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# How does global energy prices drive food prices in South Asia? Empirical evidence from Panel NARDL estimations

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## ABSTRACT

The paper aims to investigate the asymmetric relationship between global energy price (oil and coal) and regional food price in South Asia. Using monthly panel data of 5 South Asian countries from January, 2000 - June, 2021; a nonlinear ARDL estimation is conducted for both short and long run. The results suggest that short run changes in oil and coal price do not affect food prices in South Asia. However, a 1% increase in international oil price increases food price by 1.72% -2.45% and a 1% increase in international coal price increases food price by 0.64-0.76% in the long run. Interestingly, a fall in international oil and coal prices do not reduce food price in South Asia. Rather, A 1% decrease in international oil price increases food price by 1.32% - 2.47% and a 1% decrease in international coal price increases food price by 0.67%-0.85%.

Keywords: Oil price, Coal price, Food Price, Panel NARDL, Asymmetry, South Asia.
JEL Codes: Q4, Q43, E31.


## 1.0 Introduction

Energy price i.e. price of oil, natural gas or coal etc. at the international market are considered to be key macroeconomic indicators. They are also assumed to be possible sources of external shock that is capable of disrupting economic stability worldwide. The domestic impact due to a change in international energy prices may vary from country to country based on various factors such as its own fossil fuel endowments, renewable energy resources, import dependency on other countries, diverse formation of energy basket, level of economic development, technological advancement and socio-political stability etc. However, the supply-side effect due to an increase in energy prices generally tend to increase production and transportation cost, making primary productive resources scarcer and less affordable to marginal producers (Amin and Alamgir, 2021). On the demand side, fluctuations in energy prices not only affect purchasing power of consumers but also impact their purchasing decisions due to uncertainty and precautionary effects (Pal and Mitra, 2019).

Numerous literatures have examined the impact of energy prices especially oil prices on economic productivity and found that an increase in energy price impedes economic growth and boosts domestic inflation (Rasoulinezhad et al. 2023). Increasing energy price can affect food price inflation through direct and indirect channels (Jongwanich and Park, 2011). As fossil fuels are used in food production as direct inputs such as fuel for tractors, irrigation pumps and other agricultural equipment, food price may increase due to a rise in cost of domestic production. On the other hand, higher energy price especially oil price is closely linked to higher

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electricity costs, transportation cost, import costs of processed food and agricultural inputs which promote cost-push food price inflation through indirect channels. Therefore, even in countries where domestic price of energy is subsidized and regulated by the government, they also may suffer from the spill-over effect of increasing energy price in world market via the indirect channel.

Another faction of researchers has proposed an alternate theory of food price inflation based on substitution effect of increasing price of oil (Myers et al. 2014). As oil price has steadily increased in the world market over the years, many countries have focused on production and use of bio-fuel. Geographical endowment may have contributed to this decision as many oil importing countries have climate favorable towards agricultural production. If these countries reduce imports of agricultural products e.g. corn, soybean, sugarcane etc. and instead allocate them to produce bio-diesel and bio-ethanol; then there will be a shortage of food supply in the world market resulting further food price inflation (Koizumi, 2015). However, as contribution of bio-fuel is far lesser compared to oil and other fossil fuels in world energy basket, this substitution effect is likely to be insignificant in South Asia.

Over the years, the relationship between oil price and food price has received much attention and while debate may exist over the channel and direction of causality between the variables, it is widely reported that increased oil price in the world market causes a rise in food prices (Chowdhury et al. 2021, Bala and Chin, 2018; Chen et al. 2010) On the other hand, only a handful of paper has analyzed impact of other fossil fuel sources i.e. natural gas and coal prices on food price inflation (Chowdhury et al. 2021; Guo et al. 2016; Etienne et al. 2016). Moreover, majority of the existing studies have applied various methodologies based on linear techniques such as Auto regressive Distributive Lag (ARDL), Vector Auto Regression (VAR), structural VAR, Competitive General Equilibrium Model (CGE) etc. Results of these models assumes symmetrical relationship between energy and food prices which implies the magnitude of change in food price due to an increase in energy price will be equivalent to the change if energy price decreases by one unit.

However, Salisu et al. (2017) and Trujilo-Barrera et al. (2012) argue that when there is an oil price shock in terms of abrupt rise in oil prices, the producers try to shift the burden of extra production cost to consumers by increasing price of agricultural outputs i.e. food. Because of cautionary effect, they may also underinvest in agriculture sector which lowers food production and increases food price due to excess demand. Therefore, the effect of an increase in oil price is likely to be more prominent on food prices. On the other hand, if there is a decrease in oil price in the world market, producers have no incentive to lower food prices except moral obligations. Moreover, government often imposes price controls in agriculture markets to protect farmers from rapidly declining prices of agricultural outputs. Therefore, the adjustment in food prices due to a decline in energy prices is rather inconspicuous. Therefore, it is more logical to assume an asymmetric nonlinear relationship between energy and food prices.

A number of papers in recent years have explored the asymmetric nonlinear relationship between energy and food prices in the world market. For example, Karakotsios et al (2021) have examined short and long run global dynamic between crude oil price and world food price and revealed a unidirectional causality running from crude oil price to food prices. Zmami and Ben-Salha (2019) have disaggregated the food sector into five sub-categories namely sugar, vegetable oils, cereals, dairy, and meat; and analyzed the effect of oil price shocks on prices of each sub-category. Chowdhury et al. (2021) have conducted a detailed disaggregated analysis where they analyzed the impact of oil, natural gas and coal prices on world food prices. They also analyzed the impact of fossil fuel prices on rice, wheat and corn prices at the international market.

A number of country specific studies have also been conducted for India, Pakistan, China, Malaysia, and Indonesia etc. that analyzed the asymmetric relationship between oil and food prices (Abu Bakar and Masih 2018, Sarwar et al. 2020, Long and Liang 2018, Sek 2017). On the contrary, very few papers have analyzed the non-linear effect of coal and natural gas prices on food prices in country specific context. Guo et al (2016) have analyzed the nexus between coal prices and general price level using monthly data of China. Etienne et al. (2016) have examined the price transmission mechanism among natural gas, fertilizer and corn market.

South Asia as a region has been growing rapidly in the past few decades and comprises of some of the most densely populated countries in the world. Because of its dynamic economic structure, the region's demand for oil, natural gas and coal are on the rise. Moreover, the entire South Asian region is heavily reliant on fossil fuel import from rest of the world. All the countries in South Asia are net oil importers. Even though some countries in the region have internal deposits of coals, they are not self-sufficient on domestic production. These countries import a substantial amount of coal from China, Russia, Australia and other countries to meet domestic demand. However, to our knowledge, no study has analyzed the asymmetric nexus between energy price and food price in South Asia. Zakaria et al. (2021) has examined the asymmetric nexus between oil price and general inflation using panel data of 4 South Asian countries. Using cointegration analysis, VAR and IRF, they concluded that global oil prices shock leaves a permanent positive effect on inflation in South Asian countries. In this context, the aim of the paper is to explore the asymmetric nonlinear relationship between international oil and coal prices on regional food price inflation in South Asia using panel data of 5 South Asian countries namely Bangladesh, India, Pakistan, Nepal and Sri Lanka. The originality of the study is as follows: the paper will assess the asymmetric relationship not only between oil price and food price but between coal price and food price as well.

Rest of the paper is structured as follows: section 2 provides a detailed literature review of relevant papers, section 3 describes the data, empirical model and methodology, section 4 presents the results of data analysis and lastly the paper concludes with conclusion and policy suggestions in section 5.

## 2.0 Literature Review

Over the years, several country-specific and panel studies have analyzed the linear and nonlinear relationship between fuel price and food price A detailed literature review of existing papers is presented below in two segments. The first segment discusses papers that analyzed the relationship between oil price and food price and the second segment reviews papers that analyzed the relationship between coal price and food price.

### 2.1 Analyzing the dynamic between oil price and food price inflation

Chen et al. (2014) investigated the long run relationship between oil price and prices of several food grains i.e. corn, soya bean and wheat. They collected weakly data for time period 1983 -2010 and using an ARDL methodology with structural breaks, they found oil price has a positive and significant impact on grain prices in the international market. Olayungbo (2021) analyzed yearly data of 21 oil-exporting and food importing developing economies for year 2001-2015. Using a panel ARDL methodology they found oil price and food prices are negatively related in short run but oil price has a positive and statistically significant impact on food prices in the long run. They also found a one-way causality runs from food prices to oil prices using panel granger causality test. Jongwanich and Park (2011) analyzed quarterly data of 9 developing countries of Asia for year 1996-2008 and assessed the impact of global oil price and food price on domestic inflation. Using a Vector Auto-Regression (VAR) and Impulse response Function (IRF) methodology they reported that global oil price rise indeed increases domestic inflation. However, the pass-through effect is limited due to fuel and food price subsidy, and affects producer prices more than consumer prices.

In recent years, the asymmetric non-linear relationship between oil price and food price is getting more attention. Sun et al. (2023) analyzed the nexus between oil price and global food prices using monthly data from 01/1993- 09/ 2020. They applied a Quintile on Quartile regression (QoQ) methodology and revealed an oil price shock affects food price index in middle quintiles most strongly. On the other hand, the effect of an oil demand shock is most prominent between highest and lowest quintiles of food price indices. Chowdhury et al. (2021) examined the nexus between world energy price and food prices using Nonlinear Autoregressive Distributed Lag (NARDL) methodology and time frequency wavelet approaches. They confirmed the presence of asymmetry between energy prices and food prices and stated the impact of oil price increase is more noticeable than a decrease in oil prices. The impact of an increase in oil price is most dominant in the 16th month and the positive impact of oil price on food prices last till the 64th month. Karakotsios et al. (2021) studied the nexus between global oil price and food prices with structural -break. They employed monthly data from 01/2000- 12/2020 and using asymmetric cointegration and ARDL methodology they confirmed presence of asymmetric causality both in short run and in long run.

Abu-Bakar and Masih (2018) assessed the pass-through effect of oil prices on domestic food prices in India using monthly data from01/2022 to 01/2018. Using a NARDL methodology, they revealed that oil price increase has positive and statistically significant impact on domestic inflation but the impact of oil price decrease is not statistically significant. Sarwar et al. (2020) assessed the impact of global oil price change on both food price and non-food price inflation in Pakistan. Using NARDL methodology they examined quarterly data from Q3, 1990 – Q4, 2019 and reported that an increase in food price increases food and non-food price inflation but the impact of oil price decrease is statistically insignificant. Long and Liang (2018) examined the effect of global oil price change on inflation in China using Producer Price Index (PPI) as well as Consumer Price Index (CPI). The conducted linear and non-linear ARDL estimations using quarterly data from Q1,1998 – Q1,2014. Their results provide evidence of asymmetry and once again impact of positive change in oil price is more prominent of domestic inflation than a negative change in oil prices. They also reported PPI is more responsive to oil price increase than the CPI. Ibrahim (2015) examined the relationship between food price and oil price in Malaysia, He employed yearly data from 1971-2012 and conducted an NARDL estimation. An increase in oil price has positive and statistically significant impact on food prices. However, decrease in oil price does not affect food prices in short run and in long run.

### 2.2 Analyzing the dynamic between coal price and food price inflation

Chowdhury et al. (2021) analyzed the asymmetric relationship between coal price fluctuations and world food price inflation using monthly data from 01/1992 -05/2017. Using NARDL and IRF methodology, they reported both coal price increase and decrease results in food price inflation and provided evidence of asymmetry. Du et al. (2022) examined the effect of coal price changes on prices of agricultural commodities using time series data of China. Using daily data of 5 different types of vegetables for time period 2016-2021, they conducted an IRF and VAR analysis. They reported vegetables that require thermal power support in green houses, uses coal generated energy more extensively and therefore a coal price increase passes through to vegetable prices. Guo et al. (2016) examined the asymmetric relationship between coal price and general inflation in the context of China. They examined monthly data from06/98 -09/2014 using VAR and IRF methodology and reported coal price increase and decrease both leads to general price inflation in China.

## 3.0 Data, Econometric model and Methodology

### 3.1 Data

Monthly data of 5 South Asian countries namely Bangladesh, India, Pakistan, Sri Lanka and Nepal are collected from January, 2000 – June, 2021. International Oil Price (WTI) data are collected from US Energy Information and Association (EIA), International Coal Price data are collected from International Monetary Fund (IMF) and country specific Food price index (Food- CPI) data are collected from Food and Agriculture Organization (FAO) website. A descriptive statistics of compiled dataset is presented in table 1.

Table 1.
*Descriptive Statistics.*

| | Observation | Mean | Standard Deviation | Minimum | Maximum | Skewedness | Kurtosis |
|---|---|---|---|---|---|---|---|
| Food Price Index | 1,290 | 74.72474 | 31.34807 | 24.6522 | 142.1748 | 0.0003 | 0.0000 |
| Oil Price (WTI) | 1,290 | 60.71457 | 25.72699 | 16.55 | 133.88 | 0.0000 | 0.0000 |
| Coal Price | 1,290 | 74.18766 | 33.50139 | 24 | 195.1863 | 0.0000 | 0.9861 |

### 3.2 Econometric model

In this paper, we apply the following econometric model proposed by Chowdhury et al. (2021), Abu Bakr and Masih (2018) and Ibrahim (2015), where they assumed food price ($FP$) is a function of oil price (OP).

$$FP = f(OP)$$

Mathematically,

$$FP_i = \alpha_i + \beta_i OP + \varepsilon_i \text{ ---------(iii)}$$

However, recent studies have shown that the effect of oil price shocks on food price is more likely to be asymmetric; we further modify the model to take the positive and negative changes of oil price into account. The changes in oil price are decomposed into positive and negative shocks as proposed by Shin et al. (2014). Therefore we get the following equation

$$FP_i = \alpha_i + \beta_i OP^+ + \beta_i OP^- + \varepsilon_i \quad \text{---------(iv)}$$

Where, $OP^+$ and $OP^-$ represents positive and negative changes in oil prices respectively. This model will be used to evaluate the nonlinear transmission of the oil price shocks to the price of food.

Following Chowdhury et al. (2021) and Guo et al. (2016) we can also use the same model to analyze the asymmetric relationship between coal price (CP) and food price (FP). The model can be written as

$$FP_{i,t} = \alpha_i + \beta_i CP^+ + \beta_i CP^- + \varepsilon_i$$

### 3.3 Methodology

In this paper, the nexus between oil price and food price has been analyzed using a dynamic panel data model using data of 5 South Asian countries. In our dataset, T>N, therefore a nonlinear Panel ARDL model is more suitable to address the heterogeneity and the within group differences. If we apply pooled OLS regression to estimate the coefficients of the ARDL model, we will have to impose homogeneity restriction. On the other hand, if we opt for Fixed Effect (FE) estimators, then only the intercepts will be able to differ across group. In presence of heterogeneity in the dataset, both pooled OLS and FE estimator will be inconsistent and misrepresentative.

In this context, both Mean Group (MG) and Pooled Mean Group (PMG) estimators can be considered. MG estimators don't impose restrictions on cross-group parameters (i.e. intercept, coefficients and error variances) and allows them to vary in both short and long run. On the other hand, Pooled Mean Group (PMG) estimation technique developed by Pesaran et al. (1999) proposes an intermediary approach. Intercept, coefficients, and error variances are allowed to vary across group in short run but PMG estimators constrains a faction of long-run coefficients to be identical (homogenous) across groups. Standard Hausman test can help us determine if MG or PMG estimation will be suitable for a particular dataset.

We now apply the Auto Regressive Distributive Lag (ARDL) approach developed by Pesaran et al, (2001) and present the relationship between food price and oil price in a panel ARDL format

$$FP_{i,t} = \alpha_i + \beta_i OP_{i.t-1} + \gamma_i OP_t + \varepsilon_i \text{ ---------------- (v)}$$

Here, $FP_{i,t}$ is log of Food Price Index for individual country i (i = 1, 2, 3, . . . . . . . . . N) over a time period t (t = 1, 2, 3, . . . . . . . . N), $OP_t$ is the world oil price at period t, $\varepsilon_i$ = error term.

Let's assume $\sigma_i$ represents the long run parameter for each i, where

$$\sigma_i = \frac{\gamma_i}{1-\beta_i}$$

then the MG estimators for the entire panel can be written as follows

$$\hat{\sigma}_i = \frac{1}{N}\sum_{i=1}^{N}\sigma_i \quad \text{and} \quad \hat{\alpha}_i = \frac{1}{N}\sum_{i=1}^{N}\alpha_i$$

On the other hand, if we can detect heterogeneity in long run coefficients using Standard Hausman test, then PMG estimator will be more suitable.

First we present the ARDL cointegration estimation for dependent (log of domestic food price index) and independent variable (log of world oil price) assuming a symmetric nexus

$$\Delta FP_{i,t} = \beta_{0i} + \beta_{1i}FP_{i,t-1} + \beta_{2i}OP_{t-1} + \sum_{j=1}^{N1}\lambda_{ij}\Delta FP_{i,t-j} + \sum_{j=0}^{N2}\gamma_{ij}\Delta OP_{t-j} + \mu_i + \varepsilon_{i,t} \quad \text{..... (vi)}$$

Here, $\mu_i$ represents group specific effects; $-\frac{\beta_{2i}}{\beta_{1i}}$ represent long run slope coefficients; $\gamma_{ij}$ represents short run coefficients.

Now, we re-parameterize equation (vi) and write

$$\Delta FP_{i,t} = \delta_i(FP_{i,t-1} - \varphi_{0i} - \varphi_{1i}OP_{t-1}) + \sum_{j=1}^{N1}\lambda_{ij}\Delta FP_{i,t-j} + \sum_{j=0}^{N2}\gamma_{ij}\Delta OP_{t-j} + \mu_i + \varepsilon_{i,t} \quad \text{---- (vii)}$$

Here, $\varphi_{0i} = -\frac{\beta_{0i}}{\beta_{1i}}$ ; $\varphi_{1i} = -\frac{\beta_{2i}}{\beta_{1i}}$ and $\delta_i$ is the error correction term which represents the speed of adjustment.

The asymmetric version of the ARDL cointegration model can be written following Shin et al. (2014) where the oil price is decomposed into its positive and negative components. Where $OP_t^+$ represents an increase in oil price or positive oil price shock and $OP_t^-$ represents a decrease in oil price or negative oil price shock. Equation (viii) and (ix) shows the computation of $OP_t^+$ and $OP_t^-$

$$OP_t^+ = \sum_{k=i}^{t}\Delta OP_{i,k}^+ = \sum_{k=i}^{t}\max \Delta OP_{i,k}, 0 \quad \text{-----------------(viii)}$$

$$OP_t^- = \sum_{k=i}^{t}\Delta OP_{i,k}^- = = \sum_{k=i}^{t}\min \Delta OP_{i,k}, 0 \quad \text{------------------(ix)}$$

Substitute equation (viii) and (ix) in equation (vi), we can write

$$\Delta FP_{i,t} = \beta_{0i} + \beta_{1i}FP_{i,t-1} + \beta_{2i}^+OP_{t-1}^+ + \beta_{2i}^-OP_{t-1}^- + \sum_{j=1}^{N1}\lambda_{ij}\Delta FP_{i,t-j} + \sum_{j=0}^{N2}\gamma_{ij}\Delta OP_{t-j}^+ + \sum_{j=0}^{N2}\gamma_{ij}\Delta OP_{t-j}^- + \mu_i + \varepsilon_{i,t} \quad \text{------ (x)}$$

Then, we re-parameterize equation (x) in error correction format and write the asymmetric non-linear ARDL equation as

$$\Delta FP_{i,t} = \psi_i(FP_{i,t-1} - \varphi_{0i} - \varphi_{2i}^+OP_{t-1}^+ - \varphi_{2i}^-OP_{t-1}^-) + \sum_{j=1}^{N1}\lambda_{ij}\Delta FP_{i,t-j} + \sum_{j=0}^{N2}\gamma_{ij}^+\Delta OP_{t-j}^+ + \sum_{j=0}^{N2}\gamma_{ij}^-\Delta OP_{t-j}^- + \mu_i + \varepsilon_{i,t} \quad \text{--------(xi)}$$

## 4.0 Results and Interpretation

At first we conduct a Standard Hausman test to justify the selection of regression estimation technique. The null hypothesis of Hausman test assumes there is no symmetric relation between differences in coefficients. The results for both symmetric and asymmetric models are reported in Table 2. The results suggest that long-run homogeneity is present among the selected countries and therefore, a PMG ARDL model would be more suitable in this context than a MG ARDL model.

Table 2.

*Standard Hausman Test (Oil price and Food price)*

| Standard Hausman Test | Symmetric | Asymmetric |
|---|---|---|
| Test of Long-Run homogeneity restrictions on coefficients | | |
| Test: Ho: difference in coefficients not systematic | | |
| Hausman test statistics $\chi_k^2$ | 0.08 | 0.02 |
| Prob > $\chi_k^2$ | 0.7835 | 0.9889 |

Table 3 presents the results of short-run and long-run estimations from the symmetric PMG ARDL model. Since, we are conducting regression on a bi-variate equation; the estimations are susceptible to omitted variable bias. Therefore, to check the consistency and robustness of the estimations, a number of iterations with various lag lengths are conducted.

Table 3.

*PMG ARDL estimation without asymmetry (Oil price and Food price)*

| Model without asymmetry<br>Dependent Variable: *FP* | | | | |
|---|---|---|---|---|
| Variable | ARDL (2,2,2) | ARDL(1,2,2) | ARDL (2,1,1) | ARDL (1,1,1) |
| Long run estimations | | | | |
| OP | 1.746674* | 2.447531** | 1.703442** | 2.363667** |
| | (.9352332) | (1.16796) | (.7932103) | (1.026447) |
| Short run ECM estimations | | | | |
| $\Delta OP$ | -.0059213 | -.0039697 | -.004101 | -.0024656 |
| | (.002541) | (.0029393) | (.0029087) | (.0035755) |
| $\Delta OP_{t-1}$ | .0074491*** | .0056001** | | |
| | (.0015644) | (.0026911) | | |
| $\Delta FP_{t-1}$ | .4572929*** | | .4553191*** | |
| | (.057584) | | (.0578174) | |
| Convergence coefficients | -.0011846*** | -.0014288*** | -.001406*** | -.0015719*** |
| (EC) | (.000238) | (.0003019) | (.0002665) | (.0003491) |
| constant | -.0001703* | -.0011835* | -.000322* | -.0012901* |
| | (.0001811) | (.0007215) | (.0001751) | (.0007675) |
| Log likelihood | 4835.8 | 4835.8 | 4835.8 | 4835.8 |
| No. of cross sections | 5 | 5 | 5 | 5 |
| No. of observations | 1285 | 1285 | 1285 | 1285 |

***, **, and * denotes the significance at α=1, 5 and 10 %. Standard errors are reported in parenthesis.

According to the estimations generated from the symmetric PMG ARDL estimation, there is a strong positive relationship between oil price and food price in the long run as denoted by the coefficients of OP. A 1% increase in oil price in the international market increases domestic food price in South Asia by approximately 1.75% - 2.45%. Also, the relationship between oil price in the international market and domestic food prices are not statistically significant in the short run. The results seem logical because the oil prices in South Asian countries are regulated by a Government though an energy regulatory authority. Therefore, when there is an oil price surge in the international market the impact on food price is not apparent instantly. The government may decide to subsidize the oil price for a while in public interest. However, in the long run, to cope up with the increasing oil prices, government may decide to raise oil price which later transmits to food prices as well. Since production of food and agricultural commodities take time, the lagged effect of oil price (〖ΔOP〗_(t-1)) has positive and statistically impact on food prices. The results are robust as all the estimations using variation of lag-length iteration generated consistent outcomes.

However, the question arises- will the food prices decrease in same way when there is decrease in oil price in the international market? It seems much unlikely as Governments of South Asian countries rarely reduces price followed by a global fall in oil prices. Therefore, to test for the asymmetric relationship between oil price and food price, we conduct a panel NARDL PMG estimation and the results are reported in Table 4. The presence of asymmetry between oil price and food price is vividly apparent.

Table 4.

*PMG NARDL estimation with asymmetry (Oil price and Food price)*

| Model with asymmetry<br>Dependent Variable: *FP* | | | | |
|---|---|---|---|---|
| Variable | ARDL (2,2,2) | ARDL(1,2,2) | ARDL (2,1,1) | ARDL (1,1,1) |
| Long run estimations | | | | |
| $OP^{+}$ | 1.727319* | 2.449852** | 1.751238** | 2.376902** |
| | (.8844812) | (1.169499) | (.8304074) | (2.214061) |
| $OP^{-}$ | 1.643662* | 2.470202** | 1.326077** | 2.214061** |
| | (.8456387) | (1.172406) | (.6666836) | (.952471) |
| *Short run ECM* estimations | | | | |
| $\Delta OP^{+}$ | .0098176 | .0012164 | .0095734 | .0000976 |
| | (.0042956) | (.0037691) | (.0038187) | (.0043712) |
| $\Delta OP^{+}_{t-1}$ | .008375*** | .0056691** | | |
| | .0012368 | (.0021683) | | |
| $\Delta OP^{-}$ | -.0100191* | -.0048344 | -.0092892 | -.0037807 |
| | (.0044532) | (.0039611) | (.0039726) | (.0045193) |

| | | | | |
|---|---|---|---|---|
| $\Delta OP^{-}_{t-1}$ | .0081763*** | .0055432** | | |
| | .0012741 | (.0022318) | | |
| $\Delta FP_{t-1}$ | .4619932*** | | .4587199*** | |
| | (.0583309) | | (.0583805) | |
| Convergence coefficients | -.0012955*** | -.0014386*** | -.0015142*** | -.0016362*** |
| (EC) | (.0002253) | (.0003081) | (.0001095) | (.0002921) |
| constant | -.0001949 | -.0012314* | -.0001385* | -.0031431*** |
| | (.0001472) | (.0007505) | (.0001231) | (0.001) |
| Log likelihood | 4837.554 | 4837.554 | 4837.554 | 4837.554 |
| No. of cross sections | 5 | 5 | 5 | 5 |
| No. of observations | 1285 | 1285 | 1285 | 1285 |

***, **, and * denotes the significance at α=1, 5 and 10 %. Standard Errors are reported in parenthesis.

The results suggest oil price increase and oil price decrease do not have statistically significant impact on food prices in the short run. However, in the long run, a 1% increase in global oil price raises food prices by 1.72% -2.45%. However, when oil price in the international market decreases by 1% it does not reduce the food price; rather food price will still increase by approximately 1.32% - 2.47% in the long run. Our results are consistent with the findings reported by Chowdhury et al. (2021), Zmami and Ben-Salha (2019) and Long and Liang (2018). The result suggests that when oil price increases, food producers increase the price of food products to compensate for higher production and transportation cost. However, they don't adjust the price when oil price falls in the international market as the sellers prefer to sell the products at higher prices. This indicates an imperfect market mechanism exists in South Asian markets. The food producers usually justifies the pass-through effect of increasing oil prices by claiming that fuel prices were higher during the production period, and hence, there food production costs were higher due to logistics, irrigation and transportation cost. Therefore, it will not be profitable for them to sell the food items at lower prices immediately following a drop in the global prices.

A similar exercise is conducted using monthly coal prices. Table 5 represents Standard Hausman test results for coal price and food prices. Once again, we confirm presence of long run homogeneity and proceed with PMG ARDL estimations and the results are reported in table 6.

Table 5.
*Standard Hausman Test (Coal price and Food price)*

| Standard Hausman Test | Symmetric | Asymmetric |
|---|---|---|
| Test of Long-Run homogeneity restrictions on coefficients | | |
| Test: Ho: difference in coefficients not systematic | | |
| Hausman test statistics $\chi^2_k$ | 1.55 | 2.83 |
| Prob > $\chi^2_k$ | 0.2132 | 0.2435 |

Table 6.
*PMG ARDL estimation without asymmetry (Coal price and Food price)*

Model without asymmetry

| Variable | ARDL (2,2,2) | ARDL(1,2,2) | ARDL (2,1,1) | ARDL (1,1,1) |
|---|---|---|---|---|
| Long run estimations | | | | |
| $CP$ | 1.014537*** | 1.256862*** | 1.037189*** | 1.358186*** |
| | (.3209754) | (3603622) | (.3671983) | (.4437026) |
| *Short run ECM* estimations | | | | |
| $\Delta CP$ | -.0001697 | .0046277 | -.004242 | -.0005473 |
| | (.0047771) | (.0080686) | (.0052397) | (.0090722) |
| $\Delta CP_{t-1}$ | -.0122866*** | -.0155715** | | |
| | (.0031185) | (.0048968) | | |
| $\Delta FP_{t-1}$ | .4535451*** | | 0.4568811*** | |
| | (.0565589) | | (.0572826) | |
| constant | .0012648*** | .0012772*** | .0011667*** | .0011824*** |
| | (.0001804) | (.0002236) | (.0001757) | (.000379) |
| Convergence coefficients | -.0022618*** | -.0022544 | -.001925*** | -.0017313*** |
| | (.0002815) | (.0006034) | (.0002881) | (.0006529) |
| Log likelihood | 4988.772 | 4821.443 | 4984.791 | 4833.636 |
| No. of cross sections | 5 | 5 | 5 | 5 |
| No. of observations | 1284 | 1284 | 1284 | 1284 |

***, **, and * denotes the significance at α=1, 5 and 10 %. Standard errors are reported in parenthesis.

The PMG ARDL estimation without asymmetry generated both short run and long run estimations. Similar to oil prices, coal price also did not have a statistically significant impact on food prices in the short run. However, in the long run, a 1% increase in coal prices in the international market raises food price by 1.01-1.35% approximately. The positive relation between coal price and food price is consistent and statistically significant at α=1% across all lag-length variations.

Table 7.

*PMG NARDL estimation with asymmetry (Coal price and Food price)*

| Model with asymmetry<br>Dependent Variable: *FP* | | | | |
|---|---|---|---|---|
| Variable | ARDL (2,2,2) | ARDL(1,2,2) | ARDL (2,1,1) | ARDL (1,1,1) |
| *Long run estimations* | | | | |
| $CP^{+}$ | .6408628** | .6837402* | .7656081*** | .7025745** |
| | (.3203534) | (.3539462) | (.2835478) | (.3016544) |
| $CP^{-}$ | .6724099** | .6142976*** | .8328146*** | .8503317*** |
| | (.3116913) | (.3387562) | (.2786156) | (.3041674) |
| *Short run ECM* estimations | | | | |
| $\Delta CP^{+}$ | .0030527 | .0030386 | .0065465 | .0034122 |
| | (.0049613) | (.0062717) | .0084664 | (.0107639) |
| $\Delta CP^{+}_{t-1}$ | -.0141443*** | | -.015883* | |
| | (.0046724) | | (.0055041) | |
| $\Delta CP^{-}$ | .0031488 | | .0064062 | .003025 |
| | (.0049726) | | .0084456 | (.0108126) |
| $\Delta CP^{-}_{t-1}$ | -.0141295*** | | -.0160777* | |
| | (.0046703) | | (.0054948) | |
| $\Delta FP_{t-1}$ | .4522985*** | .4554811*** | | |
| | (.0561879) | (.0574624) | | |
| constant | .0029974*** | .0034069*** | .0035334*** | .0035149*** |
| | (.0004777) | (.0006113) | (.0004585) | (.0004677) |
| Convergence coefficients | -.0025348*** | -.0022033*** | -.003014*** | -.0027219*** |
| | (.0005022) | (.0005812) | (.0008502) | (.0008093) |
| Log likelihood | 4612.461 | 4672.472 | 4462.167 | 4516.075 |
| No. of cross sections | 5 | 5 | 5 | 5 |
| No. of observations | 1205 | 1205 | 1205 | 1205 |

***, **, and * denotes the significance at α=1, 5 and 10 %. Standard errors are reported in parenthesis.

However, food prices in South Asian countries do not decrease when global coal price falls. Instead, the nonlinear estimates suggest that as global coal price falls by 1%, food prices increases by approximately 0.67%-0.85%. Interestingly, the food price inflationary effect of negative coal price change is slightly higher than the positive coal price change. It may seem counter intuitive at first; however Guo et al. (2016) reported similar results of asymmetry between coal price and inflation in China. They argued the impact of increased coal prices do not completely reflects on food prices. To maintain stability and affordability of food items, secondary energy price control authorities often provide subsidies. Therefore, the transmission of coal price increase does not completely translate to food price increase in short run. However, in general energy prices are revised and adjusted upwards more frequently than it is adjusted downwards (Liu, et al. 2013). Moreover, petroleum products like oil and coal are a major source of tax revenue collection for Governments of developing countries in South Asia. It is a common practice to increase tax rates on oil and coal when the oil/coal price in international market decreases to maintain the amount of tax collection. Therefore, even when there is a fall in global coal prices, domestic producers continue to pay a higher price of coal resulting in higher food price inflation.

Next, we conduct a Granger Causality test to verify the direction of causality between oil price and food price and also between coal price and food price. The results are reported in table 8.

Table 8.

*Dumitrescu & Hurlin (2012) Granger non-causality test results:*

| Null Hypothesis | F-statistics | P-value | Decision |
|---|---|---|---|
| Oil price does not Granger cause Food Price | 5.1197*** | 0.000 | Unidirectional causality runs from Oil price to Food price. |
| Food price does not Granger cause Oil price | 0.1075 | 0.1582 | |
| Coal price does not Granger cause Food | 2.2836*** | 0.0424 | Unidirectional causality runs from Coal price to |

| | | | |
|---|---|---|---|
| Price<br>Food price does not Granger cause Coal price | 0.5785 | 0.5051 | Food price. |

## 5.0 Conclusion

The study attempted to analyze the asymmetric relationship between international energy price (oil & coal) and regional food price inflation is South Asia. A panel data of 5 South Asian countries – Bangladesh, India, Pakistan, Nepal and Sri Lanka for time Period January/2000 – June/2021 are analyzed using PMG estimations. Symmetric and asymmetric relationship between energy price (oil & coal) and food price are analyzed using linear and non-linear PMG estimations. The short-run and long-run effects were also found to be significantly different. While long run effects were positive and statistically significant, the short run effect of oil and coal price change was found to be statistically insignificant implying no pass-through effect in short run. However the lagged effect of oil and coal price changes were found to be statistically significant that implies it requires time for international prices to pass through to domestic food prices.

The results provided concrete evidence of asymmetric relationship. We find both positive and negative change in international oil price leads to regional food price inflation in South Asia in the long run. Similar results are found between international coal price and regional food prices. A 1% increase in international oil price increases food price inflation by 1.72% -2.45% and a 1% increase in international coal price increases food price inflation by 0.64-0.76%. On the other hand, A 1% decrease in international oil price increases food price inflation by 1.32% - 2.47% and a 1% decrease in international coal price increases food price inflation by 0.67%-0.85%. One reason behind this phenomenon is South Asia as a region is completely dependent on oil imports. However, because of domestic deposit of coal, a significant portion of domestic demand is fulfilled from local coal mines. Therefore, the impact of oil price increase is much higher than coal price increase. Another reason is oil has a much higher weight than coal in the energy basket in the South Asian region.

The asymmetric relationship between energy price and food price suggests imperfect market mechanism exist in South Asia. Global energy prices do not directly pass-through to domestic market due to secondary energy price controls imposed by Government regulatory authorities. The incomplete pass-through observed in South Asia is a case of serious concern as the households are paying higher prices for food items when energy prices increase in international markets but are not getting the benefit of paying lower food prices when energy prices fall in international market. It implies that producers are adjusting food prices upwards to maintain their profit margin but are not adjusting food prices downwards to make extra profit. Therefore government must strengthen market monitoring to ensure welfare of consumers. Secondly, historically it has been observed that government energy regularity bodies in South Asia rarely revises price downwards but are quick to increase price in domestic market followed by an international energy price surge. The added profit the government regulatory makes during energy price falls can be used to provide subsidies during oil price surges. Rather than politically motivated energy pricing policy, Governments in South Asia can opt for an automated dynamic fuel pricing mechanism. Dynamic pricing of fuel is a pricing strategy where the price of fuel changes based on real-time factors, such as the demand and supply, and the price in the international market. This means that the price of fuel can change more frequently, and both upward and downward. As of now, only India has such pricing strategy in effect since 2017. Countries like Bangladesh, Sri Lanka and Pakistan still revise fuel prices based on executive orders by Government authorities. Policy makers should prioritize renewable energy projects in order to gradually reduce dependency on fossil fuels in the long run.

One of the limitations of the paper is that it is based on a univariate econometric model. Other economic factors that may cause a change in food prices were not included in the model. Because of data unavailability issues, we could not disaggregate the food price CPI. It would be interesting to see how energy prices in the international market affects prices of individual food items lime rice, wheat, meat, dairy etc. One possible way to extend the model is to compare both food price CPI and PPI to assess the impacts on both producers and consumers. World economic shocks like Covid-19, Ukraine-Russia war etc. can also be included as dummy variable to extend the model. A multivariate study on the topic of energy prices and food prices in South Asia can provide further interesting information.

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