UNIVERSITY OF STUDIES OF PADUA

DEPARTMENT OF STATISTICAL SCIENCES

CORSO DI LAUREA MAGISTRALE IN
SCIENZE STATISTICHE, ECONOMICHE, FINANZIARIE E AZIENDALI

ASYMMETRY OF THE RELATIVE-PRICE CHANGES DISTRIBUTION AS INDICATOR OF FOOD SECURITY

Relatore: Prof. Nunzio CAPPUCCIO
Dipartimento di Scienze Economiche e
Aziendali "Marco Fanno"

Laureando: Ulrich Eschcol NYAMSI

Matricola N: 626383

Academic Year: 2015/2016

To Mama Dza'Dé

Abstract:
This paper proposes an indicator of food security, based on the skewness of the distribution of relative price changes. High food prices can have significant impacts on importing countries and a direct adverse effect on food security. Shocks to diverse markets generate changes in relative prices- some nominal prices rise, others fall. If all prices were perfectly flexible, such price movements would largely cancel out and leave inflation unaffected. In practice, however, certain prices tend to be sticky because price adjustments are costly. In such cases, prices are adjusted quickly only in the event of large shocks, not when the shocks are small. The positively skewed distribution of relative-price changes then results in a temporary increase in inflation. The variance and skewness of relative-price changes explain shortcomings in existing models of inflation. Therefore an indicator of skewness is used to assess food security.

Contents

Chapter 1

Introduction

Many studies offer many insights on price setting, price stickiness and determinants of inflation in the short run. Klenow and Malin (2010), found that one of the features of price setting in developing countries are more frequent price changes reflecting higher inflation rate existing in the country. Rigidities in nominal prices are central to many theories of economic fluctuations. Ball and Mankiw (1995) proposes a theory of supply shocks, based on relative-price changes and frictions in nominal price adjustment. When price adjustment is costly, firms adjust to large shocks but not to small shocks, and so large shocks have disproportionate effects on the price level. They showed that, aggregate inflation depends on the distribution of relative-price changes: inflation rises when the distribution is skewed to the right, and falls when the distribution is skewed to the left. Their model suggest measures of supply shocks that perform better than traditional measures, such as the relative prices of food and energy. Their model can be also applied to food prices and it can be explored the possibility to determine an indicator for food security.

Although rising food prices in global markets represent a serious threat to vulnerable people in developing countries, it is domestic food price inflation that determine the poverty and food security impact of international food crises (Mousseau 2009). Lustig (2008) reviewed a large set of studies on the impact of the increases in food prices on poverty and found that on average, higher food prices increase poverty in the majority of countries. The poor are hit the hardest as they spend a larger percentage of their income on food as compared with richer income groups. For example, Ivanic and Martin (2008) reported that at least 105 million people in Least Developed Countries have slipped into poverty because of the high food price inflation since 2005.

Bibi et al. (2009) analyzed the impact of the increase in food prices on child food poverty in Mali following the food crisis. The authors measured food poverty by comparing each individual's real food expenses to the expenditures required to satisfy his caloric requirements They found that increases in food prices led to an increase in food poverty among children (0-14 years old) from 41.5 percent to 51.8 percent. The total percentage of the people falling into food poverty was found to be greater in rural areas than in urban centres. Furthermore, the authors showed that urban households had a greater capacity to absorb the impact of rising food prices by reducing their non-food consumption. Indeed, the budget share of non-food consumption among urban households dropped from 48.3 percent to 41.9 percent after the food price rise while rural households changed their budget allocation from 34.4 percent to only 33.3 percent.

Some studies have also looked at the impact of the world food price increases on the nutritional status of children. Thus, Compton et al. (2010) found that the prevalence of underweight and wasting in young children went up by about half in surveys in Bangladesh, Cambodia and Mauritania following food price rises (e.g. from 17 percent to 26 percent wasting in rural Bangladesh). Among the factors responsible were cutbacks on special complementary (weaning) foods, as well as reduced consumption of more expensive and nutritious foods. Food price rises led to widespread reduction in dietary diversity, which is a predictor of micronutrient malnutrition.

This doument explores one possible indicator for food security. This indicator is based on the skewness of the distribution of the relative price changes.
In the second chapter, we present the skew-normal distribution and a measure of skewness.

In the third chapter, we analyze the distribution of relative price changes and we present tests which prove that the skew'normal fit this distribution. In chapter 4, we present the Arellano-Bond Estimator for panel data and in chapter 5, we present results which shown that inflation can be explained by the moments of the distribution of relative price changes, particularly by the asymmetry of the distribution. We found that changes in the price level are positively related to skewness of relative price changes. Results suggest that the asymmetry variable is a better measure of supply shocks than the traditional variables.We also found that, aggregate inflation depends on the distribution of relative-price changes: inflation rises when the distribution is skewed to the right, and falls when the distribution is skewed to the left.
The chapter 6 presents a Food Security Indicator related to the skewness of the distribution. We show that skewness of the distribution of relative price changes can be considered as a good indicator of food secuity.

Chapter 2

Skew-Normal Distribution

The normal distribution is one of the most used distribution in statistics, it's appropriate to represent various phenomena. It is the best tool to describe some variables whose distribution is symmetrical, with a single peak and a bell-shaped. However, there are situations in which the normal distribution is not found to be satisfactory, particularly when the set of observed data has an asymmetric distribution. Therefore, it was necessary to have a family of distributions that it is more flexible in describing these phenomena. The skew-normal can be seen as a particular case of a more general family of distributions: the *skew-normal* (Azzalini, 1985). It is a class of distributions whose law of probability is described not only from parameters of location and scale, which in the normal coincide with the mean and variance, but also by a third parameter that adjusts the shape and density that allows to handle case of asymmetry in distribution.

2.1 Probability Density Function

A variable r follows a skew-normal distribution with parameter α, if its probability density function is given by

$$f(r) = 2\phi(r)\Phi(r), \qquad r \in \mathbb{R}$$

where

$$\phi(r) = \frac{1}{\sqrt{2\pi}} \exp(-\frac{r^2}{2}) \qquad \text{e} \qquad \Phi(\alpha r) = \int_{-\infty}^{\alpha r} \phi(t) dt$$

with ϕ and Φ which are respectively, the standard normal probability density function and its cumulative distribution function.

If $Y = \xi + \omega r$, then the Y density function is:

$$f(y;\xi,\omega,\alpha) = \frac{2}{\omega}\phi(\frac{y-\xi}{\omega})\Phi(\alpha\frac{y-\xi}{\omega}), \qquad y,\xi,\alpha \in \mathbb{R}, \omega \in \mathbb{R}^+, \qquad (1.1)$$

and therefore we write $Y \sim SN(\xi, \omega^2, \alpha)$.

$\theta = (\xi, \omega, \alpha)$ are called "direct paremeters" (DP).

From a theoretical point of view, the skew-normal has the advantage of being mathematically manageable and it has many typical properties of the normal distribution:

a) If $r \sim$ SN(α), then $-r \sim$ SN(-α)

b) If $r \sim$ SN(α), then $r^2 \sim \mathcal{X}_1^2$

c) $1 - \Phi(-r; \alpha) = \Phi(r; -\alpha)$

d) The density function is unimodal; in particular the logarithm of the density is a concave function.

2.2 The shape parameter α

It is quite intuitive, the incidence of the parameter α on the density function. In particular it is interesting to note that:

- For $\alpha = 0$, we have $Y \sim N(\mu, \sigma)$; the parameters of position μ and of scale σ coincide with the mean and the square root of the variance of the distribution of Y.

- When the shape parameter α grows with positive values, it becomes more and more evident a positive skewness in the distribution; in particular we will have a thickness of the observations at the lower values, and a tail that extends to the higher values.

- When the shape parameter α decreases with negative values, we obtain a negative skewness in the distributional; in particular we will have a thickness of the observations at the higher values, and a tail that extends to the lower values.

- When α tends to infinity, we have an extreme case of complete asymmetry, which converges to *half-normal* density function.

- It is important to emphasize that, unlike other distributions proposed in the literature, the Skew-Normal (SN) family allows to switch from the symmetric case to case with skewness, changing only the value of a parameter.

2.3 Moments

Lemma 2.3.1. *If $Z \sim N(0,1)$, then:*

$$E\{\Phi(hZ+k)\} = \Phi\{k/\sqrt{1+h^2}\},$$

for h and $k \in \mathbb{R}$.

From lemma 2.3.1, it follows that the moment-generating function is:

$$M(t) = 2.exp(t^2)\Phi(\delta t),$$

where δ is given by

$$|\delta| = \sqrt{\frac{\pi}{2}}.\frac{|\hat{\gamma}_1|^{2/3}}{|\hat{\gamma}_1|^{2/3} + ((4-\pi)/2)^{2/3}}$$

and we have

$$|\delta| = \frac{\alpha}{\sqrt{1+\alpha^2}}$$

We can then define the moments of a random variable $Z \sim SN(\alpha)$:

$$\mu_z = E(Z) = \frac{2}{\pi}.\delta$$

$$\sigma_z^2 = Var(Z) = 1 - \frac{2}{\pi^2}.\delta^2$$

$$\gamma_1 = Asym(Z) = sign(\alpha)\frac{4-\pi}{2}\left[\frac{\{E(Z)\}^2}{Var(Z)}\right]^{3/2}$$

$$\gamma_2 = Kurt(Z) = 2(\pi-3)\left[\frac{\{E(Z)\}^2}{Var(Z)}\right]^2$$

which represent, respectively, the mean, the variance, the skewness and the kurtosis standardized coefficients.

2.4 Inferential Aspects

If $Y \sim SN(\xi, \omega^2, \alpha)$, the likelihood function for the direct parameter θ is:

$$l(\theta) = -n\log(\omega) - \frac{1}{2}z'z + \sum_{i=1}^{n}\log(2\Phi(\alpha z_i)) \tag{1.2}$$

where $z = \omega^{-1}(y - \xi 1_n)$, z_i is the $i\text{-}th$ component of z, and 1_n is the unit vector.
The derivative of the function in (1.1) gives:

$$\begin{cases} \sum_{i=1}^{n} z_i - \alpha\sum_{i=1}^{n}\frac{\phi(\alpha z_i)}{\Phi(\alpha z_i)} = 0 \\ \sum_{i=1}^{n} z_i^2 - \alpha\sum_{i=1}^{n}\frac{\phi(\alpha z_i)}{\Phi(\alpha z_i)}z_i - n = 0 \\ \sum_{i=1}^{n}\frac{\phi(\alpha z_i)}{\Phi(\alpha z_i)}z_i = 0 \end{cases}$$

To avoid the problem related to the Fisher information matrix, Azzalini (1985) has parameterized the problem writing:

$$Y = \mu + \sigma Z^o$$

where $Z^o = (Z - \mu_z)/\sigma_z, \quad \sigma_z = (1 - \mu_x^2)^{\frac{1}{2}}$.

The log-likelihood function is

$$l(CP) = -n\log(\sigma_z/\sigma) - \frac{1}{2}z'z + \sum_{i=1}^{n}\log(2\Phi(\alpha z_i))$$

where $z_i = \mu_z + \sigma_z\sigma^{-1}(y_i - x_i'\beta) = \mu_z + \sigma_z r_i, \quad z = (z_1, z_2, \cdots, z_n)'$

The alternative parametrization is given by $(\mu, \sigma^2, \gamma_1)$, with

$$\begin{cases} \mu = E(Y) = \xi - \omega\mu_z \\ \sigma^2 = Var(Y) = \omega^2(1 - \mu_z^2) \\ \gamma_1 = \frac{E\{(Y-E(Y))^3\}}{Var(Y)^{3/2}} = \frac{(4-\pi)}{2}\frac{\mu_z^3}{(1-\mu_z^2)^{3/2}} \end{cases}$$

μ, σ^2, γ_1 are called "centred parameters" (CP). γ_1 is the skewness coefficient given above.

2.5 An Indicator of Asymmetry

It would be more parsimonious to measure the relevant asymmetry with a single variable-one that captures both the direct effect of skewness and the magnifying effect of variance.

For an extreme value x, we define

$$Asym(x) = \int_{-\infty}^{-x} rh(r)dr + \int_{x}^{+\infty} rh(r)dr,$$

where r is the relative price change and h its density function.

Properties:

1) *Asym(x)=0,* $\forall x \in \mathbb{R}_+$ *if h is symmetrical.* In fact, if h is symmetrical then $\int_{-\infty}^{-x} rh(r)dr = -\int_{x}^{+\infty} rh(r)dr \iff Asym(x) = 0.$

2) *Asym(x) is positive when the right tail is bigger than the left tail and negative when the left tail is bigger than the right one.*

3) *Asym(x) increases in assolute value when a high variance increases the tails.*

This variable measures the mass in the upper tail of the distribution of price changes minus the mass in the lower tail. The tails are defined as relative-price changes greater than X percent or smaller than -X percent. Here the measure of skewness is defined by

$$Q = \int_{-\infty}^{+\infty} |r|.rh(r)dr,$$

with r and h are defined as above.

Q has the same properties of $Asym(x)$.

Chapter 3

Analysis of the Relative-Price Changes Distribution

In this chapter, we analyze the distribution of the relative-price changes. We will see the theoretical aspect that support the presence of asymmetry during a shock period. We will also present an empirical result showing skewed distribution in relative-price changes for agricultural crops during period of shock.

3.1 The Model

Our model is the same presented by (Ball and Mankiw, 1995). Our basic framework is a one-period model. The economy contains a continuum of industries, each with a continuum of imperfectly competitive firms. Within an industry all firms have the same desired price. Initially, all nominal prices are set at the desired level, which, in logs, is normalized to zero for all industries.Then each industry experiences a shock: the desired nominal price for the industry changes to θ. One can interpret the shock as a shift in the industry demand or cost function. The shock θ has a density function $f(.)$ across industries. The mean of θ is zero; that is, then shocks are sectoral disturbances and would leave the average price level unchanged if all prices adjusted. A firm that adjusts its price must pay a menu cost C. If it does not adjust, its desired and actual prices differ by θ. We assume that the firm's loss from this divergence is θ^2.

This implies that a firm adjusts its price only if $|\theta|$ exceeds $\sqrt{C}$. Within an industry, firms are heterogeneous in menu costs: $\sqrt{C}$ is distributed across firms with distribution function $G(.)$. Heterogeneity in menu costs implies that some firms within an industry adjust to a shock and others do not. If $G(.)$ is well behaved, the average price for the industry is a smooth function of θ. We define an industry price change as the mean of the change in individual prices, and inflation as the mean of the industry changes (with all variables in logs). It is easy to see that the distribution of industry shocks influences inflation. For an industry with shock θ, the proportion of firms that adjust-those with $\sqrt{C} < |\theta|$- is $G(|\theta|))$. Since these firms adjust their prices by θ, the industry price index changes by $\theta G(|\theta|)$.

Inflation π is the average of these price changes over industries:

$$\pi = \int_{-\infty}^{+\infty} \theta G(|\theta|) f(\theta) d\theta = \int_{0}^{+\infty} \theta G(|\theta|)[f(\theta) - f(-\theta)] d\theta$$

Properties:

1) If the shock density, $f(\theta)$, is symmetric around 0, then $f(\theta) = f(-\theta)$, therefore inflation is equal to 0. In fact, we have:
If f *is symmetric around 0* then $f(\theta) = f(-\theta)$, then

$$\pi = 0$$

2) If f is skewed, then π is generally different to zero.

3.2 Relative-Price Changes Distribution

Figures 3.1 and 3.2 present the distributions of the variation of the relative-price changes for several years and different countries. These figures show that there are considerable variations in these distributions. In these years, social or economic instability happens within the country. The data for Kenya show a left skewed distribution to the year 2008, that is, the lower tail is longer than the upper tail. This year refers to the recent food crisis and the socio-political disorder that hit the country. It is noted that the data for the years 2007 and 2009 for this country are more or less symmetrical, then the crisis generated in 2008 a skewness in data distribution. A similar observation can be done for the United States in 1973, in relation to the *OPEC oil price shock*. The years 1989 and 1990 respectively for Romania and Poland are referred to the *Fall of the Berlin Wall*. These years were period of socio-economic instability. The year 1990 for South Africa is related to the end of the Arpatheid, 1974 for the United Kingdom referred to the *OPEC oil price shock*, the year 1983 for the Sri Lankan is referred to civil war period, and the year 2011 for Morocco to the recent world economy instability.

We can see on Figure 3.3 that, over the years highlighted as years of crisis, there is an increase of prices. Furthermore, for the years that present increase of price over the precedent year, the relative-price changes distribution for that year is skewed (the median is closest to one of the extreme values). For most of the years, the increase of the price level is associated to negative skew.
How often prices change, how large are the price changes. The substantial heterogeneity in the micro data is useful to characterize the distribution of the size of price changes.

3.3 Goodness-of-Fit of the Skew-Normal Model

Let $X \sim SN(0.1, \alpha)$, a random variable, and let considering the linear transformation $Y = \mu + \sigma X, \mu \in \mathbb{R}, \sigma > 0$. We are interested to test the following hypothesis:

$$H_0 : Y \sim SN(\mu, \sigma, \alpha_0)$$

$$\text{vs}$$

$$H_1 : Y \sim SN(\mu, \sigma, \alpha)$$

where the value α is unknown. In this regard, we set:

$$M(t) = E[\exp(tY)], t \in \mathbb{R}$$

the Moment-Generating Function (MGF) of Y. If $Y \sim SN(\mu, \sigma, \alpha)$, then the MGF of Y, is:

$$M(t) = 2 \exp\{\mu t + (\sigma^2 t^2/2)\}\Phi(\mu\delta t),$$

Figure 3.1: Density function of relative-price changes-1

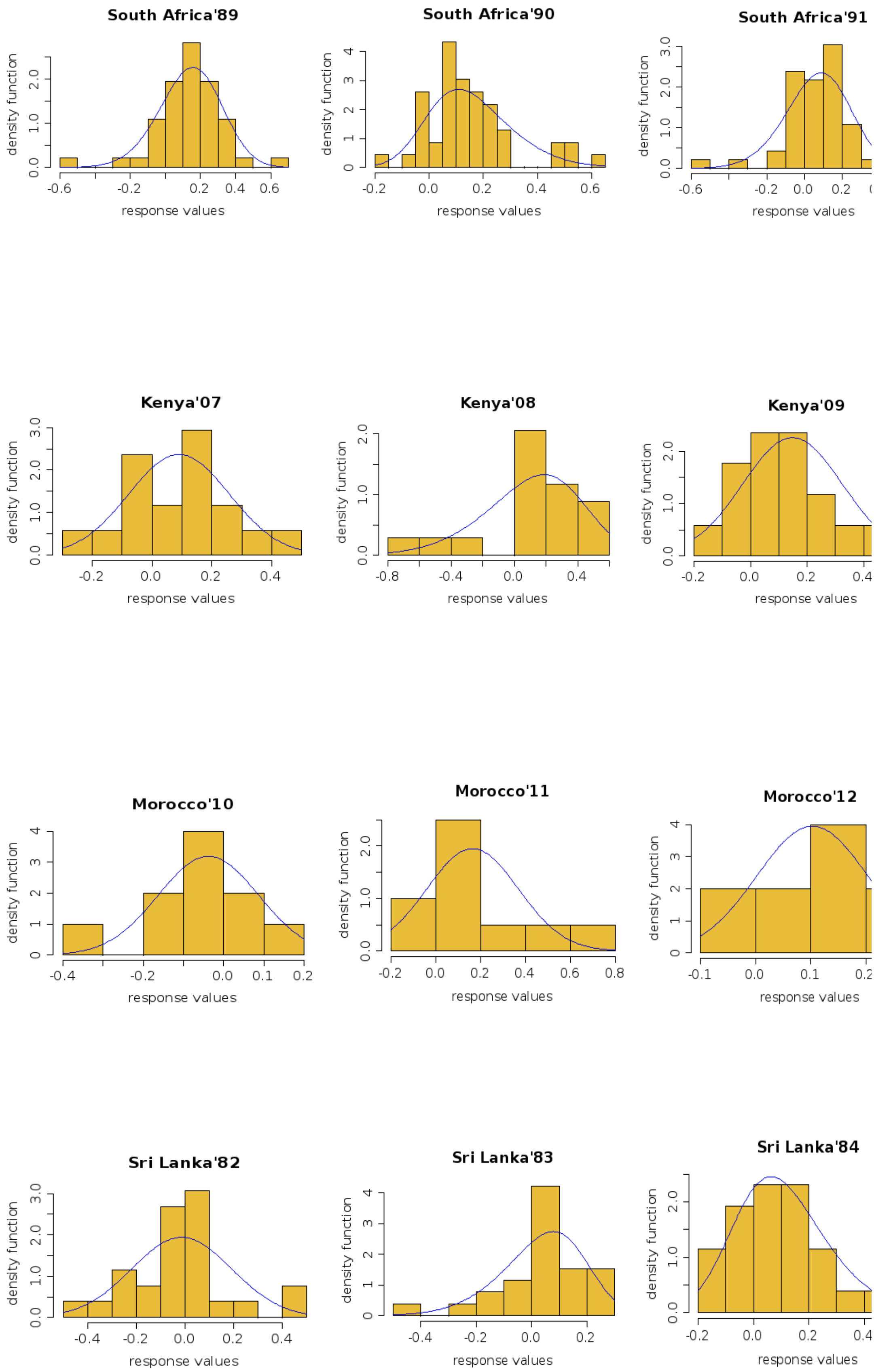


Figure 3.2: Density function of relative-price changes-2

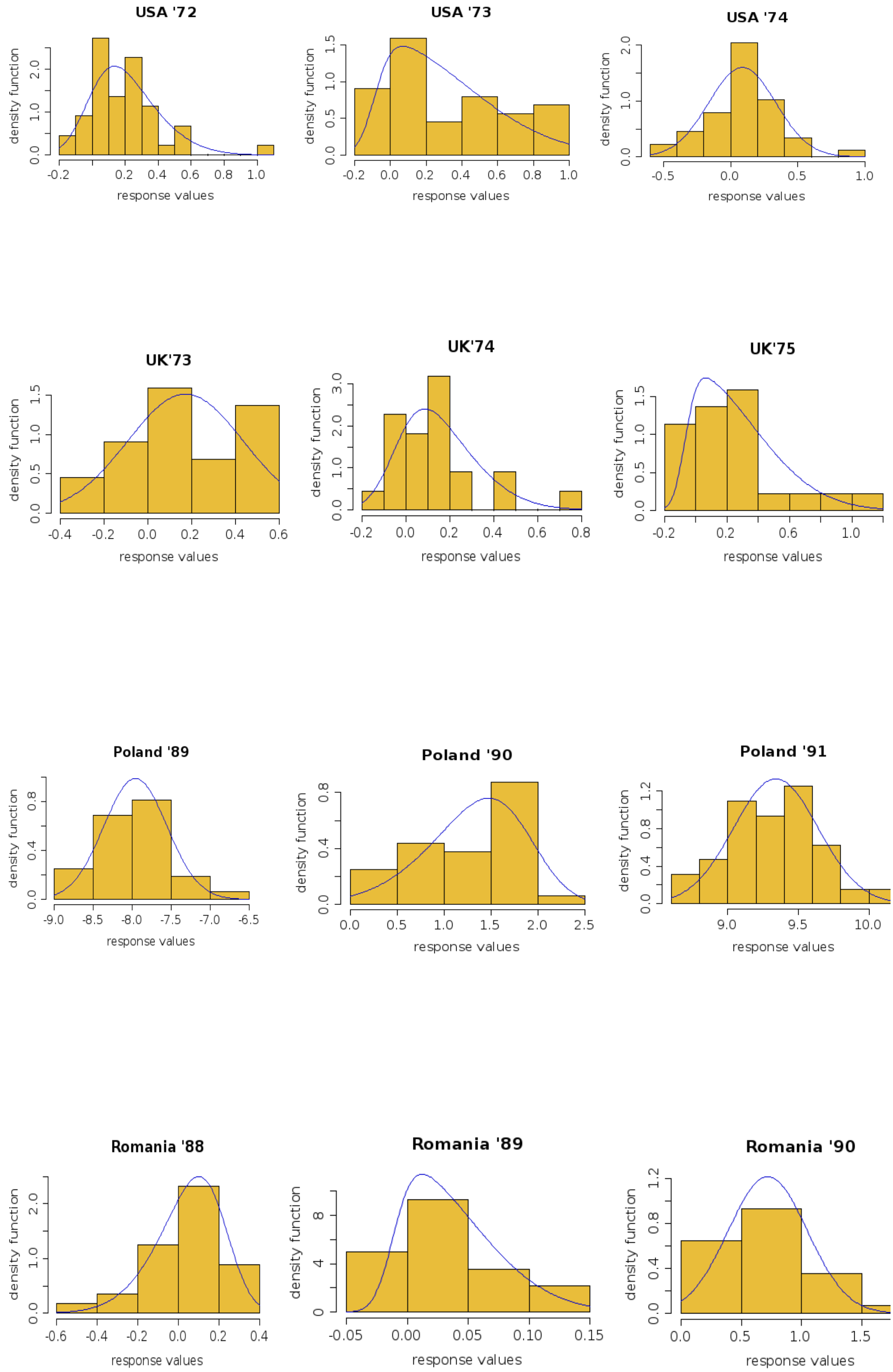
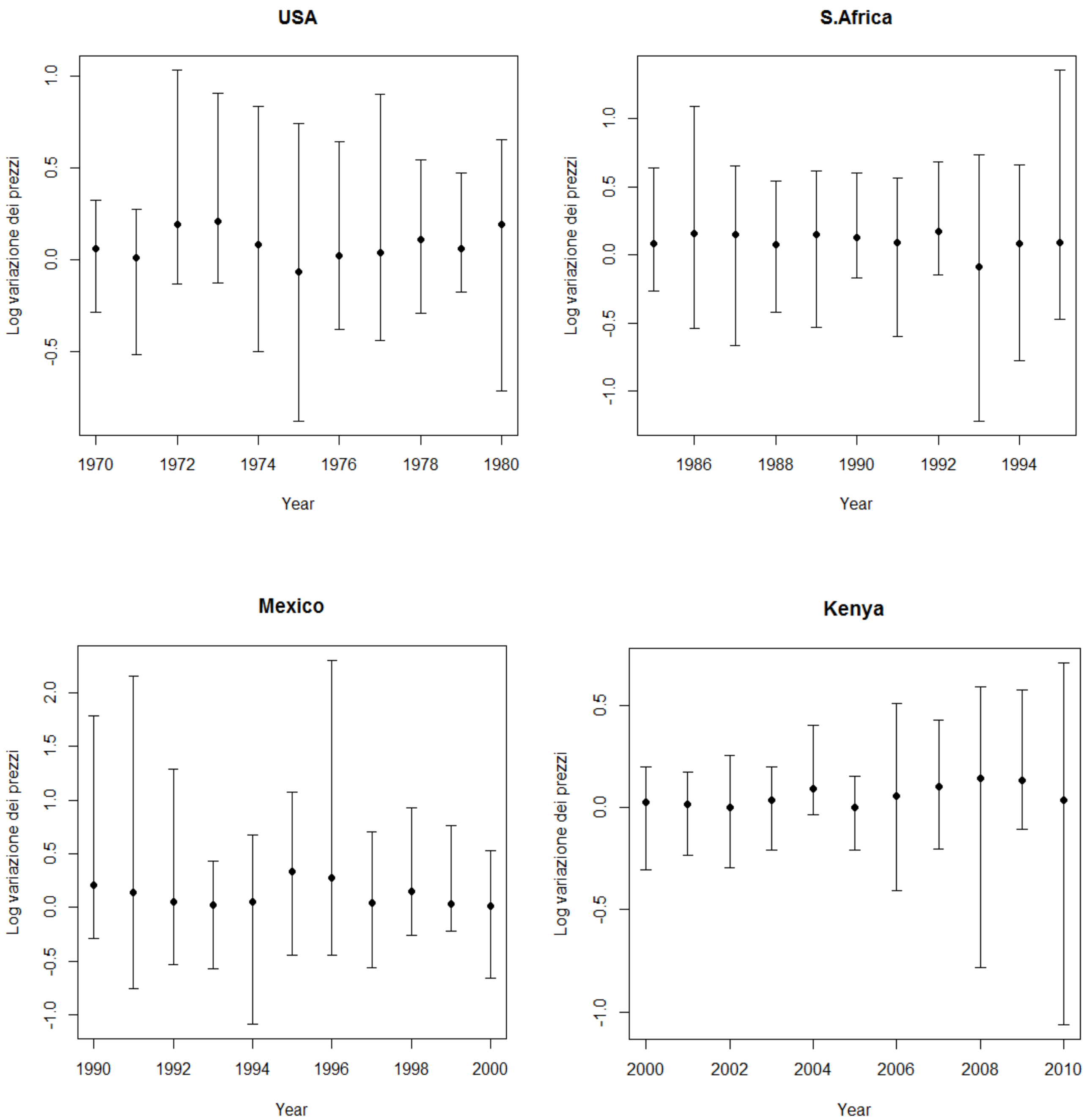


Figure 3.3: Scatter plot for median, min & max



with $\delta = \alpha/\sqrt{1+\alpha^2}$, ϕ and Φ which are respectively the density and the distribution function of a standard normal.
Therefore we can compute:

$$M'(\mu,\sigma;t) - tM(\mu,\sigma;t) = 2\exp\{\mu t + \sigma^2 t^2/2\}\big[(\mu + \sigma^2 t - t)\Phi(\sigma\delta t) + \sigma\delta\phi(\sigma\delta t)\big]$$

Furthermore, let $M(t) := M(0,1;t)$, we have:

$$\begin{aligned} M'(t) - tM(t) &= 2\delta\exp\{t^2/2\}\phi(\delta t) \\ &= \delta\sqrt{\frac{2}{\pi}}\exp\{\frac{t^2}{2}(1-\delta^2)\} \end{aligned}$$

Therefore $t \mapsto M(t)$ is the unique solution of the differential equation,

$$\begin{cases} M'(t) - tM(t) - \delta\sqrt{\frac{2}{\pi}}\exp\left[\frac{t^2}{\pi}(1-\delta^2)\right] = 0, & t \in \mathbb{R} \\ M(0) = 1 \end{cases} \qquad (1)$$

Let $Y_1, \cdots, Y_n$ the realizations of a random variable Y. To verify the null hypothesis H_0, we consider the empirical MGF:

$$\hat{M}(t) = \frac{1}{n}\sum_{j=1}^{n}\exp(t\hat{X}_j),$$

where $\hat{X}_j = (Y_j - \hat{\mu})/\hat{\sigma}, j = 1, 2, \cdots, n$ e $(\hat{\mu}, \hat{\sigma})$ is a consistent esimator of (μ, σ). Under H_0 and for large n, $\{\hat{X}\}_{j=1}^n \sim SN(\alpha_0)$, it is natural, considering (1), to base a test of H_0 on a measure of deviation from zero of the function

$$D(t) = M'(t) - tM(t) - \delta_0\sqrt{\frac{2}{\pi}}\exp\left[\frac{t^2}{\pi}(1-\delta_0^2)\right],$$

where $\delta_0 = \alpha_0/\sqrt{1+\alpha_0^2}$.
The test of the null hypothesis H_0 is based on a measure of deviation from zero of the function:

$$\hat{D(t)} = \hat{M}'(t) - t\hat{M}(t) - \delta_0\sqrt{\frac{2}{\pi}}\exp\left[\frac{t^2}{\pi}(1-\hat{\delta}_0^2)\right],$$

with $\hat{\delta}_0 = \hat{\alpha}_0/\sqrt{1+\hat{\alpha}_0^2}$, where $\hat{\alpha}$ is a consistent estimator of α.

The main advantage of the empirical MGF lies in that it is an unbiased and consistent estimator of the population MGF, and that, under specific sampling situations including the present one, it is more convenient to employ methods based on the empirical MGF, rather than classical methods utilizing the empirical distribution function. The empirical MGF has been used several times to test the Goodness-of-Fit: Epps et al. (1982), Epps and Pulley (1985), Feuerverger (1989), Ghosh (1996), Koutrouvelis and Canavos (1997), Clark et al. (2001), Koutrouvelis and Meintanis (2002), and Koutrouvelis et al. (2005).

The statistic tests are:

$$T_a = \sqrt{n} \sup_{-a \le t \le a} |D(t)|, \qquad \forall a > 0$$

and

$$\hat{T}_a = \sqrt{n} \sup_{-a \le t \le a} |\hat{D}(t)|, \qquad \forall a > 0$$

Algorithm

However since the null distribution of the test statistic depends on the value of the shape parameter α which is unknown, we resort to a parametric bootstrap procedure in order to obtain the critical point of the test as follows:

1) Compute the estimated values $\hat{\mu}, \hat{\sigma}, \hat{\alpha}$, and the values $\hat{X}_j = (Y_j - \hat{\mu})/\hat{\sigma}, j = 1, \cdots, n.$

2) Compute the statistic test $\hat{T}$ based on $\hat{X}_j$ and $\hat{\alpha}$.

3) Generate a sample bootstrap $Y_j^*, j = 1, \cdots, n$ from $SN(\alpha)$.

4) On the basis of $Y_j^*, j = 1, \cdots, n$, calculate the estimates $\hat{\mu}^*, \hat{\sigma}^*, \hat{\alpha}^*$, and therefore the observations $\hat{X}_j^* = (Y_j^* - \hat{\mu}^*)/\hat{\sigma}^*, j = 1, \cdots, n.$

5) Calculate the value of the statistic test, $\hat{T}^*$, based on the values $\hat{X}_j^*$ and $\hat{\alpha}^*$

Table 3.1: Basics statistics

	Kenya '07	Kenya'08	S.Lanka'82	S.Lanka'83	USA'72	USA'73
nobs	17	17	29	29	44	44
Minimum	-0.202	-0.783	-0.251	-1.484	-0.135	-1.125
Maximum	0.430	0.592	1.643	0.539	1.030	0.907
Media	0.089	0.108	0.1398	-0.085	0.201	0.317
Mediana	0.103	0.145	0.091	-0.136	0.192	0.207
Varianza	0.030	0.120	0.103	0.118	0.046	0.100
Dev.Standard	0.173	0.347	0.321	0.215	0.239	0.317
Skewness	**0.290**	**-1.073**	**3.405**	**-3.124**	**1.249**	**0.387**
Kurtosis	**-0.842**	**0.585**	**13.649**	**12.067**	**2.957**	**-1.284**

6) Repeat steps 3)-5), and calculate 1000 values $\hat{T}_j^*, j = 1, \cdots, n.$

7) Calculate $\hat{p}_{0.05} = \hat{T}^*_{0.950}$, where $\hat{T}^*_(n)$ is the ordered statistic.

The results are presented in Tables 3.2 and 3.3 for some countries. We observed that for almost all years the test values are lower than the critical values. So the test does not reject the "hypothesis that the data for each year are distributed as a skew-normal with "***estimated parameters***" for those years.

Table 3.2: Skewness of the distribution of the price changes

Year	Kenya Test Val.	Kenya Critical Val.	S.Africa Test Val.	S.Africa Critical Val.
1972	0.138	0.148	0.104	0.117
1973	0.474	0.148	0.073	0.098
1974	0.095	0.132	0.092	0.095
1975	0.093	0.131	0.069	0.098
1976	0.144	0.130	0.076	0.112
1977	0.147	0.137	0.016	0.098
1978	0.148	0.146	0.063	0.103
1979	0.045	0.129	0.088	0.102
1980	0.131	0.140	0.080	0.110
1981	0.122	0.125	0.052	0.110
1982	0.968	0.162	0.070	0.107
1983	0.005	0.126	0.076	0.098
1984	0.472	0.148	0.080	0.097
1985	0.127	0.129	0.093	0.129
1986	0.126	0.151	0.046	0.107
1987	0.343	0.153	0.086	0.098
1988	0.107	0.133	0.007	0.100
1989	0.093	0.132	0.075	0.100
1990	0.119	0.128	0.076	0.118
1991	0.152	0.139	0.065	0.101
1992	0.059	0.130	0.068	0.120
1993	0.043	0.594	0.040	0.095
1994	0.024	0.129	0.078	0.099
1995	0.003	0.138	0.157	0.109
1996	0.094	0.138	0.076	0.109
1997	0.024	0.128	0.372	0.172
1998	0.103	0.148	0.095	0.119
1999	0.109	0.129	0.091	0.101
2000	0.079	0.130	0.035	0.096
2001	0.035	0.134	0.012	0.094
2002	0.020	0.124	0.033	0.098
2003	0.070	0.130	0.097	0.105
2004	0.088	0.130	0.072	0.099
2005	0.037	0.129	0.046	0.112
2006	0.021	0.132	0.112	0.128
2007	0.028	0.132	0.086	0.091
2008	0.111	0.134	0.080	0.104
2009	0.040	0.130	0.016	0.091
2010	0.075	0.129	0.059	0.107
2011	0.040	0.127	0.056	0.104
2012	0.099	0.132	0.052	0.102

Table 3.3: Skewness of the didtribution of the price changes

Year	USA Test Val.	USA Critical Val.	Mexico Test Val.	Mexico Critical Val.
1972	0.061	0.125	0.064	0.096
1973	0.155	0.205	0.093	0.183
1974	0.032	0.103	0.058	0.092
1975	0.042	0.097	0.122	0.122
1976	0.078	0.105	0.097	0.093
1977	0.083	0.100	0.049	0.087
1978	0.018	0.097	0.058	0.087
1979	0.041	0.097	0.055	0.098
1980	0.082	0.100	0.086	0.088
1981	0.081	0.102	0.058	0.114
1982	0.363	0.223	0.086	0.088
1983	0.056	0.149	0.057	0.095
1984	0.056	0.100	0.116	0.099
1985	0.089	0.108	0.045	0.131
1986	0.078	0.096	0.008	0.087
1987	0.047	0.097	0.034	0.085
1988	0.087	0.161	0.021	0.086
1989	0.064	0.115	0.400	0.123
1990	0.044	0.102	0.413	0.132
1991	0.206	0.182	0.331	0.104
1992	0.005	0.101	0.086	0.095
1993	0.176	0.144	0.050	0.091
1994	0.075	0.104	0.094	0.099
1995	0.077	0.116	0.056	0.086
1996	0.081	0.099	0.185	0.103
1997	0.085	0.095	0.004	0.081
1998	0.050	0.102	0.095	0.127
1999	0.067	0.098	0.091	0.101
2000	0.039	0.102	0.035	0.096
2001	0.072	0.118	0.012	0.094
2002	0.081	0.098	0.033	0.098
2003	0.054	0.098	0.097	0.105
2004	0.068	0.098	0.072	0.099
2005	0.251	0.132	0.046	0.112
2006	0.073	0.104	0.112	0.128
2007	0.036	0.093	0.086	0.091
2008	0.067	0.138	0.080	0.104
2009	0.161	0.143	0.016	0.091
2010	0.109	0.166	0.059	0.107
2011	0.026	0.096	0.056	0.104
2012	0.054	0.127	0.052	0.102

Chapter 4

Dynamic Panel Data Models Based on GMM Estimator

4.1 Introduction

The Generalized Method of Moments (GMM) is a generic method for estimating parameters in statistical models. Estimators are derived from moment conditions. Three main motivations for their use are: (1) Many estimators can be seen as special cases of GMM, unifying framework for comparison; (2) Maximum likelihood estimators have the smallest variance in the class of consistent and asymptotically normal estimators; (3) GMM estimation is often possible where a likelihood. In this chapter, we discuss the methodology of estimation for dynamic panel data models, using Arellano-Bond estimator. It will help to model the heterogeneity of each country, assuming that the error has two components, one related to characteristics of a country which does not change with time and another one random.

4.2 The Economical Model

The evidence of a significant correlation between inflation and cross-section moments (variance and skewness) of the price distribution is widely available in the literature. If a shock occurs in a market and generates an increase in supply relative to demand, the relative price will tend to fall and an equilibrium with a lower price will be established. If no shocks occur in other markets and there are no price rigidities, the nominal price will then fall as well. But if the price is nominally rigid because an adjustment entails a cost for the firm, the shock will not necessarily lead to a nominal price fall; that will depend on whether or not the benefit of a lower price- of moving towards the optimal price- exceeds the cost of adjusting the price. The larger the shock, the greater the probability of a price adjustment. The full range of relative shocks includes a number of large positive and large negative shocks that result in a lower and a higher price, respectively, as well as numerous small shocks that do not generate price adjustments because in these cases the benefit of a price adjustment does not outweigh its cost.

We now turn to more systematic analysis of the data and test whether skewness and variance have inflationary effect on price changes. Ball and Mankiw (1995) presented regression model to assess this fact. On the right-hand side of the equations are variables describing the distribution of relative-price changes. All the regressions also include lagged inflation to capture persistence. The model tests our basic predictions about the inflationary effects of variance and skewness in relative-price changes. Then sequentially we introduce the indicator of asymmetry presented in the chapter 2.
At the difference of Ball and Mankiw (1995), we used panel data to estimate inflation.
The regression models are

$$Inflation_{it} = \rho * Inflation_{i,t-1} + \beta_1 * StandardDeviation_{it} + \beta_2 * Skewness_{it} +$$

$$\beta_3 * StandardDeviation_{it} \times Skewness_{it} + \alpha_i + \epsilon_{it}$$

and

$$Inflation_{it} = \rho * Inflation_{i,t-1} + \beta_1 * StandardDeviation_{it} + \beta_2 * Asym10 + \beta_3 * Asym25 + \alpha_i + \epsilon_{it}$$

α_i are individual-specific, time-invariant effects and ϵ_{it} are the random effects.

4.3 Variables Used

4.3.1 Inflation

For a given country and for a given year, the *Inflation* is calculated as following $\pi_t = \sum_{i=1}^{n} w_{it} \Delta log(p_{it})$, with $w_{it} = \frac{p_{it}q_{it}}{\sum_j p_{jt}q_{jt}}$ is the budget share for good i in period t, p_{it} is the price, q_{it} is the volume (quantity) and Δ is the difference operator.

The set of goods is composed of agricultural products produced in a given country. The variation of the prices will represent a sustained increase/decrease in the general price level of goods in this set over a period of one year.

4.3.2 Standard Deviation

Variance is a measure of the dispersion in a distribution. The Standard Deviation is calculated in four different ways.

a) Unweighted and Weighted Empirical Moment

The empirical standard deviation is calculated as the square root of the variance. The unweighted and weighted variance are calculated respectively as follow :

Unweighted variance in relative-price changes: $\sigma_t^2 = \sum_{i=1}^{n} (\Delta log(p_{it}) - \pi_t)^2$

Weighted variance in relative-price changes: $\sigma_t^2 = \sum_{i=1}^{n} w_{it}(\Delta log(p_{it}) - \pi_t)^2$

The weights are calculated as above.

b) Unweighted Moment Considering the Skew-Normal Distribution

We have seen that the distribution of variation of the relative price changes follows a skew-normal distribution: $r \sim SN(\alpha)$, with $\alpha \in \mathbb{R}$.

Note: *The expected-value $E(r)$ represents the weighted mean of the relative price changes of a set of commodities.*

(Azzalini, 1985) shows that :

$$E(r) = \frac{2}{\pi}.\frac{\alpha}{\sqrt{1+\alpha^2}}$$

$$\sigma_r^2 = Var(r) = 1 - \frac{2}{\pi^2}.\frac{\alpha^2}{1+\alpha^2}$$

We can compute these moments, estimating the parameter α of the distribution.

c) Weighted Moment Considering an Approximation of the Skew-Normal Distribution

(S.K. Ashour, M. A. Abdel-hameed, 2010) propose a new approximate skew normal distribution, it is easy to calculate, convenient, mathematically tractable and is in a closed form. It is particularly useful when the probability density function occurs in an expression to be used for further mathematical derivation or in programs for the skew normal distribution. Also, they propose approximate first moment second moment and variance to the skew normal distribution.

The approximation is based Hoyt approximation for the standard normal distribution using the distribution of the sum of the three mutually independent random variables each uniformly distributed over the interval of $]-3, 3]$.
So, the approximate pdf of the skew normal $h(x)$ will be

$$h(x)=\begin{cases}0 & x<\frac{-3}{2},\\ \frac{1}{8\sqrt{2\pi}}\exp^{-x^2/2}(9\alpha x+3\alpha^2x^2+\frac{1}{3}\alpha^3x^3+9) & \frac{-3}{\alpha}\leq x\leq\frac{-1}{\alpha},\\ \frac{1}{4\sqrt{2\pi}}\exp^{-x^2/2}(3\alpha x-\frac{1}{3}\alpha^3x^3+4) & \frac{-1}{\alpha}\leq x\leq\frac{1}{\alpha},\\ \frac{1}{8\sqrt{2\pi}}\exp^{-x^2/2}(9\alpha x-3\alpha^2x^2+\frac{1}{3}\alpha^3x^3+7) & \frac{1}{\alpha}\leq x\leq\frac{3}{\alpha},\\ \sqrt{\frac{2}{\pi}}\exp^{-x^2/2} & \frac{3}{\alpha}\leq x.\end{cases}$$

Therefore we can calculate the weighted moments. So we proceed as follow:

Let $(a_i)_n \sim SN(\alpha)$, and $h(x)$ its approximate density function distribution. For $i \in [2:(n-1)]$, we define $[b_i, b_{i+1}]$, with $b_i = a_i - 0.5*(a_i - a_{i-1})$ e $b_{i+1} = a_i + 0.5*(a_{i+1} - a_i)$. The b_i are at equal distances of 2 consecutives a_i. $b_0 = a_0$ e $b_n = a_n$.

Let r e w_i, respectively the annual inflation and the weight of good i used for the calculation of r.
$Variance = \sum_i^n w_i \int_{b_i}^{b_{i+1}} (a_i - r)^2 * h(x)dx$

All these variables refer to a single year.

4.3.3 Skewness

Like the Standard Deviation, the Skewness is calculated in four different ways.

a) Unweighted and Weighted Empirical Moment

The unweighted and weighted skewness are calculated respectively as follow :

Skewness in relative-price changes: $\sigma_t^3 = \frac{\sum_{i=1}^n(\Delta log(p_{it}) - \pi_t)^3}{\sigma_t^2}$

Skewness in relative-price changes: $\sigma_t^3 = \dfrac{\sum_{i=1}^{n} w_{it}(\Delta log(p_{it}) - \pi_t)^3}{\sigma_t^2}$

σ_t^2 being the unweighted variance in the unweighted case and weighted variance in the unweighted case.

b) Unweighted Moment Considering the Skew-Normal Distribution

The skewness is calculated as

$$E(r) = \frac{2}{\pi}.\frac{\alpha}{\sqrt{1+\alpha^2}}$$

$$\begin{aligned}\gamma_1 = Skewness(r) &= sign(\alpha)\frac{4-\pi}{2}\left[\frac{\{E(r)\}^2}{Var(r)}\right]^{3/2} \\ &= sign(\alpha)\frac{4-\pi}{2}\left(\frac{\alpha^2}{\frac{\pi}{2}+(\frac{\pi}{2}-1)\alpha^2}\right)^{3/2}\end{aligned}$$

From these formulas, we note that the coefficient α is a valid indicator of skewness, and its sign determines the period of inflation or deflation.

c) Weighted Moment Considering an Approximation of the Skew-Normal Distribution

Using the new approximation proposed by (S.K. Ashour, M. A. Abdel-hameed, 2010) and presented in the previous section we can compute

$$Skewness = \sum_{i}^{n} w_i \int_{b_i}^{b_{i+1}} (a_i - r)^3 * h(x)dx.$$

A value of *Skewness* equals to zero implies that the data are equally shared among the two part of the media, although this does not necessarily imply a symmetrical distribution.

4.4 The Arellano-Bond Estimator

In empirical studies using panel data, the Generalized Method of Moments estimator (GMM) suggested by Arrelano and Bond (1991) has become popular. Several moment restrictions allow to have a large set of instruments. The linear model contains explanatory variables x_t and the past values of the endogenous variable y.

$$y_{it} = \rho y_{i,t-1} + \beta' x_{it} + \alpha_i + \epsilon_{it}$$

$$\text{where } \epsilon_{it} \sim N(0, \sigma_\epsilon^2) \text{ e } |\rho| < 1$$

$i = 1, \cdots, N$ being the index for countries,

$t = 1, \cdots, T$, index for years,

x'_{it} row vectors of explanatory variables, dimension (k-1)

ρ unknown parameter of the lagged endogenous variable,

β unknown parameter vector of the explanatory variables,

α_i individual specific fixed effects.

Further we make these assumptions on the moment conditions:

- The error term is orthoghonal to exogenous variables: $E(x'_{it}\epsilon_{is}) = 0$

- The exogenous variables might be correlated with the individual effect:
$E(x'_{it}\alpha_i) \neq 0$

- The error term (i.i.d) is uncorrelated with the lagged endogenous variable: $E(y_{i,t-1}\epsilon_{it}) = 0$.

With these assumptions, the form of the matrix of instruments depends wether x_{it} is predetermined or not. If the x_{it} are predetermined, in the sense that $E(x'_{it}\epsilon_{is}) \neq 0$ for $s < t$ and zero otherwise, then only $x_{i1}, \cdots, x_{i(s-1)}$ are valid instruments in the differenced equation for period s. So that the optimal Z_i is a $(T-2)\times/(T-2)[(k-1)(T+1)+(T-2)]/2$ matrix of the form $Z_i = diag(y_{i1},\cdots,y_{is},x'_{i1},\cdots,x'_{i(s+1)}), s=1,\cdots,T-2$. On the other hand, if the x_{it} are strictly exogenous, i.e. $E(x'_{it}\epsilon_{is}) = 0, \forall t, s,$, then all the explicative variables are valid instruments and the matrix of instruments takes the form $Z_i = diag(y_{i1},\cdots,y_{is},x'_{i1},\cdots,x'_{iT}), s=1,\cdots,T-2$.

In both cases, the form of the GMM estimator is

$$\hat{\delta} = (\hat{\rho},\hat{\beta}) = (\bar{X}'ZA_NZ'\bar{X})^{-1}\bar{X}'ZA_NZ'\bar{y}$$

where $\bar{X}$ is a $(T-2)N\times k$ matrix of observations on esplanatory variables and Z are as above for the appropriate choice of Z_i. Alternative choices of A_N will produce one-step or two-step estimators (R. Judson, A. Owen, 1996):

- The ***one-step*** **estimator** is obtained using a matrix of weighting:

$$A_N = \left(\frac{1}{N}\sum_i^N Z_i'HZ_i\right)^{-1}$$

where H is a $T-2$ square matrix with twos in the main diagonals, minus ones in the first subdiagonals, and zeros otherwise.

- The ***two-step*** **estimator** is found by letting

$$A_N = \left(\frac{1}{N}\sum_i^N Z_i'\Delta\hat{e}_i\Delta\hat{e}_i'Z_i\right)^{-1}$$

where $\Delta\hat{e}_i = (\Delta\hat{e}_{i3},\cdots,\Delta\hat{e}_{iT})$ are the residuals from a consistent one-step estimator of Δy_i.

(Andreas Behr, 2003) has discussed methods of dynamic panel data estimation: the Anderson-Hsiao estimator, the Blundell-Bund estimator, the direct bias correction, another alternative bias correction method and the mentioned method here above the Arellano-Bond estimator. The Arellano-Bond GMM estimator optimally exploits all the linear moment restrictions that follow from the assumption of no serial correlation in the errors, in an equation which contains individual effects, lagged dependent variables and no strictly exogenous variables. (M.Arellano, S.Bond,1991) discussed the adaptability of this estimator to unbalanced panel.

4.5 Tests

4.5.1 Sargan Test

The Sargan test of over-identifying restrictions is given by

$$s = \hat{e}' Z(\sum_{i=1}^{N} Z_i' \hat{e}_i \hat{e}_i' Z_i)^{-1} Z' \hat{e} \sim_{H_0} \chi_{p-k},$$

where $\hat{e} = y - X\hat{\delta}$, and $\hat{\delta}$ is a two-step estimator of δ for a given Z. The null hypothesis is that the instrumental variables are valid.

4.5.2 Arellano-Bond test for the autocorretion

The Sargan/Hansen test for joint validity of the instruments is standard after GMM estimation. In addition, Arellano and Bond develop a test for a phenomenon that would render some lags invalid as instruments, namely autocorrelation in the idiosyncratic disturbance term ϵ_{it}. Of course, the full disturbance $u_{it} = \alpha_i + \epsilon_{it}$ is presumed autocorrelated because it contains fixe effects, and the estimators are designed to eliminate this source of trouble. But if the ϵ_{it} are themselves serially correlated of order 1 then, for instance, $y_{i(t-2)}$ is endogenous to the $\epsilon_{i(t-2)}$ in the error term in differences, $\Delta u_{it} = \epsilon_{it} - \epsilon_{i(t-1)}$, making it a potentially invalid instrument after all.
In order to test for autocorrelation aside from the fixed effects, the Arellano-Bond test is applied to theresiduals in differences. Since $\Delta\epsilon_{it}$ is mathematically related to $\Delta\epsilon_{i(t-1)}$ via the shared $\epsilon_{i(t-1)}$ term, negative first-order serial correlation is expected in differences and evidence of it is uninformative. Thus to check for first-order serial correlation in levels, we look for second-order correlation in differences, on the idea that this will detect correlation between the $\epsilon_{i(t-1)}$ in $\Delta\epsilon_{it}$ and $\epsilon_{i(t-2)}$ in $\Delta\epsilon_{i(t-2)}$. In general, we check for serial correlation of order l in levels by looking for correlation of order $l+1$ in differences.

If W is a matrix of data, and W^{-l} its lagged value at time l, with zero for $t \geq l$. The statistic test of the autocorrelation of Arellano-Bond is:

$$AB_{test} = (1/N) \sum_i \hat{E}_i^{-l} \hat{E}_i, \quad \text{con } \hat{E}_i = Y - X\hat{\beta}$$

which has expected value zero under the null hypotesis of absence of correlation of order l. The Central Limit Theorem ensures that this statistic test is asintotically distributed as a Normal Standard.

4.5.3 Wald Test

The Wald statistic is a test of the joint significance of the independent variables asymptotically distributed as χ_k^2 under the null of no relationship, where k is the number of coefficients estimated (excluding time dummies).

$$W = \hat{\beta}' \hat{Var}(\beta)^{-1} \hat{\beta},$$

where $\hat{\beta}$ and $\hat{Var}(\beta)$ are consistent estimators of β and $Var(\beta)$.

4.6 Results

The data come from FAOSTAT, the database of the Food and Agriculture Organisation of the United Nations (FAO). They are composed by Annual Producer Prices or prices received by farmers for primary crops as collected at the farm-gate or at the first point of sale. Data are provided through annual questionnaires for over 123 countries and for some 160 commodities. For some EU countries producer prices are sourced directly from EUROSTAT. They are yearly and cover the period 1993-1999. The two-step estimator GMM are obtained usng the function *pgmm* from the package *plm* R.

Tables 4.1 and 4.2 present the regresions on the moments using the inflation as dependant variable. The instrument used in all the regression is the lagged 3 inflation.

The table 4.1. presents the regression of the inflation as dependent variable on the unweighted and weighted moments. We can see that the coefficient of the standard deviation are always significant and positive: The larger standard deviation magnifies the aggregate price change. This observation can be done for the computed standard deviation: unweighted, weighted.

The coefficients of the skewness are not significant. For the case where we consider the skew

distribution, it may due to the fact that parameters are estimated firstly and the moments are estimated in a second time. The coefficient of the interaction between the standard deviation and the skewness is significant while considering the empirical unweighted moments.
The Sargan test shows that the lagged variables of inflation are used as instrument variables are valid. The tests of Arellano-Bond show that there is no correlation in the first differences of the errors, and then the validity of the instruments. Wald test rejects the hypothesis that the coefficients of the explanatory variables are jointly equal to zero.

The table 4.2 introduces in the regression, an indicator of asymmetry presented in the chapter 2:

$$AsymX = Asym(x) = \int_{-\infty}^{-x} rh(r)dr + \int_{x}^{+\infty} rh(r)dr.$$

with h as the density function. This indicator of skewness is computed for 10 and 25.
The theory says that inflation depends on the sizes of the tails of the distribution of changes in relative prices. Here we experiment with such alternative variables. We use the distribution of industry price changes as a proxy for the distribution of unobserved shocks, which determines inflation in our model.
The coefficients of $AsymX$ in the table 4.2 are positive and significants. $AsymX$ is positively correlated with Inflation, that is, the asymmetry of the distribution magnifies the inflation.
In the table 4.2, the regression (3) presents a coefficient of $Asym10$ not significant. It can be due to the fact that this regression includes also the variable $Asym25$. In this studied case, this latter variable can explain better the asymmetry presented in the distribution than the variable $Asym10$.
The variable $AsymX$ has an approach purely empirical in computing the skewness. Here, we dont make any assumptions about the distribution of the variable in study. At the difference of the regression in table 5.1, where the distribution are assumed to be known and the parameters are estimated. This can explain the fact that these coefficients resulted non significant in this case studied. There are various ways to measure the asymmetry in relative-price changes, but this case show a strong ground for choosing the defined variable $AsymX$.

The coefficient of $AsymX$ in the regressions in table are between 2.3 to 4.0. For instance, the coefficient of $Asym25$ is 2.396. It means that for a variation unit of $Asym25$, the Inflation will increase for 2.396 units, the other variables remaining constant. It represents a huge impact on inflation. This variable should also be important to consider if we plan to monitor inflation.

Table 4.1: Inflation and Relative Price Changes

Dependent Variable: Inflation				
	(1)	(2)	(3)	(4)
LagInflat 1	-0.320***	-0.311***	-0.318***	-0.311***
	(0.052)	(0.048)	(0.050)	(0.048)
Std.Deviation	0.334**	0.495**	0.395*	0.495**
	(0.109)	(0.165)	(0.158)	(0.165)
Skewness	0.003	-0.092	0.007	-0.092
	(0.011)	(0.126)	(0.023)	(0.126)
Skewness×Std.Deviation	0.084*	0.098	0.193	0.098
	(0.040)	(0.063)	(0.101)	(0.063)
Sargan Test	1.508	2.067	1.336	2.067
p-value	0.680	0.558	0.720	0.558
Autocorrelation test (1)	0.620	0.571	0.595	0.571
p-value	0.535	0.567	0.551	0.567
Wald test for coefficients	91.886	134.009	70.462	134.009
p-value	0.000	0.000	0.000	0.000
Wald test for time dummies	84.781	82.144	81.372	82.144
p-value	0.000	0.000	0.000	0.000

1. Regression using empirical unweighted moments.
2. Regression using empirical weighted moments.
3. Regression using Skew-Normal unweighted moments.
4. Regression using weighted moments based on an approximation of the Skew-Normal.

Table 4.2: Inflation and Relative Price Changes (**Asymmetry Index**)

Dependent Variable: Inflation			
	(1)	(2)	(3)
LagInflat 1	-0.306***	-0.116*	-0.116*
	(0.054)	(0.049)	(0.058)
Std.Deviation	0.362**	0.241·	0.299**
	(0.137)	(0.127)	(0.113)
Asym10	3.960***		1.971
	(0.937)		(1.988)
Asym25		2.855***	2.396***
		(0.392)	(0.660)
Sargan Test	1.635	2.761	4.063
p-value	0.651	0.429	0.254
Autocorrelation test (1)	0.599	-1.266	-0.943
p-value	0.548	0.205	0.345
Wald test for coefficients	109.962	192.503	273.136
p-value	0.000	0.000	0.000
Wald test for time dummies	74.026	34.143	25.626
p-value	0.000	0.000	0.000

4.7 Conclusion

In this chapter, we have used the Ball and Mankiw model to explain the inflation for a set of agricultural commodities. As demonstrated by Ball and Mankiw (1995), the second and the third moments of the distribution can explain relative price changes. In this study, we have seen that standard deviation and an index of skewness can explain inflation. This index of skewness ($AsymX$) is computed using the distribution of the relative price changes. It is significant for two different values of X: 10 and 25. It imply that, it is a valid statistical variable to assess inflation.

Chapter 5

A Food Security Indicator

5.1 Introduction

Food security, as defined by the United Nations' Committee on World Food Security, is the condition in which all people, at all times, have physical, social and economic access to sufficient safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. Over the coming decades, a changing climate, growing global population, rising food prices, and environmental stressors will have significant yet highly uncertain impacts on food security. Adaptation strategies and policy responses to global change, including options for handling water allocation, land use patterns, food trade, post-harvest food processing, and food prices and safety are urgently needed. These policy responses will be vital to improve the living conditions of farmers and rural populations across the globe.

Of several variables, food price is one of the most significant in determining the state of food security in the world. While the availability and adequacy of food worsens with food price inflation due to fallouts such as export curbs and hoarding, food accessibility is the most important consequence because inflation increases the amount of resources necessary to obtain appropriate food for a nutritionally balanced diet, especially among vulnerable groups such as the urban and rural poor, and women and children in developing countries. According to the FAO, the number of undernourished people increased from 848 million to 1,020 million between 2003-2005 and 2009 due primarily to the food and financial crisis (Von Grebmer et al., 2009). Robert Zoellick, president of the World Bank until June 2012, said that the crisis of surging food prices of 2007-2008 could mean "seven lost years" in the fight against worldwide poverty (World Bank, 2012). Food prices have increased 142 per cent in developing countries and 38 per cent in the OECD in the last decade.

The inflation being a good variable in order to assess food accessibility, this chapter looks at the index of asymmetry $AsymX$ from the distribution of food price changes as an indicator for food security.

5.2 Concept and Definition

The initial focus, reflecting the global concerns of 1974, was on the volume and stability of food supplies. Food security was defined in the 1974 World Food Summit as:

"availability at all times of adequate world food supplies of basic foodstuffs to sustain a steady expansion of food consumption and to offset fluctuations in production and prices".

In 1983, FAO expanded its concept to include securing access by vulnerable people to available supplies, implying that attention should be balanced between the demand and supply side of the food security equation:

"ensuring that all people at all times have both physical and economic access to the basic food that they need".

This concept of food security is further elaborated in terms of:

"access of all people at all times to enough food for an active, healthy life".

The 1996 World Food Summit adopted a still more complex definition:

"Food security, at the individual, household, national, regional and global levels [is achieved] when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life".

This definition is again refined in The State of Food Insecurity 2001:

"Food security [is] a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life".

Essentially, food security can be described as a phenomenon relating to individuals. It is the nutritional status of the individual household member that is the ultimate focus, and the risk of that adequate status not being achieved or becoming undermined. The latter risk describes the vulnerability of individuals in this context. As the definitions reviewed above imply, vulnerability may occur both as a chronic and transitory phenomenon. Food security exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life. Household food security is the application of this concept to the family level, with individuals within households as the focus of concern. Food insecurity exists when people do not have adequate physical, social or economic access to food as defined above.

5.3 An Food Indicator: The Indicator of Asymmetry

As emphasized by Amartya Sen (1981), food security is determined not by whether there is a sufficient amount of food available, but by whether individuals have access to it. To have access to food, and thus gain their "entitlement", as Sen pointed out, the poor need to have sufficient income to purchase this food. In other words, the market must be accessible to them.

Sen's work has motivated much development in Ethiopia, Bangladesh and elsewhere as people have recognized that most famines occur in the midst of sufficient food availability due to issues of access. In Bangladesh, for example, a famine occurred in 1974 in the midst of peak food production because millions of people, agricultural labourers in particular, lost wages because of flooding and could not afford to buy food. This empirical perspective was reinforced by more recent analyses of poverty in rural areas that, using the Household Economy Approach has shown that the poorest in rural communities are the most market dependent and therefore most likely to be affected by issues of food access, especially rising food prices (Misselhorn, 2005).

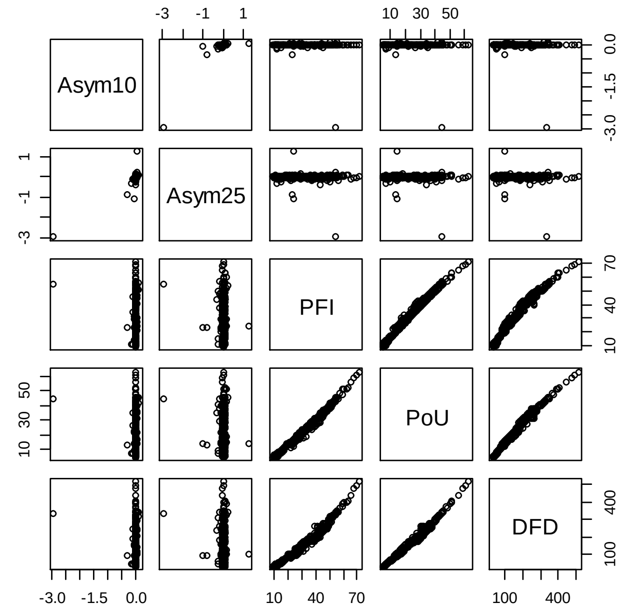
From the definition in the previous section, four main dimensions of food security can be identified (FAO):

- Physical AVAILABILITY of food;
- Economic and physical ACCESS to food;
- Food UTILIZATION;
- STABILITY of the other three dimensions over time.

We are interested here to the second component of the Food Security.

Economic and physical ACCESS to food: "An adequate supply of food at the national or international level does not in itself guarantee household level food security. Concerns about insufficient food access have resulted in a greater policy focus on incomes, expenditure, markets and prices in achieving food security objectives" (FAO, 2008). Food access depends on the household's purchasing power, which varies in relation to market integration, price policies and temporal market conditions.
As we have seen in the previous chapter, the inflation for food prices is explained by the index of skewness of the relative price changes distribution. Therefore this index which indicates the skewness of the distribution could be a valid indicator for food security.

Figure 5.1: Relationship Between Food Security Indicators



a) *Exlusivity*: Food security indicators available in FAOSTAT [1] are: Prevalence of undernourishment (%) (3-year average)(PoU), Depth of the food deficit (kcal/capita/day) (3-year average)(DFD) and Prevalence of food inadequacy (%) (3-year average)(PFI). As shown in the figure 5.1, the indicator $AsymX$ is not related to these variables. It indicates a different dimension of this component of food security. PFI, PoU and DFD are higly correlated, it means that these indicators are replaceable.

b) *Sensibility and Exhaustivity*: $AsymX$ records and describes the variations of the phenomenon. A positive value of the inflation is characterized by a negative value of $AsymX$ (negative asymmetry), that is the upper tail of the relative price changes distribution is bigger than the lower one. The same argument can be sustained for a negative value. The distribution of prices could be skewed to the right (but still has mean zero), but still, $AsymX$ can capture these shocks not observable ny measuring the inflation.

[1] Only those with available data are listed

Table 5.1: Indicator of Asymmetry for Cameroon

Year	**Inflation**	**Asym10**	**Asym25**
2006	0.124	0.001	0.026
2007	0.149	0.001	0.031
2008	0.562	0.003	0.079
2009	-0.035	-0.002	-0.024
2010	0.123	0.0002	-0.017
2011	0.027	0.0001	0.026
2012	0.004	0.001	0.009

Table 5.2: Indicator of Asymmetry for Senegal

Year	**Inflation**	**Asym10**	**Asym25**
2006	0.055	-0.002	0.008
2007	0.160	0.001	0.023
2008	0.207	0.001	0.014
2009	-0.092	-0.002	-0.017
2010	-0.051	-0.0007	-0.008
2011	0.094	0.001	0.021

c) *Sensitivity*: It is important how well the measurement responds to the stimulus. If sensitivity is too low, opportunities for response will be missed; if too high, false alarms will result. The presence of asymmetry in the distribution is a strongly indicator of presence of shocks.

d) *Fidelity*: The value of $AsymX$ is higly positively correlated to the inflation value.

e) *Significativity and Unambiguous*: The previous chapter shows that the index of skewness can explain inflation.

The tables 5.1 - 5.3 present the indicators for three countries and from 2006-2012 (2011 for Senegal). These countries have been affected by the 2008 World Food Crisis.In Cameroon's case, the inflation in 2008 for the set of commodities used is raised 3.77 times over the previous year, and $Asym10$ 3 times. The government of Cameroon announced a two-year emergency

Table 5.3: Indicator of Asymmetry for Indonesia

Year	**Inflation**	**Asym10**	**Asym25**
2006	0.112	-0.036	0.069
2007	0.137	0.003	0.011
2008	0.242	0.003	0.057
2009	-0.091	-0.0005	-0.001
2010	0.261	0.003	0.076
2011	0.768	0.011	0.057
2012	-0.011	-0.0008	-0.007

program designed to double Cameroon's food production and achieve food self-sufficiency. The inflation in 2009 is negative, it can be seen as a result of this emergency plan. We can see that the indicator $AsymX$ capture faithfully these changes. Similar argument can be done for the two other countries. This indicator also vary more or less in the same size compare to the inflation.

This result show the quality of $AsymX$ as good indicator for food accessibility, thus for food security.

Chapter 6

Conclusion

The document examines different ways in which relative price shocks affect the price level and then inflation. Using FAOSTAT data we found evidence that: Changes in the price level are positively related to the asymmetry of relative price changes. Non-Normality in the distribution of price movements has important implications for the measurement of inflation. The Ball and Mankiw model (1995) shows that the menu-cost paradigm can provide a unified interpretation of short-run fluctuations, in which frictions in price adjustment explain the effects of both demand and supply shocks. This study shows the correlation between the first and second moments of price changes.

In this study, we have defined a measure of asymmetry, which captures both variability and skewness of data. According to the year of economic or social unstability, we have observed skewness in the distribution of relative price changes and we present tests which prove that the skew-normal fit this distribution. Using the Arellano-Bond Estimator for panel data, we have presented the results which shown that inflation can be explained by the moments of the distribution of relative price changes, particularly by the asymmetry of the distribution. The results also suggest that the asymmetry variable is better measure of supply shocks than the traditional variables. Model also confirms that the relationship between asymmetries and inflation holds across all time periods. When the distribution is skewed to the right, the economy experiences an adverse shift in aggregate supply: the price level rises for given aggregate demand. Conversely, when the distribution of shocks is skewed to the left, the economy experiences a beneficial supply shock.

The model presented here is intended to capture food security. The built indicator will help to identify case of non acess to food. One of the key points is the data limitations. In other to build the indicator, it is necessary to have producer prices for each commodity.

(Obasi Ukoha, 2007) shows that inflation positively affects price variations among agricultural commodities. Thus, the policies that reduce the rate of inflation will minimize relative price variability among agricultural commodities and consequently reduce the inefficiency and misallocation of resources in agriculture that might arise from the effect of inflation. A proper understanding of the relationship between inflation and skewness is therefore of great importance for policy making and the current document is believed to provide an accurate insight in that regard.

High prices have a mixed effect on poverty and hunger, but the balance of the evidence points to a negative net effect from the recent and projected increases. The poorest are those who cannot produce enough and have to work for others or do other income-generating activities. On the national level, the impact on poverty of an increase in food prices depends upon the balance between two effects: the increase in the real income of those selling food, many of whom are much poorer-net producers are rarely if ever the poorest in the communities-and the injury to net consumers, many of whom are also relatively poor.

Indicators have been developped in other to assess accessibility to food in order to tackle hunger, but as we have seen in this document, some of them provide the same information about food acessibility. Therefore, it was important to develop another indicator to assess this dimension of food security. $AsymX$ could be a good champion for that purpose.

Bibliography

[1] A. Azzalini (1985). *A Class of Distributions Which Includes the Normal Ones.*

[2] Alison A. Misselhorn (2004). *What drives food insecurityin southern Africa? a meta-analysis of household economy studies.*

[3] Andreas Behr (2003). *A comparison of dynamic panel data estimators: Monte Carlo evidence and an application to the investment function.*

[4] Bibi, S., J. Cockburn, et al. (2009). *The Impact of the Increase in Food Prices on the Child Poverty and the Policy Response in Mali.* New York, UNICEF.

[5] Clarke, Kevin A. (2001). *Testing nonnested models of international relations: Reevaluating realism.* American Journal of Political Science 45:724-74.

[6] Compton, J., S. Wiggins, et al. (2010). *Impact of the global food crisis on the poor: what is the evidence?* London, ODI: 99.

[7] Epps, T. W. and Pulley, L. B. (1985). *Parameter estimates and tests of fit for infinite mixture distributions* . Communication in Statistics- Theory and Method 14, no. 12:3125-45.

[8] Epps, T. W., Singleton, K. J. and Pulley, L. B. (1982). *A test for separate families of distributions based on the empirical moment generating function.*Biometrika 69, 991-999.

[9] Feuerverger. (1989). *On the empirical saddlepoint approximation.* Biometrika, Vol. 76, No. 3, 457-464.

[10] Frederic Mousseau, (2009). *The High Food Challenge: A Review of Response to Combat Hunger.* The Oakland Institute and The UK Hunger Alliance.

[11] Ghosh, S. (1996). *A New Graphical Tool to Detect Non-Normality.* J. R. Stat. Soc. 1996, 58, 691-702.

[12] Ioannis A. Koutrouvelis and George C. Canavos (1997). *Estimation in the three-parameter gamma distribution based on the empirical moment generation function*.

[13] Ioannis A. Koutrouvelis, George C. Canavos and Simos G. Meintanis (2005). *Estimation in the three-parameter inverse Gaussian distribution*. Computational Statistics & Data Analysis.

[14] Ioannis A. Koutrouvelis and S.G. Meintanis (2002). *Estimating the Parameters of Poisson-Exponential Models.*Austral. & New Zealand J. Statist. 44, 233- 245.

[15] Ivanic, M. and M. Will (2008). *Implications of higher global food prices for poverty in low-income countries*. Washington, World Bank.

[16] Laurence Ball, Gregory Mankiw, (1995). *Relative-Prices Changes as Aggregate Supply Shocks*.

[17] Lustig, N. (2008). *Thought for Food: The Challenge of Coping with Soaring Food Prices.* Washington, Center for Global Development.

[18] Manuel Arellano and Stephen Bond (1991). *Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations*

[19] Obasi. O. Ukoha (2007) *Relative Price Variability and Inflation: Evidence From the Agricultural Sector in Nigeria*. African Economic Research Consortium.

[20] Peter J. Klenow, Benjamin A. Malin, John W. Dower (2010) *Microeconomic Evidence on Price-Setting*.

[21] Ruth A. Judson , Ann L. Owen (1996) *Estimating dynamic panel data models: a guide for macroeconomists*.

[22] Sen, A. (1981) *Poverty and Famines: An Essay on Entitlement and Deprivation*.Oxford, Clarendon Press.

[23] Von Grebmer, K., Nestorova, B., Quisumbing, A., Fertziger, R., Fritschel, H., Pandya-Lorch, R., & Yohannes, Y. (2009) *2009 Global Hunger Index- The challenge of hunger: Focus on financial crisis and gender inequality.* Deutsche Welthungerhilfe, International Food Policy Research Institute (IFPRI), Concern Worldwide.