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Determinants of Inflation in Selected Countries

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Abstract

This paper focuses on developing models to study influential factors on the inflation rate for a panel of available countries in the World Bank data base during 2008-2012. For this purpose, Random effect log-linear and Ordinal logistic models are used for the analysis of continuous and categorical inflation rate variables. As the original inflation rate response to variables shows an apparent right skewness, the log transformation in the linear mixed effect model seems necessery. In the ordinal logistic mixed effect model, as a new approach, the inflation rate variable is categorized based on two threshols to increase model predictibality and precision. These two models consider the potential serial correlation between annual infltion rates and categories through introducing some latent random effect parameters. The results of both models show that money growth, GDP, oil price and income levels of the available countries are significant predictors with increasing effect on the next year inflation rate category. Using the categorical inflation response variable yields some superior results where government expenditure, exchange rate and capital formation are also detected as significant determinants of ordinal inflation variable. Also, the random effect variance is highly significant in both models which shows the necessery need for consideration of the potential association of inflation variables across time.

Keywords: *Inflation; Panel studies; Mixed effect Model; Ordinal response*

JEL Classifications: *E17, E27, E31, E37, E47*

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1. Introduction

Management of the annual price level changes within a country, known as the inflation rate , is one of the important economic issues for policy makers. Actually, there are large numbers of researchers trying to recognize key determinants of inflation in different countries . From the economic perspective, these determinants have been categorized to supply side and demand side factors. Supply side factors are those economic factors which cause inflation by increasing cost of the production. Some important supply side factors include output growth, capital formation, oil and import prices, tax and wage levels, and exchange rate. On the other hand, demand side factors lead to higher inflation via creating more buying requests for goods and services in the country. Some important demand side factors are money growth , private consumption expenditure and government consumption expenditure. Most of the researchers have studied the effect of the above mentioned factors on the inflation rate using three different types of extracted sample data: 1) Variables data for a single country across time, 2) A cross-sectional sample of some countries in one occasion, 3) A panel of countries during some period of time. The first two sample types lose some information about simultaneous analysis of other countries and different periods of time, respectively. It seems that the third approach gives a more reliable sample of data for statistical analysis.

Actually, panel studies are a particular design of study in which the unit of analysis is followed at specified intervals over a long period, often many years. The key feature of panel studies is that they follow the population of interest over an extended time period and are concerned with measuring change over time for the units of analysis within the population . In contrast, Cross-sectional surveys are based on a sample of the population of interest drawn at one time point which do not allow change assessment through time.

In this paper we will try to model the most important supply and demand side determinanats of inflation rate using a panel of countries from 2008 to 2012. There are vast numbers of researches examining inflation rate variable in the litrature, some of which will be shortly reviewd in what follows.

Bruno (1995) and Bruno and Easterly (1998) examined the relationship between inflation and economic growth for 127 countries between 1960 and 1992. Their examination of these data set is historical and descriptive. They do not present a formal econometric model. Their key conclusion was that there is some evidence for growth-inflation relationship just for high inflation (rates of inflation of 40 percent and higher) countries. Also they belive that the results get stronger as one goes from the cross-section to ten- year averages to five- year averages to annual data.

Campillo and Miron (1997) examined the determinants of country-level inflation rates for a sample of sixty-two countries during the period 1973-94. They found out that prior inflation experience plays an important role in inflation performance . As another result , they showed that economic fundamentals, such as openness, political instability, and tax policy have large effects in determining inflation rate.

Mohanty and Klau (2001) studied the determinants of inflation in emerging economies. They used quarterly changes in the variable data in 14 emerging countries during 1990s. They found out that the output gap, money supply and wage level as well as some supply side factors like exchange rates, import price and oil price have a significant influence on inflation.

Pollin and Zhu (2005) used non-linear regression for 80 countries over the period 1961-2000 to estimate the relationship between inflation and economic growth. They do the test for full sample countries as well as separate tests for high, middle and low income countries. For the full data set, they have found that higher inflation is associated with moderate gains in GDP growth but for differnt income subsamples no clear pattern emerged.

Hammermann and Flanagan (2007) used a panel data analysis for 19 transition economies, during the years 1995 to 2004. Their model suggests that a central bank's incentive towards higher short-run inflation is a key reason for observed outcomes. Also, unanticipated shocks to supply and demand are important determinants of cross-country inflation.

Calderón and Schmidt-Hebbel (2008) evaluate the impact of non-monetary factors on inflation for a sample of 97 countries over the period 1975-2005. They estimate the inflation dynamics for two sets of data with different frequency, annual and five year average data, to determine the factors driving short and long run inflation. They found out that countries with inflation targeting policy and countries which adopt fixed exchange-rate regimes would face lower inflation. Also, according to their results, financial integration would help lower inflation.

Kandil and Morsy (2009) studied the determinants of inflation in Gulf Cooperation Council Countries during the period 1970 to 2007. For this purpose, they used two domestic factors: Government spending and the money supply, and two external factors: Nominal effective exchange rate and a weighted average of price in major trading partners. They found out that in both short run and long run, the inflation rate in major trading partner is the most relevant factor.

Diego et al. (2011) examined the determinants of inflation in the United States, Japan, the Euro Area and the United Kingdom, using quarterly data for 1960-2010. According to their research, the output gap and unemployment have been important drivers of inflation in the four economies in past decades. Also, short-term inflation expectations play a key role in the inflation process in the United States and the Euro Area but not in Japan or the United Kingdom. And, changes in import prices have affected inflation developments in all the economies.

In the above reviewd litrature, there is no comprehensive panel study which includes both key supply and demand side factors across all available data countries. In this paper, we will propose two random effect models to examine influential economic factors on the inflation rate of a panel of available data countries during 2008-12. For this purpose, as a new approach, we have used two response variables corresponding to the inflation rate with different measurement scales. Actually, one is the numerical reported inflation rate and the other is a three-level inflation status including three ordinal categories of, *low*, *medium* and *high* inflation. Also, using some graphical and inferential devices, the need for a logarithmic transformation seems necessery for the original inflation rate variable to make its distribution symmetric. Hence, we have fitted a log-linear mixed effect model for the former response variable, while an ordinal logistic mixed effect model has been applied for the ordinal response variable. In our proposed models, output growth, capital formation, oil price and exchange rate are included as the supply side factors. Also, money growth, private and goverment consumption expenditure are the demand side factors considered in the analysis. An important characterstic of our proposed models is the regression of each year inflation on the pervious year determinant factors which causes more predictability power for the upcomming year inflation.

The rest of the paper is organized as follows: The description and the exploratory analysis of inflation data are given in Section 2. Section 3 presents the model structure and framework for the two proposed models including their likelihood function to be used for parameter estimation. The two proposed models will be applied to the inflation data in Section 4. Also the point estimation and hypothesis testing results along with the prediction and model comparison are presented in this section. Finally, Section 5 includes some concluding remarks and possible further works.

2. Data Description

The data which will be described in this section and deal with in the model estimations are extracted from the World Bank Data Bank for all available data countries during 2008 to 2012 (Available at : http://databank. worldbank.org). We have used the annual changes in consumer price index (CPI) of each country as the inflation rate variable denoted by INF now on. Also, we have constructed a new categorical variable based on the INF variable to summarize inflation level of countries via an ordinal variable, namely $INFcat$. Actually, we have categorized all inflation rates below 2 percent as low inflation level, between 2 to 5 percent as medium inflation rate and upper than 5 percent as high inflation rate. The reason for such categories is that, during the last 10 years, 50 percent of countries had average inflation rates between 2 to 5 percent, 25 percent had an average inflation under 2 percent and 25 percent had average inflation higher than 5 percent. Using an ordinal level inflation variable could lead to some advantages comparing with the use of original INF variable. One important adavntage is that, using the ordinal scale we have the oportunity to do a comparitive study among different countries with different economic charachtrestics (for example comparing the level of inflation in two countries, one with higher economic growth or other economic factors). Also the categorized inflation approach prevent the missleading estimation results due to measurment errors and potential outliers in the reported data.

For the possible predictors of the inflation rates and levels of the countries, we have chosen the most important demand side and supply side factors to cover both demand pull and cost push inflation. In the demand side, we have used money growth, private and goverment consumption expenditure, while in the supply side, gross domestic product, capital formation, exchange rate and oil price are selected as variables which could potentially determine the inflation rates and levels. Table 1 gives some brief descriptions and notations for these variables that will be used in the data analysis. It should be mentioned that since the inflation rate as a dependent varaible has a nature of year to year growth, we have also used all the independent factors in anual growth form (or anuall changes).

Table 1: Description and Notation for the Economic Factors

Notation	Stands for	Description
MG	Money growth	Annual changes in the volumes of money and quasi money in each country
ER	Exchange rate growth	Annual changes in the currency value per us dollar in each country
CE	Private consumption expenditure growth	Annual changes in the final private consumption level in each country
GE	Government consumption expenditure growth	Annual Changes in the final government consumption level in each country
CF	Capital formation growth	Annual changes in the gross capital formation level in each country.
GDP	Gross domestic product growth	Economic Growth; Annual changes in the constant price level of gross domestic product in each country.
Oil	Oil price growth	Annual changes in the Brent spot oil price per barrel.

For oil price data, we have used the Energy Information Administration oil price statistics (Available at: http://www.eia.gov). To cover the non-homogeneity of countries with different income levels, in addition to the above mentioned variables, we have used income level (INCOME) as an ordinal independent variable which according to the World Bank Data Base has four categories as follows: Low income, lower middle income, upper middle income and high income countries.

2.1. Exploratory data analysis

The data at hand include two interesting dependent variables related to inflation: (1) The continuous inflation rate variable; (2) The ordinal inflation level variable. Due to the longitudinal nature of the present data, for the exploratory analysis it is important to study variations of different variables as time grows up. Figure 1 presents histogram of INF variable along with the curve of estimated density function during 2008-2012 period. According to this figure, there is a non ignorable right skewness in all histograms which indicates the need for some transformation to make the distribution of these variables symmetric. This high skewness is a result of large number of countries with lower inflation rates and a few number of countries with high inflation rates which fall in the right tail of the distribution.

Figure 1: Histogram of INF Variables Across 2008:2012 Years

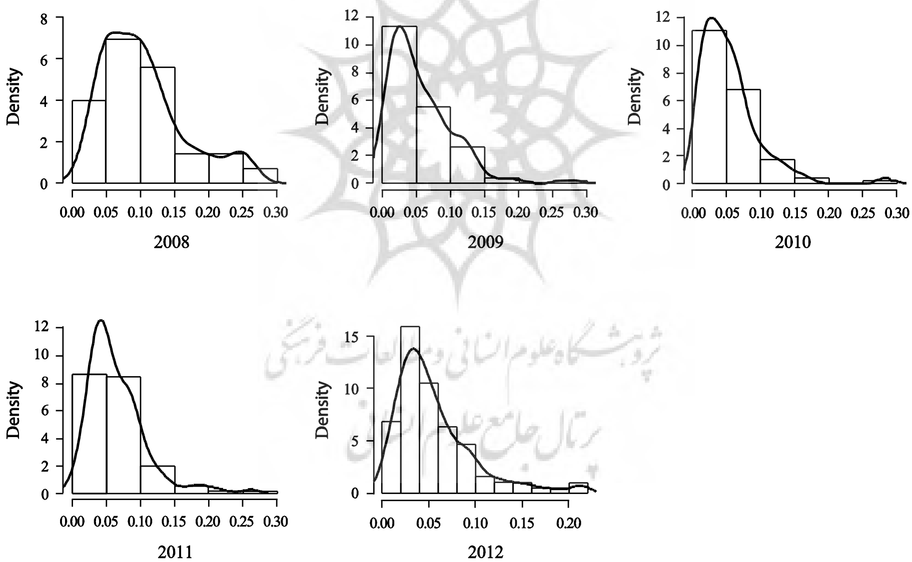


Table 2 gives the percentage of countries in different inflation categories during the time. Also Figure 2 shows the barchart of INFcat variable during the period of study. World economic boom in 2008 caused higher inflation rates all over the world and as the economic recesion started in 2009 and deepened in 2010, we could see a notable increase in the number of low inflation countries in Table 2 and Figure 2 in these years. Also, since world economy, specially in emerging economies, moved to better situations in 2011, we could see an increase in the number of countries in the medium and high inflation rate categories comparing with two previous years. Figure 3 shows two apparent peaks in the oil prices at 2008 and 2011 which are due to increase in the world oil demand as a result of mentioned better world economic situation in those years.

Table 2: Inflation Category During 2008-2012 (%)

	Year				
Inflation category	2008	2009	2010	2011	2012
Low	0.03	0.31	0.28	0.08	0.24
Medium	0.41	0.48	0.57	0.70	0.56
High	0.56	0.21	0.15	0.22	0.20
Number of available cases	115	99	107	104	94

Source: Energy Information Administration oil price statistics (Available at: http://www.eia.gov)

Figure 2: Barplots of INFcat Variable During 2008-2012

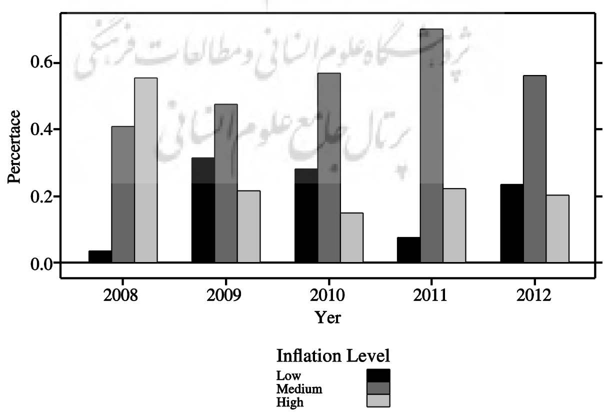
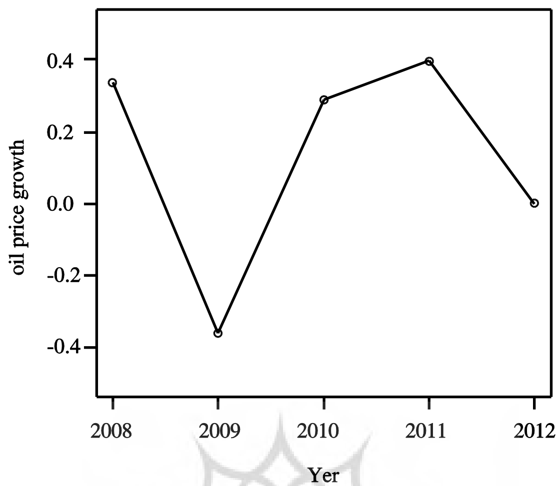


Figure 3: Volatility of the Oil Price Growth Across 2008:2012



Source: Energy Information Administration oil price statistics (Available at: http://www.eia.gov)

Now we study the relationship between different potential factors, which were described in the pervious subsection, and the two interesting dependent variables. Figure 4 illustrates the boxplots of INF variable for different income levels, panelled in five years of the study. According to this figure, in all five years of the study, richer countries have lower inflation rate as the lines connecting medians of the boxplots have a decreasing trend in all plots. This result shows that high inflation rate is the phenomenon which mostly occures in less developed with low income countries. Also as the income level of the country increases, the boxplot variations decrease which indicate less volatiled inflation rates in higher income countries. Figure 5 illustrates the median profile plot of INF variable for different income levels through time. According to this figure, the median of inflation rate is lower for higher income levels in all years except 2008 which shows a slightly different trend for the first two lower levels of income. Also this figure shows that the median inflation, in each group of countries with the same income level, has beed decreased from 2008 to 2010 and has an increase in 2011 as described before.

Figure 4: Boxplots of INF Nariables for Different Income Levels During 2008-2012

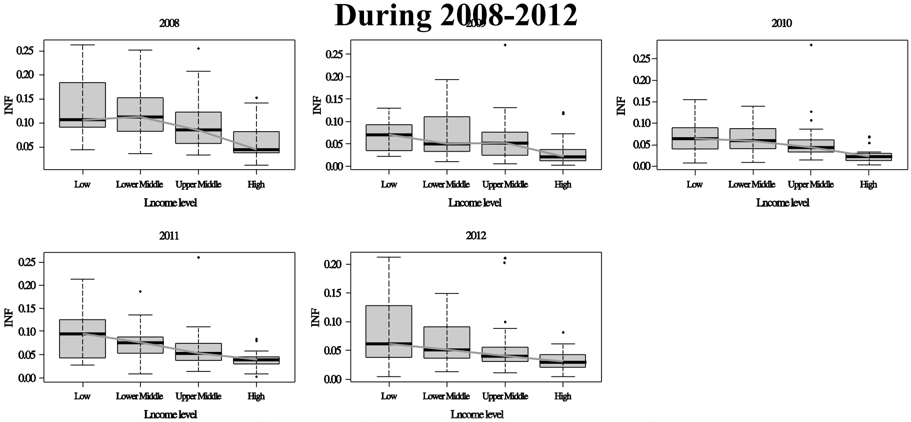
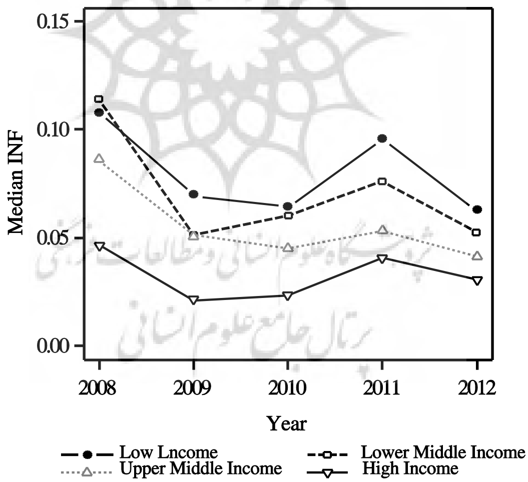
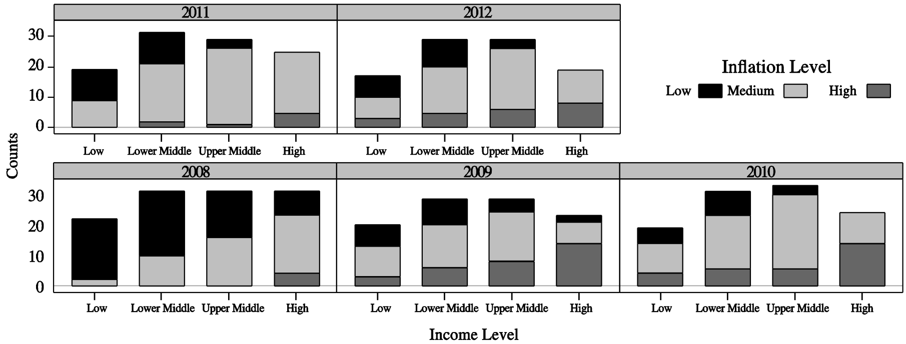


Figure 5: Median Profile of INF Variables for Different Income Levels Across 2008-2012



The barcharts of INFcat variable for different income levels in different years are presented in Figure 6. In this figure, bars represent percentages of the countries in the specefic year. The figure indicates that high inflation rates are more common in low and lower middle income countries while there is no high inflation rate country in the high income level during 2010 to 2012.

Figure 6: Barplots of INFcat Varialble for Different Income Levels Across 2008:2012



The relation between INF and the supply side and demand side factors are respectively shown in Figures 7 and 8 via scatter plot of INF with the corresponding factor across time. These two figures show that all of the above mentioned factors except CE and GE have a positive relationship with INF response variable of the next year which means that the increase in these variables during the pervious year leads to higher inflation rates for the next year. Actually, we can say that there is no observable relation between INF and the two independent variables, CE and GE.

Figure 9 presents the median profile plot for all independent variables panelled through income levels and time. According to this figure, higher levels of income lead to lower median value for all variables which could be justified since these variables are all in the year to yaer change format and this result shows that higher income countries have more stable economic nature. Due to economic slow down in 2009, there is an apparent decrease in the median of CE, CF and GDP in 2009 for the last three levels of income and the effect of this recession is deeper for high income countries. This figure also shows that the changing pattern of these independent variables is approximately parallel in all income levels except the low income level.

Figure 7: Scatter Lot of INF Variable with ER, CF and GDP through time

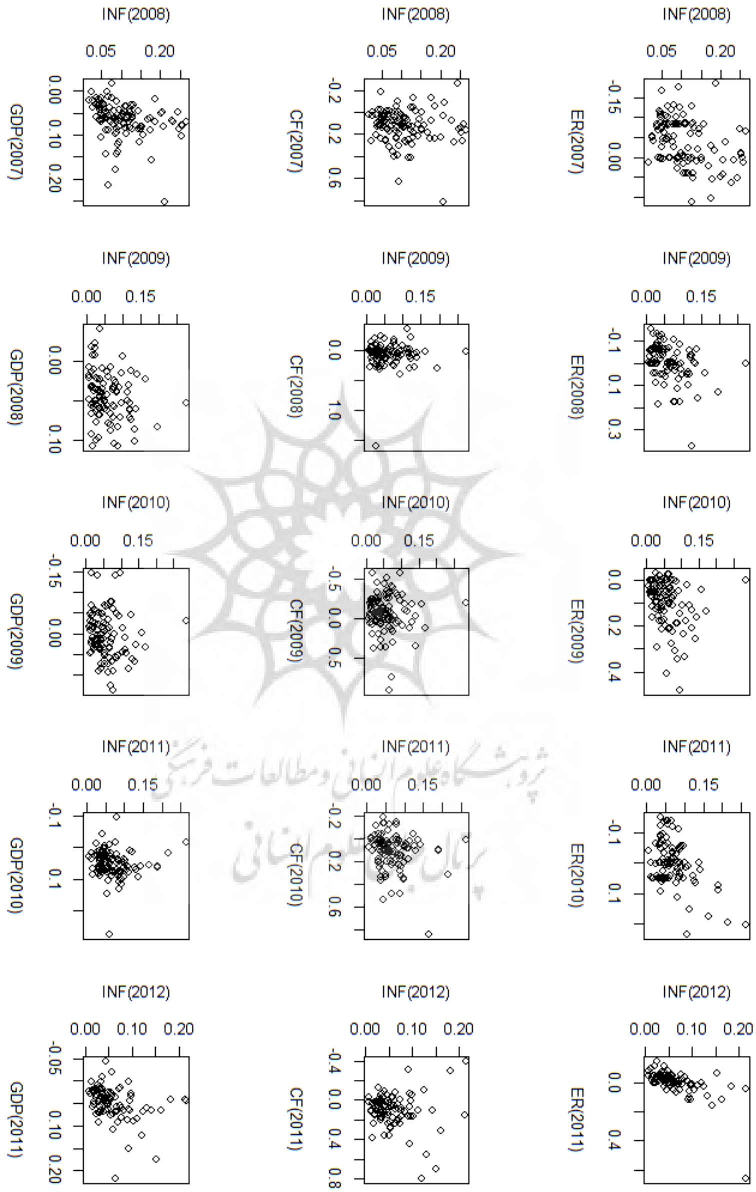
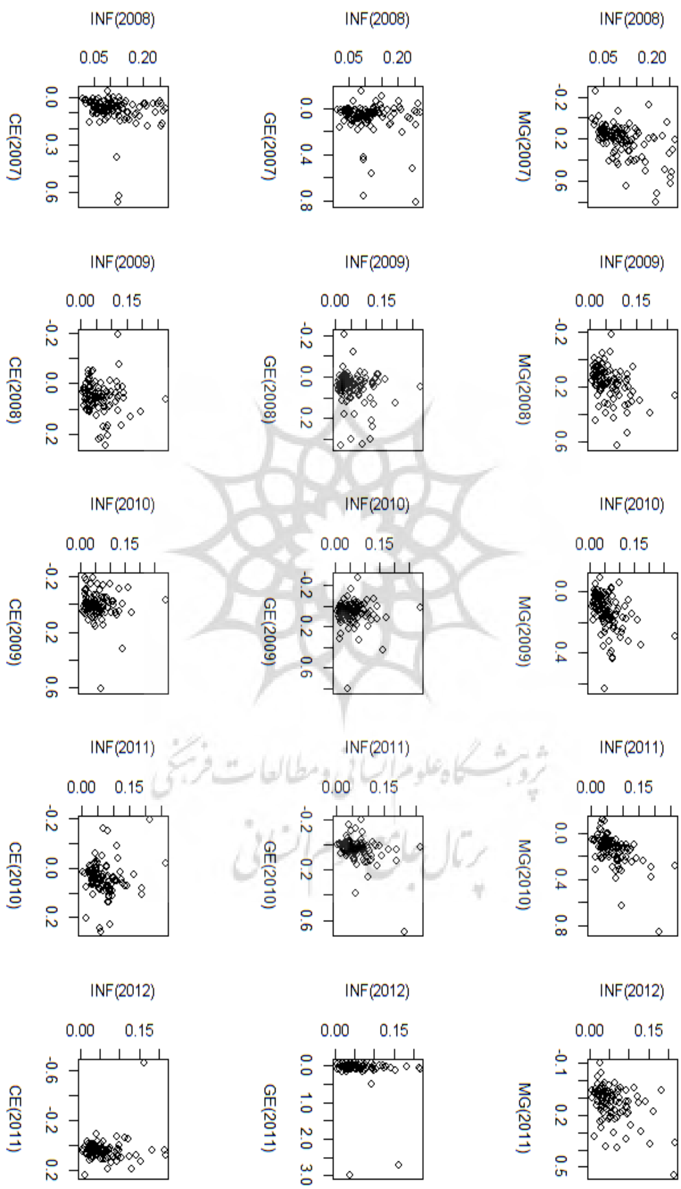


Figure 8: Scatter Plot of INF Variable with MG, GE and CE through Time

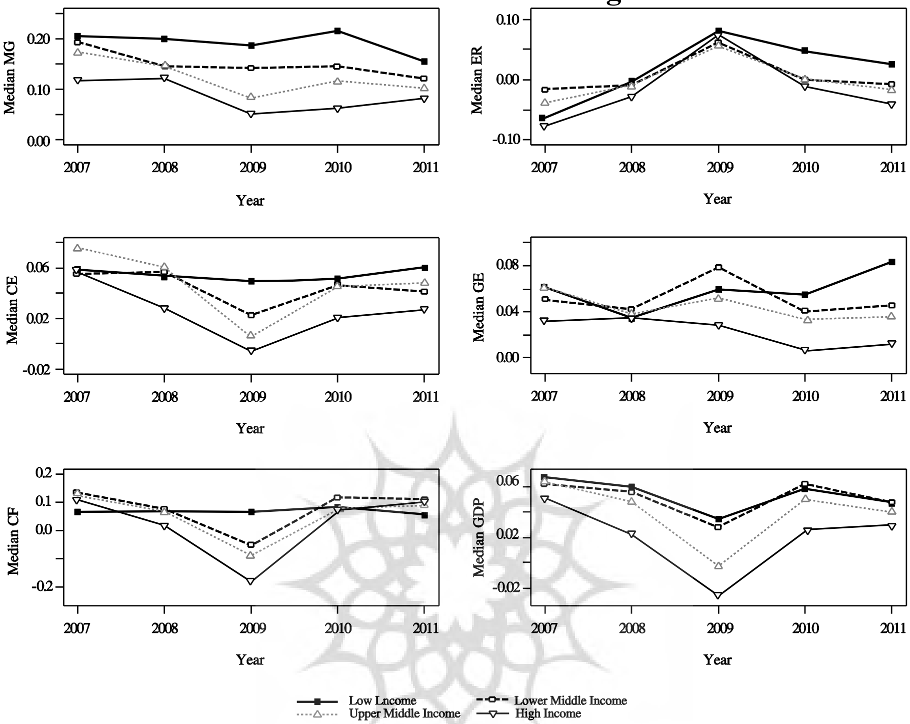


3. The Proposed Models

In this section we will present two different models along with their likelihood functions for estimation purposes , one for the analysis of log-normal panel data and the other for the analysis of ordinal categorical panel data. Actually, in most of the panel studies, the excerpted data might include an interesting response variable of continuous or discrete type which should be analysed with respect to its own scale. When the response variable has a continuous scale, often a linear or a linear after transformation model is used based on the histogram and possible distributional assumptions for the response variable . In the following subsection , assuming that the log transformation is needed (as a common occurance in most of the economic variables) for the continuous panel response variable, we will present the details of mixed effect log-linear regression model. It should be noted that this model includes linear model or other transformed models , ommitting or changing the log transformation, respectively.

In the case of discrete response variable, it should be noted that discrete or categorical variables might have two different primary types of scales, namely nominal and ordinal, where the variable categories in the first type do not have a natural ordering unlike the ordinal type. Hence, the model to be used for analysing a discrete response variable should be chosen carefully according to the actuall scale type of the response variable, otherwise misleading results or loss of information might occur. In this section, we will present the model structure and its likelihood function for the mixed effect ordinal logistic regression model which assumes an ordinal scale for the response variable as the ordinal scale is higher than nominal sclae in the measurement hierarchy. Note again that this model includes binary response as a special case and also could be changed for the case of nominal response variable applying multinomial logit models (see Agresti , 2002 for more details).

Figure 9: Median Profile of MG, ER, CE, GE, CF, GDP for Different Income Levels through Time



3.1. Mixed Effect Log-linear Regression Model

Let the continuous response variable for the i^{th} observation at time t, in a T period panel study, be denoted by Y_{it}. To model the vector of repeated measurements for each individal, i.e. $Y_i \cong (Y_{i1},\ldots,Y_{iT})$ we assume that conditional on the vector of q dimensional subject-specific random effect parameters B_i the individual responses are independent along time. Also we assume that $g(Y_{it})$, where $g(.)$ is some monotonically increasing function (e.g. log) chosen to make the values of Y_{it} approximately normally distributed, has a conditional normal distribution as follows:

$$g(Y_{it}) \mid B_i \overset{ind.}{=} N(\pi_{it}, \varpi_Y^2),\ t = 1,\ldots,T,\ \ i = 1,\ldots,N,$$

$$\pi_{it} = \varepsilon_t{}' X_{it}\ .\ \ B_i{}' U_{it},$$

$$B_i \overset{iid}{=} MVN_q(0, \varsigma_B),$$

where X_{it} represents the vector of p predictor variables for the i th observation at time t, and U_{it} is some q dimentional subset of X_{it}. Also, ε_t and and B_i in the above equation are the vector of p fixed regression coefficients and q is random effect, respectively. Based on the above mixed effect model, the likelihood function whould be:

$$L(\mathrm{T} \mid \underline{Y}, \underline{X}) = \underset{i=1}{\overset{N}{\cdot}} f(Y_i \mid X_i, \mathrm{T}) \tag{1}$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} f(Y_i \mid B_i, X_i)\,\iota(B_i)\,dB_i$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} \left\{ \underset{t=1}{\overset{T}{\cdot}} f(Y_{it} \mid B_i, X_{it}) \right\} \iota(B_i)\,dB_i$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} \left\{ \underset{t=1}{\overset{T}{\cdot}} \frac{e^{\frac{(Y_{it}\, 0\, \pi_{it})^2}{2\varpi_Y^2}}}{\varpi_Y \sqrt{2\sigma}} \right\} \iota(B_i)\,dB_i, \tag{2}$$

where, $\mathrm{T} = \{\varepsilon, \varsigma_B, \varpi_Y^2\}$, $\underline{Y}$ and $\underline{X}$, respectively denote whole set of responses and the covariates, and $X_i = (X_{i1},\ldots,X_{iT})$. Also, $\int_{B_i}$ represents q dimensional integral and $\iota(B_i)$ is the density function for $MVN_q(0, \varsigma_B)$ distribution . The first equality in the above equations is a result of independence assumption of sample subjects. Also, conditional indepency of the components of i^{th} individual response vector, Y_i, given random effects, B_i, leads to the third equality. To obtain estimation for the vector of model parameters using a likelihood approach, one should maximize the logarithm of the above mentioned likelihood function. The complexity of the likelihood function due to integrals needs an approximate optimization method to estimate model parameters.

3.2. Mixed Effect Ordinal Logistic Regression Model

Let Z_{it} denote the discrete response variable with L ordinal categories , recorded for the i^{th} observation at time t of a panel study. Applying a mixed effect approach for panel data analysis, we assume a multinomial distribution for Z_{it} given the vector of q dimensional subject-specific random effect parameters B_i which leads to the conditional indepent ordinal responses for the i^{th} individual across time:

$$Z_{it} \mid B_i \overset{ind.}{=} Multinomial(1, \Sigma_{it}),\ t = 1, \ldots, T,\ \ i = 1, \ldots, N,$$

$$B_i \overset{iid}{=} MVN_q(0, \varsigma_B),$$

where $\Sigma_{it} = (\sigma_{it1}, \ldots, \sigma_{itL})$ is the vector of probabilities corresponding to the L levels of Z_{it} , i.e., $\sigma_{itj} = Pr(Z_{it} = j \mid X_{it}, B_i)$. Now, we consider an ordinal cumulative logistic regression for modelling the effect of covariates on these response probabilities as follows:

$$Log \frac{Pr(Z_{it} \infty j \mid X_{it}, B_i)}{Pr(Z_{it} > j \mid X_{it}, B_i)} = \tau_{jt}\ .\ \delta_t' X_{it}\ .\ B_i' U_{it},\ \ j = 1, \ldots, L\,0\,1$$

$$\tau_{1t} < \tau_{2t} < \ldots < \tau_{(L01)t},\ \ t = 1, \ldots, T,$$

where $Pr(Z_{it} \infty j \mid X_{it}, B_i) = \Big|_{k=1}^{j} \sigma_{itj}$, is the cumulative probability of the j^{th} and lower levels. Also, according to the above equation, we have:

$$\sigma_{it1} = \frac{e^{\tau_{1t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}{1.\ e^{\tau_{1t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}},$$

$$\sigma_{itj} = \frac{e^{\tau_{jt} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}{1.\ e^{\tau_{jt} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}$$

$$0 \frac{e^{\tau_{(j01)t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}{1.\ e^{\tau_{(j01)t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}, \; j = 2, \ldots, L\,0\,1,$$

$$\sigma_{itL} = 1\,0 \frac{e^{\tau_{(L01)t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}{1.\ e^{\tau_{(L01)t} \cdot \delta_t 'X_{it} \cdot B_i 'U_{it}}}$$

The likelihood function for the Mixed effect ordinal logistic regression described above could be obtained as follows:

$$L(\mathrm{T} \mid \underline{Z}, \underline{X}) = \underset{i=1}{\overset{N}{\cdot}} f(Z_i \mid X_i, \mathrm{T})$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} f(Z_i \mid B_i, X_i)\, \iota(B_i) dB_i$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} \left\{ \underset{t=1}{\overset{T}{\cdot}} f(Z_{it} \mid B_i, X_{it}) \right\} \iota(B_i) dB_i$$

$$= \underset{i=1}{\overset{N}{\cdot}} \int_{B_i} \left\{ \underset{t=1}{\overset{T}{\cdot}} \underset{j=1}{\overset{L}{\cdot}} \sigma_{itj}^{I(Z_{it} = j)} \right\} \iota(B_i) dB_i,$$

where $I(Z_{it} = j)$ is an indicator function which takes the value 1 when $Z_{it} = j$ and 0 otherwise.

4. Applying the Models for Inflation Data

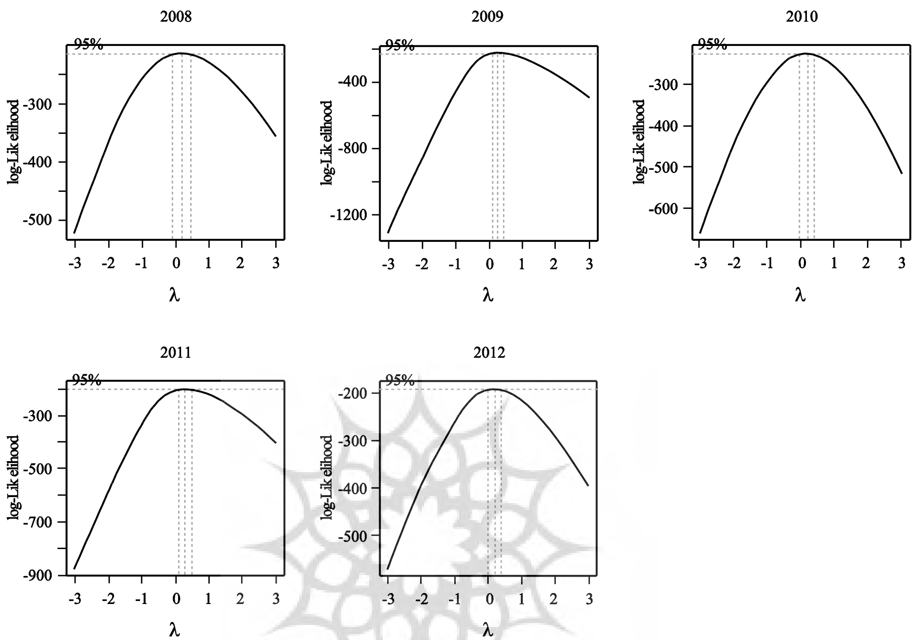
In this section we will apply the two previously mentioned models for the inflation data which is a panel data. The first model is a log-linear regression with random effect for acessing the relation between the continuous response of INF and the set of 6 independent variables $X = \{MG, ER, CE, GE, CF, GDP\}$. The second model is a mixed effect logistic model, to study the relation between the set of independent variables, X, and the INFcat response variable.

Model (I): As was illustrated in Figure 1, the INF variable is a rightly skewed variable which needs some appropriate transformation to make its distribution symmetric. To study the appropraite transformation needed for INF, one can use the Box-Cox parametric power transformation proposed by Box and Cox (1964) to reduce anomalies such as non-additivity, non-normality and heteroscedasticity. This family of power transformations is defined for positive variable Y_i, as:

$$Y_i^{(o)} = \begin{cases} \dfrac{(Y_i^{o}\ 0\, 1)}{o} & if\ \ o \approx 0, \\ log(Y_i) & if\ \ o = 0 \end{cases}$$

where o is an appropriate number which maximizes the profile log likelihood of $Y^{(o)}$. Figure 10 shows the profile log-likelihood plots of the INF variable for the parameter of the Box-Cox power transformation, o, through time. According to these plots we can choose the logarirthm transformation for the INF variable as the confidence intervals are near zero and some include it.

Figure 10: Profile Log-likelihood Plots of the INf Variable for the Parameter of the Box-Cox Power Transformation, ο, through Time



Now to apply the mixed effect log-linear model of section 3.1 for the inflation data, some adjustment should be considered due to the possibility of different set of countries in different times with different sizes. Actually, we have five set of indices for five years of study which we denote by:

$$I_t \notin \{1,\ldots,214\}, t = 2008,\ldots,2012,$$

where a whole number of 214 countries has been assumed in the original data set. Also it is assumed that I_t has $N_t \infty 214$ elements due to missing observations, where in our extracted data set, $N_{2008} = 115$, $N_{2009} = 99$, $N_{2010} = 107$, $N_{2011} = 104$ and $N_{2012} = 94$. The reason for the differnt number of countries in differnt years is that we have included all countries with available necessary information in each year in the sample. It should be noted that the available case analysis is prefered to the complete case analysis where one just includes the countries that which have been observed in all times since the number of countries included in the sample would have been reduced to 77 in each year and some loss of information and precision might occur. Using the above notation, the mixed effect log-linear model for INF [namely, Model (I)], would be:

$$
\begin{aligned}
Log(INF_{it})\,|\,b_i &\overset{ind.}{=} N(\pi_{it}, \varpi_{INF}^2),\ i \angle I_t,\ \ t = 2008,\ldots,2012,\\
&\pi_{it} = \varepsilon_0 \ .\ \varepsilon_1 MG_{i,t01} \ .\ \varepsilon_2 ER_{i,t01} \ .\ \varepsilon_3 CE_{i,t01} \ .\ \varepsilon_4 GE_{i,t01}\\
&\ .\ \varepsilon_5 CF_{i,t01} \ .\ \varepsilon_6 GDP_{i,t01} \ .\ \varepsilon_7 Oil_t\\
&\ .\ \varepsilon_8 I(Inc_i = Low) \ .\ \varepsilon_9 I(Inc_i = Lower\ Middle)\\
&\ .\ \varepsilon_{10} I(Inc_i = Upper\ Middle) \ .\ b_i,\\
&b_i \overset{iid}{=} N(0, \varpi_b^2),
\end{aligned}
$$

where, we have considered an intercept random effect parameter b_i to acount for the serial correlation between the elements of the vector of response variables for the i^{th} country, $INF_i = (INF_{i,2009},\ldots,INF_{i,2012})$. To compute the likelihood function for the above model, again some considerations should be applied due to unequal number of countries in different years. Actually, we introduce a dummy variable M_{it} which takes the value one if the i^{th} country is included in the sample at time $(i \angle I_t)$ and zero otherwise. Hence, according to equation 1 the likelihood function of Model (I) whould be:

$$
\begin{aligned}
L(\mathrm{T}\,|\,\underline{INF}, \underline{X}) &= \overset{214}{\underset{i=1}{\bullet}} \int_{b_i} \left\{ \overset{2012}{\underset{t=2008}{\bullet}} f(INF_{it}\,|\,b_i, X_{i,t01})^{M_{it}} \right\} \iota(b_i)\,db_i\\
&= \overset{214}{\underset{i=1}{\bullet}} \int_{b_i} \left\{ \overset{2012}{\underset{t=2008}{\bullet}} \left\{ \frac{e^{\frac{(log(INF_{it})0\,\pi_{it})^2}{2\varpi_{INF}^2}}}{\varpi_{INF}\sqrt{2\sigma}} \right\}^{M_{it}} \right\} \iota(b_i)\,db_i.
\end{aligned}
$$

Model(II): The second model is an ordinal logistic model with random effects which includes the INFcat variable as an ordinal response variable with three ordinal categories. According to section 3.2 and the above consideration for the different number of countries in differnt years, the mixed effect logistic model for the present data [namely, Model (II)], would be:

$$
\begin{aligned}
Log \frac{Pr(INFcat_{it} \infty j \mid X_{it}, b_i)}{Pr(INFcat_{it} > j \mid X_{it}, b_i)} = \tau_j \;.\; \delta_0 \;.\; \delta_1 MG_{i,t01} \;.\; \delta_2 ER_{i,t01} \\
.\; \delta_3 CE_{i,t01} \;.\; \delta_4 GE_{i,t01} \;.\; \delta_5 CF_{i,t01} \\
.\; \delta_6 GDP_{i,t01} \;.\; \delta_7 Oil_t \\
.\; \delta_8 I(Inc_i = Low) \;.\; \delta_9 I(Inc_i = Lower\ Middle) \\
.\; \delta_{10} I(Inc_i = Upper\ Middle) \;.\; b_i, \; j = 1,2, \\
\tau_1 < \tau_2, \; i \angle I_t, \; t = 2008, \ldots, 2012, \\
b_i \overset{iid}{=} N(0, \varpi_b^2),
\end{aligned}
$$

where $j = 1$ and $j = 2$ indicate 'low inflation' and 'medium inflation' levels of categorival inflation variable respectively. Again the likelihood function for this model would be obtained as follows:

$$
\begin{aligned}
L(\mathrm{T} \mid \underline{INFcat}, \underline{X}) &= \bullet_{i=1}^{214} \int_{b_i} \left\{ \bullet_{t=2008}^{2012} f(INFcat_{it} \mid b_i, X_i)^{M_{it}} \right\} \iota(b_i) db_i \\
&= \bullet_{i=1}^{214} \int_{b_i} \left\{ \bullet_{t=2008}^{2012} \{ \bullet_{j=1}^{3} \sigma_{itj}^{I(INFcat_{it} = j)} \}^{M_{it}} \right\} \iota(b_i) db_i,
\end{aligned}
$$

where $I(INFcat_{it} = j)$ is an indicator function which takes the value 1 when $INFcat_{it} = j$ and 0 otherwise.

4.1. Results of the two models

In this section the numerical results of parameter estimation for Model (I) and (II) will be presented. To estimate the model parameters we have used a likelihood approach, where one should maximize the likelihood function to obtain parameter estimations. However, both likelihood functions include integrals which do not allow introducing closed form ML estimators. Hence some numerical itterative approaches along with Monte Carlo methods of integral approximation should be applied to maximize likelihood functions. Actually, we have used the R program enviorment for model estimation. The function *lmer* in package *lme4* and the function *clmm* in package *ordinal* are respectively used for Model (I) and Model (II).

Table 3 presents the results of the parameter estimation for Model (I) and (II). According to the results of this table for Model (I), if the significant model covariates; MG, GDP, oil increse in a year, the mean inflation rate will also increase in the following year. Also the results illustrate that higher income countries experience less average inflation rates as expected. Parameter estimations for Model (II) indicate that an increase in MG, ER, GE, GDP and oil price will be followed by a lower odds of less inflation in the succeeding year. In contrast,when CF increases the odds of less inflation for the next year increases. The same ordering as Model (I) is true for the income levels which shows that as the income increases the odds of experiencing lower inflation levels increases. To test the significance of the variance of random effects, ϖ_b^2, in Model (I), use of conventional likelihood ratio tests produces a very conservative test because the asymptotics are different than for tests of fixed effects (the null hypothesis $H_0 : \varpi_b^2 = 0$ is on the edge of the parameter space, which means trouble). Hence, we have applied an (exact) restricted likelihood ratio test based on simulated values (Greven et al., 2008) which leads to $p0\,value < 2.2e^{016}$ (based on 10000 simulated values) for the null hypothesis of $H_0 : \varpi_b^2 = 0$. This means that there is a necessery need to include the random effects in the model to consider the possible correlation between the INF variables for each country across time. Also we use a likelihood ratio test for $H_0 : \varpi_b^2 = 0$ in Model (II). According to this method, $p0\,value = 4.368e^{016}$ which rejects H_0 and shows strong evidence for the existance of correlation between the INFcat variables across time.

The results presented in Table 2 lead to the following economic interpretations:

- Both models suggest that money growth is one of the most important determinants of inflation all over the world. This finding confirms the famous Friedman expression, "Inflation is always and every where a monetary phenomenon" (Friedman, 1963). So in any country, a sound monetary policy is required for inflation management.

- Both models suggest that some part of inflation rate changes all over the world is due to economic boom and bust (i.e. , GDP cyclical changes). Hence, to experience a high GDP growth, one has to accept some amount of increase in the inflation.

- Both models accept the important role of oil prices in determining inflation rate in world countries. So that the oil price changes as an exogenous vriable affects the inflation rate in countries with different levels of income.

- As the income level increases and moves the country toward a developed situation, the inflation rate will decline based on the results of the two models.

- Although the log-linear model failed to discover the significant effect of exchange rate, government expenditure and capital formation, the ordinal model shows that as the first two of these variables increase the odds of lower inflation category increases while an increase in the third variable leads to a higher odds of higher inflation.

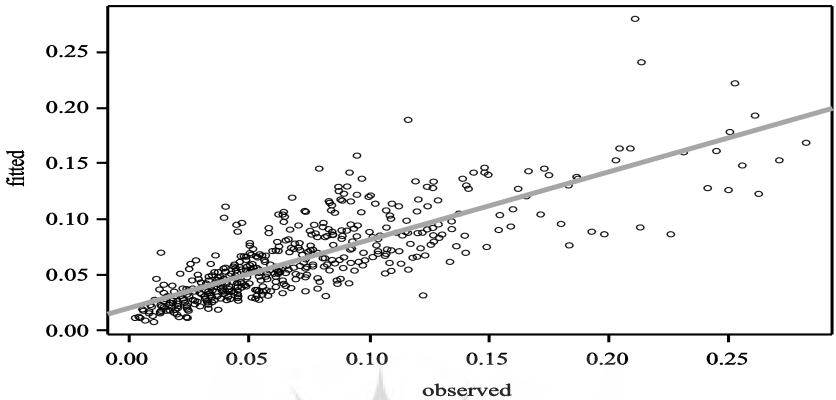
Although one of the important goals of model estimation is the inference for the data at hand, researchers are mostly interested in the prediction results for the future. In what follows, we will use some graphical, descripitive and hypothesis testing tools to assess the predictability of the Model (I) and (II). Figure 11 displays the scatter plot of observed INF variable versus its fitted values according to Model (I). There is an apparent positive trend in this figure which is shown by the red line , estimated via least square approach . Also the Pearson correlation between observed and predicted INF variable is $\upsilon = 0.82$ with $p\,0\,value < 2.2e^{016}$ for $H_0 : \upsilon = 0$ (independence). Figure 12 shows the scatter plots of observed INF with predicted INF for different years. According to these plots again Model (I)'s ability of prediction is acceptable across years.

Table 3: Results of ML Parameter Estimation of Inflation Data Corresponding to Model (I) and (II) (significant levels: '*' at 0.05, '**' at 0.1, '*' at 0.2).**

	Model (I)		Model (II)	
Par.	**Est.**	**S.D**	**Est.**	**S.D.**
MG	1.10***	0.21	-5.04***	1.15
ER	0.22	0.28	-1.92*	1.44
CE	0.17	0.31	-0.99	1.58
GE	0.14	0.12	-1.08**	0.62
CF	-0.22	0.14	0.96*	0.70
GDP	4.33***	0.74	-16.2***	3.75
Oil	0.63***	0.08	- 2.52***	0.41
$Inc(low)$	0.64***	0.15	-2.34***	0.62
$Inc(lower\ Middle)$	0.56***	0.14	-1.92***	0.55
$Inc(Upper\ Middle)$	0.45***	0.14	-1.16***	0.53
$Inc(High)$	-	-	-	-
ε_0	-3.83***	0.10	-	-
τ_1	-	-	0.50*	0.40
τ_2	-	-	5.06***	0.52
ϖ_b^2	0.24***	-	2.92***	-
ϖ_{INF}^2	0.22	-	-	-

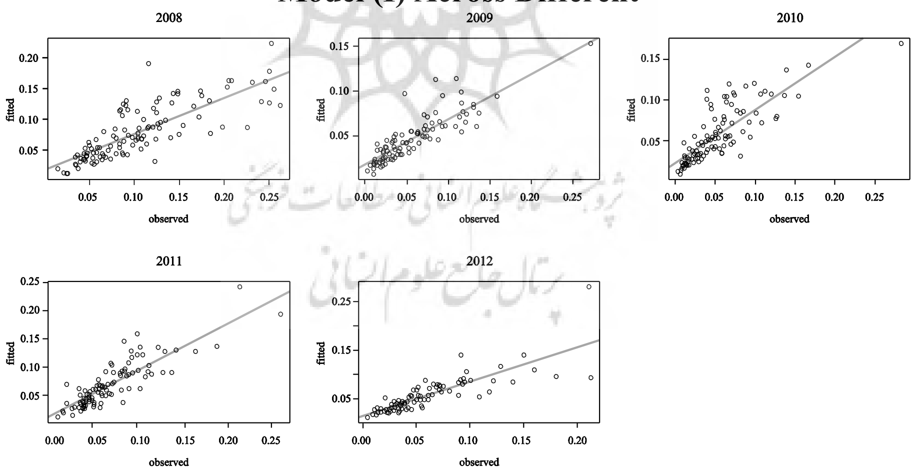
Source: Authors' calculations.

Figure 11: Scatter Plot of Observed Versus Fitted INF Based on Model (I)



*eSourc:*Authors ' findings

Figure 12: Scatter Plots of Observed Versus Fitted INF Based on Model (I) Across Different



*Source :*Authors ' findings

Table 4 gives the cross table of the observed versus predicted inflation category along with the prediction errors based on Model (II), for the overall sample in five years of the study. The numbers -1, 0 and 1 in the prediction error column, respectively indicate lower category, exact and upper category predictions. According to this table, the medium inflation level is the best predicted of the three levels and also the high category has better prediction results than the low category. However, the low and high inflation levels are likely to be predicted as medium inflation level with one level error.

Table 4: Observed Versus Predicted Inflation Category and Prediction Errors

	Predicted Category			**Prediction Error**		
Observed Category	Low	Medium	High	-1	0	1
Low	36	59	0	0.00%	37.89%	62.11%
Medium	14	244	23	4.98%	86.83%	8.19%
High	1	72	70	50.35%	48.95%	0.00%

Source: Authors' calculations.

Applying the Pearson Chi-squared statistic for testing the hypothesis of independence between observed and predicted inflation categories leads to strong rejection with $\phi^2 = 222.84$ and $p\,0\,value < 2.2e^{016}$. Also using the Kendall's measure of correlation for ordinal variables gives the value, $\hat{\omega} = 0.53$ with $p\,0\,value < 2.2e^{016}$ which again rejects the independent hypothesis, i.e., $H_0 : \omega = 0$. Figure 13 displays the mosaic plot of the cross table given in Table 4. In this figure, the width of every rectangle is proportional to the total number of countries in the corresponding observed category and the height of rectangle capture the conditional proportion of the predicted categories within the corresponding observed category. This plot illustrates the same results as Table 4 but in a graphical approach. Actually, the plot shows that most of the observed responses fall in the medium inflation level and also this level has the smallest number of false predictions.

Figure 13: Mosaic Plot of Observed Versus Predicted Categories of INFcat

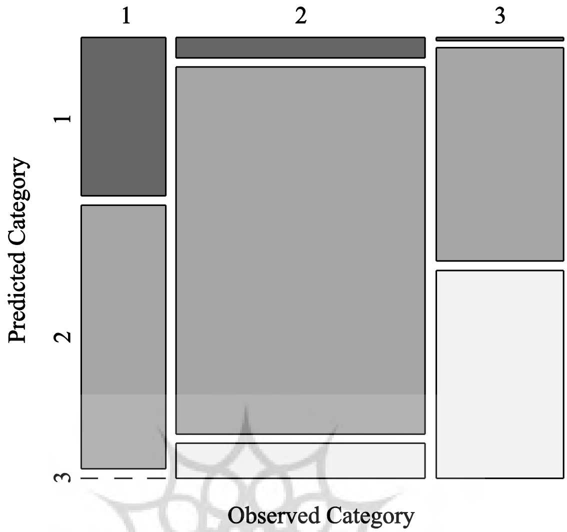
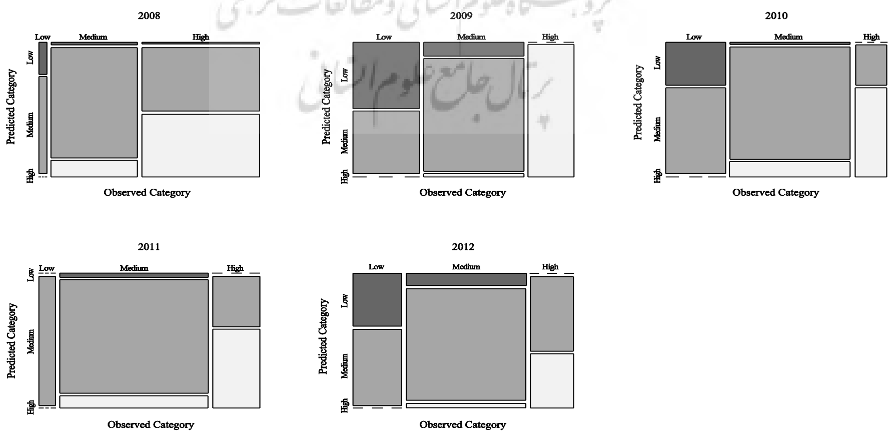


Figure 14 also represents the mosaic plot of observed versus predicted inflation categories panelled through five years of the study. These plots approximately show the same pattern as the over all plot of Figure 13.

Figure 14: Mosaic Plot of Observed Versus Predicted Categories of INFcat for Different Years



5. Conclusion

Inflation rate is one of the most important macroeconomic variables in all countries since all policy making measures need the exact foresight about the previous, current and future changes in inflation level. This fact has pushed many researchers to work on the recognition of main inflation determinants. These determinants are often categorized in two groups: Demand side factors and supply side factors. According to the current literature, the important demand side determinants of inflation are money growth, private and government consumption expenditures and the important supply side determinates of inflation are considered to be output growth, capital formation, oil prices and exchange rate.

This paper tried to model World Bank data base during 2008 - 2012 to find the level of significancy and effects of the above mentioned demand side and supply side factors on the inflation rates considering all countries with available data. For this purpose, two random effect log-linear and ordinal logistic models were presented in which the correlation between repeated measurments for each country is considered via some random ecoefficients. In these models, we have used different measurement scale response variables corresponding to the inflation rate. Actually, one is the numerical reported inflation rate and the other is a three-level inflation status including three ordinal categories of, low, medium and high inflation. Using some graphical and inferential devices, the need for a logarithmic transformation seems necessary for the original inflation rate variable to make its distribution symmetric.

Two points make this study different from the previous similar studies: 1) This study used all countries with available data during the time to analyse the effects of determinants of inflation while the previous researches focus on one country, a cross-section of countries or a limitted number of countries during the time. 2) Using the ordinal logistic model in addition to log-linear model for inflation variable and comparing the results of both models is a new approach in the inflation analysis which has not been considered by previous researchers. One important advantage of ordinal scale compared with the continuous one is that we have the opportunity to do a comparative study among different countries with different economic characteristics (for example comparing the level of inflation in two countries, one with higher economic growth or other economic factors). Moreover, the categorized inflation approach prevents the misleading estimation results due to measurement errors and potential outliers in the reported data.

Results of both fitted models show that money growth, GDP growth and oil price growth are the main effective elements in determining the inflation rate category. Actually, the increase in each of these three variables will increase the next year inflation rate (in log-linear model) or the odds of being in higher inflation categories in the next year (in ordinal logistic model). The other important result is that, while log linear model could not find any significant relation for the exchange rate, government expenditures and capital formation on the log transformed inflation rate, these variables had significant effects on the odd of inflation categories in the ordinal logistic model which shows the superiority of ordinal logistic to log-linear model. Model estimation shows that any increase in exchange rate growth and government expenditure growth increases the odds of higher inflation categories and any increase in capital formation growth decreases the odds of higher category inflation levels.

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