricultural commodities have unstable prices. This happens because various factors – natural, socioeconomic

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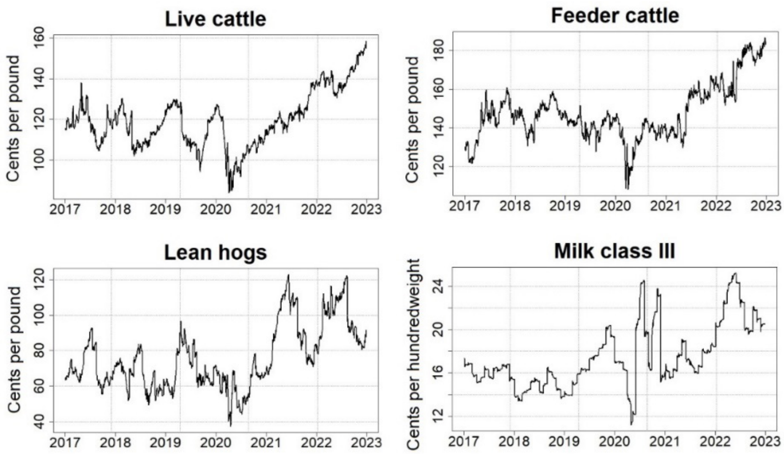
and geopolitical, affect agricultural commodities (see e.g. Tuncer, 2022; Gong and Xu, 2022; Chen et al., 2022). Recent years were particularly turbulent for the world due to the two events. First, the world has been struck by the corona virus pandemic, while later on, the war in Ukraine broke out. These happenings had tremendous effect on the prices of all agricultural commodities, while livestock agricultural commodities were not an exception (Rawtani et al., 2022). In other words, broken supply chains and imposed counter pandemic measures exerted rising prices of all grains which transferred to the prices of livestock (Dogan et al., 2022). The war in Ukraine only intensified these effects because Ukraine is the fourth largest corn producer (Saâdaoui et al., 2022). The link between grains and livestock is direct because rising prices of grains spill over to the prices of cattle, causing a lot of risk in these markets. This poses a problem for cattle breeder or investors in livestock because unstable prices can inflict huge losses to these agents (Kuzman et al., 2021), so proper understanding of risk in these markets is of utmost importance.

According to the above, this paper tries to measure risk in four futures livestock commodities markets – live cattle, feeder cattle, lean hogs and milk class III. Figure 1 graphically illustrates the prices of these four commodities in the last six years, where the volatile nature of these prices is evident. High price volatility inevitably implies presence of high risk, and the task of this paper is to measure it accurately. According to our best knowledge, very few papers analysed livestock commodities from financial aspect, e.g. Bina et al. (2022) calculated hedge ratios of feeder cattle. However, we are not aware of any papers that have measured the risk of these agricultural commodities. This leaves room for our contribution, and this is where we find a motive for this investigation.

Figure 1. Empirical dynamics of the selected livestock commodities



Notes: One pound is 0.45 kg. One hundredweight is 50.8 kg.

Source: Authors' calculations

In the process of risk measurement, variance is the most common metric. However, this measure is biased because it gives an equal weight to positive and negative returns, while market participants are only interested in the size of losses, which is measured by downside risk (Tiwari et al., 2022). In order to overcome this issue, JP Morgan bank introduced Value-at-Risk (VaR) in 1994, and from there on, VaR became a standard measure of downside risk. VaR indicates potential losses that might occur, observing only a specific quantile at the left tail of distribution (Xu et al., 2021). In other words, VaR measures the maximum loss that an asset might endure, taking into account a specified time-frame with a certain level of probability. The most commonly used VaR in the literature is parametric VaR, which assumes certain type of distribution, and this means that accurate measure of downside risk depends on the accuracy of theoretical distribution (So and Yu, 2006). This could be a serious problem because if theoretical distribution does not recognize properly empirical distribution, risk evaluation could be very wrong. In practice, the most usually used type of VaR is parametric VaR that assumes normal distribution of an empirical time-series. However, daily commodity time-series are usually plagued with heavy tails and outliers, which is particularly true in the periods of market turmoil. This could produce inaccurate downside risk measures, which can be devastating for investors if wrong decision are made.

In this regard, besides calculating parametric VaR, we also compute historical VaR, which takes into account all prior empirical developments, i.e. all idiosyncratic features of a particular time-series (Chai and Zhou, 2018). In this vein, we can compare parametric and historical VaR, determining whether and how much parametric VaR diverge from historical VaR. These results can tell us whether parametric VaR is good and reliable measure of downside risk or not, i.e. whether it can be used for future downside risk measurement of the selected assets.

In order to be thorough in the analysis, the research is done from the two different angles. First, we intentionally observe the sample of six years, which gives us an opportunity to divide the whole sample into the pre-crisis period and crisis period, where both samples then covers three years. This is a rational step because Figure 1 clearly shows that all the commodities start to record rising prices in the early 2020, i.e. when the pandemic occurred. In this way, we can compare the results of the two subsamples and determine how much downside risk is bigger in the crisis period compared to the pre-crisis counterpart.

Another aspect of this research involves addressing different attitude toward risk which market participants might have. In other words, some investors are risk-takers and some are risk-averters. Therefore, we calculate parametric and historical VaR at different probabilities, which reflect different risk level that investors are willing to take. In this respect, we can see how the level of risk evolves when different left tail quantiles are observed.

As for the existing literature, there are papers which used VaR for risk calculation in the field of agriculture, but they are oriented towards grains. For instance, Xouridas

(2015) researched the kurtosis values of 60 agricultural commodities and presents evidence that the distributions of their returns are fat-tailed. However, he argued that usefulness of the value-at-risk and expected shortfall results as risk management tools is questionable. Morgan et al. (2012) examined three tail quantile-based risk measures – Value-at-Risk, Expected Shortfall and Spectral Risk Measures, applied to the estimation of extreme agricultural financial risk for corn and soybean production in the U.S. They compared estimated risk measures in terms of size and precision, and find that they are all considerably higher than Gaussian estimates. They concluded that estimated risk measures are quite imprecise as the risks involved become more extreme. Rehman et al. (2018) measured the five major crops market price volatility risks using the VaR model in China. They stated that the method of VaR can efficiently compute the instability of the market prices and the market risk of major crops as well. According to their computed values of various major crops market risk, they found that sizes of the different major crops market risks are different. The paper of Živkov et al. (2021) measured downside risk of six major agricultural commodities – corn, wheat, soybean, soybean meal, soybean oil and oats, using parametric and semiparametric approaches. They asserted that modified Value-at-Risk and modified Conditional Value-at-Risk give more accurate downside risk results than ordinary VaR and CVaR.

Besides introduction, the rest of the paper is structured as follows. Second section presents used methodologies. Third section introduces dataset. Fourth section is reserved for the results, regarding the pre-crisis and crisis sub-periods. The last section concludes.

Used methodologies

GARCH-NIG model

In order to calculate parametric VaR, first step involves creating residuals free of autocorrelation and heteroscedasticity. In this process, we use univariate GARCH model with innovative Normal Inverse Gaussian (NIG) distribution of Barndorff-Nielsen (1997). NIG distribution can recognize heavier tails than the normal distribution and has shape and density parameters (ν and κ). Mathematical specification of the mean and variance equations in the GARCH model are presented in equations (1) and (2), respectively.

$$y_t = C + \phi y_{t-1} + \varepsilon_t, \quad \varepsilon \sim NIG(0, h_t, \nu, \kappa) \tag{1}$$

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

where y_t depicts log-returns of the particular agricultural commodity. *C* and *c* represent constants in the mean and variance equations, while ϕ is an autoregressive parameter. σ_t^2 is conditional variance in period *t*. β captures persistence of volatility, while α gauges an ARCH effect. ε_t denotes residuals that follow NIG distribution.

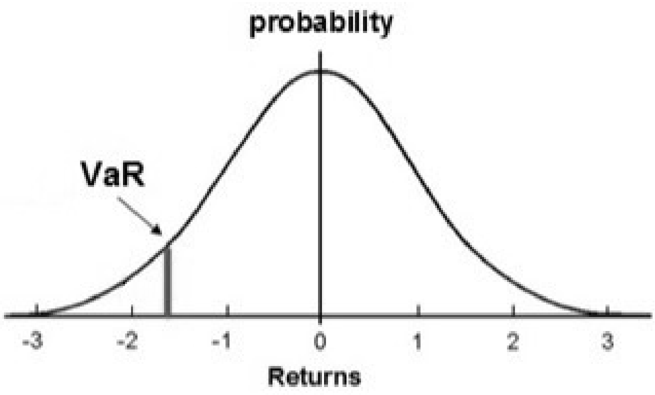
Value-at-Risk metric

This paper measures downside risk using VaR metric. Theoretically speaking, VaR calculates a loss that investor might have in a single day under certain probability. In other words, VaR observes a section or particular quantile on the left tail and does not go beyond this level. This research calculates both parametric and historical VaR, where parametric VaR assumes normal distribution, while historical VaR calculates losses of an empirical distribution. Believing that empirical distribution of the daily agricultural commodities follow Gaussian function is pretty strong assumption, and this is why deviation between parametric and historical VaR might occur. Calculating both types of VaR, we can determine how much historical VaR diverge from parametric VaR, i.e. these results can tell whether parametric VaR is good downside risk measure or not. Following Aloui and Hamida (2015), parametric VaR can be calculated by using the first two moments of normal distribution, which is as in equation (3):

$$VaR_\alpha = \hat{\mu} + Z_\alpha \hat{\sigma} \tag{3}$$

where $\hat{\mu}$ and $\hat{\sigma}$ refer to the estimated mean and standard deviation of a particular agricultural asset, respectively, and Z_α stands for the left quantile of normal standard distribution. Figure 2 graphically illustrates where the loss is placed on the normal distribution that VaR calculates. VaR observes only downside risk, which is the reason why VaR is on the left tail of distribution. The higher the probability, the closer the VaR is to the edge of the distribution. In other words, higher probability moves particular quantile to the end of distribution, which reflects greater losses. In order to reflect different risk propensities of investors, we calculate VaR at 90%, 93%, 95%, 97% and 99% probability.

Figure 2. Graphical illustration of the parametric Value-at-Risk



Source: Authors' calculations

Dataset

This paper uses daily near maturity futures of four agricultural commodities – live cattle, feeder cattle, lean hogs and milk class III, which are all traded on the Chicago Mercantile Exchange (CME). We investigate futures prices rather than spot prices because futures prices process new information much faster, making these prices more realistic. The sample covers six years, ranging from January 2017 to December 2022, and all the time-series are collected from the *investing.com* website. All time-series are transformed into log-returns according to the expression: $r_{i,t} = 100 \times log(P_{i,t}/P_{i,t-1})$, where PP denotes closing prices. Figure 3 shows transformed time-series, where can be seen that volatility is higher from 2020, which justifies dividing the analysis on the pre-crisis and crisis period. Table 1 contains full sample descriptive statistics of the four agricultural assets, i.e. the first four moments, Jarque-Bera coefficient of normality, Ljung-Box Q-statistics of level and squared residuals and the DF-GLS unit root test.

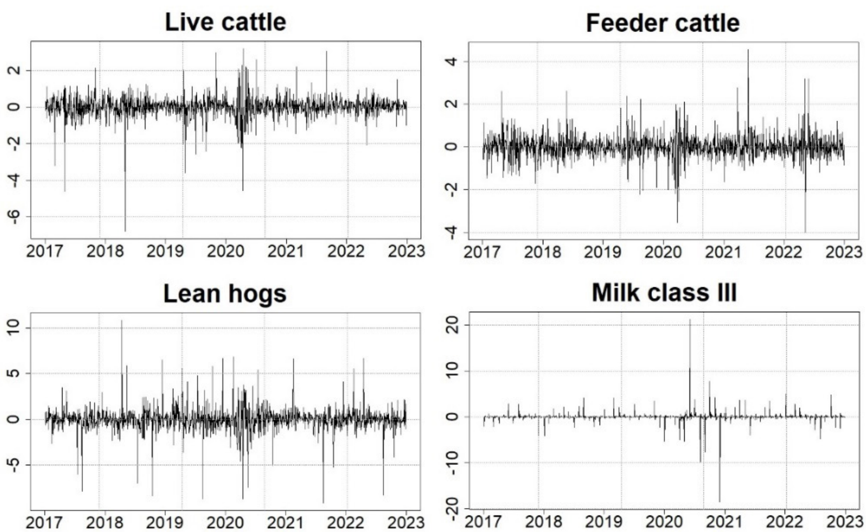
Table 1. Descriptive statistics of the selected agricultural commodities

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q^2)	DF-GLS
Live cattle	0.009	0.589	-1.667	23.616	27675.0	0.000	0.000	-10.948
Feeder cattle	0.010	0.554	0.356	12.382	5602.5	0.000	0.000	-3.263
Lean hogs	0.009	1.255	-0.365	20.009	18393.7	0.009	0.000	-9.866
Milk class III	0.005	1.006	1.429	223.769	3060919.0	0.794	0.925	-38.533

Notes: JB is value of Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) refer to p-values of Ljung-Box Q-statistics of level and squared residuals of 10 lags. 1% and 5% critical values for the DF-GLS test with 5 lags, assuming only constant, are -2.566 and -1.941, respectively.

Source: Authors' calculation.

Figure 3. Log-returns of the selected agricultural commodities



Source: Authors' calculations

According to Table 1, lean hogs have the highest standard deviation, while milk follows. This paper tries to measure risk of losses, which means that standard deviation is not an appropriate risk measure because it observes positive and negative returns equally. Risk of losses can be viewed better *via* kurtosis because kurtosis indicates presence of extreme values or outliers. However, kurtosis alone is not enough to properly measure the size of losses because it takes into account both positive and negative outliers, but it could be a good indicator. Table 1 shows that milk has by far the highest kurtosis, which is a clear sign of extreme values. In other words, milk recorded the highest daily changes in the observed period, which is clearly visible in Figure 3.

Looking at Figure 3, it could be stated that milk probably has the highest VaR in the crisis period, when VaR is measured with very high probability. This means that very edge of distribution is observed, and milk has the highest negative returns according to Figure 3. Besides, three out of four agricultural commodities have a problem with autocorrelation and heteroscedasticity according to the Ljung-Box tests, which means that GARCH model is an appropriate tool to handle these issues. All time-series are stationary according to the DF-GLS test, which is a necessary precondition for the GARCH modelling.

Table 2 contains estimated GARCH-NIG parameters, where can be seen that ARCH effect is found in the three out of four cases, while volatility persistence is present in all the time-series. Only shape distribution parameter is highly statistically significant in all the cases, which means that NIG distribution recognizes heavy tails very well. All residuals report no autocorrelation and heteroscedasticity according to the Ljung-Box tests, which means that all models are specified well. This means that estimated residuals can be used for the parametric VaR calculation.

Table 2. Estimated GARCH-NIG parameters

	Live cattle	Feeder cattle	Lean hogs	Milk class III
Panel A: GARCH parameters				
α	0.193^{***}	0.057^{***}	0.046	0.387^{***}
β	0.708^{***}	0.915^{***}	0.938^{***}	0.612^{***}
Panel B: Distribution parameters				
ν – shape	0.584^{***}	0.576^{***}	0.158^{***}	0.014^{***}
k – skew	-0.077	0.055	0.049	-0.011
Panel C: Diagnostic parameters				
LB(Q)	0.150	0.183	0.255	0.996
LB(Q^2)	0.904	0.957	0.996	0.999

Notes: LB(Q) and LB(Q^2) test denote p-values of Ljung-Box Q-statistics for level and squared residuals for 10 lags. *** represent statistical significance at the 1% level.

Source: Authors' calculations

Research results

Due to the fact that our sample comprises two intrinsically different periods – before the crisis and during the crisis, our intention is to see how the downside risk measures differ when these idiosyncratic periods are in focus. Therefore, the VaR results of the selected agricultural commodities are presented *via* the two subsections.

Pre-crisis period

This subsection presents the results of the calculated parametric and historical VaR in the relatively calm period, i.e. before the pandemic and the Ukrainian war. Table 3 contains the results, taking into account five different levels of probabilities, which reflect different attitude of investors towards risk. In other words, different probabilities observe different segment on the left tail of distribution, where lower probabilities are in line with investors who are willing to take risk, while higher probabilities are compatible with risk-averting investors. Figure 3 shows joint presentation of the calculated both parametric and historical VaR values.

Before addressing the results, it is important to say how the level of VaR risk is interpreted. Take, for example, the 90% parametric VaR of live cattle, which amounts -0.763. If empirical distribution follows normal function, this means that investor has 10% chance of losing 0.763% or more of his investment in a single day in the future. It can be seen in Table 3 that VaR increases as probability rise, which applies for both parametric and historical VaR. This is expected since higher probability observes VaR closer to the edge of distribution.

Table 3. Results of parametric and historical VaR in the pre-crisis period

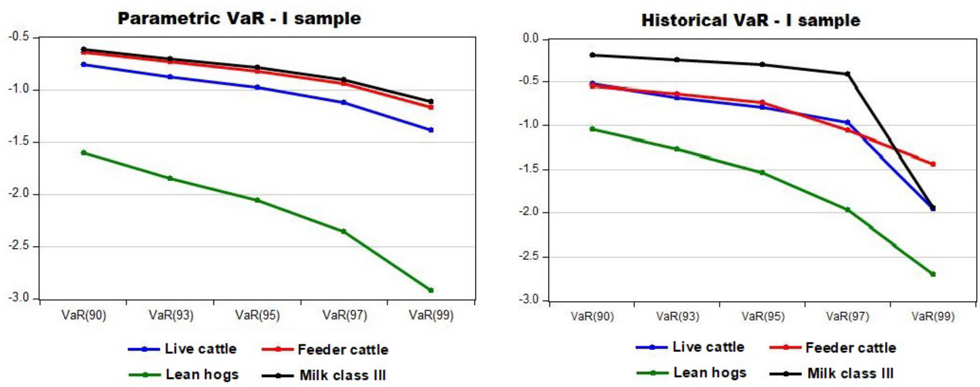
	Live cattle		Feeder cattle		Lean hogs		Milk class III	
Probability	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR
90%	-0.763	-0.519	-0.638	-0.545	-1.605	-1.048	-0.613	-0.180
93%	-0.880	-0.674	-0.736	-0.629	-1.849	-1.267	-0.707	-0.235
95%	-0.981	-0.788	-0.821	-0.730	-2.062	-1.539	-0.789	-0.299
97%	-1.123	-0.967	-0.940	-1.050	-2.359	-1.972	-0.903	-0.409
99%	-1.390	-1.958	-1.164	-1.437	-2.919	-2.699	-1.118	-1.947

Source: Authors' calculations

Looking at Figure 4, it is interesting to note that all lines of parametric VaR are parallel, while in the case of historical VaR, some lines are intersected. All parametric VaR lines are aligned because parametric VaR is determined by the first two moments, which remain the same regardless of what probability is taken into account. On the other hand, for historical VaR this is not the case because it observes empirical VaR (empirical losses). Thus, it is very possible that historical VaR values change asynchronously at different probabilities, which is exactly what is happening in our case. In other words, up to 97% historical VaR, milk has the lowest risk, while at the 99%, historical VaR of milk significantly drops. However, at very high probability, i.e. beyond 99%, which is not presented in Table 3, historical VaR of live cattle would probably be the highest because this asset has the biggest negative outlier in the first subsample (see Figure 3). Also, observing historical VaR, live cattle and feeder cattle frequently change the positions, and then, live cattle falls at 99%. This cannot happen with parametric VaR because for all livestock commodities the same theoretical distribution is assumed – normal distribution.

As for the relative VaR results, milk and feeder cattle have the lowest parametric VaR at all probabilities, while milk has the lowest historical VaR up to 97% according to Table 3 and Figure 4. Lean hogs are the riskiest commodity in the pre-crisis period taking into account all probabilities and both types of VaR. This means that lean hogs has the highest number of negative outliers in the pre-crisis period, which is well depicted in Figure 3.

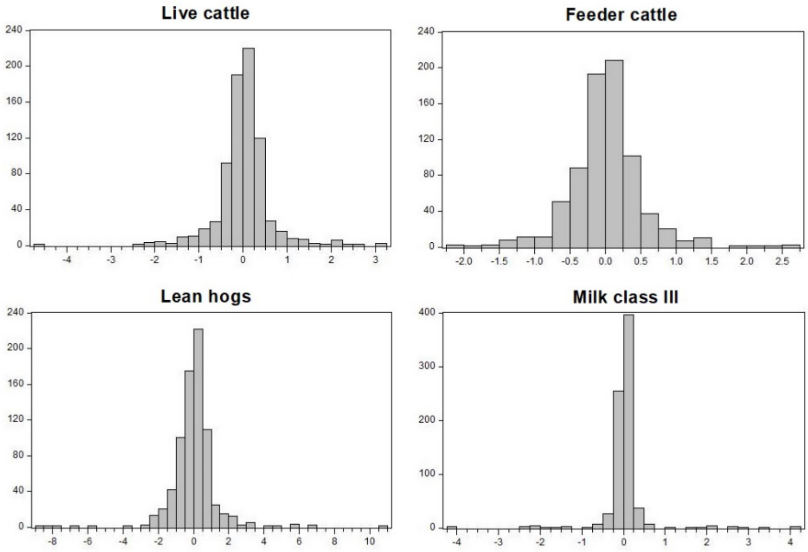
Figure 4. Parametric and historical VaR in the pre-crisis period



Source: Authors' calculations

Comparing parametric and historical VaR values, it can be seen how well parametric VaR recognizes historical VaR. According to Table 3, it is obvious that parametric VaR significantly deviates from historical VaR, which means that empirical distributions of the livestock commodities are much different than the Gaussian distribution. Figure 5 shows that all empirical distributions are leptokurtic, which means they have more kurtosis than the normal (mesokurtic) distribution. Leptokurtic distribution has higher peak and fatter tails than normal distribution, i.e. it contains more extreme values, which indicates greater tendency for outliers. This is the reason why historical VaR and parametric VaR values are so different. In other words, mesokurtic distribution has thinner tails and lower peak, and this explains why parametric VaR overestimate losses up to 97%, and underestimate losses at very high probability. This is a clear sign that parametric VaR is not a good risk measure for the livestock commodities. Our results are well in line with the papers of Xouridas (2015), Morgan et al. (2012) and Živkov et al. (2021), who all contended that classical parametric VaR is quite imprecise measure of losses.

Figure 5. Empirical distributions of the selected commodities in the pre-crisis period



Source: Authors' calculations

Crisis period

This subsection presents the results of the second subsample, which is more turbulent. In this way, we can determine how the level of risk changes in this more tumultuous period, and whether VaR positions of commodities changes. Table 4 contains calculated VaR values in the crisis subsample, while Figure 6 shows their graphical illustration. Even at the first glance, it is obvious that there are significant differences between the two subsamples.

As for parametric VaR, milk is now the riskiest commodity, while lean hogs follow. Live cattle and feeder cattle have much smaller parametric VaR at all probability levels than milk and lean hogs. However, at historical VaR, situation changes significantly. Milk is the least risky asset up to 97% probability, but it has steep fall at 99% probability. Lean hogs also record serious drop at 99% probability. These two commodities have the biggest outliers in the crisis subsample, and this explains sudden tumble at 99% probability. At probability higher than 99%, milk would probably have the highest historical VaR because it has by far the biggest outliers, which goes over -10 (see Figure 3).

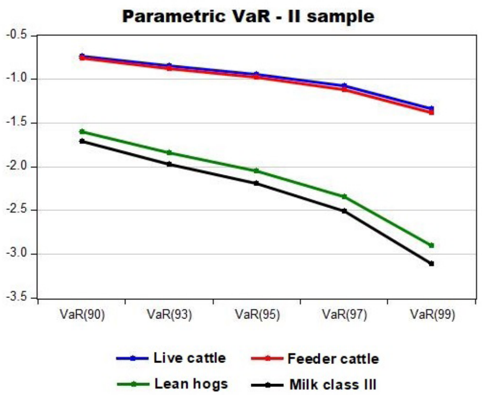
Comparing the results of the two subsamples, it is clear that second subsample is much riskier, which justifies splitting full sample into the two subsamples. Also, this indicates that the pandemic and the Ukrainian war affected significantly livestock commodities, where milk and lean hogs have the highest historical VaR at 99% probability. In other words, historical VaR at 99% of lean hogs and milk is -4.297 and -4.365, respectively, which means that there is 1% chance that loss in a single day of these two commodities could be 4.297% and 4.365%, which is pretty high. Although the probability is relatively small, it could happen, so investors in milk and lean hogs should hedge their investments in order to evade great losses.

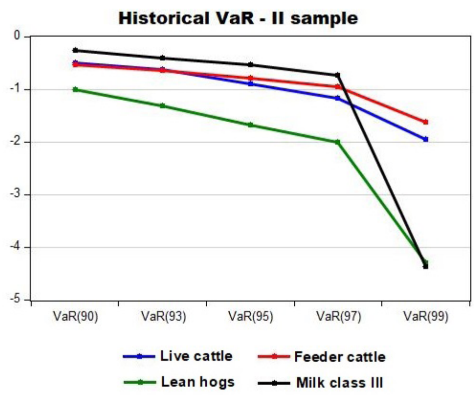
Table 4. Results of parametric and historical VaR in the crisis period

	Live cattle		Feeder cattle		Lean hogs		Milk class III	
Probability	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR	Parametric VaR	Historical VaR
90%	-0.730	-0.493	-0.757	-0.543	-1.595	-1.012	-1.709	-0.258
93%	-0.842	-0.628	-0.874	-0.645	-1.838	-1.311	-1.969	-0.403
95%	-0.940	-0.896	-0.975	-0.792	-2.050	-1.687	-2.195	-0.539
97%	-1.077	-1.172	-1.117	-0.963	-2.346	-2.006	-2.510	-0.745
99%	-1.335	-1.960	-1.385	-1.633	-2.904	-4.297	-3.106	-4.365

Source: Authors' calculations

Figure 6. Parametric and historical VaR in the crisis period

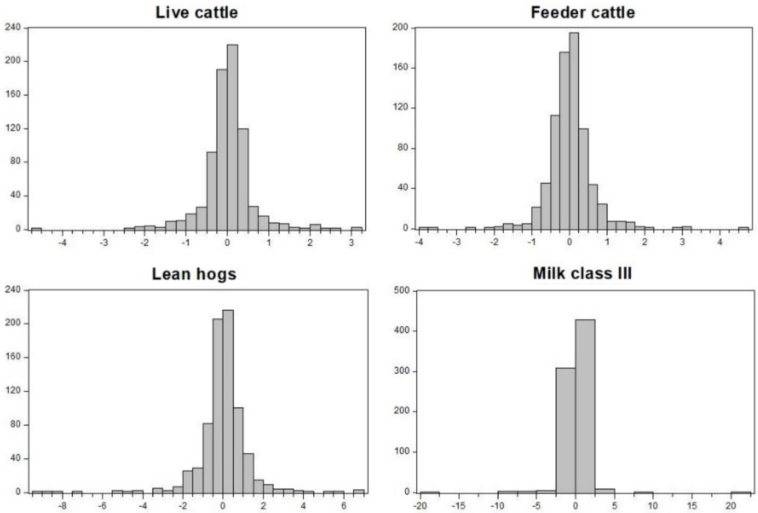




Source: Authors' calculations

Similar to the first subsample, it is obvious that empirical distributions do not match normal distribution in the second subsample (see Figure 7). In other words, they are all leptokurtic, with very pronounced fat tails. Therefore, based on the results of both subsamples, investors who want to assess the level of potential losses should utilize historical VaR rather than parametric VaR because all empirical distributions significantly deviate from normal distribution.

Figure 7. Empirical distributions of the selected commodities in the crisis period



Source: Authors' calculations

Conclusion

This paper measures risk of losses of the four livestock commodities – live cattle, feeder cattle, lean hogs and milk class III. For the risk calculation, we use parametric and historical VaR measures. The analysis divides full sample into the two subsamples in order to see how the level of risk varies when the two diametrically different periods are observed.

Based on the results, we have several noteworthy findings to report. First, risk of losses is significantly higher in the crisis subsample, which justifies dividing the full sample into the two subsamples. Second, livestock commodities bear different level of downside risk, where lean hogs are the riskiest asset in the pre-crisis period, taking into account both parametric and historical VaR measures. On the other hand, in the crisis period, milk is the riskiest asset in terms of parametric VaR, regarding all probability levels. However, in terms of historical VaR, lean hogs have the highest potential of loses between 90-97% VaR, but at 99% VaR milk takes upper hand. In the crisis period, the level of losses for lean hogs and milk exceed 4% in one day at 99% probability, which means that these commodities should be hedged if investors want to avoid great losses.

An important finding is the fact that parametric VaR significantly deviates from historical VaR in both subsamples, which means that all empirical distributions are very different compared to normal distributions. In other words, all empirical distributions have leptokurtic shape, which is characterized by heavy tails and high peak, and this is the reason why parametric VaR overestimate risk up to 97% and underestimate risk at 99% probability. This means that parametric VaR is not a good risk measure for livestock commodities because it can lead investors to wrong conclusions.

This paper can help livestock farmers and investors to understand which livestock commodity is the riskiest, and what is the best way to measure risk of potential losses. In this regard, investors would know is there any need to hedge their investments in livestock or not.

Conflict of interests

The authors declare no conflict of interest.

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