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A change-point analysis of food price shocks

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A R T I C L E I N F O

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A B S T R A C T

As the impact of climate change increases it is more likely that we will see an increase of extreme weather events leading to significant food production losses. Therefore, understanding the complexities of how production losses impact on policy (through export or import restrictions) and prices (through markets) is important for the governance of the global food system in the future. In this paper our aim is to understand the variability of food prices utilizing a statistical methodology relating to the detection of extreme values and change points in the decomposed time series of food price indices (change-point analysis). These change points are identified using the FAO total food price index and also the indices for meat, oil, cereal, dairy and sugar. The results of the study highlight for the first time specific change points within these food categories when these changes occur and also the duration of these periods before the next change.

1. Introduction

When one country experiences a food production shock – through disease, drought, flooding, hail damage or wind – there is an expectation that global food trade will fill the gap. However, if the production shock is large enough then it can lead to a commensurate impact on global food prices (Jones and Hiller, 2015). At the same time pressure on natural ecosystems through expansion and intensification of agriculture, alongside climate change, may lead to critical instabilities in the food production system. If these instabilities resulted in a significant production shortfall in a given year there may be a consequent impact on global food prices.

Between the middle of 2007 and 2008 crop failures caused by drought and low levels of global stocks (Piesse and Thirtle, 2009; Wright, 2009) led to a more than doubling of the price of major crops (wheat, maize, soybeans and rice) on international markets. For many developed countries the increase in price was easily absorbed and had little impact on food availability. For developing countries, some domestic prices increased dramatically. This increase in price, alongside a loss of income for some farmers, trigged protests and, when governments responded with violence, the outbreak of civil unrest (Natalini et al., 2015).

While there was strong evidence of low stocks and regional production losses contributing to the 2007/08 price shock there is less certainty over the impact of speculation, currency exchange rates (Headey and Fan, 2008), changes to export policies impacting supply (Martin and Anderson, 2012), or policies related to biofuels (Roberts and Tran, 2013). However, as the impact of climate change increases it is likely that we will see more extreme weather events leading to significant food production losses as has been observed over the last decade (Cramer et al., 2014). Therefore, understanding the complexities of how production losses impact on policy (through export or import restrictions) and prices (through markets) is important for the governance of the global food system in the future (Jones and Hiller, 2015). However, current models are often general equilibrium models, which by their very nature cannot explore shocks (Challinor et al., 2016), although scenarios have been used in some cases (Nelson et al., 2010; Lunt et al.,

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2016).

When attempting to understand how production shocks impact on global food prices it is important to note that there is even uncertainty about what constitutes a price shock (Piesse and Thirtle, 2009) or production shock (Jones and Phillips, 2016). The purpose of this paper is to examine the variability and trends of world food prices. In doing this, we apply econometric analysis on data available between 1990 and 2019. In particular the study investigates trend and change point detection of monthly food price indices related to meat (MPI), dairy (DPI), cereals (CPI), oils (OPI) sugar (SPI) as these are publicly available at the FAO database. Our aim is to understand the variability of food prices utilizing a statistical methodology relating to the detection of extreme values and change points in the decomposed time series of food price indices (change-point analysis). This analysis allows us to statistically identify historic price shocks, which can then be compared to production losses or other impacts on the food system and explore causal relationships.

In this context a variety of methods have been developed for time-series forecasting. In particular, a number of variations of the ARIMA (autoregressive integrated moving average) model (Box et al., 2015) are typically employed, such as the SARIMA (seasonal ARIMA) (Swain et al., 2018) which is most suitable when seasonal effects are present, or the Holt–Winters method (Winters, 1960) which is also very popular by using exponential smoothing. Another alternative is the state space model (Durbin and Koopman, 2012). However, assumptions, such as the one of stationarity, are dominant for analyzing time series real data, such as world food prices. Modeling non-stationary processes using stationary methods is likely to result in crude approximations (Mercurio and Spokoiny, 2004; Korkas and Fryzlewicz, 2017). ARIMA (and related) models work on the assumption of stationarity. If the data generating mechanism is non-stationary, one should find suitable transformation prior to using ARIMA modeling. Transformation typically refers to differencing to some order the original time series, or to subtracting the trend, e.g. through some type of decomposition. Nevertheless, many time series data encountered in real situations are non-stationary and is difficult to find transformation in order to make them stationary. This is the case of the time series of food indices, with non-stationarity being inherent due to large shocks in the prices, being additionally dominated by seasonality. To avoid issues related to the non-stationarity of our data generation process, especially those related to the potential under-estimation of the likelihood of the price shocks and the related change points in the world price values, we do not follow a time-series forecasting procedure, but the main focus is to identify in a valid and robust way the structural changes in the stochastic process that drives the food price indices. In doing this, seasonal decomposition is applied, followed by a change point analysis on the trend series, along with newly proposed trimming methods for the detection of outlying food price values.

2. Methodology

The initial time series data available by FAO are decomposed to trend, seasonality and remaining error. Subsequently, extreme value analysis through the use of suitably chosen confidence intervals on the stationary error series along with applying change point analysis on the decomposed trend lines is utilized to effectively recognize the food production trends and shocks during the 1990–2019 time period.

2.1. Statistical analysis

2.1.1. Time series decomposition

The original monthly time series of the five food price indices, and also the general food price index (FPI), are decomposed in order to obtain a time series free of seasonal variations due to the yearly seasonality inherent in such type of data. Specifically, the six seasonal time series are decomposed into a seasonal component, a long-term trend component, and a remainder (error) which will be subsequently utilized for our further econometric analyses. This approach has been favored instead of applying e.g. a SARIMA modeling approach, since that in this way it is possible to examine both the large shocks in food prices through the decomposed trend series, as well as identify non systematic changes besides large shocks, through the analysis of the error series of the original data.

In doing this, the “Seasonal Decomposition” procedure is applied, which decomposes the series into a seasonal component, a combined trend and cycle component, and an “error” component. The procedure is an implementation of the Census Method I, otherwise known as the ratio-to-moving-average method (McLaughlin, 1984; Makridakis et al., 1983). The long-term trend component consists of variation that is nonstationary and either noncyclic or cyclic. The remainder component is a time series of remainders generated when the summed seasonal and long-term trend components are subtracted from the observed data. Decompositions for our analyses have been performed with the use of the SPSS statistical software (IBM Corp and Released, 2012).

To perform the above, we have hypothesized a multiplicative time series model of the following form:

$$Y_t = T\ C\ S\ I$$

where Y_t is the original time series, T denotes the long trend of the series, C is the cycle component, S the seasonal variation and finally I is the random error. The seasonal component, S, is a factor by which the seasonally adjusted series is multiplied to yield the original series. Observations without seasonal variation will have a seasonal component of 1.

Hence, the Seasonal Decomposition procedure creates four new variables (series), namely the seasonal adjustment series, the smoothed trend series obtained after removing the seasonal variation of a series, the Smoothed trend-cycle series showing the trend and cyclical behavior present in the series and finally, the residual or “error” series, I, which comprises of the values that remain after the seasonal, trend, and cycle components have been removed from the series.

2.1.2. Detection of extreme values – outliers

An outlier is an observation point that is distant from other observations (Maddala, 1992). An outlying observation, or outlier, is one that appears to deviate markedly from other members of the sample in which it occurs (Hodge and Austin, 2004). There are various methods of outlier detection (Barnett and Lewis, 1994; Hodge and Austin, 2004). The two common approaches to exclude outliers are truncation (or trimming) and Winsorising. Trimming discards the outliers resulting in values that are limited above or below a threshold, resulting in a truncated sample. Winsorising replaces the outliers with the nearest “nonsuspect” data.

Detecting outliers by determining an interval spanning over the mean plus/minus a coefficient (e.g., 2, 2.5 or 3) standard deviations remains a common practice. Another popular method is the interquartile method (Rousseeuw and Croux, 1993). However, since both the mean and the standard deviation are particularly sensitive to outliers, this method is reported to be problematic in certain situations (Leys et al., 2013). An additional disadvantage of the method of the mean plus or minus three standard deviations is that the latter is based upon the characteristics of a Gaussian distribution. Also, this specific indicator for detecting outliers suffers from other disadvantages including the strong impact of outliers on the indicator itself, or the problematic behavior in small sample size.

For our research, to effectively overcome issues related to the standard methods for detecting outliers and extreme values in time series data (e.g. by using trimming indicators such as the $\bar{x} \pm 3SD$ and the, $\bar{x} \pm 2SD$ the former being less conservative compared to the latter), we utilize a newly proposed method for detecting outlying values in univariate statistics, namely an indicator based on the Median Absolute Deviation (*MAD*). The measure is calculated based upon the absolute deviation from the median, since the latter is a less sensitive measure of central tendency when compared to the mean. Median is a measure of central tendency which is less sensitive to outliers. The confidence intervals based on *MAD* are given by:

$$M \pm 3 \cdot MAD \text{ or } M \pm 2.5 \cdot MAD$$

according to the suggestions by Leys et al. (2013). The *MAD* in the previous representations is calculated as (Huber, 1981):

$$MAD = b \cdot M_i(|x_i - M_j(x_j)|),$$

where x_i denote the sample observations, and M_j is the median of the series. Finally, b is a constant set to the value of 1.4826. For the current analysis, the *MAD* values were calculated using the R software (R Core Team, 2013).

2.1.3. Detection of change points

Change-point analysis and detection is frequently used and there exist many procedures and algorithms suggested in the relevant literature for performing the latter. Change-point analysis is used in diverse fields such as bioinformatics (Olshen et al., 2004), econometrics (Hansen, 2001) or climate (Reeves et al., 2007).

Among the most popular algorithms proposed for multiple change-point detection is the binary segmentation algorithm (Scott and Knott, 1974; Sen and Srivastava, 1975). In order to detect multiple change points in the decomposed trend series of the food price indices, we apply the binary segmentation algorithm to the six time series. Alongside the application of the former algorithm, the single change point algorithm based on the likelihood is also utilized.

The algorithm is based on the hypothesis testing with null hypothesis being H_0: no changepoint, with alternative hypothesis being H_1: a single changepoint exists. The statistical hypothesis is tested with the use of a likelihood test statistic proposed

$$\lambda = 2(\max_{\tau} ML(\tau) - \log p(y_{1:n}|\widehat{\theta})$$

where *ML (τ)* denotes the log maximum likelihood for a given point, say, τ, which one wants to decide if it is a change point, and $\log p(y_{1:n}|\widehat{\theta})$ is the maximum log-likelihood under the null hypothesis, with *p* the probability density function associated with the distribution of the data and $\hat{\theta}$ being the maximum likelihood estimate of the parameters. Then, if *c* is the threshold for deciding if *c* is a change point, we reject the null hypothesis if $\lambda > c$.

Accordingly, the binary segmentation algorithm for the detection of multiple change points in the series of the data, first applies a single change point test statistic, and if a change point is detected then the data is split into two separate data sets at the point of the located change point. The procedure for change point detection is then applied to the two sets and the iterative process is applied until no new change point is detected by this procedure. For conducting the change-point analyses the R software has been utilized, and specifically the “changepoint” package.

3. Results

3.1. Descriptive analysis

In Fig. 1, the monthly price indices of FPI, MPI, DPI, CPI, OPI and SPI are plotted against time, covering the period between 1990 and 2019. All series are characterized by abnormaly large shocks in certain periods, whereas seasonality is also present. This results in time series being highly non stationary.

As revealed by the monthly plots in certain categories there are some years which have consistently higher prices. In the *sugar price index* the highest prices were presented in 2011 and especially during January, February and July (420.2, 418.2, 400.4 respectively) with the 19 highest prices observed during the 2-year period 2010–2011. In the *cereals price index,* 2008 has been the year with the highest prices (in 2008 there were 4 top prices, months June, March, April and February). The *Meat Price Index* is also more

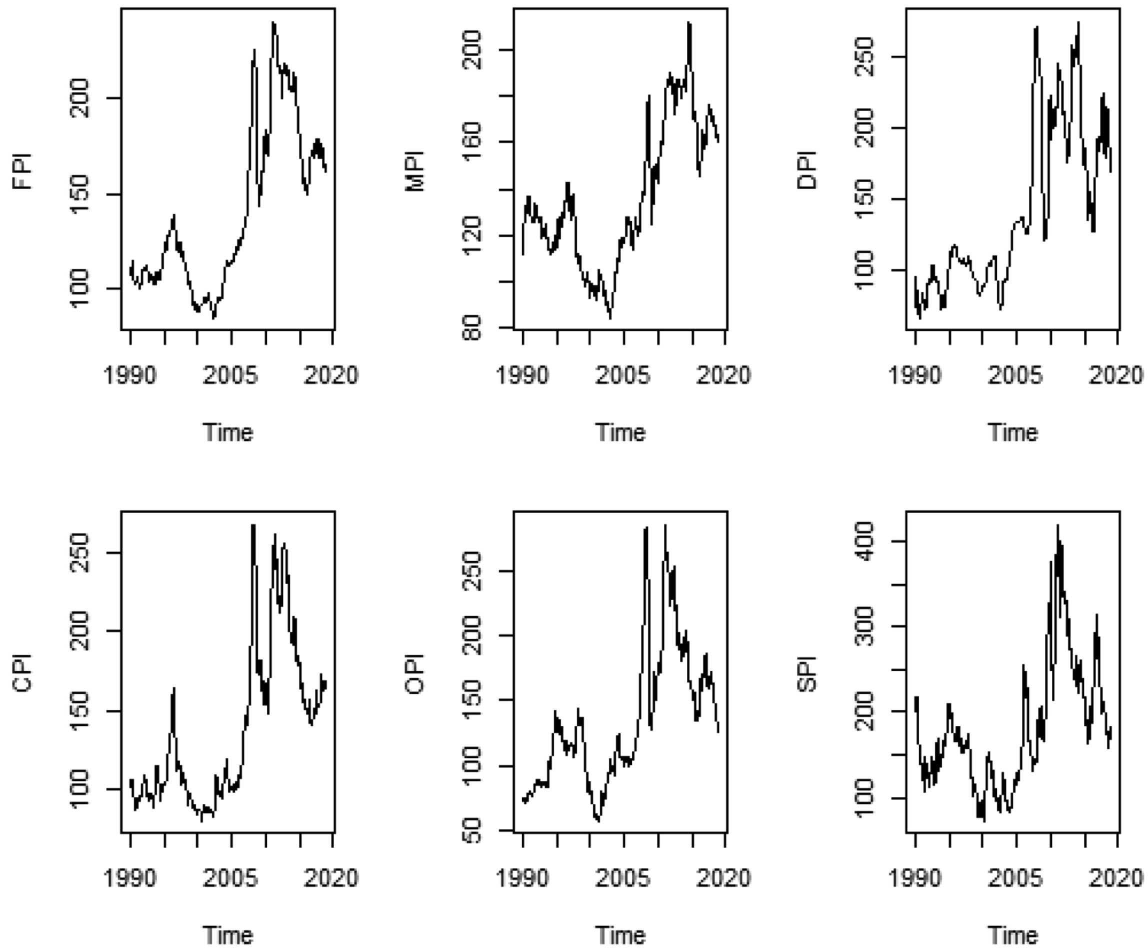

Fig. 1. Monthly trend of the food price indices between 1990 and 2019. The various plots correspond to the Food price index (FPI), meat (MPI), dairy (DPI), cereals (CPI), oils (OPI) sugar (SPI).

consistent with the 10 top prices presented in 2014 with August, September and October being the highest (212, 211, 210 respectively). The *Oils price index* has more variation with highest price presented in 2011 with February 2011 being the month with the highest price (286.5). In the *dairy price index* there is more variation with the highest prices presented in Feb 2014 (275.4) followed by October and November 2010 (271.7 and 268.5).

3.2. Decomposition of the original monthly time series of food price indices

In the current section, the decomposition of the original time series of the food price indices based on the methodology described in Section 2.2.1 is presented. Specifically, in the following figures (Fig. 2 for the FPI to and Figs. A1–A5, for MPI, DPI, CPI, OPI and SPI in the appendix) we present the residual or error series (left graph) along with the smoothed trend series (right graph) of the six indices.

Error series appear to have no visible trends, the latter being isolated in the decomposed trend series. However, random upward and downward peaks (outliers) are present for all residual error time series.

3.3. Outlier detection on the error time series

In this subsection, the results of the outlier detection applied on the decomposed error of the original food price indices are presented in detail. Specifically, the following figures (Fig. 3 for FPI and Figs. A6–A10 in the Appendix for MPI, DPI, CPI, OPI and SPI) show the corresponding $M \pm 3{\cdot}MAD$ confidence intervals based on the mean absolute deviation (MAD) for each one of the food indices.

As seen by the figures, a few outliers have been identified by the outlier detection in all index series. However, the frequency of these outliers is varying according to the specific food index. Error series exhibiting the largest variability, as shown by the inspection of the following graphs, are the CPI, OPI and SPI, whereas less variability is suggested for the FPI, MPI and DPI.

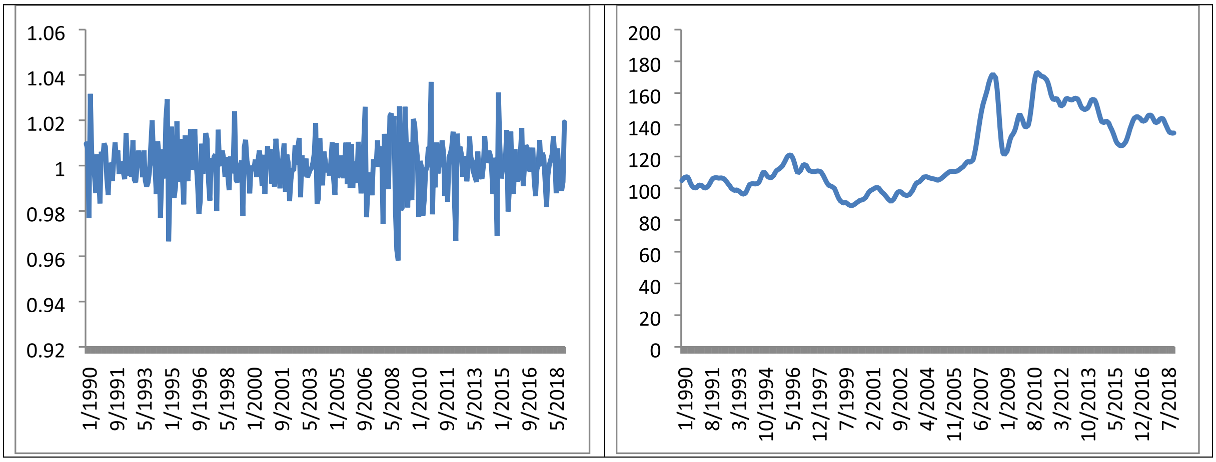

Fig. 2. Error series (on the left) and trend series (on the right) of FPI based on decomposition of the original time series.

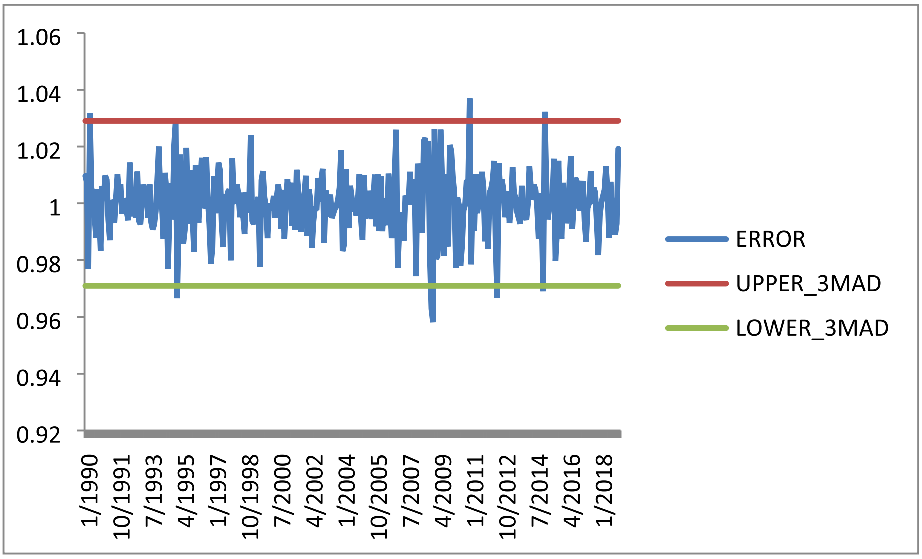

Fig. 3. Plot of error for FPI along with the confidence intervals for outlier detection (confidence intervals).

Table 1 presents the upward and downward detected outliers based upon the *MAD* statistic, in the error series of the Food Price Index (FPI). The corresponding results or the remaining price indices are included in Tables A1–A5 in the Appendix. The results correspond to the selection of the two types of intervals, i.e. the $M \pm 3 \cdot MAD$ and$M \pm 2.5 \cdot MAD$, following the suggestions of Leys et al. (2013).

As is seen by these results on the FPI outliers, both confidence intervals are in general in agreement, with a few exceptions as expected due to that the $M \pm 3 \cdot MAD$is less strict in comparison to the. $M \pm 2.5 \cdot MAD$

According to these results, the highest peaks for the **FPI** are presented in April 1990, December 1994, December 2010, January 2015 (M + 3*MAD) and the highest reduction peaks are presented in January 1995, November and December 2008, June 2012 and December 2014.

For the **Meat Price Index** (Table A1 in the Appendix) the highest peaks are observed in April 1990, November 1994, December 2010 and January 2015. The highest price drops are observed in January 1995, December 1995 and February 2009. More price peaks are captured by the M + 2.5*MAD intervals with April 1990, Feb 1991, November 1994, January 1996, December 2005, December 2010 and January 2015 having the highest peaks. The most important reductions were observed in January 1995, June 1995, December 1995, May 2004, December 2008, February 2009 and January 2011 (M − 3*MAD intervals). Additional reduction points are observed through the M + 2.5*MAD intervals with June 1995, May 2004, December 2008 and January 2011 also highlighted as outliers.

For **Dairy Price Index**, peaks (M + 3*MAD intervals) are observed in January, February and April 1990, November and December 2009 and April 2013 (Table A2 in the Appendix). Additional peaks are observed in the M + 2.5*MAD intervals including October 2015 and January 2019. Most significant drops are observed in March 1990, October 1990, December 2014 and August

Table 1
Error outliers in the FPI based upon the mean absolute deviance.

Date	FPI	Error	M + 3*MAD	M − 3*MAD	M + 2.5*MAD	M − 2.5*MAD
4/1990	110,7	1,032	√		√	
12/1994	113,6	1,029	√		√	
1/1995	104,0	0,966		√		√
12/2006	120,8	1,026			√	
1/2008	157,0	0,974				√
11/2008	124,7	0,963		√		√
12/2008	117,8	0,958		√		√
1/2009	123,5	1,026			√	
5/2009	133,4	1,026			√	
12/2010	180,4	1,037	√		√	
6/2012	145,8	0,967		√		√
12/2014	137,5	0,969		√		√
1/2015	146,4	1,032	√		√	

2015. Additional drops are picked up in the M-2.5*MAD intervals including May, November 1990, July 1991, October 1993 and February 2009, March 2010, Feb 2013, December 2017 and January 2018.

For the **Cereal Price Index**, highest peaks (M + 3*MAD intervals) are observed in September 2002, January 2009 and July 2012 with additional variations observed with M + 2.5*MAD intervals in May 1996, February 2008 and July 2017 (see Table A3). Regarding the most important reductions, these are observed (M − 3*MAD intervals) in November 2008, June 2010 and June 2012 with additional variations capture in M − 2.5*MAD intervals in October 2008 and December 2008.

Regarding the **Oil Price Index**, highest peaks are presented in August 2001 and May 2009 (M + 3*MAD intervals) with additional observed in the M + 2.5*MAD intervals, in July and June 2001 (Table A4). Regarding the most significant drops, these are presented in July 1999, November and December 2008 (M − 3*MAD intervals) with several additional picked up when looking at the M − 2.5*MAD intervals, and specifically in May and June 2001, October 2008, and March 2009.

Finally, in the **Sugar Price Index** only one variation is observed in the M + 3*MAD intervals, in February 2010 with one more picked up in the M + 2.5*MAD analysis in May 1993 (Table A5). On the other hand reductions are observed only in May 1991 (M − 3*MAD intervals) with several additional picked up within the M − 2.5*MAD intervals in July 1999, March 2000, October 2001 and May 2011.

3.4. Change point analysis for price index trend

The change point detection method is an effective tool to recognize the changes or shocks in a series of environmental, social or agricultural data. In Fig. 4 the results of the single change point analysis performed with the use of the "*changepoint*" package of R software are visualized. Change point methodology has been applied on the decomposed trend series of the six price indices.

The corresponding results relating to the multiple change point analysis based on the binary segmentation algorithm are shown below (Fig. 5).

The combined results of single and multiple change point analysis, along with the exact dates these change points occur are presented in Table 2. Table 3 presents all change points across the different price indices in chronological order and highlights major food production shocks that occurred during that period (Cramer et al., 2014; Jones and Phillips, 2016). However, in the next section factors that could be linked to these food price shocks are discussed in more detail.

As observed in Table 2, in the single change point the main extreme shock in food prices was during 2007, the year of the world food crisis. Indeed, the March, April and May of 2007 have been identified as the months of the change point for OPI, the total FPI and CPI, respectively. However, previous to these shocks, December of 2006 was a turning point in the Dairy Price Index (DPI). We should note that there seems to be a significant lagging in term of price shocks in sugar price indices and meat price indices. Shocks in the price indices of SPI and MPI are shown to take place a significant amount of time after 2007, specifically during March of 2009 for SPI and March of 2010 for MPI.

Regarding the multiple change points analysis it is observed that both the exact occurrence of change points of shocks as well as the duration of the shock windows varies significantly by the specific price index. 2002–2005 is the period where OPI, MPI, DPI and SPI reach a change point with prices starting to increase, followed by another series of increases in 2007. DPI and CPI go through a decrease in prices in the second half of 2008 followed by another increase in prices of SPI, DPI, MPI and CPI during 2009–2010. The change points captured in the analysis since 2012 reveal a gradual reduction of prices in sugar, oil and cereal.

4. Discussion

Several studies have been published highlighting the volatility of food price indices, especially after 1990, including spill over effects between products, and how these can be explained by external factors. These factors include market fluctuations, crude oil prices, biofuels, increasing demand of agricultural land, urbanization and climate change (Natcher and Weaver, 1999; Buguk et al., 2003; Prakash and Gilbert, 2011; Olah et al., 2017). In this paper we aimed to take this literature further and explore fluctuations of

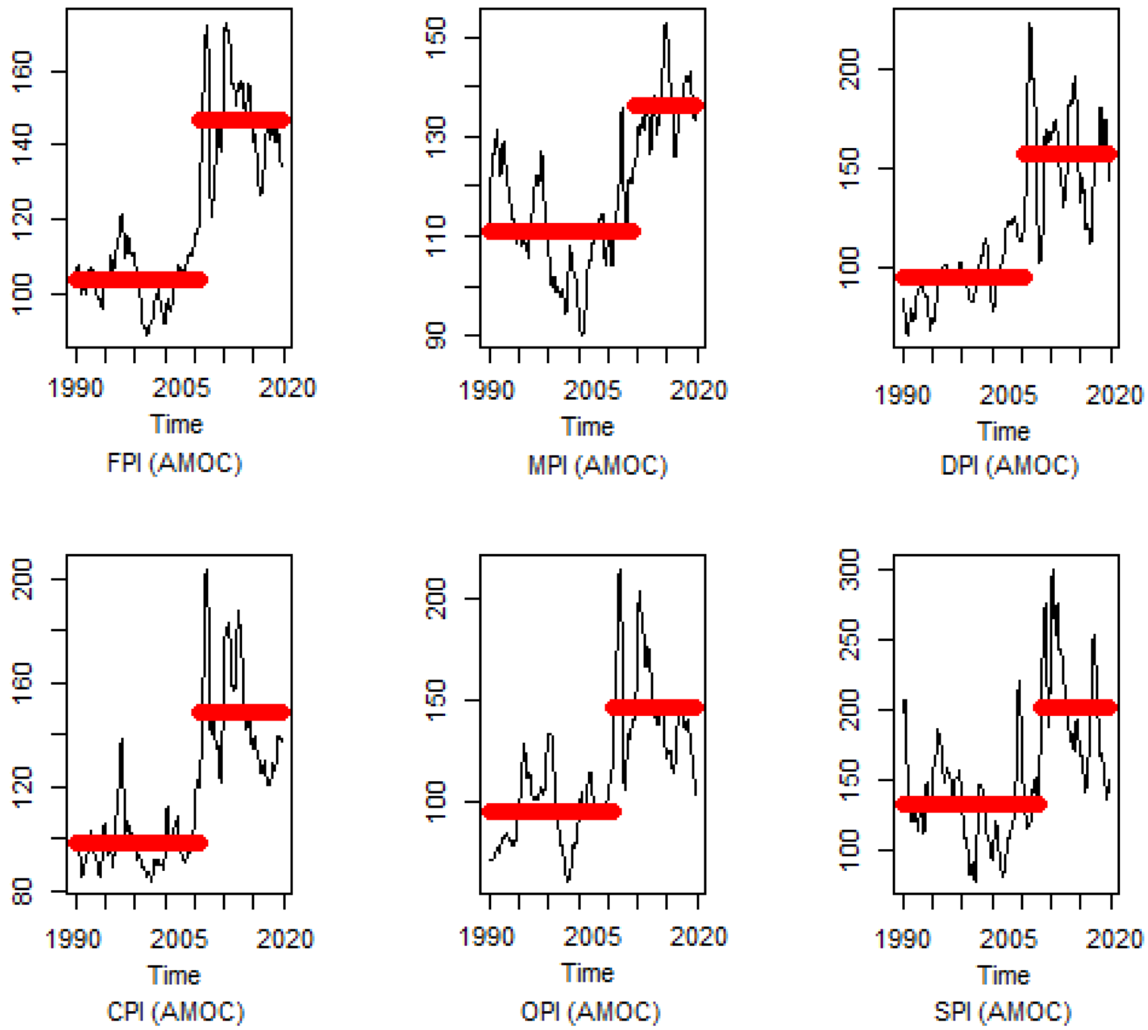

Fig. 4. Plots of single change point analysis for the food price indices.

food prices by identifying significant change points along with extended periods of change while exploring links with certain events across the globe during these periods.

Looking at each of the categories separately, in the ***Sugar price index*** there seems to be a significant lag in term of price shocks compared with the other commodities. Shocks in the price indices of SPI happen later than 2007, specifically during March of 2009. In reality SPI had experienced initially a significant increase in 2006 (captured in the multiple change points) before dropping sharply immediately after that. Then in 2009 the prices of Sugar reached the highest levels since the 1980 s. This was because during 2007 and 2008 sugar prices remained relatively stable compared to other products and as a consequence sugar production declined in many parts of the world as producers switched crops (McConnell et al., 2010). Furthermore, weather conditions affecting the two largest producers of sugar, Brazil and India, but also China, resulted in reduced production. This shortfall in production in combination with high demands for sugar from countries such as Indonesia, Pakistan and Egypt led to the price boom in 2009–2010 (Renwick et al, 2011). In addition, Brazil promoted at the same time the production of ethanol from sugarcane, which increased overall sugarcane production but led to increased competition between sugar and ethanol (McConnell et al., 2010). The EU reforms also took place at the same time however this is expected to have had a marginal impact on world prices (EC, 2004; Renwick et al, 2011). The EU's policy reforms changed the role of the EU in 2005 from a net exporter to a net importer leaving Brazil with a much stronger role in the world sugar trade (McConnell et al., 2010). Furthermore, the exchange rate of US dollar during that time is expected to have influenced the sugar prices as well (Renwick et al, 2011). We should note that although prices started to drop after the change point of 2009 this is not being picked up by the analysis as a significant change point until much later in 2012.

Regarding ***cereal prices***, the first change point is observed in 2007, the same time as the world food price crisis (FPI). Prices are then reduced in the second half of 2008 followed by another increase in prices in 2009–2010. Regarding multiple changes the CPI has one of *the smallest windows of change* compared to other commodities lasting from 2007 until 2013. Thus cereals were one of the most stable commodities up until 2007. An initial reason for the price increase in 2007–2008 period was the reduction in production

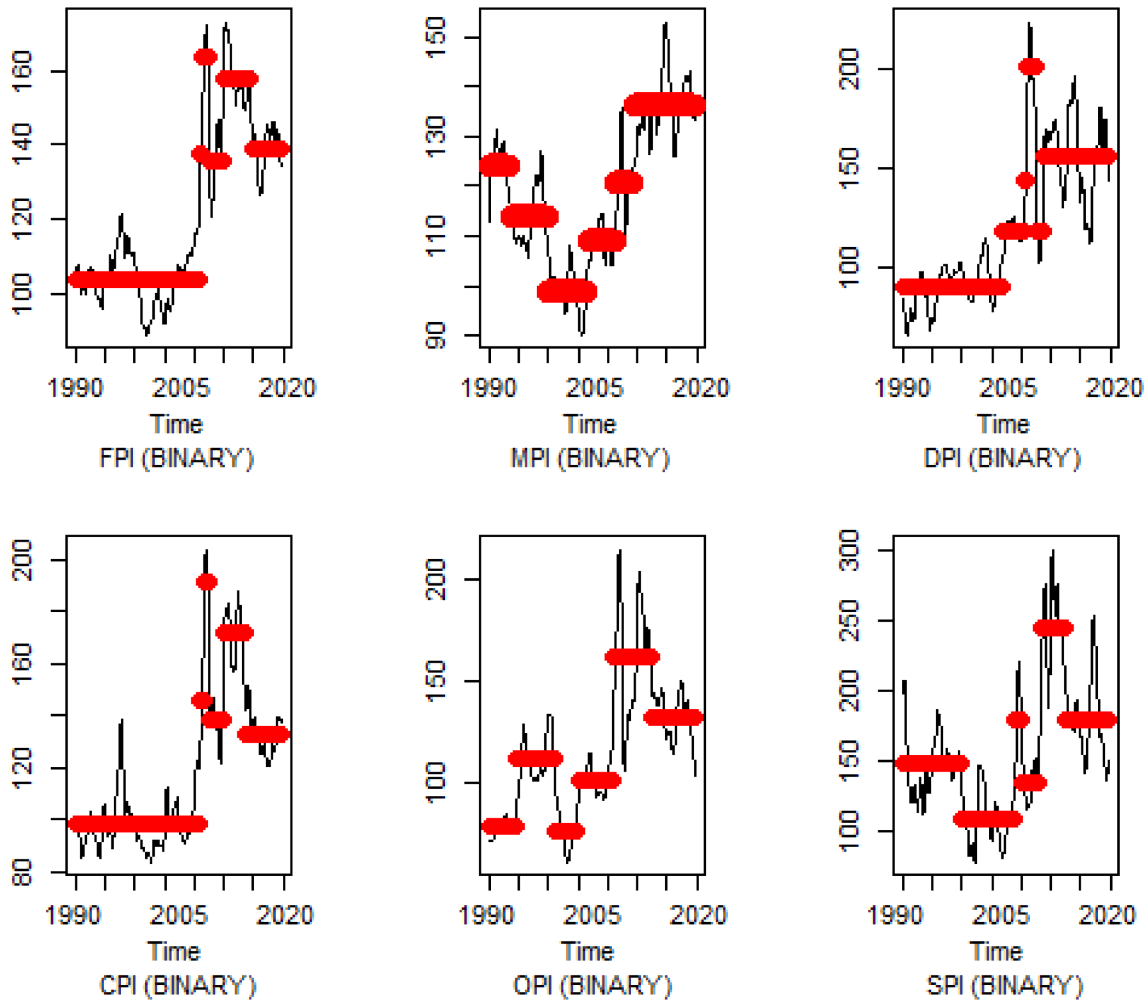

Fig. 5. Plots of multiple change point analysis (binary segmentation) for the food price indices.

Table 2
Change points (single and multiple) for the decomposed trends of the food price indices.

CHANGE POINTS	FPI	MPI	DPI	CPI	OPI	SPI
SINGLE	4/2007	3/2010	12/2006	5/2007	3/2007	3/2009
MULTIPLE	4/2007	12/1992	1/2004	5/2007	11/1993	3/1998
	9/2007	4/1998	12/2006	11/2007	3/1999	7/2005
	9/2008	10/2003	5/2007	9/2008	5/2002	9/2006
	8/2010	9/2007	8/2008	9/2010	3/2007	3/2009
	8/2014	3/2010	9/2009	9/2013	10/2012	8/2012

during 2005–2006 between 4 and 7% in key production countries (FAO, 2009) following a significant reduction in grain production from China over the previous five years (Zhang, 2011). The Australian drought (2005–2007) is expected to have had a significant role in this increase (Quiggin, 2007) leading to poor harvests and low cereals stocks combined also with rising oil price and export/import restrictions from certain countries. Furthermore, US is the most important producer and exporter of corn, and thus fluctuations in this market (depreciation of the US dollar) are expected to have influenced the world cereal market as well (Serra and Gill, 2013). The continuing increase between 2007 and 2013 is attributed to the higher prices in energy and fertilizers, increasing demand for biofuel and also failing crops (EU, 2018) followed by a decrease as prices start to return to previous levels. Another factor during this period was the instability in ethanol markets which in turn destabilised corn markets (Serra and Gill, 2013).

Any analysis of ***meat prices***, is complicated by the variety of meat products, the difficulty of finding international prices for ‘individual meat cuts’ (Morgan and Tallard, undated) but also the complex effects that weather events –such as droughts- have on production (Quiggin, 2007). World beef prices are influenced significantly by the US, the largest importer of beef in the world. The

Table 3
Change points in chronological order alongside significant production shock events identified (if any) in Cramer et al. (2014) and the global food shocks from Jones & Phillips (2016).

Food category	Month/Year	Type of change	Observed food production shocks (decrease in production only)
MPI	Dec-92	Decrease	
OPI	Nov-93	Increase	
SPI	Mar-98	Decrease	
MPI	Apr-98	Decrease	
OPI	Mar-99	Decrease	
OPI	May-02	Increase	Shocks in Australia, China (ongoing), Canada, India, USA
MPI	Oct-03	Increase	Shocks in China (ongoing), Russia, Ukraine
DPI	Jan-04	Increase	Shock in China (ongoing)
SPI	Jul-05	Increase	Record number of tropical storms and hurricanes, Shock in China (ongoing)
SPI	Sep-06	Decrease	
DPI	Dec-06	Increase	Shock in Australia and USA.
OPI	Mar-07	Increase	Shock in Ukraine.
DPI	May-07	Increase	
CPI	May-07	Increase	
MPI	Sep-07	Increase	
CPI	Nov-07	Increase	
DPI	Aug-08	Decrease	
CPI	Sep-08	Decrease	
SPI	Mar-09	Increase	Shock in Argentina
DPI	Sep-09	Increase	
MPI	Mar-10	Increase	Shock in Russia; High monsoon rainfall,
CPI	Sep-10	Increase	
SPI	Aug-12	Decrease	
OPI	Oct-12	Decrease	
CPI	Sep-13	Decrease	

MPI Index is the category in the database analysed where the first chronological change is observed. This is in 1992 and then in 1998 when prices are reduced. The decline is possibly also linked with reduction in demand both due to dietary habits but also due to the ‘mad cow disease’ and ‘food and mouth disease’ (EC, 2004). The initial decline in 1992 occurs at a similar time as the number of beef exporters drop (reduction by 2–3%) mainly due to falling shipments from the European Union and Argentina (Gatt report, 1992). These two drops would indicate that it was the drop in demand that was a causal factor. Since then, meat prices are showing a steady increase with a period from 2003 forward of gradual increase. This change can be attributed to some extent to the 2002–2003 Australian drought as meat producers who face dry weather conditions tend to initially destock, leading to an increase in supply and lower prices. As a result the effect of the drought on meat prices appears much later, in 2003 (Quiggin, 2007). The most significant change point for the whole category however is in 2010 when food prices started to increase again possibly due to increase in demand and low supply (Trostle et al., 2011).

The market for ***vegetable oils*** has significantly changed since the 1980s due to change in healthier food preferences but also the increased demand for biofuels, especially after 2000 (Rosillo-Calle et al., 2009; Trostle et al., 2011). In our analysis a single change point for vegetable oils is observed in 2007 prices changes, the same time as the food price crises. OPI’s initial change point happens in 1993 with an increase followed by a decrease in 1999. It then has a large window frame from 2002 to 2007 where there is a steady increase followed by a drop from 2012 onwards. Regarding the largest time window where a change is observed (2002–2007 increase of prices) the OPI has increased by approximately 35% during in comparison to 1998–2002 (Priyati and Tyers, 2016). There are three factors which have possibly played a significant role in the increase during this period. The first is the connection with oil and in particular biodiesel which was responsible for 1/3 of the increase in vegetable oil consumption during this first time window (Mitchell, 2008 in Priyati and Tyers, 2016). The second is an increase in consumption, and thus an increase in demand, which is observed across the world since 2005 and especially in countries with large populations such as China and India (Rosillo-Calle et al., 2009). Finally, weather conditions in 2007–2008 led to significant reductions in production (Rosillo-Calle et al., 2009) such as the severe drought in Australia.

Finally, regarding the ***dairy price index***, December 2006 is the most important single point increase. Other crucial change points are the increase that started in January 2004, and continues in December 2006, May 2007, the decrease in August 2008 and then again the increase from 2009. These findings are in accordance with existing evidence highlighting that since 2000 the cost of production of the key dairy product, milk, has constantly increased (double or triple) (Hemme et al., 2013). Fluctuations in 2008–2009 (2009 being the year with the most important dairy crisis in the EU (EU, 2018) were significantly influenced by the levels of production in Oceania (Oceania’s global market share has doubled since the 1980s, OECD-FAO, 2011) where initially there was a price boom due to lower production and then a significant price drop due to increase in milk production. Furthermore, dairy products prices are strongly dependent on grains which have also been influenced by the droughts in Australia in 2000s.

When comparing the incidence of change points in each of the price indices with the error outliers from the MAD analysis there appears to be little evidence of a link between the two. If the error outliers are a signifier of more volatility in global trading, then these extremes in short term volatility do not appear to occur at times associated with change points. This may have been expected if markets become more volatile shortly before or after a major change point however we find no evidence of this and therefore conclude that short term extreme volatility is not a good indicator for a change point.

At this point we would like to highlight one limitation of our study. The current analysis does not identify peaks and drops in recent years. This is probably because we are exploring time 'windows' and thus we would need data further in the future to see if current fluctuations are a clear trend. From the existing literature however there seems to be several concerns regarding price peaks in certain food categories for the next 2 years (vegetable oil and dairy especially). These are definitely linked with weather conditions and also other environmental factors. From the literature review it is clear that environmental factors and specifically extreme weather events such as droughts have influenced fluctuations in certain indices. These refer mainly to weather conditions in the most important exporters (eg Brazil, Australia) but also general market trends.

5. Conclusions

In the literature of food prices there are several studies exploring the reasons explaining peaks and drops of food prices. This study aims to contribute to this discussion by identifying for the first time a) specific change point within different food categories that these changes occur and b) the duration of these periods before the next change. These change points have been identified for the various international price indices including food, meat, oil, cereal, dairy and sugar.

We find several change points where there has been a significant and prolonged increase or decrease in the price of these agricultural products. Most, but not all, of these change points can be linked to significant events within the food production supply chain including extreme weather impacts on food production such as losses due to droughts. However, at this stage it is not possible to causally link these production shocks to the change points in prices. This is because of the complex, and multiple set of factors, that influence food availability and trading.

Future research should explore the long-term weather patterns in different countries in relation to these indices in order to identify the interrelationships between food prices and weather conditions and spill over effects from a geographical point of view. In particular, as climate change is expected to increase the severity or frequency of these events the scale of potential impact on food production is significant. Therefore, it is also true to say that historical analysis may not be a good guide for future policy planning although lessons can still be drawn from understanding how production shocks were either mitigated against or contributed to price shocks. It is through price shocks that significant impacts on society and the economy are seen.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A. Appendix

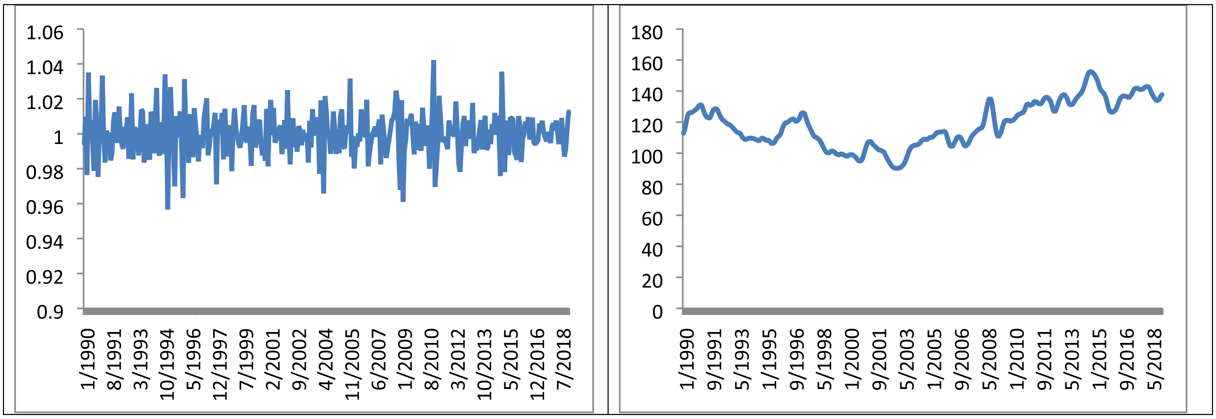

Fig. A1. Error series (on the left) and trend series (on the right) of MPI based on decomposition of the original time series.

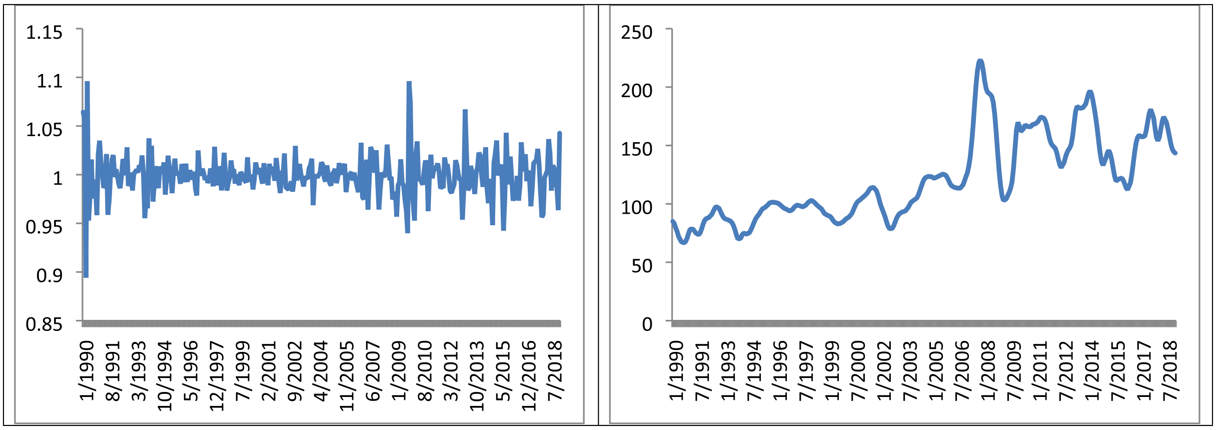

Fig. A2. Error series (on the left) and trend series (on the right) of DPI based on decomposition of the original time series.

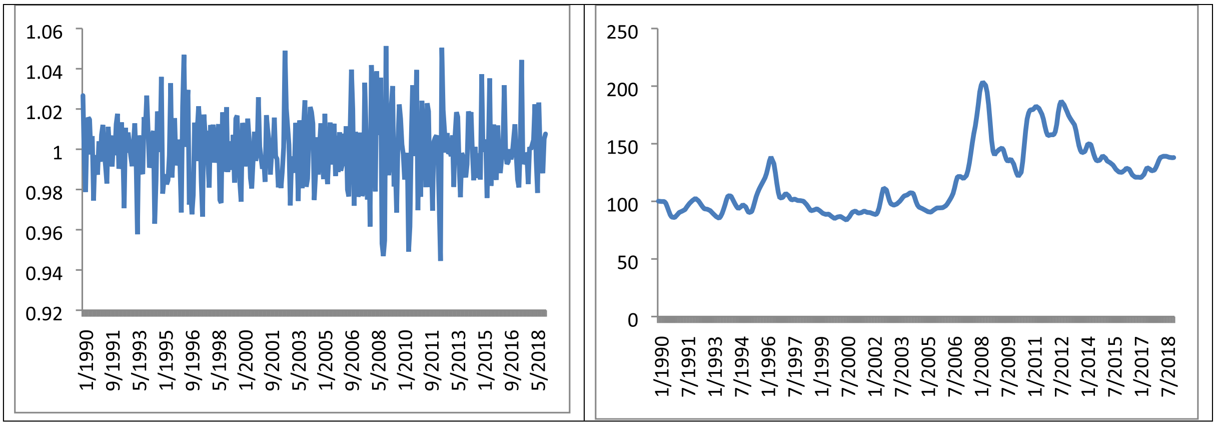

Fig. A3. Error series (on the left) and trend series (on the right) of CPI based on decomposition of the original time series.

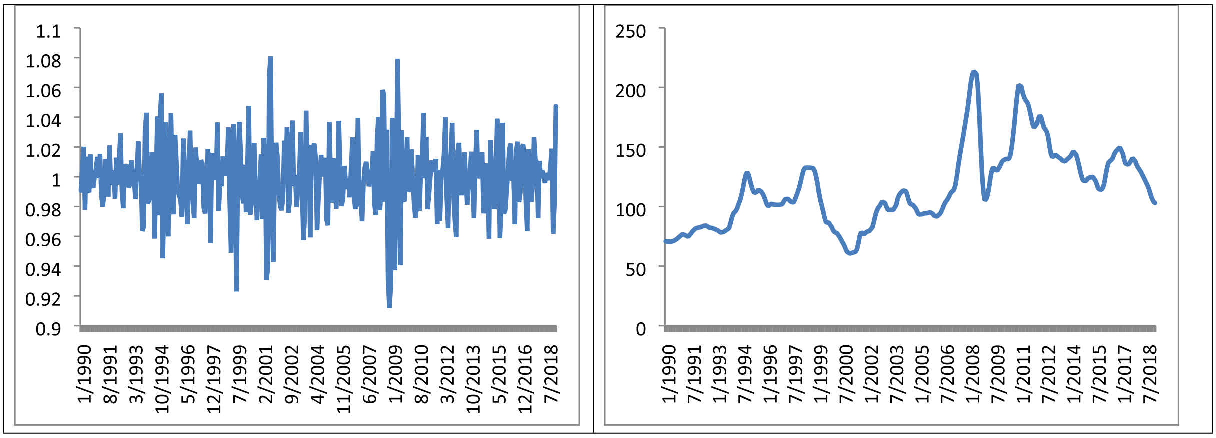

Fig. A4. Error series (on the left) and trend series (on the right) of OPI based on decomposition of the original time series.

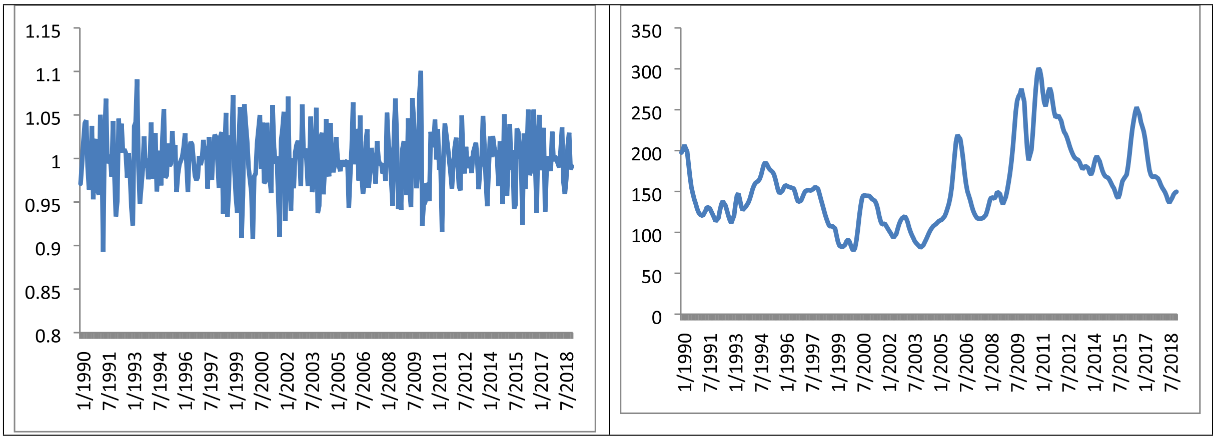

Fig. A5. Error series (on the left) and trend series (on the right) of SPI based on decomposition of the original time series.

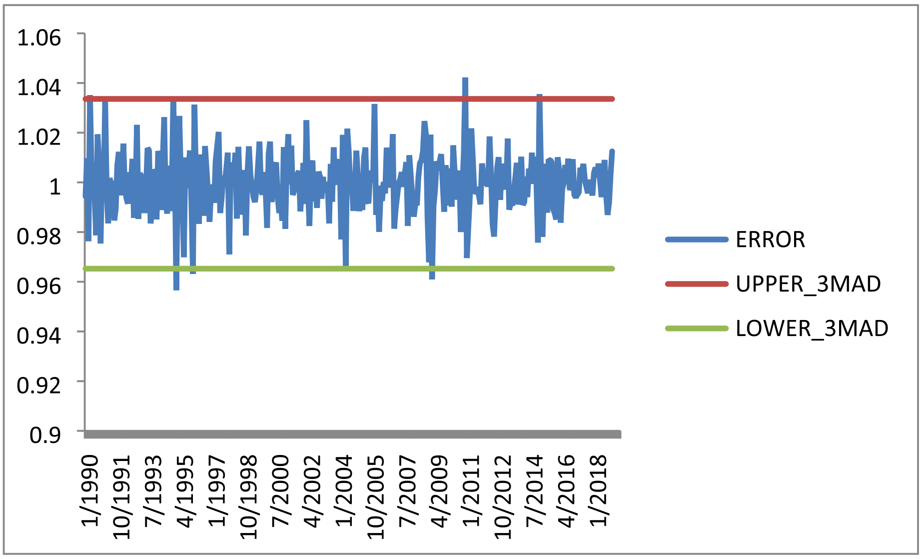

Fig. A6. Plot of error for MPI along with the confidence intervals for outlier detection (confidence intervals).

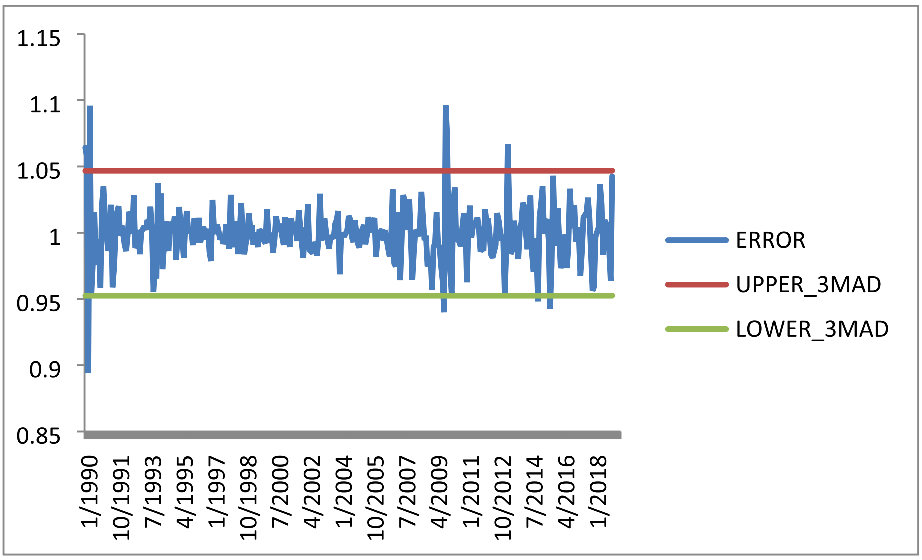

Fig. A7. Plot of error for DPI along with the confidence intervals for outlier detection (confidence intervals).

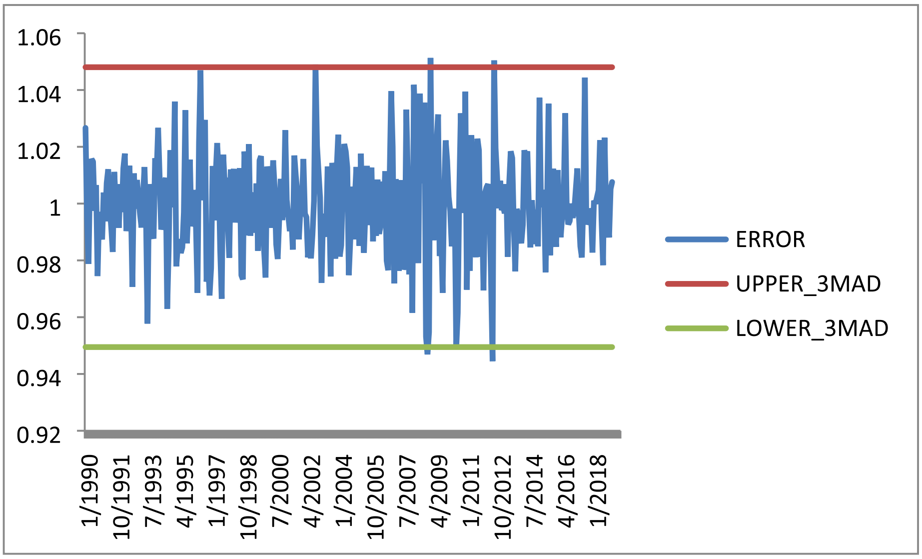

Fig. A8. Plot of error for CPI along with the confidence intervals for outlier detection (confidence intervals).

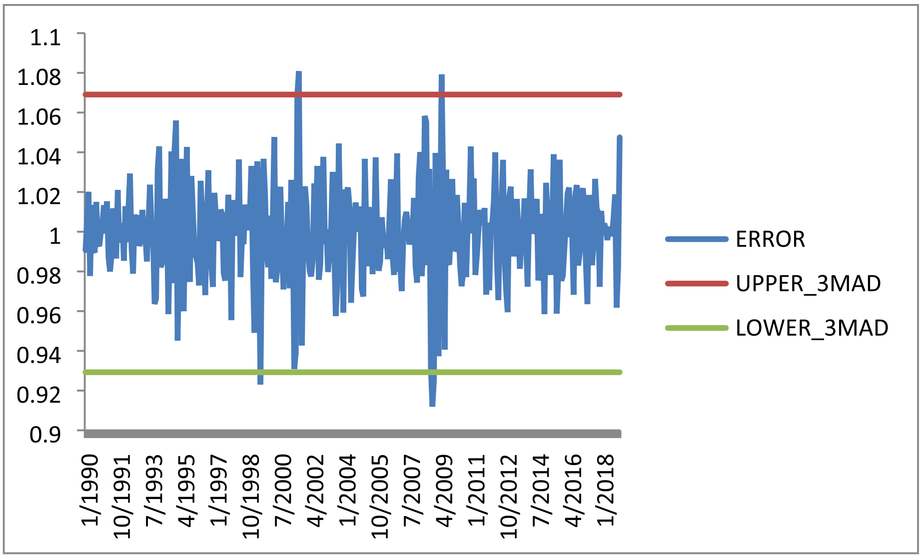

Fig. A9. Plot of error for OPI along with the confidence intervals for outlier detection (confidence intervals).

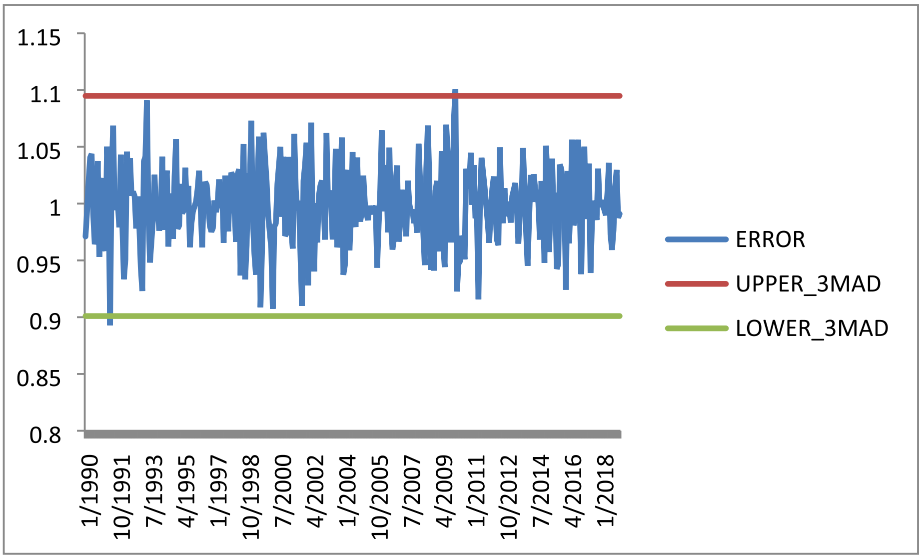

Fig. A10. Plot of error for SPI along with the confidence intervals for outlier detection (confidence intervals).

Table A1
Error outliers in the MPI based upon the mean absolute deviance.

Date	MPI	Error	M + 3*MAD	M – 3*MAD	M + 2.5*MAD	M – 2.5*MAD
4/1990	127,0	1,035	√		√	
2/1991	133,2	1,034			√	
11/1994	114,9	1,034	√		√	
1/1995	100,3	0,957		√		√
6/1995	103,2	0,970				√
12/1995	107,7	0,963		√		√
1/1996	116,1	1,031			√	
5/2004	102,9	0,966				√
12/2005	115,2	1,031			√	
12/2008	111,0	0,968				√
2/2009	103,8	0,961		√		√
12/2010	136,7	1,042	√		√	
1/2011	123,0	0,969				√
1/2015	150,2	1,035	√		√	

Table A2
Error outliers in the DPI based upon the mean absolute deviance.

Date	DPI	Error	M + 3*MAD	M – 3*MAD	M + 2.5*MAD	M – 2.5*MAD
1/1990	91,3	1,064	√		√	
2/1990	89,1	1,058	√		√	
3/1990	71,3	0,894		√		√
4/1990	82,6	1,096	√		√	
5/1990	67,9	0,953				√
11/1990	68,6	0,958				√
7/1991	69,9	0,959				√
10/1993	67,4	0,955				√
2/2009	99,7	0,957				√
10/2009	139,0	0,939		√		√
11/2009	179,9	1,097	√		√	
12/2009	184,6	1,074	√		√	
3/2010	153,7	0,953				√
2/2013	153,1	0,954				√
4/2013	188,9	1,067	√		√	
12/2014	128,8	0,948		√		√
8/2015	110,9	0,943		√		√
10/2015	127,4	1,043			√	
12/2017	151,8	0,956				√
1/2018	149,3	0,960				√
1/2019	151,1	1,043			√	

Table A3
Error outliers in the CPI based upon the mean absolute deviance.

Date	CPI	Error	M + 3*MAD	M − 3*MAD	M + 2.5*MAD	M − 2.5*MAD
5/1996	146,0	1,047			√	
9/2002	115,2	1,049	√		√	
2/2008	205,4	1,042			√	
10/2008	145,4	0,953				√
11/2008	136,1	0,947		√		√
12/2008	134,4	0,955				√
1/2009	150,1	1,051	√		√	
6/2010	118,9	0,950		√		√
6/2012	157,7	0,944		√		√
7/2012	183,8	1,050	√		√	
7/2017	133,5	1,044			√	

Table A4
Error outliers in the OPI based upon the mean absolute deviance.

Date	OPI	Error	M + 3*MAD	M − 3*MAD	M + 2.5*MAD	M − 2.5*MAD
7/1999	78,7	0,923		√		√
5/2001	60,3	0,931				√
6/2001	64,4	0,939				√
7/2001	79,0	1,069			√	
8/2001	83,3	1,081	√		√	
6/2008	222,0	1,058			√	
10/2008	117,4	0,932				√
11/2008	103,7	0,912		√		√
12/2008	99,4	0,925		√		√
3/2009	109,5	0,937				√
5/2009	142,4	1,079	√		√	
7/2009	121,3	0,941				√

Table A5
Error outliers in the SPI based upon the mean absolute deviance.

Date	SPI	Error	M + 3*MAD	M − 3*MAD	M + 2.5*MAD	M − 2.5*MAD
5/1991	105,2	0,893		√		√
5/1993	155,8	1,091			√	
7/1999	75,9	0,909				√
3/2000	73,4	0,907				√
10/2001	100,8	0,910				√
2/2010	289,0	1,101	√		√	
5/2011	225,3	0,916				√

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