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Measuring the risk-adjusted performance of selected soft agricultural commodities

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Abstract: In this paper, we used several elaborate return-to-risk methods to investigate the risk-adjusted performances of five soft commodities. Regarding only the level of risk, we found that cocoa had the highest risk of losses, followed by orange juice. Cotton and coffee had the lowest risk of losses. However, according to the return-to-risk output, cotton was the worst asset in which to invest because it had negative average returns. In contradistinction, sugar had a relatively high risk of losses but also the highest average returns, which put it in the first place according to the Sharpe, Sortino and modified Sharpe ratios. Although orange juice had the second-worst downside risk performance, it came in second place according to the return-to-risk ratio because it had relatively high average returns.

Keywords: conditional volatility model; downside risk; return-to-risk methods

The unstable price evolution of agricultural commodities in the past two decades has led to considerable interest on the part of both academics and market participants. Agricultural commodities are specific goods, susceptible to various natural factors such as extreme weather events caused by global warming, insect infestation, plant diseases and weeds, which inevitably affect their global supply (Guth and Smedzik-Ambrozy 2020). Furthermore, agricultural products are subject to significant global demand deviation, which in total causes considerable variability of agricultural commodity prices. According to Vuta et al. (2019), in situations in which global agricultural prices fall, producers face the risk of not being able to cover production costs, and commodity traders are unable to cover their purchasing costs. Developing countries are particularly vulnerable to agricultural price volatility because they depend on significant income volumes from their commodity exports. However, before they use any hedging strategy, market participants have to be aware of the size of the risk exposure. More specifically, crucial to any successful hedging strategy is the determination of the desired risk-return level. This knowledge is important because every goal that requires maximised returns also implies accepting maximum risks (Palanska 2020). Knowing about risk-adjusted returns of particular assets can indicate to investors what the optimal choice is for where to put their money, and producers can learn whether they need to conduct any hedging strategies.

Given this information, we have tried in this paper to add to the literature by investigating the risk-adjusted performance of five soft agricultural commodities – cotton, coffee, sugar, cocoa and orange juice. The primary motivation to conduct this research stems from the fact that none of the authors of existing papers, according to our knowledge, tried to measure downside risk and risk-adjusted returns in the sophisticated way that we are using. All of these agricultural products are in high global demand, and coffee, cocoa and cotton stand out as the key cash crop commodities that significantly contribute to many national economies of the developing world. Similar to the major agricultural markets, such as corn, wheat and soybeans, these

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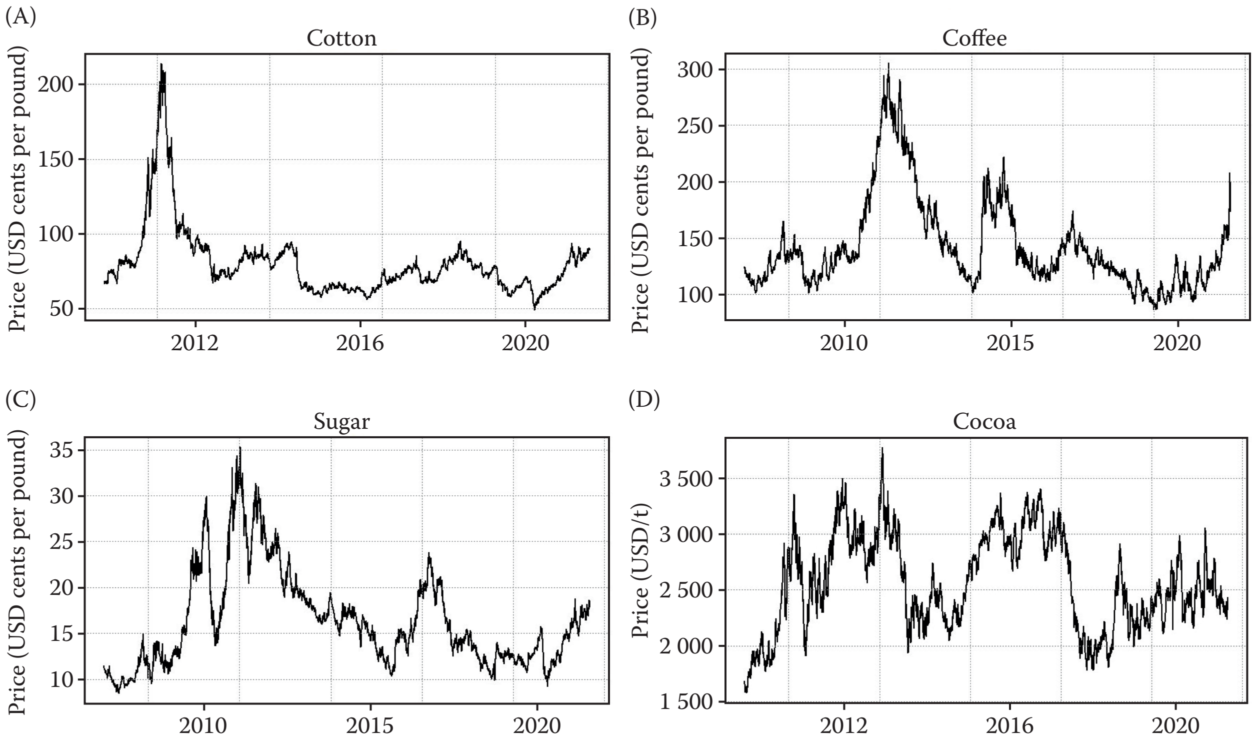
five soft commodities also went through serious price swings in the past decade, which Figure 1 illustrates.

Large price oscillations inevitably imply the presence of high price risk, but as has been said, very few papers have addressed this issue, which leaves plenty of room for our contribution. For instance, Janzen et al. (2018) investigated how cotton future prices change according to four factors – real economic activity, cross-commodity co-movement, precautionary demand for inventories, and current net supply. They reported limited evidence that financial speculation caused cotton prices to spike in 2008 or 2011. However, they concluded that the 2008 price spike was driven mostly by precautionary demand for cotton and that the 2011 spike was caused by a net supply shortfall. Babirath et al. (2021) studied the question of whether sugar can stand as a hedge for a falling equity market in the US. They revealed that sugar has served as a hedge against falling equity markets during the outbreak of the financial crisis in 2007, but it did not serve as a hedge against the devastating losses caused by the coronavirus pandemic in 2020. However, they found no statistically significant influence of equity prices on sugar prices.

The goal of this paper is to use several risk measures to calculate multiple return-to-risk ratios for the selected soft commodities. We take this approach because consideration of only one risk factor is not enough, given that risk is a complex category. This complexity means that different risk characteristics of an investment may be important for the investor and that the calculation of only one return-to-risk ratio could lead to misleading conclusions.

For this task, we used several sophisticated methodological approaches. To start with, the risk level is usually calculated by using common variance or a more complex approach – parametric value at risk (VaR).



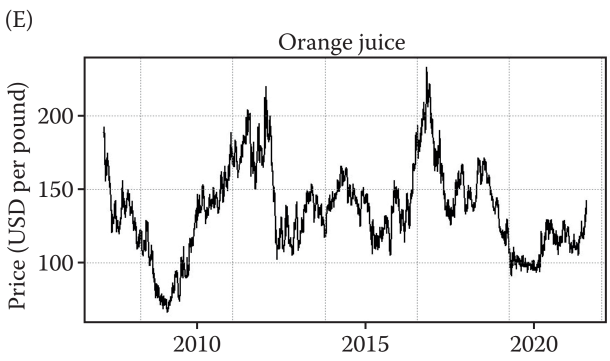


Figure 1. Empirical dynamics of five soft agricultural commodities: (A) cotton, (B) coffee, (C) sugar, (D) cocoa, and (E) orange juice

Source: Authors' own calculations based on data from Investing.com (2021)

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However, both methods have their drawbacks. Common variance is an inappropriate risk measure because it gives equal weight to positive and negative returns, which in turn produces biased conclusions about the level of risk. Because of this very obvious setback of common variance, a more elaborate approach of risk measurement was developed – parametric VaR – which takes into account only downside risk, a risk that is really important for market participants. Over time, parametric VaR has become one of the most popular tools for downside risk measurement (Altun et al. 2017; El Ghourabi et al. 2020; He et al. 2020).

However, VaR also has a number of limitations that can be very serious. First, VaR can produce erroneous risk measures if it is used in raw empirical time series that are not independently and identically distributed. Therefore, to overcome this issue, we first created white noise error returns by using a generalised autoregressive conditional heteroscedasticity (GARCH) model in combination with normal inverse Gaussian distribution (NIG), which can recognise asymmetric and fat-tailed properties of empirical time series. Second, common VaR cannot accurately measure downside risk in situations in which the expected loss is greater than or equal to VaR at certain confidence levels. Because of this inaccuracy, a more conservative downside risk measure was developed – conditional VaR (CVaR). However, both VaR and CVaR have one deficiency, which is related to the fact that parametric measures are accurate only in situations in which empirical time series follow Gaussian distribution, which is a very unlikely scenario for daily commodity prices. This deficiency occurs because parametric risk measures consider only the first two moments, mean and variance, whereas the third and fourth moments (skewness and kurtosis) are left unaccounted for. To circumvent this potentially very serious disadvantage of common VaR and CVaR metrics, we used semiparametric, instead of parametric, downside risk measures, which take into account all four moments. This approach is based on the Cornish-Fisher expansion, and it is better known as modified VaR (mVaR), which was introduced by Favre and Galeano (2002). To our knowledge, only Živkov et al. (2021) have used this methodology in the field of agriculture. However, they researched six grain commodities, which leaves plenty of room for our investigation of soft commodities.

After the calculation of various risk measures, the next task was to gauge the trade-off between the risks and returns of the five soft commodities by using several risk-adjusted ratios. The first ratio is the Sharpe ratio, which is a well-known and standard return-to-risk indicator that measures the relation between risk-free returns and common standard deviation. The second ratio is the Treynor ratio, which puts into relation risk-free returns and a measure of systemic risk, which is β. Because the ordinary Sharpe ratio measures both positive and negative returns, the next two ratios, the Sortino ratio and the modified Sharpe ratio, improve and complement the ordinary Sharpe ratio. In particular, the Sortino ratio does not use common standard deviation that stems from both positive and negative returns, but rather the standard deviation of only negative portfolio returns, which is known as 'downside deviation'. The Sortino ratio measures average downside deviation, and the modified Sharpe ratio is an even stricter indicator that measures only a particular set of negative returns under certain levels of probability, which are placed at the left tail of the distribution. In other words, the modified Sharpe ratio puts into relation risk-free returns and modified CVaR metrics that do not rely on the strong assumption of normality.

According to our knowledge, this paper is the first in which the authors gauge the downside risk of soft commodities by using very elaborate risk measures. We also have calculated different return-to-risk ratios of soft commodities, which has not been done before.

MATERIAL AND METHODS

GARCH model. Calculating bias-free estimates of downside risks means that the first task is to create white noise error terms that have no problem with autocorrelation and heteroscedasticity. In this process, we used a symmetric GARCH model in combination with an untraditional NIG distribution. Unlike most conventional distributions (Gaussian, Student *t*, generalised error distribution), which have only one shape parameter, NIG distribution has two parameters, $\varepsilon \sim NIG\left(0, \sigma_t^2, \tau, \nu\right)$, where: τ and ν – skew and shape parameters, respectively. In this way, GARCH-NIG produces more accurate residuals, compared with those of GARCH models with other traditional distributions. As did Živkov et al. (2016), we resolved possible autocorrelation in the GARCH model by using the first autoregressive term in the mean equation. The variance equation by default can deal with the heteroscedasticity problem. Equations (1, 2) present specifications of the mean and variance equations in the GARCH model:

$$y_t = C + \phi y_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim z_t \sqrt{\sigma_t^2} \tag{1}$$

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

where: ϕ – autoregressive term, C, c – constants in the mean and variance equations; z_t – independently and identically distributed process; y_t – log returns of the selected soft agricultural commodities; σ_t^2 – conditional variance; ε_t – error term (depicts the independently and identically distributed process of NIG distribution); α, β – parameters that fulfil the conditions $\alpha \geq 0$ and $\beta \geq 0$.

Measuring downside risk. As we have said, the traditional parametric VaR risk measure has a number of weaknesses, so instead of parametric VaR, we used semiparametric VaR, also known as 'mVaR', which overcomes deficiencies of the common VaR and produces more accurate risk measures; mVaR takes into account all four moments of distribution, unlike traditional VaR, which considers only the first two moments. Accordingly, *mVaR* is described by Equation (3):

$$mVaR_\alpha = \hat{\mu} + Z_{CF,\alpha}\hat{\sigma} \tag{3}$$

where: $\hat{\mu}$, $\hat{\sigma}$ – estimated mean and standard deviation, respectively; $Z_{CF,\alpha}$ – non-normal distribution percentile based on the Cornish-Fisher expansion.

Equation (3) is adjusted for skewness and kurtosis, and Equation (4) shows the full expression:

$$Z_{CF,\alpha} = Z_\alpha + \frac{1}{6}\left(Z_\alpha^2 - 1\right)S + \frac{1}{24}\left(Z_\alpha^3 - 3Z_\alpha\right)K - \\ -\frac{1}{36}\left(2Z_\alpha^3 - 5Z_\alpha\right)S^2 \tag{4}$$

where: S – skewness; K – kurtosis; Z_α – left quantile of the normal standard distribution.

Besides *mVaR,* we also calculated modified CVaR (*mCVaR*) because this metric provides a better approximation of risk in situations in which mVaR is exceeded. This measure indicates an average expected loss, where mVaR shows only a certain left-tail quantile. Figure 2 illustrates the difference between mVaR and mCVaR.

Equation (5) shows how *mCVaR* is calculated:

$$mCVaR_\alpha = -\frac{1}{\alpha}\int_0^\alpha mVaR(x)\,dx \tag{5}$$

Measures of risk-adjusted returns. In the previous section, we explained an efficient way of measuring risk, but this is only one side of the coin because it is even more important for investors, traders and producers to know what the gain is of investing in soft commodities. In this respect, we calculated four different return-to-risk ratios that take into account different risk measures as the denominator.

First is the Sharpe ratio (Sharpe 1966), which measures investment returns in excess of the risk-free rate of return – that is, the risk-free rate of return is divided by the standard deviation, as in Equation (6):

$$Sharpe\ ratio = \frac{R_i - R_f}{\sigma} \tag{6}$$

where: R_i – average daily return of an asset (i); R_f – risk-free rate; σ – standard deviation of a particular asset.

For the risk-free rate, we used yields of 3 month treasury bills.

The second indicator is the Treynor ratio (Treynor 1965), which measures the risk-free rate of return in relation to systemic risk, represented by β. In other words, the Sharpe ratio measures the returns earned per unit of risk of the asset or portfolio, whereas the Treynor ratio measures the returns earned per unit of market risk or β [Equation (7)]. Beta (β) is calculated by dividing the covariance of a particular soft commodity (R_i) and the whole market (R_M) – $COV(R_i, R_M)$ by the variance of the whole market (σ_M^2). The whole market is represented by the Standard and Poor's (S&P) 500 index.

$$Treynor\ ratio = \frac{R_i - R_f}{\beta};\quad \beta = \frac{COV\left(R, R_M\right)}{\sigma_M^2} \tag{7}$$

The Sortino ratio (Sortino and Price 1994) and modified Sharpe ratio (Gregoriou and Gueyie 2003) are the third and fourth indicators, and they upgrade the ba-

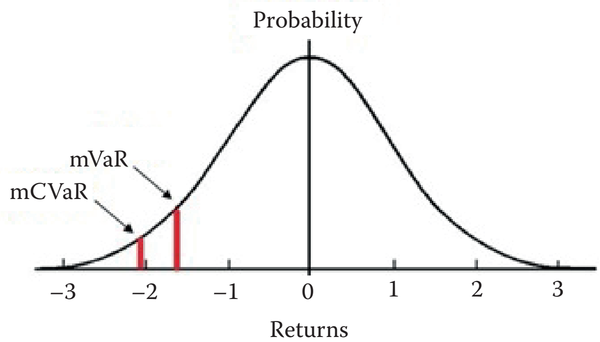

Figure 2. Graphical illustration of mVaR and mCVaR

mVaR – modified value-at-risk; mCVaR – modified conditional value-at-risk

Source: Authors' own illustration

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sic Sharpe ratio. The Sortino ratio measures standard deviation calculated on negative portfolio returns (σ_D), and the modified Sharpe ratio measures downside risk calculated on mCVaR metrics. For the purpose of this research, we used an absolute value of *mCVaR* at 99% probability. Equations (8, 9) illustrate how the Sortino and modified Sharpe ratios, respectively, are calculated:

$$\textit{Sortino ratio} = \frac{R_i - R_f}{\sigma_D} \tag{8}$$

$$\textit{Modified Sharpe ratio} = \frac{R_i - R_f}{|mCVaR|} \tag{9}$$

Data set. In this paper, we analysed five daily soft commodities – cotton, coffee, sugar, cocoa and orange juice. We used futures prices rather than spot prices because futures prices process all available information faster than spot prices do, which makes them more credible. For calculation, we considered relatively long time series to produce more realistic results of risk-adjusted returns. Our intention was to encompass the world financial crisis period, if possible, because this event created significant fund transfers between financial and commodity markets and caused a lot of price volatility. More specifically, for coffee, sugar and cocoa, the starting date is January 2007, for orange juice, it is April 2007, and for cotton, it is October 2009 because of data unavailability. We collected all data from the Investing.com website, which contains data from the Chicago Mercantile Exchange.

Accurate estimation of downside risk measures requires data free of empirical noise, such as autocorrelation and time-varying variance. In that regard, Table 1 presents Ljung-Box Q-statistics for level and squared returns, which provide information about the presence of the aforementioned noise in the empirical time series. In particular, the Ljung-Box Q [LB(Q)] test suggests that three of five assets had problems with autocorrelation, whereas all time series report a heteroscedasticity problem. To resolve these issues, we used a GARCH model. GARCH requires stationary time series, so we calculated an augmented Dickey-Fuller (ADF) test, which indicated that none of the time series had a unit root (Table 1). Also, Table 1 shows Jarque-Bera test results, which clearly indicated that all commodities did not have a Gaussian distribution. This finding justifies the use of the GARCH-NIG model because this particular distribution has two parameters that can recognise both skewness and kurtosis.

To test the adequacy of the GARCH-NIG models, we present the LB(Q) and LB(Q^2) test results of the estimated models in Table 2. The results show that GARCH residuals had no problem with autocorrelation and heteroscedasticity, so they can be used for downside risk calculations.

Figure 3 plots the estimated conditional volatilities, which provide a preliminary perspective on the risk of the selected assets. All plots contain a value of $\overline{\sigma}^2$, which is an average conditional volatility. According to these values, orange juice was the riskiest, followed by sugar. However, the basic problem with variance

Table 1. Diagnostic tests of empirical time-series

Diagnostic tests	Cotton	Coffee	Sugar	Cocoa	Orange juice
LB(Q)	0.002	0.273	0.422	0.012	0.003
LB(Q^2)	0.000	0.000	0.000	0.000	0.000
ADF	–52.083	–62.561	–61.690	–62.050	–57.357
JB	1 369.9	574.3	1 524.4	9 216.6	1 607.8

LB(Q), LB(Q^2) tests – P-values of Ljung-Box Q-statistics of level and squared residuals of 20 lags; ADF – augmented Dickey-Fuller; JB – value of Jarque-Bera coefficients of normality; assuming only constant, 1% and 5% critical values for ADF test with 10 lags are –3.439 and –2.865, respectively

Source: Authors' own calculations based on data from Investing.com (2021)

Table 2. Diagnostic tests of estimated GARCH models

	Cotton	Coffee	Sugar	Cocoa	Orange juice
LB(Q)	0.869	0.619	0.570	0.203	0.623
LB(Q^2)	0.796	0.125	0.180	0.108	0.167

GARCH – generalised autoregressive conditional heteroscedasticity; LB(Q), LB(Q^2) tests – P-values of Ljung-Box Q-statistics of level and squared residuals of 20 lags

Source: Authors' own calculations based on data from Investing.com (2021)

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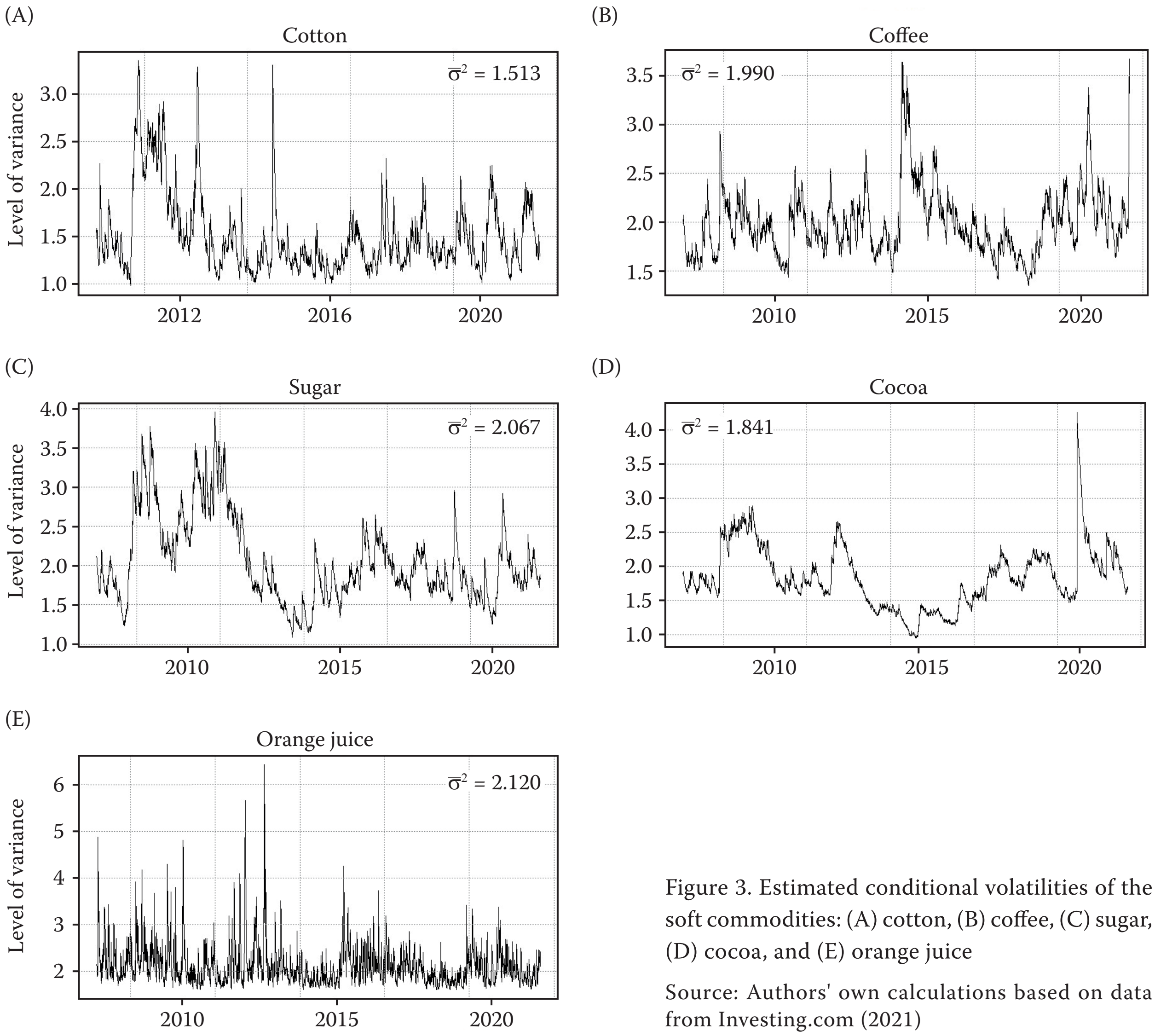

Figure 3. Estimated conditional volatilities of the soft commodities: (A) cotton, (B) coffee, (C) sugar, (D) cocoa, and (E) orange juice

Source: Authors' own calculations based on data from Investing.com (2021)

as a measure of risk is the fact that this metric takes into account both positive and negative deviations from the mean, so it tells nothing about potential loss that investors might sustain. Therefore, the variance result may be misleading because some other assets may induce bigger losses than orange juice, but variance cannot detect them. This is why we present the results of the semiparametric risk measures in the next section.

RESULTS AND DISCUSSION

Downside risk measures. To calculate downside risk, we used two elaborate approaches – mVaR and mCVaR. The main advantage of these two methods is that they can overcome very strict assumptions of normal distribution, considering all four moments of the distribution. Semiparametric risk measures reward favourable features of distribution, such as positive skewness and low kurtosis, and penalise adverse traits, such as negative skewness and high kurtosis. Accordingly, semiparametric risk measures might be lower than parametric counterparts if the distribution has good characteristics; otherwise, the mVaR and mCVaR will be higher than ordinary VaR and CVaR.

To calculate *mVaR* and *mCVaR*, we used white noise error terms created from a GARCH-NIG model. To have a preliminary insight into what to expect, we present in Table 3 the first four moments of the created residuals. According to Table 3, coffee was the only commodity with positive skewness and also the lowest kurtosis, which could reflect the relatively low *mVaR* and *mCVaR* measures.

However, before we present the results of semiparametric risk measures, one issue needs to be addressed,

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Table 3. First four moments of the created residuals

	Mean	SD	Skewness	Kurtosis
Cotton	–0.019	1.561	–0.312	6.237
Coffee	0.010	2.012	0.142	4.973
Sugar	0.028	2.117	–0.040	6.143
Cocoa	–0.006	1.897	–0.207	10.612
Orange juice	0.019	2.150	–0.188	6.377

Source: Authors' own calculations based on data from Investing.com (2021)

which is that mVaR and mCVaR are not appropriate to calculate under any level of probability because they can yield erroneous values. Cavenaile and Lejeune (2012) researched the adequacy of semiparametric VaR and asserted that mVaR can be used consistently over only a limited interval of confidence level. They contended that the mVaR metric should never be calculated under a 95.84% probability and that the use of higher confidence levels is limited by the value of skewness. Table 4 reveals levels of skewness and their corresponding confidence levels. Guided by Cavenaile and Lejeune (2012), we considered five confidence levels: 96, 97, 98, 99 and 99.5%.

Table 5 presents the *mVaR* and *mCVaR* results, and Figure 4 graphically illustrates the results. According to the findings, cotton had the lowest *mVaR*, whereas for *mCVaR*, cotton shared the first position with coffee. For instance, under 96% probability, *mVaR* indicated that 2.9% (or higher) could be the minimum loss that investors in cotton might sustain. All other soft commodities had a higher risk under this level but also under all other levels. *mCVaR* is regarded as a better approximation of downside risk in situations in which loss exceeds the *mVaR* level, and *mCVaR* indicates what the worst average loss would be under a certain degree of probability. According to Table 5 and Figure 4, cotton and coffee shared the first position according to *mCVaR.* Despite negative skewness and relatively high kurtosis, cotton came in first place, but only because it had the lowest second moment, that is, because of its standard deviation. Cocoa had the worst downside risk performances because of very high kurtosis. Orange juice was the second worst because it had the second highest kurtosis and relatively high negative skewness. After calculation of semiparametric risks, it is clear that conditional variance is a bad and deceptive risk indicator because cocoa had relatively low variance but the high potential to induce losses.

Results of risk-adjusted returns. Calculating the downside risk is relevant for investors when they make decisions about where to invest, but the level of risk is just one side of the story and, as such, is not enough to provide the full perspective; investors are even more keen to know what the potential benefit of an investment is. In that regard, we considered four different

Table 4. Minimum skewness for mVaR consistency under certain degree of probability

Confidence level (%)	96.0	97.5	99.0	99.5	99.9
Minimum skewness	–3.30	–1.62	–0.98	–0.79	–0.59

mVaR – modified value-at-risk
Source: Cavenaile and Lejeune (2012)

Table 5. Results of semiparametric downside risk measures

Downside risks	Probability	Cotton	Coffee	Sugar	Cocoa	Orange juice
	96.0	–2.935	–3.343	–3.738	–3.525	–3.915
	97.0	–3.358	–3.816	–4.269	–4.339	–4.494
mVaR	98.0	–3.984	–4.375	–5.058	–5.603	–5.357
	99.0	–5.136	–5.374	–6.515	–8.057	–6.953
	99.5	–6.383	–6.431	–8.101	–10.854	–8.692
	96.0	–4.580	–4.869	–5.819	–6.994	–6.193
	97.0	–5.062	–5.288	–6.429	–8.023	–6.861
mCVaR	98.0	–5.770	–5.894	–7.327	–9.576	–7.845
	99.0	–7.054	–6.976	–8.962	–12.493	–9.639
	99.5	–8.428	–8.114	–10.720	–15.717	–11.566

mVaR – modified value-at-risk; *mCVaR* – modified conditional value-at-risk
Source: Authors' own calculations based on data from Investing.com (2021)

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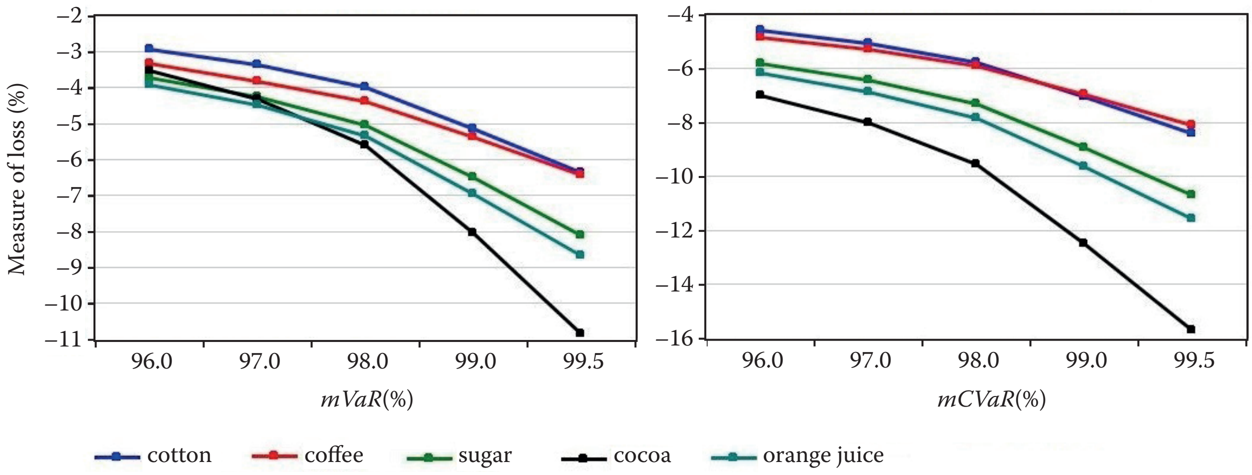

Figure 4. Joint presentations of (A) mVaR and (B) mCVaR

mVaR – modified value-at-risk; mCVaR – modified conditional value-at-risk
Source: Authors' own calculations based on data from Investing.com (2021)

return-to-risk ratios (Sharpe, Treynor, Sortino and modified Sharpe), which provided a deeper insight into return-to-risk performance. Table 6 presents these findings, and Figure 5 provides their graphical illustration. The general rule is that the higher the ratio, the better the return-to-risk performance of a particular asset.

According to the results, the situation changed significantly regarding the best and worst performances of soft commodities; cotton was no longer the best asset, but the worst, with all negative values for all four ratios. The same applied for cocoa, which was the second worst. The reason is that both commodities had an average negative mean (Table 3), which indicates the average fall of prices during the observed period, which inevitably produces negative return-to-risk ratios.

As for the other three soft commodities, their prices rose, on average, during the observed period, making comparisons between their calculated ratios make sense. The Sharpe ratio is the first indicator and also the basic one, but it is relatively unsophisticated because it measures risk-free returns vis-à-vis common standard deviation. Sugar had the best Sharpe ratio because sugar had the highest mean, which means that sugar prices had the highest average rise during the observed period. The standard deviations of sugar, coffee and orange juice were relatively equal, so the value of the mean played a decisive role.

The Treynor ratio measures the relation between risk-free returns and the level of systemic risk, which is β. Beta (β) basically indicates the sensitivity of soft commodity returns to movements of the underlying benchmark, which is the whole market, in our case represented by the S&P 500 index. According to the Treynor ratio, orange juice had the best result, because the β of orange juice was the lowest, amounting to 0.125. This finding means that orange juice had the least synchronous movements with the whole market, which was good for diversification in combination with the S&P 500 index. Beta (β) values for sugar and coffee were 0.222 and 0.221, respectively, which put these soft commodities in second and third places, taking into account the mean of these assets.

Unlike the Sharpe ratio, the Sortino ratio has the average downside risk as the denominator, which for sugar, coffee and orange juice amounted to 1.449, 1.304, and 1.511, respectively. Because sugar had the highest mean, the Sortino ratio put sugar in the first place. Even though orange juice had the highest average downside

Table 6. Results of four return-to-risk indicators

	Cotton	Coffee	Sugar	Cocoa	Orange juice
Sharpe ratio	–0.012	0.005	0.013	–0.003	0.009
Treynor ratio	–0.061	0.023	0.111	–0.027	0.230
Sortino ratio	–0.017	0.008	0.019	–0.004	0.012
Modified Sharpe ratio	–0.002	0.001	0.003	–0.000	0.002

Source: Authors' own calculations based on data from Investing.com (2021)

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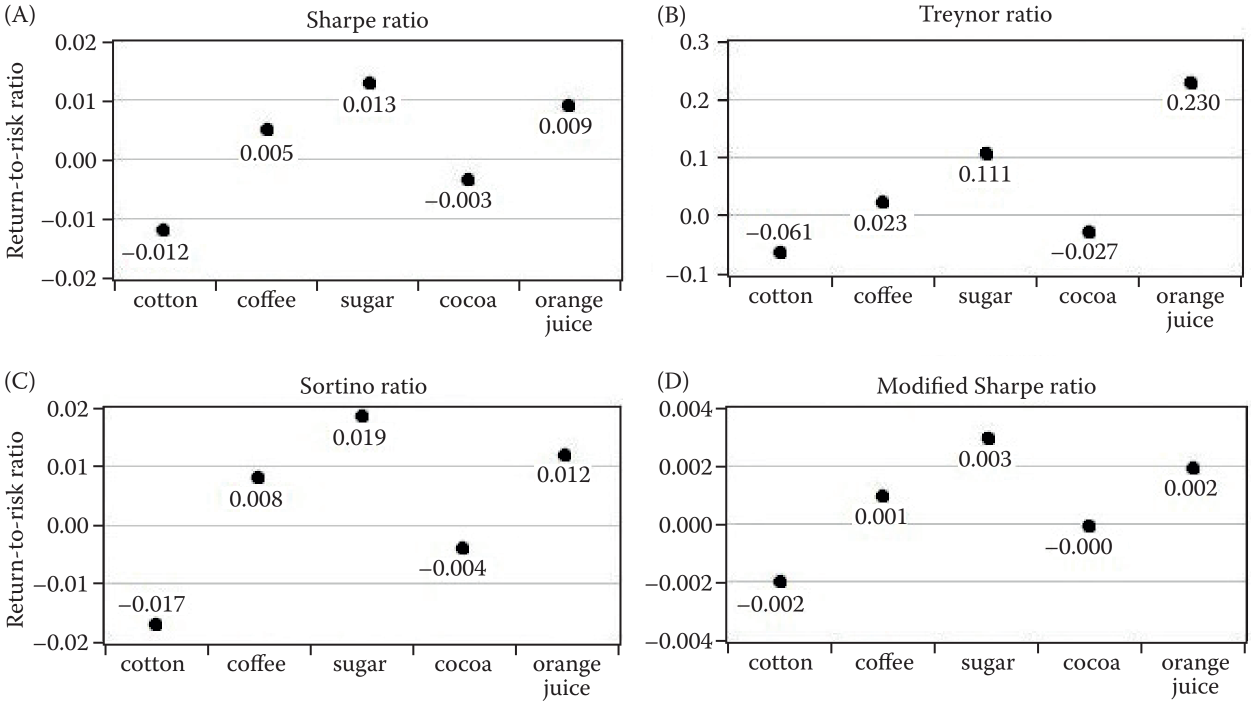

Figure 5. Joint presentation of four return-to-risk ratios: (A) Sharpe ratio, (B) Treynor ratio, (C) Sortino ratio, and (D) modified Sharpe ratio

Source: Authors' own calculations based on data from Investing.com (2021)

risk, it came in second place because of its relatively high mean. Coffee had the lowest average downside risk of these three commodities, but also the lowest average returns, which put coffee in third place.

The last return-to-risk ratio is the modified Sharpe ratio, which has as its denominator an absolute value of mCVaR. This indicator gauges in the most strict manner the amount of loss that an investor might sustain, and we observed the *mCVaR* at the 99% probability. Sugar having a relatively high *mCVaR* indicator brought significantly closer the modified Sharpe ratios of sugar and orange juice. However, sugar came in the first place because of the highest average returns.

CONCLUSION

In this paper, we researched the risk-adjusted returns of five soft agricultural commodities. In this process, we used several sophisticated methods of risk and return-to-risk calculations.

First, we used two semiparametric risk measures and determined that cocoa, followed by orange juice, had the highest probability to produce losses for traders and investors. Cotton and coffee had the lowest risk of losses. However, the risk is only one side of the story and is insufficient for fully informed decision-making about where to invest. In that regard, we computed several return-to-risk ratios to determine which asset produced the highest earnings relative to the level of risk, which changed the situation dramatically. Cotton was the worst asset to invest in because its average returns were negative, which was reflected in four negative return-to-risk ratios. Sugar had a relatively high risk of losses, but it had the highest average returns, which puts it in first place with the Sharpe, Sortino and modified Sharpe ratios. Although orange juice had the second-worst risk performance, it was in second place from the aspect of return-to-risk because it had relatively high average returns.

According to the results, those who work with cotton and cocoa need to hedge these investments because they produce losses. Sugar was the most favourable investment because it had the highest risk-adjusted returns, whereas orange juice was the best asset to combine with the market index because it had the lowest β.

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