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FINANCE

Measuring market risk for an agricultural exporter firm: a Copula approach

Medición del riesgo de mercado en una firma exportadora agrícola: una aproximación haciendo uso de Cópulas

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Abstract

Purpose – The purpose of this paper is to analyse the effect of market risk on the revenues perceived by an agricultural producer, namely, a coffee exporter firm.
Design/methodology/approach – To model this risk, copula models and extreme value theory are used to perform more robust estimations, which take into account the multivariate dependence between the risk factors. As a final point, different quantitative measures of risk, such as the value at risk and the expected shortfall, are estimated as an indicator of the maximum expected loss.
Findings – One of the principal findings is that for an agricultural exporter firm, there is an optimal decision between exporting to another country and selling the commodity in the national market. The choice regarding the levels exported will determine the firm's amount of risk and expected return.
Research limitations/implications – One of the limitations found in modelling the risk/return of the firm is the data. Not much data on the structure of the firm can be found, and many of the firms are averse to providing such information.
Practical implications – The purpose of the paper is to create a measure of risk to analyse the future of the firm, generating a measure of expected risk and return that takes into account the uncertainty of the future. The applications can be applied to measure the risk of a potential investment and real option valuation.
Originality/value – This paper applied multiple coherent measures of financial risk to an agricultural commodity exporter firm. This can be novel, especially in the context of a non-financial firm.

Keywords Copula, Extreme value theory, Coffee, Market risk, Agricultural risk

Paper type Research paper

Resumen

Propósito – La finalidad de este artículo es realizar un análisis del efecto del riesgo de mercado en el ingreso de un productor agrícola, específicamente, una firma exportadora de café.

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Metodología – Para modelar el riesgo, se hace uso de modelos a partir de Teoría del Valor Extremo y Cópulas, esto permite obtener estimaciones robustas en presencia de dependencia entre el conjunto de factores de riesgo. Finalmente, se estiman diferentes medidas cuantitativas de riesgo, como el Valor en Riesgo (VeR) y la Perdida Esperada (ES), como medidas de la máxima perdida esperada.
Resultados – Uno de los principales resultados, es que para una firma exportadora agrícola, existe una decisión óptima entre exportar o vender el bien en el Mercado nacional. La elección de la cantidad exportada determinará la cantidad de riesgo y retorno a la que estará expuesta la firma.
Limitaciones/Implicaciones – La principal limitación en modelar el riesgo/retorno de la firma son los datos. No hay mayor información pública de la estructura de la firma, y en la mayoría de casos las firmas son adversas a proveer esta información para la investigación.
Implicaciones prácticas – La finalidad del artículo es crear una medida de riesgo para analizar el futuro de la firma, esta aproximación al riesgo y retorno esperado tiene en cuenta la incertidumbre que afronta la firma del futuro. Las aplicaciones potenciales pueden ser el análisis de riesgo de una inversión y la valoración de una opción real.
Originalidad/Valor – Este artículo aplica diferentes medidas coherentes de riesgo financiero a una firma exportadora de bienes agrícolas. Esta metodología es innovadora, en especial en el contexto de firmas no financieras.

Palabras clave Cópula, Teoría del Valor Extremo, Café, Riesgo de Mercado, Riesgo Agrícola

Tipo de documento Trabajo de investigación

1. Introduction

For a firm in any economic sector, the best choice of investment is one of its most important daily tasks. Such a choice will determine not only the expected value of future profits and economic growth, but also the real option of business continuity. The choice between all the investment possibilities is made based on future cash flows and the risk associated with the investment. These future cash flows do not depend only on endogenous variables, but also on exogenous ones such as the exchange rate (ER) and variations on the price of commodities, which influence the future performance of the firm.

Traditionally, the literature on engineering and finance makes the assumption that cash flows will behave in a linear and stable fashion that can be determined, or that can even be assumed as deterministic. The most common models and indexes used to determine the viability of a project are the net present value (NPV), the internal rate of return, and the weighted average cost of capital.

The issue with a deterministic identification is that the variable of interest does not often behave as expected, but rather depends on exogenous variables with stochastic behaviour, like the state of the economy and some other macroeconomic factors. Based on these facts, models like the Capital Asset Pricing Model (CAPM) and the arbitrage pricing theory, proposed by Sharpe (1964) and Ross (1976) consider external factors in the valuation of financial assets. Although these models incorporate those factors, they do not incorporate the uncertainty of the market into the model, rather, the future is treated as a weighted average of the behaviour of the exogenous variables.

Based on the idea of measuring the uncertainty, many methodologies have appeared to estimate a robust measure of market risk. The first of these is an application of a generalized autoregressive conditional heteroskedasticity (GARCH) and extreme value theory (EVT) modelled to estimate a value at risk (VaR) (Feng *et al.*, 2012), or an expansion of it using rolling windows to generate a dynamic approximation (Yang and Lin, 2011). Second are the measures that apply an ARMA-GARCH-EVT approximation to generate a measure of the market risk using a VaR (Wang and Wang, 2014). Another type of more robust measure includes estimation based on copulas to generate multiple scenarios to use in turn to estimate a VaR (Zhang *et al.*, 2014).

In the context of firm decisions and optimal selection of investments, the amount of literature dealing with uncertainty is not significant. Some of the measures, summarized in Mun (2008) and King and Wallace (2012), are based on stochastic programming and applied to different fields of firm decision. On the other hand, approaches like those by Manotas

(2009) and Manotas and Toro (2009) estimate multiple scenarios, using Monte Carlo simulations, of a cash flow of an investment and evaluate the NPV of a project in the presence of uncertainty. Regardless of whether simulations are used to deal with uncertainty, this measure does not generate a robust estimation of the exogenous factors that define the variable of interest.

To take into account all the approximations presented above, in the present study, an estimation algorithm is applied – presented in Uribe *et al.* (2015) – using an autoregressive integrated moving average models (ARIMA), dynamic conditional correlation GARCH (DCC-GARCH), EVT, and copula approach to construct a measure of market risk for the future values of the firm's income. This measure takes into account the stylized facts of the prices as extreme events (Morgan *et al.*, 2012), and the dependence between the exogenous variables that determine the firm's income. Additionally, parametric VaR and expected shortfall (ES) are estimated on the multiple scenarios as the firm's risk measures.

The algorithm of estimation is applied in this paper to a hypothetical agricultural producer firm – specifically a Colombian coffee exporter – given that these are exposed to exogenous factors like the internal and external price of the commodity, the ER, and variations on the quantity of the demand. An agricultural producer was chosen to apply this algorithm based on the fact that most of these types of agricultural commodities have a high level of volatility, and therefore, face high levels of uncertainty (Xouridas, 2015). As a result, most of the decisions that the firm takes have to take into the account the market volatility of the factors that affect the cash flow, especially commodity prices.

A coffee producer was chosen based on the fact that the production is concentrated among few producers; hence, the volatility (risk) that each firm faces for being exposed to the variation of one external factor is high. Thus, the Colombian coffee sector firm is analysed based on the country's tradition as one of the biggest coffee producers in the world (ICO, 2015).

The results suggest that there exists a high risk in the coffee market, due to a left bias in the distribution towards lower incomes perceived by the firm. Despite this, they also suggest that in extreme events, there is a possibility of obtaining high incomes, but there is only a low probability of doing so. These events reflect the structure of the distribution of the copula that fit the data, the *t*-student, which characterizes for symmetrical heavy tails.

The importance of measuring the market risk for the agricultural firm is related to the fact that the benefits are conditioned to the price of a commodity. The agricultural prices, as mentioned before, are highly volatile, and so, the trade-off between risk and benefits that the firm perceives is also higher. The firms traditionally assume that the income is a deterministic variable, and the future decisions taken into account are related to that value, more than a distribution of possible incomes. As the prices fluctuate on a daily basis, the income may be as volatile as the commodity. Hence, it is necessary to periodically measure the risk that the firm affronts and the factors that generate that risk. In the case of this paper, the risk of the hypothetical firm is related to national and international coffee prices and the ER of the national currency to USD.

Measuring firm risk, in the presence of market risk, allows us to establish measures to be taken in case of an episode of downside losses, as the whole structure of income and costs can be modelled. The econometric model involves a construction of multiple feasible scenarios that incorporates not only the dependence structure of the variables of interests, but the possible changes in each variable. The possibility of generating multiple feasible scenarios implies that other traditional measures such as the Riskmetrics and the Gaussian VaR have to be improved.

The rest of the paper is organized as follows. Section 2 presents a brief review of the estimation algorithm using ARIMA, DCC-GARCH, EVT, and Copula that generates the multiple scenarios, which will be used as the risk distribution measures: the VaR and ES.

Section 3 displays the empirical results that were obtained from the estimation of the risk measure for the coffee firm and the backtesting measures. Finally, the conclusions are presented in Section 4.

2. Econometric framework

In order to construct a robust model to assess firm risk (gain or loss), the estimation model will follow the algorithm presented in Manotas (2009). First, the input variables have to be defined, as they will explain and restrict the results obtained from the model. The input variables can be external (i.e. macroeconomic, prices, and industry) or internal (i.e. inventory policy and efficient levels), which define the cost-benefit relationship. Based on these variables, the future income is defined and simulated; therefore, the relationship between the variables must be estimated.

Furthermore, an output variable, endogenous to the firm (i.e. income or the EBITDA) needs to be defined and will serve as a term of valuation. The risk analysis will be structured on the variable, as the measure of risk implemented in the paper, the VaR and ES, will measure the risk associated to the values that it may take.

The input variables used in this paper are external factors related to the trade of the commodity such as the national and international price of coffee and the ER. To determine the relationship between the variables, a Copula approach is used to capture the lineal and non-lineal relationships between the variables, especially in the case of extreme events. This measure was proposed following McNeil *et al.* (2005) and Uribe *et al.* (2015), as their approach takes into account the uncertainty faced by the firm and investor in the future, using a robust estimation of multiple scenarios.

The first step to establishing the relationships between the series of risk factors is to filter the logarithm of the returns to take into account stylized effects of financial series, such as heteroscedasticity and autocorrelation. For that reason, an ARIMA and a DCC-GARCH approach is followed; the first based on the estimation procedure of Box and Jenkins (1970), and the second following Bollerslev (1986) and Engle (2002). This part of the methodology focusses on the estimation of the first and second moments, identifying the general behaviour of the series. From this process, the standardized residuals are computed, so they can be modelled following EVT.

Once the series are filtered, a pseudo-sample is constructed of each of the factors, and with this, the density and marginal distributions are estimated using a semi-parametric approach based on the EVT, as suggested by Morgan *et al.* (2012). The marginal distributions used under this approach consider the stylized fact that the financial series have heavy tails; hence, there is a higher possibility of experiencing an extreme event. The pseudo-sample is estimated as:

$$F_i(z_i) = u_i \quad \forall i = 1, .., N \tag{1}$$

where z_i are the standardized residuals, $F_i(\cdot)$ is the distribution function based on EVT, i are the N input factors, and u_i is the pseudo-sample estimated for each series. The distribution function is constructed semi-parametrically, where the central part of the distribution is estimated using an empirical distribution and the tails, following the peaks over the threshold (POT) model of the EVT, as described in McNeil *et al.* (2005).

The POT model assumes that the excess of amounts – the returns that exceed a certain threshold – follow a generalized Pareto distribution (GPD) (Fisher and Tippett, 1928; Gnedenko, 1943). The distribution can be expressed as:

$$G_{\xi,\beta}\begin{cases} 1-\left(1+\frac{\xi x}{\beta}\right)^{-\frac{1}{\xi}} & \text{if } \xi \neq 0 \\ 1-\exp\left(-\frac{x}{\beta}\right) & \text{if } \xi = 0 \end{cases} \tag{2}$$

where β is a scale parameter, ξ is a parameter of shape, $\boldsymbol{v_i}$ is the chosen threshold (the 95th percentile in this case), and x is the exceedance over the threshold from the standardized residuals.

Based on the estimation algorithm, the next step is to describe and compute the dependence between the input variables (risk factors) using a multivariate approach known as copula. The copula is a joint distribution function that contains the structure of dependence between all the marginal distribution functions of the input factors. As a result, it generates a dependence structure, expressed in quantiles, that allows an estimation of the dependence in the tails of the distribution: the extreme events (Dowd, 2005).

Following McNeil *et al.* (2005), a N-dimensional Copula can be defined as a distribution function in $[0, 1]^N$ that realizes a mapping from a hypercube into an unit interval [0, 1]. It can be expressed as $C(u) = C(u_1, u_2, \ldots, u_N)$, where C is the multivariate distribution function that are copulas. Sklar's (1959) Theorem states that if F is a joint distribution function with margins $F_1, F_2, \ldots, F_N$, then there exists a copula such that for all $z_i \in R = [-\infty, \infty]$, $i = 1, \ldots, N$:

$$F(z_1, z_2, \ldots, z_N) = C(F_1(z_N), F_2(z_2), \ldots, F_N(z_N)) \tag{3}$$

Hence, if $C(\bullet)$ exists, all the dependence structure of the input series is contained in the copula function. To determine the type of copula function that has the best fit, five copula models are estimated and compared: Clayton, Gumbel, Frank, Normal, and t-student (Zivot and Wang, 2006). Clayton copula has inferior tail dependence, the Gumbel copula has superior tail dependence, the Frank copula has truncated tails, the normal copula does not present dependence in the tails, and the t-student has symmetric and heavy tails.

To determine the copula that best fits the data, four information criteria are used to compare the copulas, as suggested by Joe (1997) and Zivot and Wang (2006). These criteria are: The logarithm of maximum likelihood (LMV), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC), and the Hannan-Quinn (HQ).

Once the copula with the best fit is selected, multiple scenarios are simulated using Monte Carlo techniques based on the estimated parameters. This simulation generates a marginal distribution for each one of the factors (u_i). Nevertheless, this distribution cannot be analysed in terms of risk, which is why each one of the distributions have to be modelled to compute the standardized residuals. Thereby, the tails of the marginal distributions are estimated using the inverse of the GPD and the inverse of the empirical to the central part of the distribution. From this process, the marginal distribution of the standardized returns r_i is estimated.

The returns (R_i) of the input factor i can be calculated as:

$$R_i = 20 \cdot \mu_i + \sqrt{20} \cdot r_i \cdot \sigma_i \tag{4}$$

where μ_i is the forecast estimated of the next period using the ARIMA model for factor i, r_i is the standardized residuals, and σ_i is the forecast of the next period's standard deviation estimated by the DCC-GARCH model for factor i. Taking into account that the factors occur daily and that the volume exported by the firm has a monthly frequency, following Melo and Granados (2011), the μ_i is multiplied by the number of transactional days (20) and the deviation by the square root of the same number. This is done to escalate the daily VaR to a multiperiod, monthly version, so that it can be estimated as conditional to the volume exported by the firm.

Based on the previously estimated returns and the last day of historical price, the distribution of the next period's forecast prices of the risk factors can be calculated. The prices are calculated as:

$$P_{i,t+1} = P_{i,\, t} \cdot exp(R_i) \tag{5}$$

where $P_{i,t}$ is the price of factor i in period t.

The effect of each price variation is determined by the choice of the variable of interest, as the loadings of each variation affect the final value. In the case of the firm's income, the input factors can be viewed as a portfolio of two assets, national or international prices, and the export volumes treated as a weight of risk exposure.

The VaR and the ES are calculated in order to analyse the effect of the variations of each of the factors on the income and measure the overall risk based on the scenarios estimated. The VaR is a risk measure that models uncertainty associated to the market risk, as it takes the distribution of past returns and quantifies the expected loss. It can be defined as a measure of the maximum loss expected from a portfolio of assets in a determined period, based on a confidence level α (Christoffersen, 2003). A novel improvement is the inclusion of another measure, the ES. This measure can be defined as an expected loss in extreme events, and is therefore an improvement to the VaR which is criticized for underestimating the risk of an asset (Hull, 2015; Dowd, 2005; Artzner *et al.* 1999).

The VaR estimated can be expressed as[1]:

$$\mathrm{VaR}_{(1-\alpha)} = P_{i,(1-\alpha)} \cdot \mathrm{Vol}_{i,(1-\alpha)} + \left[\sum P_{j,\,(1-\alpha)} \cdot \mathrm{Vol}_{j,\,(1-\alpha)}\right] \cdot \mathrm{ER} \tag{6}$$

where P is the price of the risk factor, Vol are the volumes of coffee exported, ER is the exchange rate currency/dollar, j are the international risk factors (international price of the coffee), and i are the national factors (national price of coffee). This definition can be divided into two parts; the national segment, defined as $P_{i,(1-\alpha)} \cdot \mathrm{Vol}_{i,(1-\alpha)}$ that is the national value of the sales in the country currency, and an international segment, defined as $[\sum P_{i,(1-\alpha)} \cdot \mathrm{Vol}_{j,(1-\alpha)}] \cdot$ ER which is the international value of the sales in USD.

3. Results

To analyse the algorithm of estimation, three external factors were used: the Arabica Coffee futures Continuous Contract No. 1 (KC1), the buying price for the coffee in Colombia, and the ER of Colombian peso to the dollar (COP/US). The futures contract was taken from the Intercontinental Exchange (ICE) as the future continuous contract No. 1 from the New York Market for Arabica coffee, the type produced in Colombia[2]. The buying price for Colombia was taken from the Colombian Growers Coffee Federation (Fedecafe). The ER between the dollar and the Colombian peso was taken from the Central Bank of Colombia, *Banco de la República,* and taken on a daily basis, the series span the period from January 2003 to December 2013.

Figure 1 displays the behaviour of each one of the series that generates risk to the firm's income. Based on the figure, it can be concluded that the behaviour of both, the internal and futures contract, exhibit a significant similar trend in the study sample. The difference is in the 2009-2010 period, where the internal price presented a rise in the price, while the KC1 remained stable. This price change happens because the internal price is regulated by the government and Fedecafe, and so the commodity is bought at a higher price to protect the producers in case of a price decline.

The series of the three risk factors may present non-stationary behaviour in the mean, common in financial series, as they present frequent trends. Performing an estimation using non-stationary data may generate complications in the process of modelling the series' behaviour. Consequently, the augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) unit root test was performed on each one of the series, to determine the existence of non-stationary effects. Depending on the case, each variable was transformed until its mean became stationary.

Based on the ADF test presented in Table I, the null hypothesis that the series are not stationary is accepted with multiple confidence levels. Consequently, each one must be

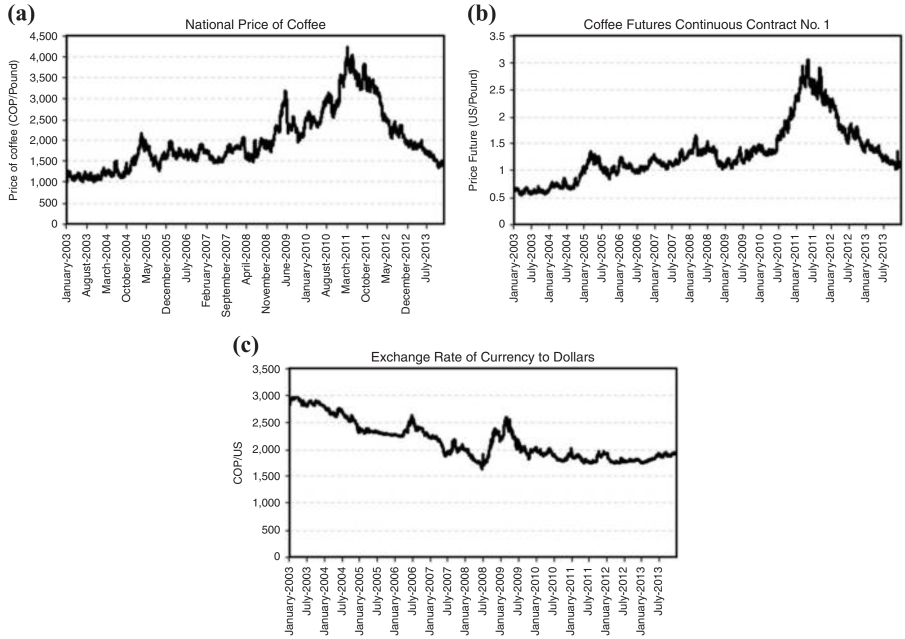

Figure 1.
Risk factors of a coffee exporter firm

Notes: Internal Price is the quantity of COP per pound of coffee, The KC1 is the price in cents per pound of coffee, and the COP/USD exchange rate
Source: ICE, Fedecafe and Banco de la República. Author's Calculation

Table I.
Augmented Dickey-Fuller (ADF) test for unit root

Risk factor	Statistic	ADF	ADF (intercept and trend)	ADF (intercept)
National price	Statistic	−0.29	−2.13	−1.79
	p-value	0.67	0.53	0.38
Futures (KC1)	Statistic	0.35	−1.64	−1.38
	p-value	0.79	0.78	0.59
Exchange rate	Statistic	−1.35	−2.60	−2.23
	p-value	0.16	0.28	0.19

Notes: The null hypothesis of the ADF test is the existence of at least one unit root. The test is divided into three steps. The first determines whether there is a unit root present in the series without a trend and drift; the second, whether the series are trend-stationary using trend and intercept; and the third test proves the existence of a stochastic trend

differentiated to stabilize in mean. Therefore, the price logarithm was calculated for each of the input series (Figure 2).

The returns present a non-constant variance, known as heteroscedasticity, as some periods are characterized by higher levels of volatility than others and clusters tend to be present in some periods of time. These stylized facts of the financial series motivate the use of econometric methods that take into account these special properties, such as the use of conditional heteroscedasticity measures and extreme value modelling.

Once the returns were obtained, their mean was modelled using ARIMA, as the series were all integrated of order one, I(1)[3]. The model was adjusted to each one of the series, and given that they presented different behaviours, the models also differed for each one.

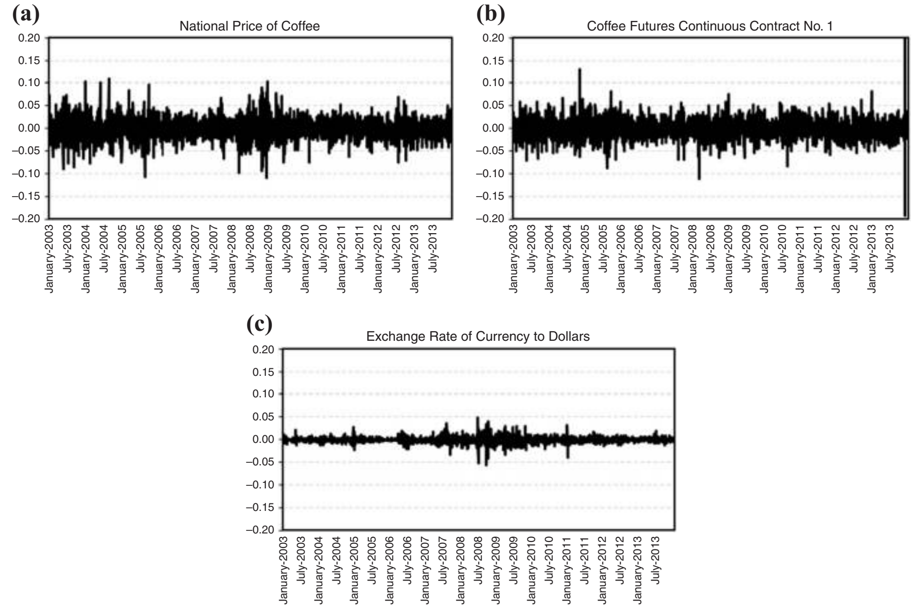

Figure 2.
Logarithmic returns of the risk factors

Successively, the variance of the series was modelled jointly using a DCC-GARCH, which takes into account the joint volatility. From the models estimated for the first and second moments of the series, using the ARIMA and DCC-GARCH, the forecasts to be used in the simulation estimation were calculated (Equation (4)) and residual series were filtered[4].

With the residuals estimated, the pseudo-sample was constructed by adjusting the series to a specific distribution. To model the heavy tails, characteristic of financial series, the tails of the distribution were constructed using EVT. This methodology requires the tails to be modelled as a GPD (Equation (2)) and the centre, following an empirical distribution. The results of this procedure are the marginal distributions of the input factors that follow a uniform distribution in the interval (0, 1)[5]. From the marginal distributions of each factor, different types of Copulas were estimated to determine which best fit the relation of dependence, especially in extreme events.

The Copula with the best fit – the Akaike, Bayesian, and HQ – was selected based on different information criteria[6]. The copula that fit the data most adequately was the *t*-student copula, characterized by its symmetric heavy tails. The copula chosen implies that the big changes in the price of factors may occur simultaneously and with high probability; hence there is a higher probability of downside risk. Based on the copula and the estimated parameters, 10,000 observations were simulated for each of the factors in the model. These simulations, computed from the distribution, considered the dependence relations between the series and, therefore, were a robust approximation to the possible behaviour of the series in the next period. Afterwards, from the parameters of the GPD function, the quantile of the original function was estimated followed by a simulation of the new standardized residuals for all three risk factors. Subsequently, the series were destandardised using the forecasts of the first and second moments from Table II. Equation (4) was then used to calculate the distribution of the new forecasts of the returns.

The series estimated were used to calculate the income of a hypothetical firm that exports approximately 90 per cent of the volume of its coffee (see Table III), keeping only 10 percent for the domestic market. Considering the percentage of world exports, the company is a net exporter of coffee and many of its risk exposure factors are linked to ER and international coffee price behaviours. As a result, it can be supposed that it would generate a high inflow of dollars in its current account and will be exposed to variations in the ER. Moreover, it is also likely for the expected returns to be more volatile than they are for a domestic producer firm.

The relationship between the estimated and the original returns is detailed in Table IV, where we can see that the estimated returns reflect the original returns relatively well. Both the ER and the KC1 present maximum levels (positive) below the original, and minimum levels are considerably lower. This might suggest that the occurrence of extreme and negative events have a greater impact within the estimated scenarios. The latter can be corroborated by analysing the 95th percentile of returns, the VaR of the factor returns, where the maximum expected loss in 95 per cent of cases is higher than that of the original returns.

From the returns shown in Table IV, the income estimates are computed using Equations (5) and (6) presented in the methodology. These estimates are then used to generate each one of the 10,000 feasible scenarios for the firm's possible inflow of money. These scenarios show a general characteristic in that they are skewed to the right; that is, that the values above the average are much more dispersed than the negative values. This behaviour can be analysed in Figure 3, which presents a histogram of the future earnings of the company and two risk measures, VaR and the ES.

Table II. Forecast of the first and second moments of the distribution

Risk factor	Mean (μ)	SD (σ)
National price	0.0003	0.0285
Futures (KC1)	0.0004	0.0219
Exchange Rate	−0.0001	0.0047

Note: The mean is calculated using the ARIMA model for each risk factor and the standard deviation using the DCC-GARCH

Table III. Characteristics of the hypothetical coffee firm

Operational income	$149,909,037,648
National Income – Pasilla Sales	$15,426,637,769
National Income – Cisco Sales	$262,886,355
Value of the sales (national)	$10,088,244,950
Value of the sales (international)	$124,067,047,687
Volume of coffee produce (lbs)	46,535,336
% of international volume	89.79%
% of national volume	10.21%

Table IV. Characteristics of the estimated returns

	Risk factor		
Statistic	Futures	National	ER
Mean	0.0004	0.0003	−0.0001
SD	0.02	0.03	0.00
Quantile 95	−0.03	−0.04	−0.02
Original quantile 95	−0.03	−0.03	−0.01
Maximum	0.21	0.30	0.04
Original maximum	0.23	0.12	0.05
Minimum	−0.29	−0.25	−0.03
Original minimum	−0.19	−0.11	−0.06

Although the VaR is relatively close to the average, it is COP$1,800 million below the original average utility of the hypothetical firm (see Table V). The expected income of the firm for the next period is of COP$27 billion. This is higher than the median income, showing a higher future expected return. The lower average income expected, given by the ES, is COP$25 billion, a dispersion of two billion from the average.

To measure the market risk for the firm, it is necessary to determine the future decisions to be taken in order to manage the potential losses and make efficient decisions. In the case of the measures used in this study, it allows us to understand the source of the risk, and minimize it by lowering exposure to a national or international market. Following Equation (6), the volume of coffee exported, and so the amount of exposure to a particular market, can be reduced if the volume is transferred to lower risk markets. Considering that there is a risk/return trade-off presented in the portfolio theory, the returns will decrease but the risk of an extreme event will be lower.

To determine whether the ARIMA-DCC-GARCH-EVT-copula VaR methodology outperforms other risk measures, multiple backtesting are applied to different models such as; historical, Gaussian, Riskmetrics, GARCH, and AR-GARCH VaR. The backtesting procedures analysed are the duration-based approach (Christoffersen and Pelletier, 2004) and the conditional (Christoffersen, 1998; Christoffersen *et al.*, 2001) and unconditional (Kupiec, 1995) coverage VaR exceedances test. These models, based on the data for the hypothetical producer, allow us to compare the models and determine which provides an improved measure of the firm's risk. The results of the analysis are provided in Tables VI and VII.

Based on the results of the likelihood ratio test statistic in Table VI, it can be concluded that the fact that the exceedances of the VaR measures have no memory cannot be rejected. As expected, the Historical and Gaussian VaR, have the higher test statistics, as the measure remains constant throughout the whole period. Furthermore, the conditional and unconditional coverage VaR exceedances test is presented in Table VII. This test provides evidence to reject the null hypothesis of correct exceedances for the Historical and Gaussian VaR, as the actual exceedances are not close to those expected. The ARMA-DCC-GARCH-EVT-Copula VaR outperforms the other risk measures, as the likelihood ratio for both, the conditional and unconditional test, is the lowest and the actual exceedances are the nearest to those expected with a unity difference.

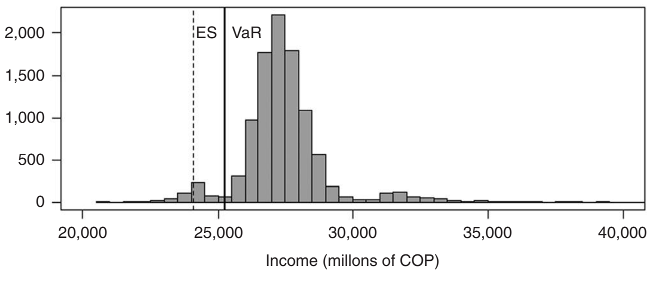

Figure 3. Value at risk and expected shortfall of the future income of the firm

VaR 95%	ESF 95%
$25,01,17,86,393	$23,84,46,52,015
Future expected income (month)	
$27,16,72,16,452	
Average income (month)	
$26,86,91,31,844	

Table V. Value at risk and expected shortfall of the income

Table VI. Christoffersen and Pelletier VaR duration test

Risk measure	Unrestricted log-likelihood	Restricted log-likelihood	Likelihood ratio test statistic
Historical VaR	−128.1154	−128.1154	0.9961308
Gaussian VaR	−124.5217	−124.5218	0.9863822
Riskmetrics VaR	−193.1638	−193.7546	0.2770442
GARCH(1,1) VaR	−145.3687	−145.5712	0.5245876
AR-GARCH VaR	−148.8741	−148.9674	0.6657469
ARMA-DCC-GARCH-EVT-copula VaR	−181.2988	−181.4369	0.5991859

Notes: The null hypothesis of the duration test is that duration between exceedances has no memory. The test was carried out using a one-step ahead VaR (95 per cent) for 1,000 days of returns

Table VII. Conditional and unconditional coverage VaR exceedances test

			Unconditional coverage test			Conditional coverage test		
Risk measure	Expected exceedences	Actual exceedences	LR statistics	Critical value	*p*-value	LR statistics	Critical value	*p*-value
Historical VaR	50	29	10.87	3.84	0.00	10.90	5.99	0.00
Gaussian VaR	50	28	12.04	3.84	0.00	12.09	5.99	0.00
Riskmetrics VaR	50	52	0.07	3.84	0.79	2.32	5.99	0.31
GARCH(1,1) VaR	50	46	0.89	3.84	0.34	0.95	5.99	0.62
AR-GARCH VaR	50	41	1.49	3.84	0.22	1.51	5.99	0.47
ARMA-DCC-GARCH-EVT-copula VaR	50	49	0.02	3.84	0.89	0.43	5.99	0.81

Notes: The null hypothesis of the unconditional test is that the VaR measure provides the correct amount of exceedances. The conditional coverage test null is that there is a correct and independent amount of exceedances. The test was carried out using a one-step ahead VaR (95 per cent) for 1,000 days of returns

4. Conclusion

Risk analysis of future cash flows is vital for investment decisions within a firm. Many of the analyses commonly carried out, represent a deterministic world in which decision making is a general and single measure of future episodes. Nevertheless, the future entails uncertainty and is stochastic in nature. To address this problem, in this study, the methodology proposed in Uribe *et al.* (2015) is adapted to the estimation algorithm of Manotas (2009) for the coffee market, specifically to the income of a net exporting firm. This estimation takes into account all the feasible scenarios that can occur based on the distribution of the returns and their dependence structure.

An expected value for the next period was estimated based on the multiple scenarios that enable decision making regardless of the outcome at the end of the year. Furthermore, the values of two of the most widely used measures of market risk in the literature, the VaR and ES, were estimated. These two measures approximate to the lower expected values that can take the income of the firm, and are a measure of the risk involved in the company. As a consequence, these tools are not only a means of risk measurements for a company's decision making, but also represent a robust measure of investment evaluation in a company based on the fundamentals.

Despite of the fact that the algorithm of estimation using an ARIMA-DCC-GARCH–EVT-copula approach broadens the analysis of investment decision and improves the measurement of market risk in the agricultural sector, there are still limitations to this model. Future studies should perform in-depth analyses of the behaviour of the commodity, using more complex models that take into account that most financial series present multiple regimes or depend on the state economy. Additionally, an adequate modelling may allow an estimation of the future income, and generate the expected cash flows of the firm, as well as measure the market risk in time.

Another approach can take into account the variations in the risk of alterations in the export volumes as a portfolio maximization problem. Analysing the exports as a portfolio asset, allows us to approximate the decision of an efficient allocation that maximizes the returns perceived by the firm and lowers its exposure to market risk.

Notes

1. The ES can be calculated as the expected value of income values beyond the $(1-\alpha)\%$ of the distribution obtained in the simulation. Hence, the average losses exceed the VaR.
2. The use of only three variables to analyse the dynamics of the firm is due to the lack of information regarding the structure of the firm and the public data regarding volumes and market. Other variables that could be incorporated are the exported volume, internal prices of coffee by-products, gasoline prices and other production inputs.
3. The election of a univariate model over a multivariate model such as a VAR or VEC, is related to the forecast and fit measure. It is known that the ARIMA model has better fit and short-run forecast accuracy, as lags of other variables are not incorporated into the estimation, so the adjustments do not present noise or a bias generated by variations of other variables.
4. Specification test for the ARIMA and DCC-GARCH models are presented in the Appendix, in Tables AI-AIII.
5. The results of the estimation of the EVT parameters are presented in Table AIV in the Appendix, as well as the Kolmogorov-Smirnov test parameters and *p*-value for each of the marginal distributions.
6. Results are presented in Table AV in the Appendix.

References

Artzner, P., Delbaen, F., Eber, J.-M. and Heath, D. (1999), "Coherent measures of risk", *Mathematical Finance*, Vol. 9 No. 3, pp. 203-228.

Bollerslev, T. (1986), "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics*, Vol. 31 No. 3, pp. 307-327.

Box, G. and Jenkins, G. (1970), *Time Series Analysis: Forecasting and Control*, Holden-Day, San Francisco, CA.

Carmona, R. (2014), *Statistical Analysis of Financial Data in R*, Springer-Verlag, New York, NY.

Christoffersen, P. (2003), *Elements of Financial Risk Management*, Academic Press, San Diego, CA.

Christoffersen, P. and Pelletier, D. (2004), "Backtesting value-at-risk: a duration-based approach", *Journal of Financial Econometrics*, Vol. 2 No. 1, pp. 84-108, available at: http://jfec.oupjournals.org/cgi/doi/10.1093/jjfinec/nbh004

Christoffersen, P., Hahn, J. and Inoue, A. (2001), "Testing and comparing value-at-risk measures", *Journal of Empirical Finance*, Vol. 8 No. 3, pp. 325-342.

Christoffersen, P.F. (1998), "Evaluating interval forecasts", *International Economic Review*, Vol. 39 No. 4, pp. 841-862, available at: http://ideas.repec.org/a/ier/iecrev/v39y1998i4p841-62.html

Dickey, D.A. and Fuller, W.A. (1981), "Likelihood ratio statistics for autoregressive time series with a unit root", *Econometrica*, Vol. 49 No. 4, pp. 1057-1072.

Dowd, K. (2005), *Measuring Market Risk*, 2nd ed., John Wiley & Sons, West Sussex.

Engle, R. (2002), “Dynamic conditional correlation”, *Journal of Business & Economic Statistics*, Vol. 20 No. 3, pp. 339-350.

Feng, Z.-H., Wei, Y.-M. and Wang, K. (2012), “Estimating risk for the carbon market via extreme value theory: an empirical analysis of the EU ETS”, *Applied Energy*, Vol. 99, pp. 97-108, available at: http://dx.doi.org/10.1016/j.apenergy.2012.01.070

Fisher, R. and Tippett, L. (1928), “Limiting forms of the frequency distribution of the largest or smallest members of a sample”, *Proceedings of the Cambridge Philosophical Society*, Vol. 24, pp. 180-190.

Gnedenko, B. (1943), “Sur La Distribution Limite Du Terme Maximum D’Une Serie Aleatoire”, *Annals of Mathematics*, Vol. 44 No. 3, pp. 423-453.

Hull, J. (2015), *Risk Management and Financial Institutions*, 4th ed., John Wiley & Sons, NJ.

ICO (2015), “Exports of all forms of coffee by exporting countries to all destinations”, available at: www.ico.org/prices/m1.htm (accessed November 12, 2015)

Joe, H. (1997), “Multivariate models and dependence concepts”, Chapman and Hall/CRC, London.

King, A.J. and Wallace, S.W. (2012), *Modeling with Stochastic Programming*, Springer, New York, NY.

Kupiec, P.H. (1995), “Techniques for verifying the accuracy of risk measurement models”, *The Journal of Derivatives*, Vol. 3 No. 2, pp. 73-84.

Manotas, D.F. (2009), “Optimal economic project selection under uncertainty: an illustration from an utility company”, *Ingeniería y Competitividad*, Vol. 11 No. 2, pp. 41-52.

Manotas, D.F. and Toro, H.H. (2009), “Análisis de decisiones de inversión utilizando el criterio valor presente neto en riesgo (VPN en riesgo)”, *Revista de la Facultad de Ingeniería de la Universidad de Antioquia*, Vol. 49, pp. 199-213.

McNeil, A.J., Frey, R. and Embrechts, P. (2005), *Quantitative Risk Management: Concepts, Techniques, and Tools*, Princeton University Press, Princeton.

Melo, L.F. and Granados, J.C. (2011), “Regulación y valor en riesgo”, *Ensayos sobre Política Económica*, Vol. 29 No. 64, pp. 110-177.

Morgan, W., Cotter, J. and Dowd, K. (2012), “Extreme measures of agricultural financial risk”, *Journal of Agricultural Economics*, Vol. 63 No. 1, pp. 65-82.

Mun, J. (2008), *Advanced Analytical Models: Over 800 Models and 300 Applications from the Basel II Accord to Wall Street and Beyond*, John Wiley & Sons, NJ.

Ross, S.A. (1976), “The arbitrage theory of capital asset pricing”, *Journal of Economic Theory*, Vol. 13 No. 3, pp. 341-360.

Sharpe, W.F. (1964), “Capital asset prices: a theory of market equilibrium under conditions of risk”, *The Journal of Finance*, Vol. 19 No. 3, pp. 425-442.

Sklar, A. (1959), “Fonctions de répartition à n dimensions et leurs marges”, *Publications de l’Institut de Statistique de L’Université de Paris*, Vol. 8, pp. 229-231.

Uribe, J.M., Manotas-Duque, D.F. and Ulloa, I. (2015), “Modelación de la Incertidumbre en el Sector Empresarial a través de Cópulas, unpublished manuscript, Department of Economics, Universidad del Valle

Wang, J. and Wang, R. (2014), “Evaluating electricity price volatility risk in competitive environment based on ARMAX-GARCHSK-EVT model”, *International Journal of Computer Applications in Technology*, Vol. 50 Nos 3/4, pp. 174-179.

Xouridas, S. (2015), “Agricultural financial risks resulting from extreme events”, *Journal of Agricultural Economics*, Vol. 66 No. 1, pp. 192-220, available at: http://doi.wiley.com/10.1111/1477-9552.12083

Yang, J. and Lin, P. (2011), “Dynamic risk measurement of futures based on wavelet theory”, *Seventh International Conference on Computational Intelligence and Security, IEEE*, pp. 1484-1487.

Zhang, B., Wei, Y., Yu, D., Lai, X. and Peng, Z. (2014), “Forecasting VaR and ES of stock index portfolio: a Vine copula method”, *Physica A: Statistical Mechanics and its Applications*, Vol. 416, pp. 112-124.

Zivot, E. and Wang, J. (2006), *Modeling Financial Time Series with S-PLUS®*, Springer, New York, NY.

Appendix

Based on the estimated parameters of the GPD function in Table AI, both the future price as the national price fit an ordinary Pareto function, while the ER fits a type II Pareto distribution that has truncated tails. Following the results, as the higher scale parameter is associated with heavy tails

	ICE		National price		TRM	
	t-statics	*p*-value	*t*-stastics	*p*-value	*t*-stastics	*p*-value
Sign bias	1.09	0.28	0.26	0.80	0.35	0.73
Negative sign bias	0.89	0.37	0.13	0.90	0.94	0.35
Positive sign bias	0.08	0.94	0.43	0.72	0.52	0.60
Joint effect	6.59	0.09	2.45	0.47	1.46	0.69

Table AI.
Sign bias test

	ICE		National price		TRM	
Lag	*t*-statistics	*p*-value	*t*-statistics	*p*-value	*t*-statistics	*p*-value
1	0.65	0.42	0.00	0.99	0.02	0.88
2	3.57	0.1	0.56	0.75	0.78	0.67
3	3.68	0.29	0.75	0.86	0.78	0.85
4	4.33	0.3	0.90	0.92	0.97	0.91
5	4.46	0.48	1.47	0.91	1.06	0.95
6	4.92	0.55	1.49	0.96	1.60	0.95
7	5.09	0.64	2.48	0.92	1.72	0.97
8	5.95	0.65	2.61	0.95	1.90	0.98
9	5.99	0.74	3.24	0.95	1.96	0.99
10	6.22	0.79	3.25	0.97	3.62	0.96
11	6.40	0.84	4.16	0.96	4.31	0.96
12	6.53	0.88	4.22	0.97	4.48	0.97

Table AII.
Ljung-Box test for the standardized residuals

	ICE		National price		TRM	
Lag	*t*-statistics	*p*-value	*t*-statistics	*p*-value	*t*-statistics	*p*-value
1	0.01	0.92	0.02	0.89	0.01	0.91
2	0.01	0.99	0.69	0.71	0.50	0.78
3	0.01	1.00	0.89	0.83	0.56	0.91
4	0.07	1.00	6.98	0.14	0.91	0.92
5	0.25	1.00	10.63	0.06	22.51	0.81
6	0.38	1.00	11.79	0.07	44.65	0.61
7	10.63	0.99	11.86	0.11	44.66	0.73
8	12.19	1.00	16.94	0.03	44.86	0.81
9	21.79	0.99	18.62	0.03	54.24	0.80
10	24.66	0.99	21.19	0.02	10.69	0.38
11	32.81	0.99	22.69	0.02	12.13	0.35
12	44.92	0.97	24.44	0.02	14.81	0.25

Table AIII.
Ljung-Box test for the squared standardized residuals

	Parameters of the right tail		Parameters of the left tail		KS statistic	
	Scale	Shape	Scale	Shape	Statistics	*p*-value
National	0.5668	0.2382	0.4155	0.2242	0.0159	0.8634
Futures	0.7339	0.1329	0.6275	0.1360	0.0195	0.6540
ER	0.7178	−0.0211	0.5233	−0.0177	0.0227	0.4589

Table AIV.
Parameters of EVT and Kolmogorov-Smirnov test

Table AV. Estimated copulas and information criteria

Copula type		Coefficients	SE	LMV	AIC	Information criteria BIC	HQ
Normal	ρ 1	0.79	0.00	1,362.08	1,361.08	−2,716.21	−2,720.01
	ρ 2	0.00	0.02				
	ρ 3	0.02	0.02				
Clayton	τ	0.37	0.01	282.87	281.87	−557.79	−561.59
Gumbel	τ	1.19	0.01	221.33	220.33	−434.72	−438.52
Frank	τ	1.65	0.06	263.51	262.51	−519.08	−522.88
t-student	ρ 1	0.82	0.01	1,510.73	1,508.73	−3,005.57	−3,013.18
	ρ 2	−0.01	0.02				
	ρ 3	0.01	0.02				
	df	6.34					

(Carmona, 2014), it can be concluded that the futures possess heavier tails than the other risk factors, especially in the left tail.

To determine whether pseudo-sample (u_i) fits a uniform (0, 1) distribution, the Kolmogorov-Smirnov test is applied to each series. The results suggest that, with 99, 95 per cent, and 90 per cent of confidence, it cannot be rejected the null hypothesis that the series fit the uniform distribution.

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