

Does extreme rainfall lead to heavy losses in the food industry?

Chuvas Extremas Induzem Perdas Elevadas na Indústria de Alimentos?

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Abstract

Purpose – Managing the risks associated to world food production is an important challenge for governments. A range of factors, among them extreme weather events, has threatened food production in recent years. The purpose of this paper is to analyse the impact of extreme rainfall events on the food industry in Brazil, a prominent player in this industry.

Design/methodology/approach – The authors use the AR-GARCH-GPD hybrid methodology to identify whether extreme rainfall affects the stock price of food companies. To do so, the authors collected the daily closing price of the 16 food industry companies listed on the Brazilian stock exchange (B3), in January 2015.

Findings – The results indicate that these events have a significant impact on stock returns: on more than half of the days immediately following the heavy rain that fell between 28 February 2005 and 30 December 2014, returns were significantly low, leading to average daily losses of 1.97 per cent. These results point to the relevance of the need for instruments to hedge against weather risk, particularly in the food industry.

Originality/value – Given that extreme weather events have been occurring more and more frequently, financial literature has documented attempts at assessing the economic impacts of weather changes. There is little research, however, into assessing the impacts of these events at corporate level.

Keywords Extreme events, Weather, Extreme value theory, Food industry, Stock prices

Paper type Research paper

Resumen

Propósito – O gerenciamento de riscos associados à produção mundial de alimentos é um desafio importante para governantes. Diversos fatores, entre eles os eventos climáticos extremos, têm ameaçado a produção de alimentos nos últimos anos. Neste artigo nós analisamos o impacto de eventos de chuvas extremas na indústria de alimentos no Brasil, um dos maiores produtores mundiais.

Diseño/metodología/enfoque – Empleamos a metodología híbrida AR-GARCH-GPD para verificar se chuvas extremas afetam o preço das ações das empresas de alimentos. Para isso, coletamos os preços de fechamento diário de 16 empresas do setor de alimentos listadas na Bolsa de Valores do Brasil [B3], em janeiro de 2015.

JEL Classification — G1, G3, Q1, Q5

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Resultados – Os resultados sugerem que esses eventos exercem impacto significativo sobre o retorno das ações: em mais da metade dos dias imediatamente posteriores à chuva extrema ocorrida entre 28/02/2005 e 30/12/2014, os retornos foram significativamente baixos, levando a perdas médias diárias próximas de 1,97%. Esses resultados apontam para a relevância da necessidade de instrumentos para proteção contra riscos climáticos, particularmente na indústria de alimentos.

Originalidad/valor – Tendo em vista que eventos climáticos extremos têm ocorrido com uma frequência cada vez maior, a literatura de finanças tem documentado tentativas de avaliar os impactos econômicos das mudanças climáticas. No entanto, nota-se a carência de pesquisas para avaliar os impactos desses eventos no nível das empresas.

Palabras clave Eventos Extremos, Clima, Teoria de Valores Extremos, Indústria de Alimentos, Preço de Ações

Tipo de papel Trabajo de investigación

1. Motivation

Our planet's climate has been receiving special attention from international organisations (World Bank, 2015b), governments (Ghosh, 2010), companies and the academic community (Hirshleifer and Shumway, 2003). The impacts of climate variables on companies from different sectors, one of the most sensitive of which is food, have been the focus of research in recent years. Not only do extreme impact weather events lead to food shortages, they are also considered to be extremely relevant by international organisms because of their potential to influence economic and social balance at the international level (World Economic Forum, 2018).

Food companies, therefore, deserve the attention of researchers, and none more so than those located in Brazil, one of the world's leading food producers. Despite the fact that business performance depends heavily on climate, literature on the impacts of climate variables on the market performance of food companies is scarce, especially that which refers to emerging markets (Rosenzweig *et al.*, 2001; Jones and Thornton, 2003). Based on these arguments, our main contribution is to provide unprecedented empirical evidence of the impact of rainfall on the stock prices of listed food companies in a relevant food producing country.

The specific weather event studied is extreme rainfall. Cabrera *et al.* (2013) stated that farmers and investors are affected by the direct or indirect losses caused by excessive rainfall. We analyse whether or not these events have an influence on food sector stock prices, and if they do, how big this impact is. Why do we use financial returns to recognise the impact of extreme rainfall on food companies? Economic theory states that the price of an asset reflects the expected present value of its risk-adjusted future earnings. This statement, together with the market efficiency hypothesis, tells us that any information about future weather conditions should be reflected in the stock price, as any extreme rainfall will be reflected in a firm's returns.

Brazil is an ideal candidate for this study. A country of continental dimensions, it is an expressive producer and exporter of various agricultural products (CEPEA, 2015), due to its favourable soil and climate conditions and the technological development of its agribusiness. It does, however, suffer from adverse weather (drought, hail and rain, especially) that can directly or indirectly affect its agricultural production (Marengo *et al.*, 2009). The agribusiness sector in Brazil is responsible for a representative proportion of its GDP (approximately 23 per cent in 2015), for underpinning the country's trade balance and for guaranteeing food security, thus avoiding a disorderly increase in the price of food and other agricultural commodities (CEPEA, 2015)[1].

For each company we considered, the initial date of our study sample corresponds to the day its stocks were first publicly traded on the Brazilian stock exchange, called the (B3). The final date is always 30 December 2014. The daily rainfall figures correspond to the main region in which each company operates (Pérez and Yun, 2013) and were taken from the INMET Meteorological Database for Teaching and Research (BDMEP, 2015)[2]. We consider daily rainfall in excess of 50 mm to be extreme, as detailed by Walter (2007).

Since this work concentrates on evaluating the impact of extreme climate events, the method used refers to the adjustment of the distribution tail of a financial series, disregarding the not-very-informative character of the distribution centre. As a result, this adjustment required a structured procedure to estimate the VaR, so its predictive performance is accurate (Mendes, 2000).

As financial series are generally temporally dependent and tend to exhibit volatility clusters, the distribution of the financial returns in the value at risk (VaR) calculation is adjusted using a GARCH-EVT approach (McNeil and Frey, 2000a, b; Chesney *et al.* 2011; Yi *et al.* 2014; Danielsson *et al.*, 2016). This type of approach is also supported by Kuester *et al.* (2006), who show that the performance of the GARCH-EVT hybrid method is superior to other methods, such as GARCH-Normal and GARCH-*t*-Student. Other research into VaR estimates uses the GARCH and EVT approach, including the works of Longin (2005), Bali *et al.* (2008), Zhao *et al.* (2010), Karmakar (2013) and Chavez-Demoulin *et al.* (2016).

We use traditional temporal series techniques to model the return on stocks, since financial return series tend, generally speaking, to deal with temporal dependence and volatility clusters. Daily returns are therefore adjusted using an AR-GARCH model (McNeil and Frey, 2000a, b; Mendes, 2000; Chesney *et al.*, 2011). The VaR is estimated, based on the standardized residuals for this model and using the extreme value theory (EVT) (Zhao *et al.*, 2010). The VaR is calculated using an AR-GARCH-GPD model[3]. VaR measures are estimated for the day following extreme rainfall events to analyse the impact of these occurrences on the stocks being studied. If the negative return on the stock (in module) is greater than the estimated VaR, then the impact of the extreme rainfall is considered to be significant.

The results show that extreme rainfall events had a significant impact on stock returns in more than half the events and caused average daily losses of 1.97 per cent on the day following the extreme rainfall. In terms of market value this represents a total average daily loss of around \$682.15m.

As the companies analysed have no positions in weather derivatives, this work indicates how important it is for food producing company managers to concern themselves with mitigating risks arising from extreme rainfall, since this can improve their productivity by reducing the financial restrictions to agricultural production (Cornaggia, 2013). This study also highlights the importance of having weather derivatives (hedge instruments) available in the financial market.

The paper is included in the literature on evaluating the economic impacts of extreme weather events. It contributes to the limited bibliography that exists on the relationship between weather variables and a company's valuation. It also uses the EVT to establish whether financial losses on stocks are significant when an extreme event occurs. This work is structured as follows. Section 2, following this introduction, presents the theoretical reference in which we review the literature related to the topic of this study in a way that links it to the EVT, which supports this study. In Section 3, we present a set of data and detail the methodology used. We present and discuss the results obtained in Section 4, and Section 5 presents our final considerations.

2. Theoretical and empirical bases

2.1 Related literature

There are few articles that study the relationship between the areas of agriculture and climatology (Bush, 2010). A subset of these studies deals with the effect of weather variables on the behaviour of the stock market (Symeonidis *et al.*, 2010; Murphy *et al.*, 2012). Keef and Roush (2002) linked the daily return data of the New Zealand stock market to weather information. The authors argued that the effect of swings in weather variables, like temperature and wind, on stock returns depends on the specific location of the investor, with wind having a negative influence on returns.

Kang *et al.* (2010) studied the effect of the weather on the return and volatility of the financial market in Shanghai. The authors concluded that temperature has a negative effect on the return for domestic investors, but has no effect on foreign investors, a result that is in line with the work of Keef and Roush (2002), who emphasised the importance of the geographic location of the investor on stock returns. Swings in rainfall and temperature lead to volatility in the financial market in Shanghai, and this has an impact on both local and foreign investors.

Using data from countries in Asia, Europe and North America, Cao and Wei (2005) found that the returns of the respective stock exchanges are negatively associated with temperature. Levy and Galili (2008) stated that the significance of the weather effect on the financial market in Israel, generally speaking, depends on the type of investor (institutional or individual). The studies of Shu (2008); Chang, Chen, Chou and Lin (2008); Chang, Nieh, Yang and Yang (2008), which analyse the effect of weather on the Taiwanese market, corroborate this result. Chang, Chen, Chou and Lin. (2008); Chang, Nieh, Yang and Yang (2008), also analysing the effects of humidity and cloud cover, stated that on very cloudy days returns on the stock market in Taiwan are generally smaller.

Using weather data for the city of New York and stocks traded on the New York Stock Exchange (NYSE), Trombley (1997) concluded that the impact of climate change on the North American stock exchange is variable over time[4]. Chang, Chen, Chou and Lin (2008); Chang, Nieh, Yang and Yang (2008) also examined the relationship between climate change and the NYSE and concluded that the impacts of rainfall and temperature are only significant when trading opens. Akhtari (2011), however, stressed that the relationship between weather and the stock market in New York does not depend on the time of day the trading occurs, but that there is a cyclical weather pattern effect on the NYSE stock exchange throughout the year.

Hirshleifer and Shumway (2003) examined the behaviour of the stock returns on sunny days for 26 stock exchanges in the period between 1982 and 1997. The authors indicated that a greater incidence of the sun's rays (sunny days) is significantly correlated with daily stock returns.

In a more general context, Prodan (2013) argued that the significance of the weather effect depends on a series of factors, among which: the definition of the weather variables; the type of investor; the location of the companies being analysed; and the procedure and statistical test used in the research. The different conclusions reached in similar research may be explained by the variability of these factors. This argument is relevant, since we limit our work to Brazilian food companies and the "rainfall" weather variable, and because we do not deal with the type of investor in each company.

Using temperature and rainfall data from 329 weather stations and wheat production data in Europe, Iglesias *et al.* (2000) studied seven wheat producing regions in Spain. Based on a spatial analysis, the authors found that an increase in temperature and a reduction in rainfall have a negative effect on wheat production. Considering various industrial sectors in Germany, Bergmann *et al.* (2016) stated that extreme weather events affect companies' capacity to achieve sales growth.

The magnitude of the predicted impact of climate change on food production in Africa varies widely between studies. Challinor *et al.* (2007) claimed that most of the studies on Africa highlight the negative impact of climate change on food productivity, which can lead to price increases. They also stated that governments should establish better institutional and macroeconomic conditions to help companies adapt to climate change at local, national and transnational levels.

This argument is supported by Swan *et al.* (2010), who analysed the impact of the variation in food prices in Africa. The authors emphasised how important it is for governments to plan adequate interventions in order to protect the means of subsistence, because of the effects of increases in food prices. Bush (2010) similarly explored the phenomenon of the disruption to food supply that was unleashed by price peaks in Africa at the time of the financial crisis of 2007–2008.

Thornton *et al.* (2010) developed simulations for corn and beans – two widely grown crops in Africa – and identified that climate change affects African agricultural production in a significantly negative way. Using food and weather data from Latin countries, Rosenzweig *et al.* (2001) suggested that food production is directly sensitive to temperature increases and rainfall reductions. A similar result is presented by Defeo *et al.* (2013), whose argument points out that climate change has a long-term effect on small-scale fishing.

Sietz *et al.* (2012) claimed that small farmers in Peru are threatened by the possibility of drought, frost and heavy rain. The authors stated that climate change is affecting food security in the country in terms of production and availability. This study corroborates the work of Vörösmarty *et al.* (2013), who stated that the rural population of South America is more sensitive to extreme rainfall than the urban population.

Jones and Thornton (2003) studied the possible impacts of climate change on corn production in Latin America and Africa. The results suggest that there has been a 10 per cent reduction in corn production in these regions, which is equivalent to losses of \$2bn per year. The authors also stressed that climate change needs to be assessed within a family context, so that the poorest and most vulnerable people who are dependent on agriculture can receive suitable advice and guidance, the objective being to reduce poverty (Parry *et al.*, 1999; Vörösmarty *et al.*, 2013).

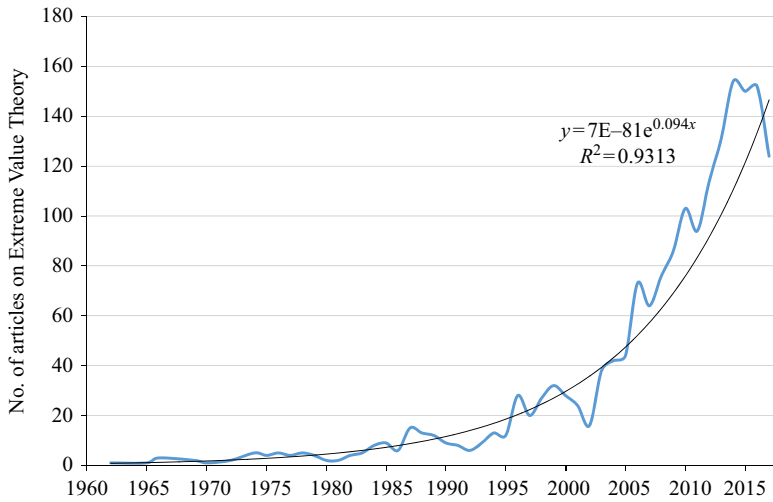
Using data for Latin America and the USA, Murphy *et al.* (2012) analysed the importance of instruments that manage risks associated with food price volatility and climate change, since extreme weather events will tend to become more frequent in the future and, as a result, the risks and uncertainties in the global food system may increase (Wheeler and von Braun, 2013). The effect of risk management on grain producers in the USA is discussed in the study of Cornaggia (2013). This author found that hedge operations improve productivity by reducing financial restrictions on agricultural producers. Ma *et al.* (2017) employed the Peaks Over Threshold model in the EVT to characterize the distribution tail of catastrophic losses from global warming; we use part of this procedure in this paper.

2.2 Risk and extreme value theory

In this study, the stock prices of Brazilian food companies are evaluated using the occurrence of extreme rainfall. To find out whether there are extremely negative returns when these weather events occur, we use the EVT. This theoretical line has received increasing attention in recent years in different fields of knowledge, as shown in Figure 1. Original work in the field of finance by Longin and Solnik (2001), McNeil and Frey (2000a, b), Longin (1996), Poon *et al.* (2004), Longin (2000), Kuester *et al.* (2006) has been recently supplemented by contributions from the studies of Martins-Filho *et al.* (2018), Li and Perez-Saiz (2018), Kumar (2017), Di Bernardino and Palacios-Rodríguez (2017).

The procedure consists in calculating the VaR using the EVT based on returns that are adjusted by an AR-GARCH model and observing whether the negative stock return after a day of extreme rainfall is greater (in module) than the VaR.

The VaR methodology was initially used to control the internal risk of financial institutions. It is defined as the loss on a trading portfolio resulting in the probability p of losses equalling or exceeding the VaR in a given trading period. Kuester *et al.* (2006) documented an extensive and detailed review and made comparisons between various alternative methodologies to estimate the VaR. Among the various methodologies that exist, the EVT is recommended for statistically analysing events that are highly improbable, in other words, for analysing the maximum or minimum values of a random variable, order statistics or values that exceed a certain threshold (Embrechts *et al.*, 1997).



Notes: Elaborated by the authors from data collected on the Scopus platform. This figure shows the number of articles regarding extreme value theory (EVT) applications published over the last few decades. We considered all the articles indexed in the Scopus platform, in which the expression “Extreme Value Theory” was found in the title, in the abstract or in the keywords. The first article found was published in 1962, and we considered only papers published by the end of 2017 in six areas of knowledge: mathematics, engineering, economics, business and accounting, Earth sciences, environmental sciences and agriculture and biological sciences, this procedure implicated in 1,790 articles

Figure 1.
Extreme value theory
literature evolution
(1962–2017)

In this work, we consider the “peaks over thresholds” approach and parametric models. Considering a random variable X over a certain threshold u and defining the variable $Y = X - u$, the generalised Pareto distribution (GPD) distribution can be represented by the following equation:

$$W_{\xi, \delta}(Y) = 1 - (1 + \xi Y / \delta)^{-1/\xi}, \tag{1}$$

where δ and ξ correspond to scale parameters and the tail density of the GPD distribution, respectively.

Some of the methodologies used to determine threshold u can be found in the study of Chavez-Demoulin *et al.* (2014). No method is considered optimal, however, for choosing the appropriate threshold, although a 5 or 10 per cent threshold is considered a good approximation for u (Del Brio *et al.*, 2014). Due to the observation window sizes (500, 750 and 1,000) used to fit the models, a 10 per cent threshold of the largest observations was assigned to the present work, as McNeil and Frey (2000a, b) and Chesney *et al.* (2011) did. Scarrott and MacDonald (2012) presented a detailed review of the statistical literature with the various methodologies used to estimate the threshold. By way of illustration, Section 2.2.1 presents some of the methodologies used to estimate the threshold.

To implement the EVT, the standardized residuals were ordered using order statistics: $z_{(1)}, \dots, z_{(n)}$. The distribution given in (1) was therefore adjusted to fit the excess residuals over the threshold $z_{(k+1)}$, in other words, to fit the data $Z = (z_{(1)} - z_{(k+1)}, \dots, z_{(k)} - z_{(k+1)})$,

where k corresponds to the amount of data in the distribution tail. The \hat{z}_q quantile estimated for the distribution tail is, therefore, given by the following equation (McNeil and Frey, 2000a, b):

$$\hat{z}_q = z_{(k+1)} + \left(\hat{\delta}_k / \hat{\xi}_k \right) \left(\left(\frac{1-q}{k/n} \right)^{-\hat{\xi}_k} - 1 \right), \quad (2)$$

where n is the total amount of data (standardized residuals); and q the quantile of the distribution associated with the losses. Finally, the VaR was estimated as shown in the following equation:

$$\widehat{VaR}_{i,q} = \hat{\mu}_{i,t+1} + \hat{\sigma}_{i,t+1} \hat{z}_{i,q}, \quad (3)$$

where $\hat{\mu}_{i,t+1}$ is the estimate of the conditional mean of the returns of the AR(1) model; and $\hat{\sigma}_{i,t+1}$ the estimate of the conditional volatility of the GARCH process (1,1) of stock i on day $t+1$. As the daily stock returns are adjusted using an AR-GARCH model and the estimated VaR is based on standardized residuals, the basis of which is the EVT using the GPD, we say that the calculation of the VaR is estimated on the basis of an AR-GARCH-GPD model.

2.2.1 Threshold estimation. The tractional method of POT considers the observations $Z = (z_{(1)} - u, \dots, z_{(k)} - u)$ of the statistics of order $z_{(1)}, \dots, z_{(k)}$ a certain threshold u . Thus, from a certain threshold u , such a method is based on the decomposition of the tail of the F_Z distribution. The choice of the appropriate threshold u implies a balance between bias and variance of the estimators of the coefficients of the GPD distribution under analysis (Chavez-Demoulin *et al.*, 2014). However, there is arbitrariness in choosing such a threshold. It should be noted that small values of u provide more information by reducing variance. On the other hand, higher u values lead to less bias.

Thus, graphical techniques are employed to try to find a balance between bias and variance of the estimators, as highlighted, for example, in the studies of Chavez-Demoulin *et al.* (2014), Smith (1987) and Davison and Smith (1990). In the present paper, because a threshold is used with 10 per cent of the largest observations, it is worth mentioning that an extensive comparative study of graphical simulations made in the study of Chavez-Demoulin (1999) suggests the use of 10 per cent of the largest observations as a threshold. Moreover, with such a threshold, Chavez-Demoulin and Embrechts (2004) showed that small variations on the threshold of 10 per cent have little impact on the estimation.

Among these graphic techniques, the Hill estimator which is a function of the order statistics $X_{(1,n)}, \dots, X_{(k,n)}$ can also be employed (McNeil and Frey, 2000a, b; Kim and Kim, 2015; Kellner and Rösch, 2016). From this, the Hill estimator is defined by the following equation:

$$H_{k,n} = (1/k) \sum_1^k \log (X_{(i,n)} / X_{(k,n)}). \quad (4)$$

Thus, the Hill graph is constructed by the Hill estimator in a range of variation of the values of k vs the threshold. The value of $X_{k,n}$ where the Hill estimator tends to become stable will be chosen as the optimal threshold (Yang *et al.*, 2018). It is also possible to use the mean square error (MSE) method (Longin and Solnik, 2001; Giles *et al.*, 2016; Silva-González *et al.*, 2017), which consists in selecting several possible thresholds where for each of them, the excess of the returns is calculated for the adjustment of the respective GPD. Thus, the parameter of the GPD is estimated several times by the bootstrap method, and the MSE of the estimated parameter is estimated. The threshold chosen will be the one with the lowest MSE (Yang *et al.*, 2018). Lima *et al.* (2018), in turn, used a non-parametric approach to

estimate the GPD parameters. When considering the threshold varying in time, they employ a Bayesian paradigm via MCMC simulation for estimation of the GPD model. As we can see, there is still no closed form for proper threshold definition.

3. Empirical strategy

As argued by Chesney *et al.* (2011), a study of the possible impact of extreme events on the behaviour of stock prices may be conducted by comparing the return on stocks on the day following the extreme event, with the VaR estimated for that day and computed using different confidence levels. If the negative return on the stock on the day following an extreme weather event is greater (in module) than the respective estimated VaR, then we can conclude that this particular extreme event has had a significant impact on the return on the stock being analysed (Chesney *et al.*, 2011).

If t is the day on which extreme rainfall occurred, in other words, a day when the rainfall exceeded 50 mm; $R_{i,t+1}$ is the financial return on stock i on day $t+1$; and $\widehat{VaR}_{i,t+1}$ is the estimated VaR for day $t+1$ and if $R_{i,t+1} < -\widehat{VaR}_{i,t+1}$, then the event that occurred on day t is considered to have had a significant impact on the financial return of the stock being evaluated. In order to complement the analysis, for each VaR estimated in the described manner, the expected shortfall (ES) will also be estimated in order to evaluate the expected value of the worst returns $\alpha\%$, unlike the VaR that considers only the value that separates this $\alpha\%$ worse returns. According to Taamouti (2009), formally, ES can be defined by the following equation:

$$ES_t^\alpha = E(x|x \geq VaR_t^\alpha). \quad (5)$$

As highlighted by Rockafellar and Uryasev (2002), one of the main advantages of ES in relation to VaR is the fact that the ES presents the additional property of sub-additivity that classifies it as a coherent risk measure. Further details on ES can be found, for example, in the studies of Kellner and Rösch (2016), Boonen (2017), Degiannakis and Potamia (2017) and Müller and Righi (2018).

3.1 Data

To check whether the occurrence of extreme rainfall has an impact on companies in the Brazilian food industry, we collected the daily closing prices in reais (R\$) of food company stocks. In January 2015, there were 16 companies in the food sector listed on the BM&FBovespa, split into five segments: agriculture, coffee, meat and meat derivatives, grain and dairy products.

According to these segments, and aiming to achieve greater robustness to adjust the models, the criteria we used for selecting the companies were: the extent; liquidity; regularity; and consistency of the financial series. Only companies that were still publicly quoted on the stock exchange on 30 December 2014 were considered.

Companies for which there was missing or inconsistent information in the database, or that had no stock price data before 30 December 2014, were not considered in the sample. Companies whose financial data contained fewer than 1,300 observations were also not used because of the maximum size of the observation windows (1,000 days) used to estimate the AR-GARCH models. The initial date for each stock corresponds to the day the company first went public on the Brazilian stock exchange, the BM&FBovespa, the cut-off date for all companies being 30 December 2014. Because of our choice criteria, only 6 of the 16 listed companies were selected, as shown in Table I.

The time intervals used to analyse each stock were different, since the start date of the database for each stock was the day on which the latter was first publicly traded on the Sao Paulo Stock Exchange, formerly the BM&FBovespa and known as (B3) since June 2017.

Table I.
Food industry
companies analysed

| Company | ISIN | Code | Industry | NAICS | Data ^a | Value (US\$Mi) ^b |
|---------------------|--------------|-------|----------------------|--------|-------------------|-----------------------------|
| Renar Maçãs S.A. | BRRNARACNOR6 | RNAR3 | Agriculture | 111331 | 28 February 2005 | 9.26 |
| SLC Agrícola S.A. | BRSLCEACNOR2 | SLCE3 | Agriculture | 111191 | 15 June 2007 | 526.21 |
| Vanguarda Agro S.A. | BRVAGRACNOR2 | VAGR3 | Agriculture | 111191 | 21 November 2006 | 206.86 |
| Minerva S.A. | BRBEEFACNOR6 | BEEF3 | Meat and Derivatives | 112111 | 19 July 2007 | 556.64 |
| BRF Brasil S.A. | BRBRFSACNOR8 | BRFS3 | Meat and Derivatives | 112111 | 19 May 2009 | 20,886.68 |
| JBS S.A. | BRJBSSACNOR8 | JBSS3 | Meat and Derivatives | 112111 | 28 March 2007 | 12,441.06 |

Notes: Information obtained from the Sao Paulo Stock Exchange. ^aInitial closing date of the share price; ^bmarket value of the companies on 30 December 2014 (in millions of dollars). Dollar quotation on 30 December 2014, R\$2.65

For example, according to Table I, the interval of time for Renar Maçãs is the period between 28 February 2005 and 30 December 2014.

To assess the impact of rainfall on the returns on food company stocks, daily rainfall data were collected for the main regions where the companies operate, a procedure recommended by Pérez and Yun (2013) and Prodan (2013). These rainfall figures in Brazil were collected from the Brazilian Meteorology Institute (INMET), an official Brazilian body linked to Brazil's Ministry of Agriculture, Livestock Farming and Supplies.

After checking the geographic position of the main region in which each of the companies operates, we accessed INMET's Meteorological Database for Teaching and Research website (BDMEP, 2015) to identify the weather-monitoring stations closest to these regions (Prodan, 2013). Daily rainfall data were then collected according to the time intervals analysed for each selected company. It is worth stressing that the BDMEP database is in accordance with the international standards of the World Meteorological Organization (BDMEP, 2015).

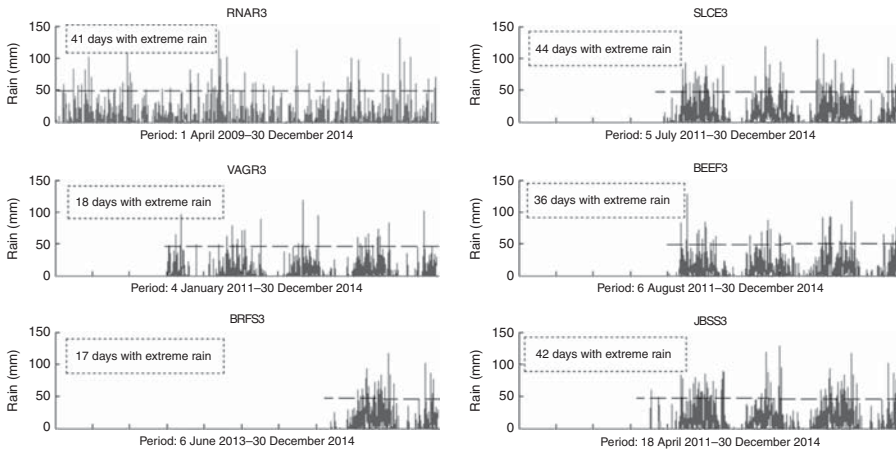
For companies operating in more than one geographical region we considered the maximum daily rainfall figures of the closest respective meteorological stations to investigate only days of extreme rain (daily rainfall over 50 mm). This makes it possible to capture the effect of extreme rain in the different locations where each company operates. Figure 2 shows the daily rainfall in the main regions in which the six companies studied operate.

Because we used windows with up to 1,000 daily price observations to adjust the models, the initial date of each rainfall series starts 1,000 days after each analysed company went public. The final date is always 30 December 2014. In addition to the rainfall impact, idiosyncratic company events and systematic happenings can affect the stock price (Cutler *et al.*, 1989). As these events are not correlated to rain, however, we believe that if a large number of observations exceed the VaR, we can state that extreme rainfall has a negative impact on returns.

3.2 Model

Since this work concentrates on evaluating the occurrence of extreme weather impacts on stock prices, the methodology used refers to the adjustment of the distribution tail of the financial series, while ignoring the not-very-informative nature of the distribution centre. As a consequence, this adjustment requires a structured procedure to estimate the VaR to make sure that its predictive performance is accurate (Mendes, 2000).

In this work, the autoregressive model AR(1) is adjusted to the return series with the idea of eliminating serial autocorrelation between observations. The residuals of the AR(1) model are adjusted by a GARCH(1,1) – Normal model due to its conditional heteroscedasticity.



Notes: Daily rainfall (mm). The initial date of each series begins 1,000 days after the company went public. The final date is 30 December 2014 and is the same for all series. The horizontal dashed line corresponds to 50 mm of rainfall in the day. The x -axis corresponds to the daily observations and the y -axis corresponds to the quantity of daily rainfall

Figure 2.
Daily rainfall in the
period analysed

Consequently, the standardized residuals of this AR-GARCH model, in general, no longer have volatility clusters and temporal dependence, as required by the EVT to adjust the GPD (Mendes, 2000). These standardized residuals, therefore, are adjusted by the GPD to arrive at the VaR. We did not use orders greater than those of the AR(1)-GARCH(1,1) model for parsimony and effectiveness, as documented in the studies of McNeil and Frey (2000a, b) and Chesney *et al.* (2011).

With regard to the rainfall data in the main region where each company operates, we identified the days on which extreme rain (daily rainfall > 50 mm, according to Muniz *et al.*, 2014) occurred. On each of the days identified we considered observation windows corresponding to the historic daily stock log-returns up to the day of this extreme event. Sub-samples with 500, 750 and 1000 historic daily observations were used to adjust the AR(1)-GARCH(1,1)-GPD models to estimate the VaR for the day after the extreme event and comparing it with the series return. To make the working methodology clearer, we constructed a flowchart (Figure 3) showing the whole procedure used.

In this approach, the dynamics of the daily returns according to the following equation:

$$R_{i,t} = \mu_{i,t} + \sigma_{i,t}Z_{i,t}, \tag{6}$$

where $R_{i,t}$ represents a series of negative log-returns of daily observations of a stock i on day t , and the $Z_{i,t}$ residuals correspond to a white noise process assumed to follow a standard normal distribution. As suggested by McNeil and Frey (2000a, b) and Chesney *et al.* (2011), for parsimony and effectiveness we considered an AR(1) model for the conditional mean dynamics $\mu_{i,t}$ and a GARCH(1,1) to adjust conditional volatility $\sigma_{i,t}^2$. Therefore:

$$\mu_{i,t} = \phi R_{i,t-1}, \tag{7}$$

$$\sigma_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2, \tag{8}$$

where $\alpha_{i,0} > 0$, $\alpha_{i,1} > 0$, $\beta > 0$, $\varepsilon_{i,t} = R_{i,t} - \mu_{i,t}$ and $\alpha_{i,1} + \beta < 1$. The GPD distribution parameters were estimated from the residuals of the adjusted AR-GARCH model, because these

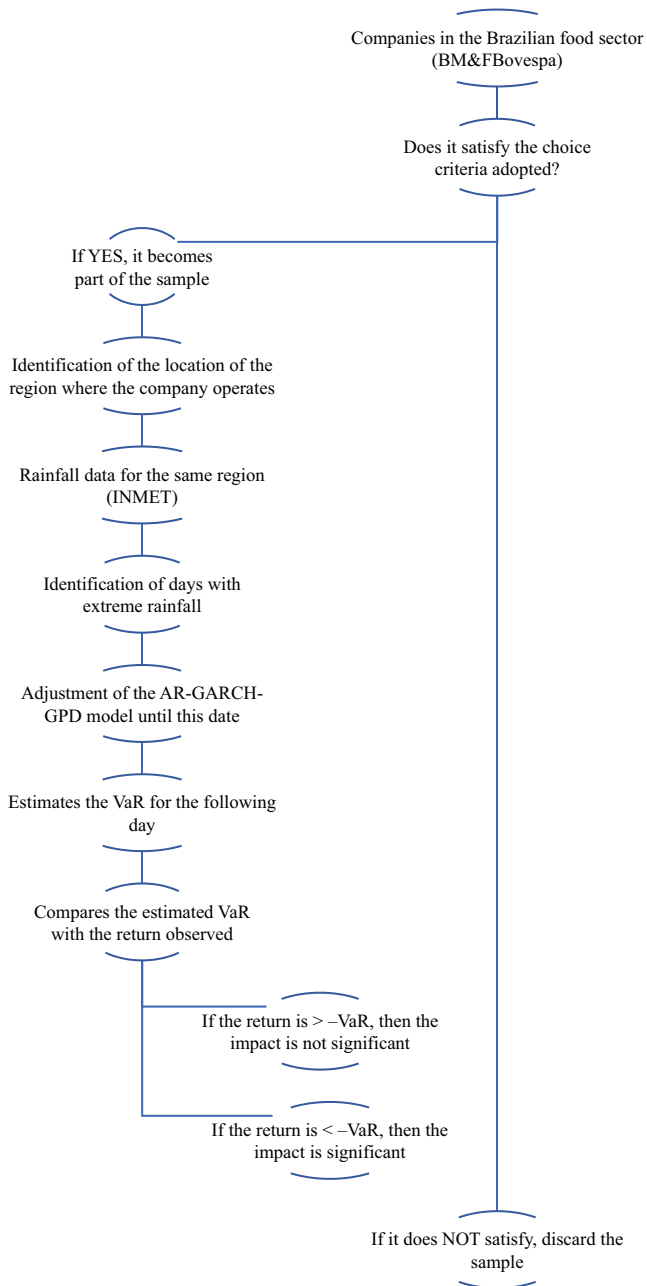


Figure 3.
Flowchart of the
procedure used

innovations had no volatility clusters and no temporal dependence, both conditions required for the application of GPD. In the operation to adjust the empirical data in the main region in which each analysed company (Pérez and Yun, 2013) operates, we used the number of days on which extreme rainfall (rainfall daily > 50 mm, according to the work of

Muniz *et al.* (2014) occurred. On each day identified as having extreme rainfall, we considered corresponding observation windows of historical daily log-returns until the day of that extreme event. As a result, we used sub-samples with 500, 750 and 1,000 historical daily observations to adjust the AR(1)-GARCH(1,1)-GPD models. The intention was to use these sub-samples to analyse the back testing conducted using the Kupiec test.

We estimated the parameters $(\hat{\phi}, \hat{\alpha}_0, \hat{\alpha}_1, \hat{\beta})$ of the AR(1)-GARCH(1,1) model using these financial return samples. Consequently, the series of conditional means $(\hat{\mu}_{t-n+1}, \dots, \hat{\mu}_t)$ and the series of conditional standard deviations $(\hat{\sigma}_{t-n+1}, \dots, \hat{\sigma}_t)$ were obtained recursively, using (7) and (8). In view of the adjustment to the AR(1)-GARCH(1,1) model, we were able to obtain the standardized residuals presented in (9), which are independent and identically distributed, which is one of the conditions for the application of EVT (Embrechts *et al.*, 1997):

$$(z_{i,t-n+1}, \dots, z_{i,t}) = ((R_{i,t-n+1} - \hat{\mu}_{t-n+1}) / \hat{\sigma}_{t-n+1}, \dots, (R_{i,t} - \hat{\mu}_t) / \hat{\sigma}_t). \tag{9}$$

In view of the above, we adjusted the distribution tail of the standardized residuals given in (9) using EVT. This approach was developed from the distribution of the excesses (considering 10 per cent as the threshold) of the standardized residuals applying the GPD given by (1). We therefore ordered the standardized residuals using order statistics and the GPD distribution given in (1) was adjusted to fit the excess residuals above the threshold used (10 per cent of the largest observations), so the \hat{z}_q quantile estimated for the distribution tail was estimated by (2). Finally, we estimated the VaR using Equation (3).

4. Results

Table II shows the main descriptive statistics of the daily series of log-returns of each stock for the six companies analysed. We can see in Table II that the daily means of all stock returns are close to 0 and the skewness and kurtosis measures point to the non-normality of the series – ratified by the Jarque–Bera statistic – which was significant for all stocks analysed at 1 per cent.

By way of illustration, the AR(1)-GARCH(1,1)-GPD model was initially estimated for the full sample for the six stocks we analysed. The estimated coefficients and test statistics used are shown in Table III.

As reported in Table III, the coefficients of the adjusted AR-GARCH models were almost all (except the AR(1) coefficient of JBSS3) significant at 1 per cent (Chesney *et al.*, 2011). The Ljung–Box tests for both residuals and the square of the residuals of each series were not significant; in other words, the tests indicate that the residuals and their squares had no

| | Stocks analysed | | | | | |
|-------------|-----------------|----------|----------|-----------|-----------|----------|
| | RNAR3 | SLCE3 | VAGR3 | BEEF3 | BRFS3 | JBSS3 |
| Mean | -0.00071 | 0.000051 | -0.00211 | -0.00025 | 0.001001 | 0.000189 |
| SD | 0.042 | 0.030 | 0.038 | 0.027 | 0.017 | 0.034 |
| Kurtosis | 11.84 | 14.42 | 19.24 | 3.09 | 2.03 | 4.51 |
| Skewness | 1.46 | 0.14 | 1.89 | 0.03 | 0.15 | -0.08 |
| Minimum | -0.24877 | -0.24675 | -0.17271 | -0.17306 | -0.07380 | -0.25169 |
| Maximum | -0.43410 | 0.32528 | 0.43146 | 0.12391 | 0.092910 | 0.24066 |
| Jarque–Bera | 6.49*** | 16.07*** | 31.93*** | 729.14*** | 241.94*** | 16.19*** |
| <i>n</i> | 2,421 | 1,866 | 2,004 | 1,842 | 1,391 | 1,919 |

Notes: Descriptive statistics calculated from the daily log-returns series for each share *i*. Jarque–Bera corresponds to the Jarque–Bera statistic for testing the null hypothesis of normality of the series. *n* corresponds to the total number of daily observations for each share. **p* < 0.1; ***p* < 0.05; ****p* < 0.01

Table II.
Descriptive
statistics of the
log-returns series

Table III.
AR(1)-GARCH(1,1)
models for full
samples

| | RNAR3 | SLCE3 | Stocks VAGR3 | BEEF3 | BRFS3 | JBSS3 |
|-------------------------------|------------------------|------------------------|------------------------|-----------------------|-----------------------|------------------------|
| <i>Panel A: AR(1)</i> | | | | | | |
| $\hat{\phi}$ | -0.0651*** (0.0108) | 0.0085*** (0.0017) | -0.0131*** (0.0021) | 0.0243*** (0.0023) | -1.06e-05 (0.0295) | -0.0656** (0.0224) |
| <i>Panel B: GARCH(1,1)</i> | | | | | | |
| $\hat{\alpha}_0$ | 7.59e-06*** (1.57e-06) | 1.46e-05*** (2.83e-06) | 5.84e-05*** (3.20e-06) | 8.47e-06** (2.35e-06) | 9.49e-05** (3.66e-05) | 2.66e-05*** (6.84e-06) |
| $\hat{\alpha}_1$ | 0.0641*** (0.0058) | 0.0652*** (0.0066) | 0.2276*** (0.0124) | 0.0559*** (0.0068) | 0.0855** (0.0259) | 0.0687*** (0.0096) |
| $\hat{\beta}$ | 0.9316*** (0.0059) | 0.9152*** (0.0086) | 0.7724*** (0.0079) | 0.9320*** (0.0079) | 0.5803*** (0.1459) | 0.9049*** (0.0142) |
| AIC | -9.999.20 | -8.405.10 | -8.047.40 | -8.391.60 | -7.410.40 | -7.928.40 |
| Jarque-Bera | 0.0001*** | 0.0001*** | 0.0001*** | 0.0001*** | 0.0001*** | 0.0001*** |
| Ljung-Box (res) | 0.4775 | 0.5173 | 0.1455 | 0.0649 | 0.5969 | 0.3348 |
| Ljung-Box (res ²) | 0.3374 | 0.4163 | 0.8975 | 0.9414 | 0.4161 | 0.7719 |
| <i>Panel C: GPD</i> | | | | | | |
| $\hat{\xi}$ | 0.5043*** (0.0043) | 0.5378*** (0.0088) | 0.5445*** (0.0152) | 0.5013*** (0.0887) | 0.5224*** (0.1006) | 0.5805*** (0.0943) |
| $\hat{\zeta}$ | 0.0859*** (0.0119) | 0.0991** (0.0229) | 0.0426*** (0.0033) | 0.0201*** (0.0085) | 0.0800*** (0.0244) | 0.0132*** (0.0068) |

Notes: The values in parentheses correspond to the standard deviation of the estimated coefficient. The result of the Jarque-Bera test corresponds to the already calculated p -value. The Ljung-Box test was done for the residues (res) and residues squared (res²) of the AR(1)-GARCH(1,1) model. The results of the Ljung-Box tests correspond to the calculated p -value. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

serial autocorrelation. Accordingly, the indication that the residuals are independent and identically distributed expresses the fundamental conditions needed for the adjustment that was made based on the EVT using the GPD, the estimated coefficients of which were all significant. These results, therefore, are important in this study since the significance of the impact of extreme rainfall on the respective return of the stocks was carried out based on the VaRs estimated using the methodology presented.

Bearing in mind the aim to identify the impact of extreme rainfall and its magnitude using the methodology presented, we calculated the VaRs (with confidence intervals of 90, 95 and 99%) for the day after the extreme event[5]. At the three levels of confidence and for each sub-sample (500, 750 and 1,000 observations) we used, the estimated VaR was stable, as also reported in Karmakar (2013). Using each VaR estimate we found, we analysed the log-returns on the day following the extreme rainfall and compared them with the respective predicted VaR. When the negative log-returns were greater in module than the estimated VaR, we considered that the extreme events have a significant impact on the return on stocks (Chesney *et al.*, 2011).

To identify those extreme events that were considered significant, we re-estimated the AR-GARCH-GPD model every day. Therefore, we have a different VaR model for each extreme event in each sub-sample (500, 750 and 1,000 observations) and for each level of confidence (90, 95 and 99%). We adjusted 1,782 models for the subsequent estimation of the associated VaR, the individual results of which are not shown in this study.

Here we only show the results for the 95% level of confidence for the 1,000 observation sub-sample, as these specifications are the best fit for the VaR for the whole sample using the Kupiec test. In this respect, the methodology most widely used in the back testing literature for the VaR analyses the series of violations of the estimated VaR; in other words, those days on which the loss incurred was greater than the estimated VaR using the risk model. The probability of VaR violation at the p significance level will be equal to p , so if the model is correctly specified, the series of violations will be independently and identically distributed using the Bernoulli distribution with parameter p . The total number of violations will, therefore, follow a binomial distribution (Chesney *et al.*, 2011). Kupiec (1995) developed a widely known test based on this number of violations, which statistically identifies whether the number of violations is consistent with the significance level of the estimated VaR; in other words, it tests the null hypothesis that the model correctly estimates the quantile of the distribution being analysed.

Table IV shows that the VaR was correctly estimated at a 95% confidence level, considering 10 per cent significance for all companies analysed. We see, therefore, that the estimated VaR was correctly specified using the AR(1)-GARCH(1,1)-GPD (Ergün and Jun, 2010; Huang *et al.*, 2014) model for the six stocks we analysed because, based on the Kupiec test and considering a mobile window with 1,000 observations, the number of violations was not significant at the 1 per cent level.

By considering the specified models correctly, we have the final results that are reported in Table V. These show that in the period analysed (between 18 April 2011 and 30 December 2014), there were 42 days with extreme rainfall in the main region in which JBS operates. Of this total and from the methodology we developed, we found that 22 occurrences (52.38 per cent of the total) had a significant impact on the return on the stock, the average loss of which was 2.59 per cent on the day following the extreme event. As a result, JBS lost approximately \$322m of its market value, on average, because of extreme rainfall.

We also see that the number of days with extreme rainfall in absolute terms was less for BRF (17 events), since the interval of time considered when analysing it was less than for the others. In relative terms, however, approximately 76.5 per cent of the days with extreme rainfall had a significant impact on the return on BRF's stock[6]. The size of the impact due to extreme rainfall is the smallest of the six stocks analysed (average daily loss of 0.66 per cent). BRF shows that it is concerned with climate change in its financial statements, but it

| | Window extension | | | Window extension | | | |
|--------------------|------------------|--------|--------|--------------------|--------|--------|--------|
| RNAR3 | 1,000 | 750 | 500 | SLCE3 | 1,000 | 750 | 500 |
| VaR _{95%} | 112 | 127 | 144** | VaR _{95%} | 95 | 101 | 105 |
| <i>p</i> -value | 0.3929 | 0.5819 | 0.0374 | <i>p</i> -value | 0.8580 | 0.4193 | 0.2222 |
| VaR _{99%} | 26 | 31 | 39** | VaR _{99%} | 20 | 19 | 29** |
| <i>p</i> -value | 0.7179 | 0.1833 | 0.0055 | <i>p</i> -value | 0.7641 | 0.9372 | 0.0260 |
| VAGR3 | 1,000 | 750 | 500 | BEEF3 | 1,000 | 750 | 500 |
| VaR _{95%} | 107 | 112 | 128*** | VaR _{95%} | 81 | 121*** | 132*** |
| <i>p</i> -value | 0.4903 | 0.2350 | 0.0062 | <i>p</i> -value | 0.2269 | 0.0031 | 0.0001 |
| VaR _{99%} | 27 | 24 | 44*** | VaR _{99%} | 33*** | 39*** | 58*** |
| <i>p</i> -value | 0.1380 | 0.3885 | 0.0001 | <i>p</i> -value | 0.0021 | 0.0001 | 0.0001 |
| BRFS3 | 1,000 | 750 | 500 | JBSS3 | 1,000 | 750 | 500 |
| VaR _{95%} | 78 | 92*** | 113*** | VaR _{95%} | 105 | 162*** | 132*** |
| <i>p</i> -value | 0.3078 | 0.0083 | 0.0001 | <i>p</i> -value | 0.3509 | 0.0001 | 0.0003 |
| VaR _{99%} | 19 | 25*** | 41*** | VaR _{99%} | 29** | 49*** | 42*** |
| <i>p</i> -value | 0.1936 | 0.0072 | 0.0001 | <i>p</i> -value | 0.0365 | 0.0001 | 0.0001 |

Notes: The values corresponding to the VaR correspond to the number of violations occurred in the VaR estimated by the AR(1)–GARCH(1,1)–GPD model. Below each VaR has the respective *p*-value in parentheses calculated by the Kupiec test for 95 and 99% confidence. Window size (500, 750 and 1,000 observations) refers to the number of observations used in the moving window to estimate the above model and subsequent VaR estimate. **p* < 0.1; ***p* < 0.05; ****p* < 0.01

Table IV.
Number of VaR violations and kupiec test

| | Stocks | | | | | |
|------------------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| | RNAR3 | SLCE3 | VAGR3 | BEEF3 | BRFS3 | JBSS3 |
| Initial date ^a | 1 April 2009 | 5 July 2011 | 4 January 2011 | 6 August 2011 | 6 June 2013 | 18 April 2011 |
| Final date ^b | 30 December 2014 | 30 December 2014 | 30 December 2014 | 30 December 2014 | 30 December 2014 | 30 December 2014 |
| No. of extreme events ^c | 41 | 44 | 18 | 36 | 17 | 42 |
| No. of impacts ^d | 15 | 23 | 10 | 20 | 13 | 22 |
| % Impact ^e | 36.59 | 52.27 | 55.56 | 55.56 | 76.47 | 52.38 |
| Magnitude ^f (%) | 3.41 | 1.49 | 1.70 | 1.99 | 0.66 | 2.59 |

Notes: Estimated model for 1,000 observations with a 95% confidence level. ^aThe initial analysis date for checking extreme rainfall was considered to start 1,000 days after the first log-return observed for each share. This is to enable an initial sample of up to 1,000 observations for estimating the VaR; ^blast day of observations; ^cnumber of days on which extreme rainfall occurred in the period analysed; ^dnumber of days on which there was a significant impact; ^enumber of days (in percentages) with impacts considered to be significant; ^faverage daily loss calculated for the days on which there were significant impacts

Table V.
Impact of extreme rainfall on stock prices

holds no positions in weather derivatives. The company only has a hedge against the price of agricultural commodities, since the main inputs of its production originate from grains, soybeans and corn (BM&FBovespa, 2015b). By way of illustration, we give an example of an observation in which extreme rainfall caused a significant impact; on 12 February 2014, 60 mm of rain fell in the main region where BRF operates.

The VaR_{99%} was estimated at 0.58 per cent for 13 February 2014, but the loss on BRF's stock on 13 February 2014 was 0.6255 per cent, which represents a loss of approximately \$131m of its market value. We know that this loss may be linked to other factors, but if the negative return on the stock exceeds the VaR on various occasions when there is extreme rainfall, this provides evidence that this event is having an impact on stock price. JBS, which is in the same sub-sector as BRF, had approximately 52.4 per cent significant impacts on its

returns in the period analysed and a sizeable expected loss of 2.59 per cent on the day after the extreme rain event[7].

Despite BRF and JBS being from the same sub-sector, the impacts arising from extreme rainfall and its effects proved to be different in terms of their stock returns. This may be due to different factors, such as: the companies operate in different regions, the different intervals of time being analysed (Trombley, 1997) and the types of investors in these companies' stocks (Levy and Galili, 2008). This analysis is supported by Keef and Roush (2002), who stated that weather impact depends on the specific region in which each company operates.

Given these results and since the stocks of BRF and JBS represent a significant proportion of the total market value of the IBOVESPA (around 6.5 per cent in April 2015), this information may become relevant to investors in the stock market. To minimise risk arising from extreme rainfall, investors could structure a portfolio of investments with stocks that have positive correlations with extreme rainfall in order to hedge their positions, in a way similar to that proposed by Chesney *et al.* (2011). As a form of hedge, the authors suggested holding portfolios that contain banking sector stocks (in the 25 countries analysed), which showed a negative significance due to the risk of terrorism.

Minerva experienced approximately 55.6 per cent days of extreme rainfall that had an impact on their returns; in other words, more than half the days with rainfall in excess of 50 mm had a negative impact on the financial return of their stock. SLC Agrícola and Vanguarda Agro suffered around 54 per cent significant impacts and expected losses were close to 1.5 per cent on the day after the extreme rainfall. As these two companies focus more on producing agricultural commodities (cotton, soybeans and corn), rain can lead to delays in harvesting, or even affect the quality of the grains (BM&FBovespa, 2015c; Embrapa, 2015). The apple producer, Renar Maçãs, suffered a significant extreme rainfall-related impact, but one that was, nevertheless, less significant (around 36.5 per cent) than for the other companies analysed. The size of the expected loss impact (3.41 per cent), however, was the biggest of the six stocks analysed. As its production is concentrated in a single city, the company is the most vulnerable to rainfall (Sietz *et al.*, 2012).

Since the periods assessed are different for each stock and company locations are different, the impacts of extreme rainfall on the stocks we analysed vary. These findings are in line with those of Vermeulen *et al.* (2012), who found that the impact of climate change on the food system tends to be temporally and geographically variable around the world. Based on these results, we can state that there is evidence that the occurrence of extreme rainfall has a significant impact on the stocks of Brazilian food companies. The impact is not irrelevant: the daily average size of loss of the stocks analysed was 1.97 per cent, which in terms of market worth, represents an average loss of approximately \$682.15m in a single day for just six companies.

In order to verify the magnitude of the possible losses close to $VaR_{99\%}$, $ES_{97.5\%}$ was estimated using the definition presented in Equation (5). The results obtained are presented in Table VI.

According to results reported in Table VI, for each of the six stocks, the $ES_{97.5\%}$ was relatively higher than the $VaR_{99\%}$. This difference was not so significant, indicating that the VaR is a good measure to estimate the risk assessed, since $ES_{97.5\%}$ estimates the expected

| | Stocks | | | | | |
|---------------|-----------|-----------|-----------|-----------|-----------|-----------|
| | RNAR3 (%) | SLCE3 (%) | VAGR3 (%) | BEEF3 (%) | BRFS3 (%) | JBSS3 (%) |
| $VaR_{99\%}$ | 3.82 | 2.11 | 2.25 | 2.54 | 1.10 | 3.02 |
| $ES_{97.5\%}$ | 4.03 | 2.87 | 2.98 | 3.04 | 1.83 | 3.95 |

Note: Estimated model for 1,000 observations with a $VaR_{99\%}$ and $ES_{97.5\%}$

Table VI.
 $VaR_{99\%}$ and $ES_{97.5\%}$

value of the worst losses above the respective $\text{VaR}_{97.5\%}$. Compared to $\text{VaR}_{99\%}$, expected losses around $\text{VaR}_{99\%}$ are estimated.

Murphy *et al.* (2012) stressed the importance of using weather risk management instruments in Latin America, where they are only just being implemented. Since the companies analysed had no positions in weather derivatives, the results of this work corroborate Murphy *et al.* (2012), showing how important it is for companies in the food sector in Brazil to use rain derivatives as a way of controlling risks arising from extreme rainfall.

5. Concluding remarks

The main source of uncertainty in agricultural production is the weather (Musshoff *et al.*, 2011). Food production, which is part of daily life, is threatened by a series of factors, among them extreme weather events (World Bank, 2015b). Assessment studies of extreme risks associated with the food industry are, as a result, important for the appropriate management of these companies. Food security is, moreover, an important subject for food industry firms, portfolio managers, governments, and, in particular, society (World Bank, 2014). The aim of this paper was to study the impact of extreme weather events on companies involved in the food industry in Brazil, a country that is a major global player in this sector.

We analysed the stocks of six companies in the Brazilian food sector listed on the Brazilian stock exchange. To do so, we first adjusted the log-returns of the individual financial series of the stocks using AR(1)-GARCH(1,1) models. We then used the innovations generated by the models and the EVT to estimate the VaR when the rainfall is extreme. If the negative return of the company (in absolute amounts) on the day immediately following extreme rainfall is lower than the VaR, we can say that extreme rainfall had a significant impact on the return on the stock. Since we use the parametric approach in the EVT with the hypothesis that tail distributions follow the GPD, we can state that we use AR-GARCH-GPD models.

The results indicate that for five of the six stocks analysed, over 50 per cent of the extreme rainfall events had a significant impact on returns on their stocks. Significant extreme impacts reached 36.59 per cent with the remaining company, although the size of the loss on the day following the extreme rainfall event was the biggest (3.41 per cent) among the companies analysed. We conclude, therefore, that the Brazilian food industry is significantly affected by extreme rainfall. These results are important in terms of encouraging good governance in Brazilian companies so they consider weather derivatives (Sullivan and Gouldson, 2017). The results also provide support for encouraging the Brazilian stock exchange in creating and offering rainfall derivative contracts, which are already offered in the USA, as Cabrera *et al.* (2013) pointed out.

Using ES to assess the sensitivity of the VaR to the magnitude of the losses around ES, the results were found to be relatively close, suggesting that the VaR is a good measure for the evaluation of extreme rainfall risk.

There are limitations in this research that should be recorded, among which the fact that other climate variables could be analysed, such as the impact of rainfall on other sectors of the economy (Hoekstra, 2014). The number of companies used in this study (six) is another limiting factor and several other tools and methodologies could be employed to assess the extreme rainfall risk (Chesney *et al.*, 2011). Comparisons of the suitability of these models could be developed, and multivariate models could be used to estimate the VaR, as pointed out by Santos *et al.* (2013).

Future research in this field should consider using a larger number of companies, drought data, information from other sectors in the Brazilian economy and other emerging economies so that sectoral comparisons can be developed and analysed given the changes brought about by extreme climate events globally. We also believe that considering a firm's idiosyncratic aspects may lead to further analysis of the impact of weather events on stock prices. Such aspects include governance and the nature of ownership.

Notes

1. Between 2000 and 2014 the Brazilian agribusiness trade balance grew by around 468 per cent. Of the over \$500bn net that was generated in this period, more than \$80bn was generated in 2014 alone (CEPEA, 2015).
2. INMET – Brazilian Meteorology Institute.
3. GPD is the acronym for generalised Pareto distribution. Gnedenko (1943) showed that the tails of a great spectrum of probability distributions stock common properties: tail distributions converge on the generalised Pareto distribution when the initial quantile of the tail increases.
4. Saunders (1993) had already pointed to a systematic effect of local weather conditions on the price of stocks traded on the NYSE.
5. We considered the day after the event (not the day itself) since we do not know the time the rain occurred on the day. The accumulated rainfall may have occurred after the stock exchange closed, for example, or at isolated moments during the day.
6. This result is relevant since this company is one of the biggest in the country. The participation of the BRF stock in the Brazilian stock exchange's most important index, IBOVESPA, is 3.47 per cent (April 2015 value; see BM&FBovespa, 2015a).
7. JBS had a 3.02 per cent participation in IBOVESPA in April 2015.

References

- Akhtari, M. (2011), "Reassessment of the weather effect: stock prices and wall street weather", *Undergraduate Economic Review*, Vol. 7 No. 1, pp. 51-70.
- Bali, T.G., Mo, H. and Tang, Y. (2008), "The role of autoregressive conditional skewness and kurtosis in the estimation of conditional var", *Journal of Banking & Finance*, Vol. 32 No. 2, pp. 269-282.
- BDMEP (2015), "Banco de dados meteorológicos para ensino e pesquisa do inmet", January, available at: www.inmet.gov.br/portal/index.php?r=bdmep/bdmep (accessed 5 January 2015).
- Bergmann, A., Stechemesser, K. and Guenther, E. (2016), "Natural resource dependence theory: impact of extreme weather events on organizations", *Journal of Business Research*, Vol. 69 No. 4, pp. 1361-1366.
- BM&FBovespa (2015a), "Bm&fbovespa a nova bolsa", April, available at: www.bmfbovespa.com.br/ (accessed 10 April 2015).
- BM&FBovespa (2015b), "Bm&fbovespa a nova bolsa", August, available at: [www.bmfbovespa.com.br/](http://www.bmfbovespa.com.br/shared/iframe) shared/iframe (accessed 25 August 2015).
- BM&FBovespa (2015c), "Bm&fbovespa a nova bolsa", May, available at: [www.bmfbovespa.com.br/](http://www.bmfbovespa.com.br/cias-listadas/empresaslistadas/Resumo Empresa Principal) cias-listadas/empresaslistadas/Resumo Empresa Principal (accessed 2 May 2015).
- Boonen, T.J. (2017), "Solvency II solvency capital requirement for life insurance companies based on expected shortfall", *European Actuarial Journal*, Vol. 7 No. 2, pp. 405-434.
- Bush, R. (2010), "Food riots: poverty, power and protest", *Journal of Agrarian Change*, Vol. 10 No. 1, pp. 119-129.
- Cabrera, B.L., Odening, M. and Ritter, M. (2013), "Pricing rainfall futures at the CME", *Journal of Banking & Finance*, Vol. 37 No. 11, pp. 4286-4298.
- Cao, M. and Wei, J. (2005), "Stock market returns: a note on temperature anomaly", *Journal of Banking & Finance*, Vol. 29 No. 6, pp. 1559-1573.
- CEPEA (2015), "Centro de estudos avançados em economia aplicada", February, available at: [http://](http://cepea.esalq.usp.br) cepea.esalq.usp.br (accessed 12 February 2015).

- Challinor, A., Wheeler, T., Garforth, C., Craufurd, P. and Kassam, A. (2007), "Assessing the vulnerability of food crop systems in Africa to climate change", *Climatic Change*, Vol. 83 No. 3, pp. 381-399.
- Chang, S.-C., Chen, S.-S., Chou, R.K. and Lin, Y.-H. (2008), "Weather and intraday patterns in stock returns and trading activity", *Journal of Banking & Finance*, Vol. 32 No. 9, pp. 1754-1766.
- Chang, T., Nieh, C.-C., Yang, M. J. and Yang, T.-Y. (2008), "Are stock markets returns related to the weather effects? Empirical evidence from Taiwan", *Physica A: Statistical Mechanisms and its Applications*, Vol. 364, pp. 343-354.
- Chavez-Demoulin, V. (1999), "Bayesian inference for small-sample capture-recapture data", *Biometrics*, Vol. 55, pp. 727-731, doi: 10.1111/j.0006-341X.1999.00727.x.
- Chavez-Demoulin, V. and Embrechts, P. (2004), "Smooth extremal models in finance and insurance", *Journal of Risk and Insurance*, Vol. 71 No. 2, pp. 183-199.
- Chavez-Demoulin, V., Embrechts, P. and Hofert, M. (2016), "An extreme value approach for modeling operational risk losses depending on covariates", *Journal of Risk and Insurance*, Vol. 83 No. 3, pp. 735-776.
- Chavez-Demoulin, V., Embrechts, P. and Sardy, S. (2014), "Extreme-quantile tracking for financial time series", *Journal of Econometrics*, Vol. 181 No. 1, pp. 44-52.
- Chesney, M., Reshetar, G. and Karaman, M. (2011), "The impact of terrorism on financial markets: an empirical study", *Journal of Banking & Finance*, Vol. 35 No. 2, pp. 253-267.
- Cornaggia, J. (2013), "Does risk management matter? Evidence from the US agricultural industry", *Journal of Financial Economics*, Vol. 109 No. 2, pp. 419-440.
- Cutler, D.M., Poterba, J.M. and Summers, L.H. (1989), "What moves stock prices?", *The Journal of Portfolio Management*, Vol. 15 No. 3, pp. 4-12.
- Danielsson, J., James, K.R., Valenzuela, M. and Zer, I. (2016), "Model risk of risk models", *Journal of Financial Stability*, Vol. 23, pp. 79-91, available at: <https://doi.org/10.1016/j.jfs.2016.02.002>
- Davison, A.C. and Smith, R.L. (1990), "Models for exceedances over high thresholds", *Journal of the Royal Statistical Society; Series B (Methodological)*, Vol. 52 No. 3, pp. 393-442.
- Defeo, O., Castrejón, M., Ortega, L., Kuhn, A.M., Gutiérrez, N.L. and Castilla, J.C. (2013), "Impacts of climate variability on Latin American small-scale fisheries", *Ecology and Society*, Vol. 18 No. 4, p. 30, available at: <http://dx.doi.org/10.5751/ES-05971-180430>
- Degiannakis, S. and Potamia, A. (2017), "Multiple-days-ahead value-at-risk and expected shortfall forecasting for stock indices, commodities and exchange rates: inter-day versus intra-day data", *International Review of Financial Analysis*, Vol. 49, pp. 176-190.
- Del Brio, E.B., Mora-Valencia, A. and Perote, J. (2014), "VaR performance during the subprime and sovereign debt crises: an application to emerging markets", *Emerging Markets Review*, Vol. 20, pp. 23-41.
- Di Bernardino, E. and Palacios-Rodríguez, F. (2017), "Estimation of extreme component-wise excess design realization: a hydrological application", *Stochastic Environmental Research and Risk Assessment*, Vol. 31 No. 10, pp. 2675-2689.
- Embrapa (2015), "Empresa brasileira de pesquisa agropecuária", May, available at: www.embrapa.br/publicacoes (accessed 25 April 2019).
- Embrechts, P., Klüppelberg, C. and Mikosch, T. (1997), *Modelling Extremal Events*, Vol. 33, Springer Science & Business Media, New York, NY.
- Ergün, A.T. and Jun, J. (2010), "Time-varying higher-order conditional moments and forecasting intraday VaR and expected shortfall", *The Quarterly Review of Economics and Finance*, Vol. 50 No. 3, pp. 264-272.
- Ghosh, J. (2010), "The unnatural coupling: food and global finance", *Journal of Agrarian Change*, Vol. 10 No. 1, pp. 72-86.

- Giles, D.E., Feng, H. and Godwin, R.T. (2016), "Bias-corrected maximum likelihood estimation of the parameters of the generalized Pareto distribution", *Communications in Statistics – Theory and Methods*, Vol. 45 No. 8, pp. 2465-2483.
- Gnedenko, B.V. (1943), "Sur la distribution limite du terme maximum d'une série aléatoire", *Annals of Mathematics*, Vol. 44 No. 3, pp. 423-453.
- Hirshleifer, D. and Shumway, T. (2003), "Good day sunshine: stock returns and the weather", *The Journal of Finance*, Vol. 58 No. 3, pp. 1009-1032.
- Hoekstra, A.Y. (2014), "Water scarcity challenges to business", *Nature Climate Change*, Vol. 4 No. 5, pp. 318-320.
- Huang, C.-K., Huang, C.-S. and Chikobvu, D. (2014), "Extreme risk, value-at-risk and expected shortfall in the gold market", *International Business & Economics Research Journal*, Vol. 14 No. 1, pp. 107-122.
- Iglesias, A., Rosenzweig, C. and Pereira, D. (2000), "Agricultural impacts of climate change in Spain: developing tools for a spatial analysis", *Global Environmental Change*, Vol. 10 No. 1, pp. 69-80.
- Jones, P.G. and Thornton, P.K. (2003), "The potential impacts of climate change on maize production in Africa and Latin America in 2055", *Global Environmental Change*, Vol. 13 No. 1, pp. 51-59.
- Kang, S.H., Jiang, Z., Lee, Y. and Yoon, S.-M. (2010), "Weather effects on the returns and volatility of the Shanghai stock market", *Physica A: Statistical Mechanics and its Applications*, Vol. 389 No. 1, pp. 91-99.
- Karmakar, M. (2013), "Estimation of tail-related risk measures in the Indian stock market: an extreme value approach", *Review of Financial Economics*, Vol. 22 No. 3, pp. 79-85.
- Keef, S.P. and Roush, M.L. (2002), "The weather and stock returns in New Zealand", *Quarterly Journal of Business and Economics*, Vol. 41 Nos 1-2, pp. 61-79.
- Kellner, R. and Rösch, D. (2016), "Quantifying market risk with value-at-risk or expected shortfall? – consequences for capital requirements and model risk", *Journal of Economic Dynamics and Control*, Vol. 68, pp. 45-63, available at: <https://doi.org/10.1016/j.jedc.2016.05.002>
- Kim, J.H. and Kim, J. (2015), "A parametric alternative to the hill estimator for heavy-tailed distributions", *Journal of Banking & Finance*, Vol. 54, pp. 60-71, available at: <https://doi.org/10.1016/j.jbankfin.2014.12.020>
- Kuester, K., Mittnik, S. and Paoletta, M.S. (2006), "Value-at-risk prediction: a comparison of alternative strategies", *Journal of Financial Econometrics*, Vol. 4 No. 1, pp. 53-89.
- Kumar, D. (2017), "A study of risk spillover in the crude oil and the natural gas markets", *Global Business Review*, Vol. 18 No. 6, pp. 1465-1477.
- Kupiec, P.H. (1995), "Techniques for verifying the accuracy of risk measurement models", *The Journal of Derivatives*, Vol. 3 No. 2, pp. 73-84.
- Levy, O. and Galili, I. (2008), "Stock purchase and the weather: individual differences", *Journal of Economic Behavior & Organization*, Vol. 67 No. 3, pp. 755-767.
- Li, F. and Perez-Saiz, H. (2018), "Measuring systemic risk across financial market infrastructures", *Journal of Financial Stability*, Vol. 34, pp. 1-11, available at: <https://doi.org/10.1016/j.jfs.2017.08.003>
- Lima, S.R., Nascimento, F.F.D. and Ferraz, V.R.D.S. (2018), "Regression models for time-varying extremes", *Journal of Statistical Computation and Simulation*, Vol. 88 No. 2, pp. 235-249.
- Longin, F. (2005), "The choice of the distribution of asset returns: how extreme value theory can help?", *Journal of Banking & Finance*, Vol. 29 No. 4, pp. 1017-1035.
- Longin, F. and Solnik, B. (2001), "Extreme correlation of international equity markets", *Journal of Finance*, Vol. 56 No. 2, pp. 649-676.

- Longin, F.M. (1996), "The asymptotic distribution of extreme stock market returns", *Journal of Business*, Vol. 69 No. 3, pp. 383-408.
- Longin, F.M. (2000), "From value at risk to stress testing: the extreme value approach", *Journal of Banking and Finance*, Vol. 24 No. 7, pp. 1097-1130.
- McNeil, A.J. and Frey, R. (2000a), "Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach", *Journal of Empirical Finance*, Vol. 7 No. 3, pp. 271-300.
- McNeil, A.J. and Frey, R. (2000b), "Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach", *Journal of Empirical Finance*, Vol. 7 Nos 3-4, pp. 271-300.
- Ma, Z., Ma, C. and Xiao, S. (2017), "Pricing zero-coupon catastrophe bonds using EVT with doubly stochastic poisson arrivals", *Discrete Dynamics in Nature and Society*, Vol. 2017, 14pp, available at: <https://doi.org/10.1155/2017/3279647>
- Marengo, J., Jones, R., Alves, L. and Valverde, M. (2009), "Future change of temperature and precipitation extremes in South America as derived from the prices regional climate modeling system", *International Journal of Climatology*, Vol. 29 No. 15, pp. 2241-2255.
- Martins-Filho, C., Yao, F. and Torero, M. (2018), "Nonparametric estimation of conditional value-at-risk and expected shortfall based on extreme value theory", *Econometric Theory*, Vol. 34 No. 1, pp. 23-67.
- Mendes, B. (2000), "Computing robust risk measures in emerging equity markets using extreme value theory", *Emerging Markets Quarterly*, Vol. 4 No. 2, pp. 25-41.
- Müller, F.M. and Righi, M.B. (2018), "Numerical comparison of multivariate models to forecasting risk measures", *Risk Management*, Vol. 20 No. 1, pp. 29-50.
- Muniz, S., de Assis, J.M.O. and de Souza, W.M. (2014), "Tendências de mudanças climáticas na bacia do rio una, pernambuco – brasil (trends of climate change on the Una River Basin, Pernambuco – Brazil)", *Revista Brasileira de Geografia Física*, Vol. 7 No. 2, pp. 243-257.
- Murphy, A.G., Hartell, J., Cárdenas, V. and Skees, J.R. (2012), *Risk Management Instruments for Food Price Volatility and Weather Risk in Latin America and the Caribbean: The Use of Risk Management Instruments (Tech. Rep.)*, Inter-American Development Bank, New York, NY.
- Musshoff, O., Odening, M. and Xu, W. (2011), "Management of climate risks in agriculture – will weather derivatives permeate?", *Applied Economics*, Vol. 43 No. 9, pp. 1067-1077.
- Parry, M., Rosenzweig, C., Iglesias, A., Fischer, G. and Livermore, M. (1999), "Climate change and world food security: a new assessment", *Global Environmental Change*, Vol. 9 No. S1, pp. S51-S67.
- Pérez, F. and Yun, H. (2013), "Risk management and firm value: evidence from weather derivatives", *The Journal of Finance*, Vol. 68 No. 5, pp. 2143-2176.
- Poon, S.H., Rockinger, M. and Tawn, J. (2004), "Extreme value dependence in financial markets: diagnostics, models, and financial implications", *Review of Financial Studies*, Vol. 17 No. 2, pp. 581-610.
- Prodan, I. (2013), *The Effect of Weather on Stock Returns: A Comparison between Emerging and Developed Markets*, Anchor Academic Publishing (aap_verlag), New York, NY.
- Rockafellar, R.T. and Uryasev, S. (2002), "Conditional value-at-risk for general loss distribution", *Journal of Banking & Finance*, Vol. 26 No. 7, pp. 1443-1471, available at: [https://doi.org/10.1016/S0378-4266\(02\)00271-6](https://doi.org/10.1016/S0378-4266(02)00271-6)
- Rosenzweig, C., Iglesias, A., Yang, X., Epstein, P.R. and Chivian, E. (2001), "Climate change and extreme weather events: implications for food production, plant diseases, and pests", *Global change & Human Health*, Vol. 2 No. 2, pp. 90-104.
- Santos, A.A., Nogales, F.J. and Ruiz, E. (2013), "Comparing univariate and multivariate models to forecast portfolio value-at-risk", *Journal of Financial Econometrics*, Vol. 11 No. 2, pp. 400-441.

- Saunders, E.M. Jr. (1993), "Stock prices and wall street weather", *The American Economic Review*, Vol. 83 No. 5, pp. 1337-1345.
- Scarrott, C. and MacDonald, A. (2012), "A review of extreme value threshold estimation and uncertainty quantification", *REVSTAT – Statistical Journal*, Vol. 10 No. 1, pp. 33-60.
- Shu, H. (2008), "Weather, investor sentiment and stock market returns: evidence from Taiwan", *Journal of American Academy of Business*, Vol. 14 No. 1, pp. 96-102.
- Sietz, D., Choque, S.E.M. and Lüdeke, M.K. (2012), "Typical patterns of smallholder vulnerability to weather extremes with regard to food security in the Peruvian Altiplano", *Regional Environmental Change*, Vol. 12 No. 3, pp. 489-505.
- Silva-González, F., Heredia-Zavoni, E. and Inda-Sarmiento, G. (2017), "Square error method for threshold estimation in extreme value analysis of wave heights", *Ocean Engineering*, Vol. 137, pp. 138-150, available at: <https://doi.org/10.1016/j.oceaneng.2017.03.028>
- Smith, R.L. (1987), "Estimating tails of probability distributions", *The Annals of Statistics*, Vol. 15 No. 3, pp. 1174-1207.
- Sullivan, R. and Gouldson, A. (2017), "The governance of corporate responses to climate change: an international comparison", *Business Strategy and the Environment*, Vol. 26, pp. 413-425, available at: <https://doi.org/10.1002/bse.1925>
- Swan, S.H., Hadley, S. and Cichon, B. (2010), "Crisis behind closed doors: global food crisis and local hunger", *Journal of Agrarian Change*, Vol. 10 No. 1, pp. 107-118.
- Symeonidis, L., Daskalakis, G. and Markellos, R.N. (2010), "Does the weather affect stock market volatility?", *Finance Research Letters*, Vol. 7 No. 4, pp. 214-223.
- Taamouti, A. (2009), "Analytical value-at-risk and expected shortfall under regime-switching", *Finance Research Letters*, Vol. 6 No. 3, pp. 138-151.
- Thornton, P.K., Jones, P.G., Alagaraswamy, G., Andresen, J. and Herrero, M. (2010), "Adapting to climate change: agricultural system and household impacts in East Africa", *Agricultural systems*, Vol. 103 No. 2, pp. 73-82.
- Trombley, M.A. (1997), "Stock prices and wall street weather: additional evidence", *Quarterly Journal of Business and Economics*, Vol. 36 No. 3, pp. 11-21.
- Vermeulen, S.J., Campbell, B.M. and Ingram, J.S. (2012), "Climate change and food systems", *Annual Review of Environment and Resources*, Vol. 37 No. 1, pp. 195-222.
- Vörösmarty, C.J., de Guenni, L.B., Wollheim, W.M., Pellerin, B., Bjerklie, D., Cardoso, M. and Colon, L. (2013), "Extreme rainfall, vulnerability and risk: a continental-scale assessment for South America", *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, Vol. 371 No. 2002, pp. 1-17.
- Walter, A. (2007), "As mudanças climáticas e a questão energética", *Revista Multiciência. Campinas. Edição*, Vol. 2007 No. 8, pp. 29-47.
- Wheeler, T. and von Braun, J. (2013), "Climate change impacts on global food security", *Science*, Vol. 341 No. 6145, pp. 508-513.
- World Bank (2014), "World development report 2014: risk and opportunity – managing risk for development", World Bank, New York, NY.
- World Bank (2015b), "Por que o seu almoço está em risco?", World Bank, New York, NY, April, available at: www.worldbank.org/pt/events/2014/11/20/brazil-seminarevaluation-risks-agriculture (accessed 25 April 2019).
- World Economic Forum (2018), "Global risk report 13th edition", World Economic Forum, New York, NY, available at: www3.weforum.org/docs/WEF_GRR18_Report.pdf (accessed 25 April 2019).
- Yang, X., Zhang, J. and Ren, W.X. (2018), "Threshold selection for extreme value estimation of vehicle load effect on bridges", *International Journal of Distributed Sensor Networks*, Vol. 14 No. 2, pp. 1-12.

Yi, Y., Feng, X. and Huang, Z. (2014), "Estimation of extreme value-at-risk: an EVT approach for quantile GARCH model", *Economics Letters*, Vol. 124 No. 3, pp. 378-381.

Zhao, X., Scarrott, C., Oxley, L. and Reale, M. (2010), "Extreme value modelling for forecasting market crisis impacts", *Applied Financial Economics*, Vol. 20 Nos 1-2, pp. 63-72.

Further reading

World Bank (2015a), World Bank, January, New York, NY, available at: <http://data.worldbank.org/country/brazil> (accessed 25 April 2019).

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