

Deviations from Core Prices and Income Inequality in the Arab World

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Abstract

A genetic algorithm is proposed to extract the core trend of inflation in selected countries of the Arab World. The genetic estimator is based on the behavior of a semelparous organism, the Gould Octupus (Octupus Mimus): the females of the octopus mimus stop feeding before spawning and die after reproduction, due to the drastic biochemical alterations and the irreversible structural deterioration of the muscle and the digestive gland. The deviations from the core trend were used to evaluate if short term shocks in prices are drivers of income inequality, as these shocks could have a distributional impact on purchasing power. Bayesian quantile regression was used to test this hypothesis.

Keywords: Bayesian quantile regression, inflation, inequality, Arab countries **JEL codes:** C11, C21, E31, O57

1 Introduction

Ncube et al. (2014) understand the Arab Spring as a refusal to keep tolerating the gross socio-economic *inequality* perpetuated by the long-entrenched elite in power that ruled Arab countries. As inequality may interact with poverty and cause social and political inestability inside a country, a reduction in conflicts can be achieved with social and economic policies based on empirical evidence about the determinants of inequality.

Inflation is one of the variables that has been linked to inequality. Based on cross-country studies, Al-Marhubi (1997) found that countries with higher average inflation have higher inequality, and Li et al. (2002) found that inflation worsens income distribution as it increases the income share of the rich. Using data of Brazil from 1982 to 1990—a period of high inflation rates—Cardoso et al. (1995) found that infla-

tion makes inequality wider, pushing the middle income groups into poverty. For Cardoso et al. (1995) this result is caused by the loss of value of money, that has a different impact on the rich compared to the poor, as the smooth of consumption its difficult for people with less resources. Easterly and Fischer (2001) further found that inflation reduces the shares of income that belong to the lowest quintile of the income distribution, thus reducing real minimum wage and increasing poverty. This effect can be enhanced by the differences on the consumption patterns of the population across income groups; see *inter alia* Son and Kakwani (2006).

This study seeks to analyze the relation between inflation and inequality in the Arab World, using modern extraction techniques of shocks in prices and quantile regression. A Semelparous Genetic Algorithm was used to extract long-term core inflation and Bayesian quantile regression was used to estimate the effect of the

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deviations from this core—i.e. the effect of short-term inflation shocks—on income distribution across eleven Arab countries.

Section 2 explains the methods used on the study. Section 3 shows the results and Section 4 concludes.

2 Methods

Estimation of Core inflation and deviations in prices with Semelparous Genetic Algorithms. Core inflation can be defined as an unobserved medium-to-long term trend in prices. Let $\{x_t\}_{t=1}^T$ be the time series of the consumer price index, π a vector with the time series of inflation $\{\pi_t\}_{t=1}^T$ calculated through $\pi_t = \Delta log(x_t)$, t a trend vector, and $\omega_x(\lambda_s)$ the discrete Fourier transform (d.f.t) of π_t on the frequency band $\lambda_s \in [\lambda^a, \lambda^b]$. Gonzales (2012) proposed the use of Semelparous Genetic Algorithms to construct a spectral measure of core inflation, with core inflation π^c equal to $\pi^c = \pi - \tilde{\pi}$, being $\tilde{\pi}$ a vector of deviations (shocks) in prices. A spectral estimator of $\tilde{\pi}$ is

$$\widehat{\widetilde{\pi}} = \pi_{\omega} - \pi_{\omega} \left[\left(\mathbf{t}_{\omega}' \mathbf{t}_{\omega} \right)^{-1} \mathbf{t}_{\omega}' \pi_{\omega} \right]$$
 ,

where $\pi_{\omega} \in \mathbb{R}$ and $t_{\omega} \in \mathbb{R}$ come from the inverse d.f.t. of $\omega_{\mathbf{pi}',\mathbf{pi}'}^{-1}(\lambda_s)$ and $\omega_{\mathbf{t}',\mathbf{t}'}^{-1}(\lambda_s)$. This estimator was suggested by Corbae et al. (2002).

The estimator $\tilde{\pi}$ properly isolates the low-frequency shocks in inflation when the frequency band $\lambda_s \in \{\lambda^a, \lambda^b\}$ maximizes the signal-to-noise ratio \eth_x , with μ the average of the core inflation signal and σ^2 the mean squared error of the statistical fluctuation around μ . See Schroeder (1999).

Box 1 shows a Semelparous Genetic Algorithm to find the values of $\lambda_s \in \{\lambda^a, \lambda^b\}$ that maximize $\eth_{\mathbf{x}}$. In the algorithm there is an extinction process with a single reproductive episode before death (i.e. semelparity), just as in the reproductive strategy of the cephalopodous Octopus mimus (Figure 1): the females of the Octopus mimus stop feeding before spawning and dye after the birth of paralarvae; Zamora and Olivares (2004) noted that this behavior is related to the histological changes associated with the reproductive event of the Octopus mimus, as the ovary of this species, after spawning, does not have the cells to enable a new reproductive cycle. The drastic biochemical alterations and the irreversible structural deterioration of the muscle and the digestive gland decrease the life expectancy of this species and induce degenerative changes after reproduction.

Figure 1. Octupus Mimus Península de Santa Elena (Ecuador)



Box 1: Semelparous genetic algorithm based on the behaviour of the *Octupus Mimus*

Genesis:

- 1. In g = 0, a population i = 1, 2, ..., p is created, with $\lambda_{q,i}^a \sim \mathcal{U}(\cdot), \ \lambda_{q,i}^b \sim \mathcal{U}(\cdot)$
- 2. $\mathbf{x}_{i}^{c} = \pi \pi_{\omega} \mathbf{t}_{\omega} \left[(\mathbf{t}_{\omega}' \mathbf{t}_{\omega})^{-1} \mathbf{t}_{\omega}' \pi_{\omega} \right]$ is estimated, 3. $\eth_{\pi i}$ is calculated,

Natural selection:

4. $\eth_{\pi,i}$ is sorted $(\eth_{\pi,(1)} \leq \eth_{\pi,(2)} \leq \cdots \leq \eth_{\pi,(p)})$. Then, (1-d)p (0 < d < 1) individuals are selected, with $\lambda^{a}_{g,(j)}$ and $\lambda^{b}_{g,(j)}$ (j = 1, 2, ..., (1 - d)p) of p, $\eth_{\pi,(1)} \leq \eth_{\pi,(2)} \leq \cdots \leq \eth_{\pi,(1-d)p}$

Evolution (mutation):

- 5. Given $\theta \sim \mathcal{B}(\cdot, \cdot)$, $\varpi \in [0, 1]$ and $m_i \sim \mathcal{N}(0, 1)$, $\lambda_{g+1,i}^a = \theta \lambda_{g,i}^a + (1 - \theta) \lambda_{g,i}^b + \varpi m_i$, $\lambda_{g+1,i}^b = \theta \lambda_{g,i}^b + (1 - \theta) \lambda_{g,i}^a + \varpi m_i$.
 - 6. Steps 2 to 5 are repeated during g = 0, 1, ..., j generations.

In g = 0, a random initial population of *i*-couples of frequencies $\lambda_{g,i}^a$ and $\lambda_{g,i}^b$ (i = 1, 2, ..., p) is created, using a continuos uniform distribution function $\mathcal{U}(\cdot)$. Each couple is used to estimate spectral measures of the core inflation π_i^c and the signal-to-noise ratios $\eth_{\pi^c,i}$ associated to these *i*-cores.

In a process similar to natural selection, a fraction (1-d) of the population p is selected. Emulating the survival of the fittest (Darwin, 1866), the leftovers are discarded with a d mortality rate. The sub-population

of survivors are couples of $\lambda_{g,i}^a$ and $\lambda_{g,i}^b$ with the highest signal-to-noise ratios.

Evolution is allowed through the reproduction and mutation of the survivors. A new generation of couples $\lambda_{g+1,i}^a$ and $\lambda_{g+1,i}^b$ is generated from the convex combination of diploid cells,

$$\lambda_{g+1,i}^{a} = \theta \lambda_{g,i}^{a} + (1 - \theta) \lambda_{g,i}^{b} + \varpi m_{i},$$
$$\lambda_{g+1,i}^{b} = \theta \lambda_{g,i}^{b} + (1 - \theta) \lambda_{g,i}^{a} + \varpi m_{i},$$

i.e. every generation after creation has two sets of chromosomes (λ^a, λ^b) and one of these dominates the offspring. The contribution of each chromosome to the next generation is given by $\theta \sim \mathcal{B}(\cdot, \cdot)$, with $\mathcal{B}(\cdot)$ a Beta distribution function. $\varpi \in [0, 1]$ is a mutation degree defined by the random variable $m_i \sim \mathcal{N}(0, 1)$.

Due to the reproduction of the fittest, the new generation of spectral frequencies have values similar to those of the optimal previous generation, but mutation allows certain amendments to avoid local optima.

With the new generation of size (1 - d)p, new estimates of core inflation are obtained. The steps 2 two 6 are then repeated during the next g = 1, ..., j-generations, until only one couple λ_j^a and λ_j^b survives. This last couple of survivors are the optimal values of λ_s that allow both a proper extraction of core inflation and the deviations from the core.

Bayesian quantile regression. Let y_i be a response variable and \mathbf{x}_i a $k \times 1$ vector of covariates for the *i*th observation. If $q_p(\mathbf{x}_i)$ denotes the *p*th $(0 quantile regression function of <math>y_i$ given \mathbf{x}_i , the relationship between $q_p(\mathbf{x}_i)$ and \mathbf{x}_i can be modelled as $q_p(\mathbf{x}_i) = \mathbf{x}'_i \beta_p$, where β_p is a vector of unknown parameters of interest.

The quantile regression model is given by $y_i = \mathbf{x}'_i \beta_p + \epsilon_i$, (i = 1, ..., n), where ϵ_i is the error term whose distribution (with density $f_p(\cdot)$) is restricted to have the *p*th quantile equal to zero, that is, $\int_{-\infty}^{0} f_p(\epsilon_i) d\epsilon_i = p$.

Quantile regression estimation for β_p proceeds by minimizing

$$\sum_{i=1}^{n} \rho_{\mathcal{P}} \left(y_i - \mathbf{x}_i' \boldsymbol{\beta}_{\mathcal{P}} \right)$$

with $\rho_{\rho}(\cdot)$ the loss function,

$$ho_{
ho}(u) = u \{
ho - I(u < 0) \}$$
 ,

and $I(\cdot)$ the indicator function. Yu and Moyeed (2001) proposed a Bayesian modelling approach for general quantile regression by noting that minimizing

 $\sum_{i=1}^{n} \rho_p (y_i - \mathbf{x}'_i \beta_p)$ is equivalent to maximizing a likelihood function under the asymmetric Laplace error distribution. Kozumi and Kobayashi (2011) considered Bayesian quantile regression models using the asymmetric Laplace distribution and proposed Markov Chain Monte Carlo (MCMC) methods based on a Gibbs sampling algorithm with a location-scale mixture representation of the asymmetric Laplace distribution. Following Yu and Moyeed (2001), Kozumi and Kobayashi (2011) considered the linear model given by $y_i = \mathbf{x}'_i \beta_p + \epsilon_i$, (i = 1, ..., n) and assume that ϵ_i has the asymmetric Laplace distribution with density

$$f_{\rho}(\epsilon_i) = \rho(1-\rho) \exp{-\rho_{\rho}(\epsilon_i)},$$

where p determines the skewness of distribution, and the pth quantile of this distribution is zero. To develop a Gibbs sampling algorithm for the quantile regression model, Kozumi and Kobayashi (2011) utilize a mixture representation of the asymmetric Laplace distribution based on exponential and normal distributions: Let zbe an standard exponential variable and u a standard normal variable. If a random variable ϵ follows the asymmetric Laplace distribution, ϵ can be represented as a location-scale mixture of normals given by

$$\epsilon = \theta z + \tau \sqrt{z} u$$
,

where,

$$heta=rac{1-2p}{p(1-p)} \quad ext{and} \quad au^2=rac{1}{p(1-p)}$$

and the response y_i can be equivalently rewritten as,

$$y_i = \mathbf{x}'_i \boldsymbol{\beta}_{\mathcal{P}} + \theta z_i + \tau_{\sqrt{z_i}} u_i,$$

for $z_i \sim \mathcal{E}(1)$ and $u_i \sim \mathcal{N}(0, 1)$ mutually independent and $\mathcal{E}(\cdot)$ and exponential distribution with mean equal to 1. As the conditional distribution of y_i given z_i is normal with mean $\mathbf{x}'_i \beta_p + \theta z_i$ and variance $\tau^2 z_i$, the joint density of $\mathbf{y} = (y_1, \dots, y_n)'$ is given by

$$f\left(\mathbf{y}|\boldsymbol{eta}_{\mathcal{P}},\mathbf{z}
ight) \propto \left(\prod_{i=1}^{n} z_{i}^{-1/2}
ight) \exp\left\{-\sum_{i=1}^{n} rac{(y_{i}-\mathbf{x}_{i}^{\prime} \boldsymbol{eta}_{\mathcal{P}}- m{ heta} z_{i})^{2}}{2 au^{2} z_{i}}
ight\},$$

for $\mathbf{z} = (z_1, \ldots, z_n)'$. To proceed to a Bayesian analysis, Kozumi and Kobayashi (2011) assume the prior $\beta_p \sim \mathcal{N}(\beta_{p0}, \mathbf{B}_{p0})$, where β_{p0} and \mathbf{B}_{p0} are the prior mean and covariance of β_p , respectively. A Gibbs sampling algorithm for the quantile regression model is constructed by sampling β_p and \mathbf{z} from their full conditional distributions; the full conditional density of β_p is given by

$$oldsymbol{eta}_{oldsymbol{
ho}} | \mathbf{y}, \mathbf{z} \sim \mathcal{N}\left(\hat{oldsymbol{eta}}_{oldsymbol{
ho}}, \hat{\mathbf{B}}_{oldsymbol{
ho}},
ight)$$





where,

$$\hat{\mathbf{B}}_{p}^{-1} = \sum_{i=1}^{n} \frac{\mathbf{x}_{i}\mathbf{x}_{i}'}{\tau^{2}z_{i}} + \mathbf{B}_{p0}^{-1}$$

and

$$\hat{\boldsymbol{\beta}}_{\boldsymbol{\rho}} = \hat{\mathbf{B}}_{\boldsymbol{\rho}} \left\{ \sum_{i=1}^{n} \frac{\mathbf{x}_{i}(y_{i} - \boldsymbol{\theta} z_{i})}{\tau^{2} z_{i}} + \mathbf{B}_{\boldsymbol{\rho} \mathbf{0}}^{-1} \boldsymbol{\beta}_{\boldsymbol{\rho} \mathbf{0}}
ight\}.$$

3 Results

World Bank data of inequality, inflation, GDP per capita, elderly population, female labour, government consumption, foreign direct investment, rural population, age-population dependency, technology use-using internet use as a proxy-and data on the external balance were used to measure the impact of inflation shocks on income inequality in 11 countries of the Arab World: Djibouti, Egypt, Iraq, Jordan, Mauritania, Morocco, Qatar, Sudan, Syria, Tunisia and Yemen. These countries were selected due to its data availability between the years 2000 and 2014.

Table 1 shows the results of using Semelparous Genetic Algorithms (henceforth, SGA) to estimate core inflation in these selected Arab countries. An initial population of 100 couples of λ^a and λ^b were used in the SGA, with a mutation degree of $\varpi = 0.15$ and a mortality rate of 80%. Local extinction to a single optimal couple $\hat{\lambda}^a$ and $\hat{\lambda}^b$ was achieved after three generations.

SGA selected a lower frequency band of $\hat{\lambda}^a = 2$ months for all the countries in the sample, but the upper frequency $\hat{\lambda}^b$ is different among nations, with countries as Syria having a long-term inflation trend up to 13 months, whereas countries like Morocco have a medium-term core-inflation trend of 2 to 5 months. Figure 2 shows an example of the SGA estimation procedure for Tunisia, where the inflation trend moves between 2 and 6 months. Results for the other countries in the sample are available upon request.

A point estimator of the shocks in prices $(\sigma_{\hat{\pi}})$ was calculated with the standard deviation of the spectral noise in prices (i.e. the deviations from core inflation) in each country. Sudan, Syria and Yemen present the highest shocks in prices, while Morocco, Qatar Mauritania and Tunisia have considerably lower deviations from the core, i.e. price shocks in these countries were lower compared to other regions in the Arab world (Table 1).

Table 1. Shocks in prices $(\sigma_{\hat{\pi}})$ Selected Arab Countries

Country	$\hat{\lambda^a}$	$\hat{\lambda^{b}}$	$\sigma_{\widehat{\widetilde{\pi}}}$
Djibouti	2	12	0.89
Egypt, Arab Republic	2	11	0.93
Iraq	2	8	0.69
Jordan	2	10	0.63
Mauritania	2	8	0.18
Morocco	2	5	0.37
Qatar	2	9	0.31
Sudan	2	11	3.33
Syrian Arab Republic	2	13	2.80
Tunisia	2	6	0.19
Yemen, Rep.	2	10	1.27

The shocks in prices $(\sigma_{\widehat{\pi}})$ were used in a Bayesian quantile regression to estimate the impact of the deviations in prices on inequality in the Arab World. Gini coefficients were used to measure inequality. GDP per capita (at constant 2005 USDs), the ratio of the population of 65 years or more over the working age population, female labor force (as a percentage of total labor force), general government final consumption expenditure (as percentage of GDP), net inflows of foreign direct investment (as a percentage of GDP), rural population (as a percentage of total population), the young-age dependency ratio (as a percentage of working-age population), internet users (per 100 people) and external balance on goods and services (as a percentage of GDP) were used as control covariates. In the Bayesian regression, $\beta_{p0} = (0, 1, 0, 1, 5, 0, -1, 5, 5, 0, 1), \ \mathbf{B}_{p0} = \mathbb{I}_{11}$ -with \mathbb{I}_k a $k \times k$ identity matrix— and a shape and scale parameter of 10 and .01 respectively were used as priors. The election of the variables and the elicitation intervals start crossing zero, thus suggesting that the

of the priors was based on previous empirical evidence about variables related to inequality¹. Eleven thousand runs of the MCMC chain were simulated and the first 1000 draws were discarded as the burn-in period.

Figure 3. Quantile results of the impact of the deviation in prices on income inequality in selected Arab countries



Figure 3 and Table 2 show the results of the Bayesian estimation. The 95% credible intervalsconditional on the assumptions of the study-suggest that the effects of the shocks in prices are only relevant for countries with inequality above the five decile, i.e. those Arab countries with a Gini coefficient higher than $\mathcal{D}_5 = 0.36$; moreover, the income distribution effect of inflation increases as inequality increases (Figure 3) and in $\mathcal{D}_5 = 0.36$ and below this decile, the 95% credible

Technology could be determinant of inequality, and can in fact raise inequality, according to Barro (2000), if technology imply an advantage for the people who can afford technological innovations, as e.g. internet access. Nonetheless, the effect of technologial innovations depends on how long the innovation was introduce into the economy. The degree of openness of an economy was also mentioned by Barro (2000) as a determinant of inequality, because when a country is endowed with human and physical a decrease on the wages of unskilled workers is observed, but in countries that are relatively highly endowed in unskilled labor, greater openness to trade would tend to raise the relative wages of unskilled labor and lead, accordingly, to less income inequality.

GDP per capita of a country was suggested as a determinant of inequality by Barro (2000). According to Barro (2000), at early stages of development, the relation between the level of per capita product and the extent of inequality tends to be positive, but in more advance levels of development the full relationship between an indicator of inequality, as the Gini coefficient, and the level of per capita product is described by a Kuznets curve.

In the case of the share of population older than 65 years old, this variable was selected as a covariate because a positive correlation between elderliness and income distribution was found by Alfonso et al (2008) and Lee et al. (2013). Female labour was selected as a covariate because female labour participation was found as a positive determinant of inequality by Acar and Dogruel (2012) in a study realized with seven MENA countries, using panel data; Acar and Dogruel (2012) argued that earning inequalities between men and women could cause that effect. In terms of government consumption, Afonso et al. (2010) found that public policies significantly affect income distribution, directly via social spending, and indirectly via high quality education/human capital and sound economic institutions. Rural population is related to the geographical determinants of inequality in the Arab region analyzed by Hassine (2015) using household survey data.

	Decile					
	\mathcal{D}_1	\mathcal{D}_3	\mathcal{D}_5	\mathcal{D}_7	\mathcal{D}_{9}	
Constant	-0.0293	0.0383	0.0176	0.0655	0.0578	
	(-1.66, 1.59)	(-1.68, 1.62)	(-1.64, 1.67)	(-1.63, 1.72)	(-1.56, 1.73)	
Inflation shocks	1.1139	1.1132	1.4435	1.9763	2.1573	
	(-0.44, 2.67)	(-0.44, 2.63)	(0, 2.67)	(0.9, 2.74)	(1.25, 2.78)	
GDP per capita	0.0003	0.0003	0.0004	0.0004	0.0004	
	(1.2e-4, 4.6e-4)	(1.3e-4, 4.6e-4)	(2.3e-4, 4.8e-4)	(3.1e-4, 4.9e-4)	(3.3e-4, 4.9e-4)	
Elderly population share	-0.3173	0.1505	0.4999	0.8274	0.8887	
	(-0.82, 0.45)	(-0.75, 0.63)	(-0.25, 1.13)	(0.38, 1.27)	(0.52, 1.31)	
Female labour	0.1219	0.1152	0.0487	0.2357	0.2897	
	(-0.31, 0.61)	(-0.3, 0.59)	(-0.43, 0.42)	(-0.51, 0.2)	(-0.53, 0.12)	
Government consumption	0.7071	0.7562	1.0461	1.3445	1.4539	
	(-0.24, 1.55)	(-0.12, 1.56)	(0.08, 1.86)	(0.31, 2.07)	(0.42, 2.12)	
Foreing direct investment	-0.346	0.2946	0.081	0.0284	0.0026	
	(-0.65, 0.03)	(-0.67, 0.13)	(-0.59, 0.32)	(-0.54, 0.32)	(-0.49, 0.32)	
Rural population	0.016	0.0479	0.1985	0.3131	0.355	
	(-0.35, 0.3)	(-0.28, 0.34)	(-0.19, 0.52)	(-0.1, 0.6)	(-0.05, 0.62)	
Dependency ratio	0.2267	0.1921	0.0446	0.0514	0.0872	
	(-0.02, 0.51)	(-0.07, 0.47)	(-0.25, 0.4)	(-0.32, 0.33)	(-0.34, 0.29)	
Technology use	0.4999	0.4557	0.288	0.1959	0.166	
	(0.28, 0.72)	(0.21, 0.69)	(0.04, 0.58)	(-0.01, 0.49)	(-0.02, 0.44)	
External balance	-0.3379	0.2934	0.1716	0.116	0.0896	
	(-0.68, 0.01)	(-0.63, 0.07)	(-0.51, 0.11)	(-0.44, 0.11)	(-0.4, 0.13)	

 Table 2. Bayesian quantile regression estimates*

(*) 95% Credible intervals below each point estimate

shocks in inflation do not affect income distribution in Arab countries with higher equality.

In terms of control covariates, Table 2 shows that the impact of GDP per capita on inequality is positive and relevant with a 95% probability for all the quantiles of income distribution, while variables as the elderly population share and government consumption are only relevant to explain inequality in those countries with higher levels of inequality.

4 Discussion

Semelparous genetic algorithms and Bayesian quantile regression were used to test the impact of shortterm inflation shocks on income inequality in selected Arab countries. The results with a 95% probability conditional on the assumptions of the study—suggest that inflation shocks have a differentiated impact on

inequality, as the credible intervals show that inflation only affects countries with higher levels of inequality, with an increasing effect as inequality rises. Similar results were found by *inter alia* Cardoso et al. (1995), Li et al. (2002) and Albanesi (2007). Albanesi (2007) concludes that this non-linear relationship between inflation and inequality, with a higher slope of the relation at higher inequality, arises in countries with more inequality because in these countries there is a bigger gap between high and low-income households, reducing the bargain capacity of low-income families and thus making them more vulnerable to inflation shocks.

The findings of the study indicate that monetary policies focused on maintain low levels of core inflation and supply-side policies of control in prices can not only mantain economic stability in Arab countries, but also reduce the impact of shocks in prices over the conditions of the poor, thus reducing social inestability in the Arab World.

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