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OIL SHOCKS AND TRANSPORTATION PRICES IN AN ENERGY CONSTRAINED SMALL OPEN ECONOMY: EVIDENCE FROM BANGLADESH

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Abstract

We consider the impact of oil shocks on consumer transportation prices in an energy constrained small open economy using monthly data from Bangladesh between July 2003 and December 2020. Within a multivariate modelling approach, we find that higher availability of oil reduces inflationary pressure in transportation, and while we observe that prices of all other goods and services impart a positive pressure, the supply of oil inversely influences transportation prices. Estimating the variance of the inflation to find that both long and short run volatility of transportation prices are bounded and mean reverting. In addition, the impact of the volatility is symmetric, implying similar persistence of both positive and negative shocks.

Transport inflation in Bangladesh, like other small oil energy constrained countries, is usually addressed through increasing the imports of oil. However, as the community of nations adopt renewable energy strategies in the face of environmental imperatives, Bangladesh will likely follow the trend. This presents an opportunity to address present oil dependency and transport inflation with policies that explicitly consider the long run renewable energy future..

Keywords

Oil, ARMA, GARCH, Bangladesh, Transportation, Small Open Economy, Oil Shock

JEL Codes: O13 Q41 Q48

1. Introduction

Different sub-classes of inflation exert heterogeneous impacts on different income categories as well as on different spatial distributions. In Bangladesh, poor and lower middle-income households face higher inflationary pressure both in rural and urban regions. On the other hand, much of the inflationary pressure of Bangladesh in the recent decades, particularly since 2010, comes from non-food sources such as transport, rent and other services. While food inflation is dominant mostly in urban areas, non-food inflation equally impacts the spatial regions (Hussain and Zaman, 2008). Urbanization in Bangladesh is 39.95 percent, typical of its lower middle-income category, which averages 43.00 percent.[1] In light of the oversize role that transport inflation plays in the non-food basket, we examine transport prices and their determining factors.

[1] https://ourworldindata.org/urbanization.

Bangladesh is typical of an East Asian small open economy regarding energy acquisition and use. The energy dependence rate- that proportion of energy that an economy must import- in Bangladesh between 1971 and 2014 averaged 16.63 percent as compared to 18.78 percent in the East Asia & Pacific[2] region and 15.81 percent in all of South Asia.[3] Fuel imports as a percentage of merchandise imports in Bangladesh between 1973 and 2013 averaged 10.79 percent as compared to 9.95 percent in the East Asia and Pacific region.[4] The energy market is highly regulated, where the state is the only purchaser of oil. As such, we loosely describe Bangladesh is indicative of a small energy constrained economy.

We are motivated to compare transport prices to consumer prices because, despite similar mean and variance in levels, their first difference reveals that transport prices and consumer prices behave distinctly in Bangladesh. From figure 1, note the first difference of the transport prices series is almost always positive, while the first difference of consumer prices displays both positive and negative fluctuations at regular intervals. In other words, as consumer prices rise and fall month to month, transport prices only rise. This puzzle suggests the likelihood of other determining factors in the economy for which transport prices behave in this way.

Our research contributes to the understanding of the policy challenges facing small economies, such as Bangladesh, whose constrained energy market is publicly regulated. Our investigation is the only one that we know of, to model transport prices from Bangladesh and to demonstrate that when market mechanisms do not work, the volume of oil supply influences transport prices. Second, we further provide an estimate for the extent of fossil fuel dependency of the transport sector in Bangladesh, which has implications for both the environment and energy security. In fact, per capita carbon emissions in Bangladesh have risen by 200% from the year 2000 to 2019, while the neighboring India and Pakistan have augmented emissions by only 105% and 55% respectively (GCP:2021). The transport sector of Bangladesh, being highly dependent on fossil fuel, is expected to take initiatives for decarbonization. In accordance with the commitment on affordable clean energy (Goal 7) and climate action (Goal 13) of the Sustainable Development Goals (SDGs), Bangladesh is expected to implement the action plan by 2030. Third, we consider monthly data whereas most of the other studies are based on yearly observations. This is significant as the causes and effects of the variables under consideration are observable in much shorter than a year's interval (Granger and Newbold, 2014). Anecdotal evidence suggests that the transport sector does not delay a year to raise their tariff in response to fuel shocks (Report, 2011).

2. Methodology

The transportation sector of Bangladesh faces two basic challenges. There is immediate issue is the consumer burden of transportation costs; addressed primarily through fuel subsidies. While the general expectation in the long term is to follow the world trend toward greater adoption of alternative fuels to alleviate the pressure from oil dependency, that trend does not address the immediacy of Bangladesh's energy dependence. Although international oil price shocks directly pass through to the transport sector in Bangladesh, China (Zhang, 2014) and similarly oil dependent economies, oil price variations alone do not adequately explain the upward variation in transportation prices, particularly given the degree of market intervention present (Kojima, 2009). We note from table 1 that the correlation coefficients between oil price change volatility and prices are relatively low, suggesting that residential consumers appear to respond to fuel price volatility with changes to the volume of oil demanded instead. One possible explanation is that the government is the only market operator in the energy sector of Bangladesh where the energy supply chain is fully regulated (Moazzem, 2019). In Bangladesh, transport prices variations mostly depends on the availability of oil rather than on oil prices.

To identify its determining factors, we assume that the transport price index (TPI)[5] is likely to be influenced by the consumer price index of goods and services net of transportation (XCPI).[6] Similarly, transport prices may also influence the prices of other goods and services within the economy. Oil, on the other hand, being the principal fuel for the transport system, is likely to influence transport prices both directly and indirectly via the prices of other goods and services (Chowdhury et al., 2021). Emphasizing

[2] World Development Indicators (2022), Country Code EAS.
[3] World Development Indicators (2022), Country Code SAS.
[4] World Development Indicators (2022), excludes high income countries, Country Code EAP.
[5] TPI exerts 4.17 percent weight to the CPI computation.
[6] XCPI is the weighted measure of Consumer Price Index (CPI) except TPI.

the pivotal role of oil, Kilian and Park (2009) show that global crude oil shocks account for around a quarter of the total long-run variation in the US real stock returns. By contrast, Stern (2015) argues that energy in an economy becomes instrumental for output only when there is scarcity of energy resources. We address this puzzle with the following questions in the context of Bangladesh. First, how much of the oil supply shocks pass through to the transport price index? Second, does the transport price index and the consumer price index net of transport show similar trajectories in their dynamic evolution? Third, does XCPI influence TPI or vice versa?

Our proposed modeling framework consists of exogenous oil supply and endogenous prices of transportation and other goods & services. Prior to estimating the full model, the sequential ordering of the endogenous variables is performed by autoregressive distributed lag (ARDL) bounds testing and vector error correction model (VECM) Granger causality. Based on that specification, an Auto-Regressive Moving Average (ARMA) model is used to evaluate conditional mean of the transport price index and a Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model is used to evaluate its volatility. We then specify an exponential GARCH (EGARCH) model to ascertain if positive and negative volatility asymmetrically impact transport price variation. We find that overall consumer prices impact directly transport prices without feedback, whereas oil shocks impact negatively to transportation prices. We also conclude that neither short nor long-run volatility of transport prices are explosive but rather bounded and mean reverting.

While households face various economic challenges, oil shocks draw a disproportionate amount of attention from policymakers and media. One likely reason for this is the limited scope for substitution of energy (Stern, 2011). Furthermore, the indispensable requirement of energy in the modern economy cannot be evaluated only by its percentage share of GNP (Moroney, 1992). Second, oil is becoming very price sensitive as we see a steady decline in the short run price elasticity of oil demand since the 1980s (Baumeister and Peersman, 2013). As a result, any unforeseen shock to oil availability has the potential to destabilize the socio-political environment of a country. The recent mass-scale public demonstrations against fuel price hikes in Belgium, Bulgaria, Burkina Faso, India, Iran, Sierra Leon, and other regions around the globe, signify the critical role of oil in the economy. Third, oil shocks are a leading indicator for other macroeconomic variables which impart economy-wide ripple effects. On several occasions, the US economy has faced widespread economic turmoil because of these shocks (Kilian, 2008).

Oil shocks can stem from exogenous supply disruption, from demand shocks due to economic expansion, or from precautionary demand for cushioning volatility (Kilian, 2009). The responses to shocks differ widely depending on whether the countries import or export oil. Cashin et al. (2014) show that the supply driven oil shocks typically induce a long-term slump to the economic activities of oil-importing countries, while the impact is positive for their oil-exporting counterparts. Similarly, supply and demand shocks have different scope of impact on the economy. Analyzing historical oil supply and price data, Baumeister and Hamilton (2019) conclude that supply shocks impart a long lasting global economic activity reduction, while shocks due to oil demand have only transitory economic implications. In the United States, oil supply shocks have only mild inflationary pressure compared to demand driven oil shocks (Kilian, 2008), indicative that the energy intensity of GDP is decreasing around the globe in recent years (Stern, 2017). Although the general price level does not vary much due to oil supply disruption, the energy intensive sectors such as transportation experience direct pass-through effects due to negative oil supply shocks (Zhang, et al., 2014). Micro-economic analysis on commuters reinforces the conjecture that fuel shocks influence transportation significantly, regardless of the length of travel (Graham and Glaister, 2004).

Modeling of oil shocks and economic activities has evolved significantly during the last four decades. Starting with the seminal work of Hamilton (1983) where he notes that oil supply disruptions are followed by oil price upsurges from 1948 to 1972. Based on the insight and subsequent improvement in the time series estimation techniques, Hamilton (2003) further develops a quantitative model with reasonable predictive power. Since then, oil shocks have been modeled based on the assumption that the source of shocks is not necessarily important to analyzing its impact. Challenging the idea of homogeneity of all oil shocks, Kilian (2009) and Killian and Murphy (2012) propose a structural vector autoregressive (SVAR) model to disentangle oil supply and demand shocks. Employing a less restrictive method, Baumeister and Hamilton (2019) construct a Bayesian inference-based model of SVAR to demonstrate that the price elasticity of oil supply shocks estimated by Kilian and Murphy (2012) is underestimated while oil demand shocks are over estimated.

Apart from estimating the structural parameters, volatility transmission models are increasingly being used to estimate market returns and risk premium. Using univariate and multivariate ARCH and GARCH models, Hammoudeh, et al. (2004) find that there is a significant bi-directional relationship between stock returns and oil shocks. Volatility transmission is observed widely across disparate countries as well as across geopolitical groupings such as Gulf Cooperation Council (GCC) or the European Union. (See Argen, 2006; Malik and Hammoudeh, 2007; Malik and Ewing, 2009; Arouri et al., 2011; Arouri, et al., 2012; Jouini and Harrathi, 2014). The extent of impact of volatility ensued from oil shocks on all the economic sectors are, however, not symmetric. Elyasiani, et al. (2011) indicate that oil user industries are the ones most vulnerable to this uncertainty. Similarly, the expectation of investors based on the prevailing financial environment may also influence the outcome. Mollick and Assefa (2013) show that until the financial crisis of 2008-09, oil prices impacted negatively on stock returns. Post crisis, the relationship reverses.

Literature on consumer price modeling in Bangladesh is very limited, while any study on transport price volatility is absent altogether. Using annual data, Paul (2013) considers the CPI from 1976 to 2009 in a bivariate exponential GARCH framework to conclude that inflation volatility unidirectionally impacts economic growth positively while mean inflation and economic growth influence each other negatively. Hossain (2015), by contrast, finds that from 1950 to 2012, inflation volatility and inflation persistence adversely impact economic growth. To determine the driving factors of inflation in Bangladesh, Mujeri, et al. (2009) specify inflation as a function of the output gap in a dynamic framework to demonstrate that the real sector can explain inflation better than the monetary aggregates. Similarly, the weak transmission of monetary policy in Bangladesh is echoed by Nasir (2011), who concludes that institutional rigidity is driving inflation rather than money supply.

We focus on the ever-increasing transport prices of Bangladesh and the economy-wide implication of this price surge. Higher domestic logistical costs erode the global competitive advantage of the key exports such as readymade garments (Rahaman and Hasan, 2015). Contributing to the persistent rise, transportation sector of Bangladesh is very inefficient in utilizing energy compared to other neighboring countries (Chowdhury et al., 2021).

3. **Modelling Approach**

We model an energy dependent, yet market constrained, small open economy. It does not produce fossil fuels and must import petroleum products to meet domestic demand. The quantity of imported oil is determined by the government. As such, we expect to observe cost-push inflation more often than demand-pull inflation in the event of oil shocks. Presuming that within an energy constrained economy, energy-intensive production does not flourish (Abeberese, 2017), we do not consider the reverse causality from inflation to oil demand. We follow Darby (1982) who postulates that imported oil influences the aggregate production function, which determines output and eventually inflation. Figure 2 is a path diagram to illustrate our presumed interactions between oil supply and the inflation indices. As demand for energy is sufficiently inelastic and there is a limit to energy substitution, higher price levels generally follow negative oil shocks to the economy. Volatility in oil supply also induces precautionary demand shocks as market expectation shifts in securing more oil to cushion uncertainty (Killian, 2009). Empirical studies reinforce the idea that markets overreact in the short run due to oil supply shocks (Huang, et al., 2021).

We propose the following dynamic function to illustrate the determinants of the transport price index.

$$TPI_t = f\left(TPI_{t-1}, XCPI_t, Oil_t, \sigma_t^2\right) \qquad (1.1)$$

Apart from including transport price lags (TPI_{t-1}), consumer prices net of transport ($XCPI_t$) and oil supply (Oil_t), we also introduce variance (σ_t^2) dynamics as a function of transport prices to examine the extent of precautionary demand shocks due to volatility in the transport prices. We model the conditional variance to assess how the volatility evolves dynamically over time, which provides us information on the stability of the market in the short run and the long run. The conditional variance is defined as follows.

$$\sigma_t^2 = g\left(\sigma_{t-i}^2 \middle| C, \sigma_{t-i}^2 \middle| UC\right) \qquad (1.2)$$

C and *UC* represent the conditional and unconditional variances and *i*'s are the lags.

Our modeling approach is based on several assumptions regarding the nature and dynamics of the variables. First, we assume that the consumer price index net of transportation is contemporaneously exogenous or predetermined. Therefore, transport prices are not determined by consumer prices net of transport on the same temporal domain, rather the history of the consumer price net of transport may have shaped the current transport price. Second, the quantity of oil supply is strictly exogenous. In Bangladesh, oil procurement is an administrative decision and the availability of oil in the global market is dependent on geopolitical factors. Third, prices of all other goods and services influence transport prices but not vice versa. Therefore, the transport price index is a dependent variable while the consumer price net of transport is independent. We test the validity this assumption before proposing the final specification. Finally, the transport price may also influence the consumer price net of transport as both the prices are endogenous in the economy. Hence, we denote the causality from the transport price index to the consumer price index net of transport with a dashed line in the path diagram of figure 2.

The key variables employed are transport price index, consumer price index for all goods and services net the transportation price and total quantity of petroleum products (Oil) imported on monthly basis (million barrels) for the period of July 2003 to December 2020. Compiled by Bangladesh Bureau of Statistics (BSS), the consumer price index is an aggregate index of weighted prices, weights shown in the parenthesis, consisting of food (58.84 percent), clothing & footwear (6.85 percent), gross rent, fuel & lighting (16.87 percent), furniture, furnishing & others (2.67 percent), medical care & health expenses (2.84 percent), transport & communications (4.17 percent), recreation, entertainment, education & cultural services (4.13 percent), misc. goods & services (3.63 percent). This monthly index consists of an aggregation of the prices of 318 rural and 422 urban goods and services of Bangladesh (Shahiduzzaman, 2006). From this aggregate, we take the transport price series denoted as transport & communication, indicating domestic price level of public commuting and freight movement. Similarly, we also construct the consumer price index net of transportation series from this aggregation excluding transport prices. We use two base periods (1995-96 and 2005-06) to construct our sample. For consistency, we convert the whole sample into a single series, keeping the later base points (2005-06) as reference. The monthly series of quantity of oil import is estimated from monthly import payment for petroleum products compiled by Bangladesh Bank (BB, 2021). We convert payments in millions of barrels per month using the global petroleum price index from Index Mundi (2021) as an approximation of the total monthly oil available to Bangladesh.

The descriptive statistics are presented for both level and first difference to compare the distribution of the variables in table 1. The differenced variables are more inclined towards normal distribution than their level counterparts. The three variables are highly correlated in levels while the correlations are much lower or even of opposite sign in their first differences. As all the variables are trending upward in level, the high correlation is expected to be contributed by the trend components compared to the de-trended series. The correlation matrix of the first difference variables provides a more realistic association pattern among the variables. Note that all the variables have a strong autocorrelation even up to 12 months. To test this, we report the Ljung-Box Q-statistic, where the null hypothesis is no autocorrelation. All the series, both in levels and first differenced, fail to reject the null hypothesis at any significant levels. The strong presence of autocorrelation indicates the likely existence of a unit root in the series.

The prevalence of autocorrelation is displayed in the plots, especially in the differenced ones. For instance, from figure 1, the differenced graphs of transport price index and the consumer price index bet of transport follow a particular cycle over the entire period, indicating the influence of the previous month's value on the successive months. Similarly, oil imports display both an upward trend and cycle at level, but when first differenced, the trend is no longer visible. The cycle, however, continues roughly around a constant mean at zero in figure 3.

We consider whether any seasonality is exhibited by the monthly series. Visual inspection of the variable plots does not suggest any repetitive patterns. To confirm, we test for month-to-month seasonality in the data and found that no month is statistically different than the mean outcome of the variables (see Appendix Table A1). One possible reason for the lack of seasonality in the variables is that the price level upsurge in Bangladesh is normally contributed by two festival months, Eid al-Adha and Eid al-Fitr, which are 2.5 months apart and revolve in subsequent months of the year. The high demand for travel and transportation and, consequently, their prices during these two months of a year, do not suggest a seasonal pattern. We also investigate the variance trajectory from the variance plots of the variables. We see the presence of volatility clustering in figure 4, which implies that the overall volatility of the variables follows an autoregressive process like that of their dynamic mean counterparts. Volatility clustering is first observed by Mandelbrot (1967) where he postulates that in a clustered series, small variations are followed by small ones and the large variations are by large ones. From this pattern of the volatility dynamics, important information can be extracted for both mean and variance forecasting of the respective series.

We illustrate quantile-quantile plots to check the normality and commonality of distribution of variables as we estimate the models by maximum likelihood method where we assume a normal distribution of the errors. Plotted against the first difference in the transport price index (D.TPI), the two other variables, the first difference in the consumer price net of transport (D.XCPI) and the first difference in the oil price (D.Oil), look to be roughly normally distributed, as assessed by the 45 degrees lines in figure 5.

In our theoretical model specification, the third assumption was that the transport price index is dependent variable and consumer price index net of transport, along with other covariates, are independent. To test the assumption's validity, we determine whether transport price index or consumer price index net of transport follow each other in the short and the long run. First, we determine the order of integration of the series, and based on that, we apply the auto regressive distributed lag (ARDL) bounds testing approach to identify any long run cointegrated relationship. We then specify the resulting cointegrating equation into the error correction model (ECM) to estimate the speed of adjustment of the cointegrating variables along with other short and long run coefficients. Finally, we perform a Granger causality test with the estimates to determine the direction of causality.

Although the plots of the variables in levels show non-stationarity, we conduct Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests to confirm the presence of unit roots. For optimum lag selection, we use Akaike information criterion (AIC) and found that the transport price index requires three lags while the consumer price index net of transport and the oil series need four lags each in the testing specification. The null hypotheses for either test is that the variables follow unit root processes. We find all the variables are non-stationary in levels and are covariance stationary in their first differences. In table 2, the Phillips–Perron test confirms the Augmented Dickey-Fuller test for the transport price series and the consumer price of transport series, but the oil series appears to be stationary in levels as well when first differenced. Upon inspecting the upward trend of the Oil series in Figure 3, we follow the Augmented Dickey-Fuller test results and determine the series follows a unit root process only in levels.

While the first differences variables are covariance stationary or I(1), there exists a possibility of long run relationship especially between the transport price index and the consumer price index net of transport. To test this, we specify an auto regressive distributed lag (ARDL) bounds test following Pesaran, et al. (2001).[7] The bounds testing specification is defined follows.

$$\Delta TPI_t = a_0 + \alpha_1 TPI_{t-1} + \alpha_2 XCPI_{t-1} + \sum_{i=0}^{k} \beta_{1i} \Delta TPI_{t-i} + \sum_{i=0}^{l} \beta_{2i} \Delta XCPI_{t-i} + u_t \tag{1.3}$$

$$\Delta XCPI_t = b_0 + \gamma_1 TPI_{t-1} + \gamma_2 XCPI_{t-1} + \sum_{i=0}^{k} \delta_{1i} \Delta TPI_{t-i} + \sum_{i=0}^{l} \delta_{2i} \Delta XCPI_{t-i} + v_t \tag{1.4}$$

The specifications of equation (1.3) and (1.4) are constructed in a dynamic unrestricted error correction model (UECM) framework, where both long run variables are in levels with first lag and short run variables in their first difference form with multiple lags included. To make the errors independent and identically distributed (iid), the appropriate number of lags are included with the help of information criteria. To test whether the transport price index is cointegrated with consumer price index net of transport in equation (1.3), we consider the null hypothesis, $H_0 : \alpha_1 = \alpha_2 = 0$, against the cointegrated alternative, $H_1 : \alpha_1 \neq \alpha_2 \neq 0$. The rejection of the null indicates that the level variables are important for the specification, implying cointegration of the dependent variable with the independent ones. As the asymptotic distributions of the F-statistic for I(0) or I(1) variables are non-standard, we adopt two sets of asymptotic critical values, as proposed by Pesaran, et al. (2001). The first set assumes that all the variables are I(0), implying a short run relation only. The 2nd set of critical values assumes I(1), implying cointegration and a long run relationship. The test results are presented in Table 3, where the lag lengths are selected by Akaike information criterion, and the residuals are checked for serial correlation by the Durbin–Watson

[7] Our data set is relatively small with only 210 observations. Philips (2018) shows by Monte Carlo experiments that, compared to Johansen or Engle-Granger cointegration procedures, the auto regressive distributed lag technique performs better, especially in a small sample.

statistic to indicate the model's fit to the data. The F-statistic of 5.01 for equation (1.3) is above the 10 percent upper bound indicating 90 percent significance. On the other hand, the F-statistic for equation (1.4) of 0.65 implies no cointegration of the consumer price index net of transport with the transport price index. We therefore conclude that transport price index alone is maintaining the long run relationship with consumer price index net of transport in its dynamic evolution.

Upon confirming cointegration, we specify a bi-variate vector error correction model with the transport price index and the consumer price index net of transport as follows.

$$\Delta\Upsilon_t = \alpha\beta'\Upsilon_{t-1} + \sum_{i=1}^{p-1}\Gamma_i\Delta\Upsilon_{t-1} + v + \varepsilon_t \tag{1.5}$$

Υ_t is a 2 × 1 vector of variables [TPI_t, $XCPI_t$], α and β are 2 × r matrices, where r is the number of linearly independent cointegrating vectors, which we have shown to be 1. α is the loading matrix defining the adjustment speed and β is long run cointegrating matrix. Γ_i is a short run 2 × 2 matrix of coefficients, v is a vector of constants and ε_t is the iid disturbance. We specify three lags that fall to two due to the difference operator, Δ. The estimation results of equation (1.5) are as follows.

$$\hat{\alpha} = \begin{bmatrix}-0.022^{***} & 0.000\end{bmatrix};\ \hat{\beta} = \begin{bmatrix}1.000 & -1.010^{***}\end{bmatrix};\ \hat{v} = \begin{bmatrix}0.004 & 0.580^{***}\end{bmatrix};$$

$$\hat{\Gamma}_1 = \begin{bmatrix}0.14^{**} & 0.07\\ 0.29^{***} & 0.32^{***}\end{bmatrix};\ \hat{\Gamma}_2 = \begin{bmatrix}0.18^{**} & -0.10^{**}\\ 0.08 & -0.24^{***}\end{bmatrix}$$

Our estimates indicate a well specified model. The coefficients of the adjustment- the loading matrix, $\hat{\alpha}$, and that of long run cointegration matrix, $\hat{\beta}$, are in correct signs. Note that the parameter on the transport price index is negative and significant with relatively slow adjustment toward the long run path at a rate of 2.2 percent per month. The adjustment coefficient of the consumer price index net of transport is positive, as expected, although not significant. This implies that, on average, if the transport price moves too high above its equilibrium path, adjustment returns it toward the consumer price index net of transport while the consumer price index net of transport does not adjust toward the transport price index at the same time. This is consistent with the autoregressive distributed lag model bounds testing results, where we see the transport price index is cointegrated with the consumer price index net of transport but not vice versa. Finally, from the short run coefficient matrices, $\hat{\Gamma}_i$, we Granger causality test to investigate if the history of one variable explains another variable. The short run causality results are presented in table 4 where we note, from the χ^2 statistics and associated p-values in parenthesis, that the transport price index Granger causes the consumer price index net of transport at 1 percent significance, while the consumer price index, net of transport, does not Granger cause the transport price index at 5 percent significance.

Our evidence suggests that the transport prices have very little or no influence on consumer prices, net of transport, in either the long or the short run. Consequently, we specify the transport price index as a dependent variable as opposed to the consumer price index net of transport is independent in our model specification in equation (1.1).

We have shown the consumer price index net of transport is contemporaneously independent of the transport price index in both short and long run. We have further ruled out the possibility of simultaneous relationship between the transport price index and the consumer price index net of transport from our model specification. We proceed to estimate the transport price index through a recursive relationship defined as follows:

$$\Upsilon_t = E\left(\Upsilon_t \middle| \mathrm{H}_{t-i}\right) + \upsilon_t \quad \forall i = 1, 2, \ldots \tag{1.6}$$

H_{t-i} is the history of the information set from the recursive path and υ_t is innovation or white noise.

The models are estimated by maximum likelihood assuming a normal distribution of the error terms. After estimation, we test for autocorrelation via the Ljung–Box Q-statistic and confirm the errors are iid via autoregressive conditional heteroskedasticity (ARCH-LM) tests for up to 12 lags.

Based on our covariance stationary time series data, we estimate the above-mentioned specification with an autoregressive moving average model within a generalized autoregressive conditional heteroskedasticity framework. ARMA is a univariate process where the contemporaneous outcome is explained by the history of recurrent outcomes and innovations. Since its inception by Box and Jenkins (1970), the method is widely used in time series modeling and forecasting. The general specification of our model is defined as follows.

$$\Upsilon_t = a_0 + \sum_p \phi_p \Upsilon_{t-p} + \sum_q \psi_q \varepsilon_{t-q} + \varepsilon_t \qquad (1.7)$$

Υ_t is current outcome, ε_t is the normally distributed error with constant variance, ϕ_p and ψ_q are coefficients for the autoregressive (AR) and moving average (MA) components of the model. Autoregressive moving average models assume both mean and variance are constant over time. While the stationarity process ensures a constant mean of the series, it does not ensure the variance is constant. We therefore examine the impact of volatility on the model.

Proposed by Engle (1982) and Bollerslev (1986), generalized autoregressive conditional heteroskedasticity models are used extensively in financial data that display time-varying volatility. The framework is a combination of the mean equation (2.8) and the variance equation (2.9).

$$\Upsilon_t = a_0 + \sum_p \phi_p \Upsilon_{t-p} + \sum_q \psi_q \varepsilon_{t-q} + \theta X_t + \xi \sigma_t^2 + \varepsilon_t \quad (1.8)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-p}^2 + \beta \sigma_{t-q}^2 \qquad (1.9)$$

σ_t^2 is time-varying variance and X_t represent the exogenous variables where θ and ξ are their respective coefficients. The inclusion of variance within equation (1.8) captures the marginal impact of volatility of Υ_t at the mean of Υ_t. The variance equation (1.9) describes the contemporaneous volatility from the history of recurrent conditional and unconditional variances, where α and β are the respective short and long run volatility coefficients.

Although the GARCH model is used extensively in literature, the estimates are somewhat restrictive. On some occasions the oscillatory behavior of the variance is excluded by imposing assumptions. To minimize the drawbacks, Nelson (1991) proposes a less restrictive exponential estimation technique.

$$\ln\left(\sigma_t^2\right) = \omega + \alpha \left|\frac{\varepsilon_{t-p}}{\sigma_{t-q}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln\left(\sigma_{t-q}^2\right) \qquad (1.10)$$

Equation (1.10) considers whether a shock has a symmetric or asymmetric effect on volatility via the coefficient, γ, where positive significance implies that positive shocks impart higher volatility compared to negative shocks, and vice versa. Often termed, the news shock, if the dynamics of volatility are indifferent from positive or negative shocks, the estimate of γ is likely to be insignificant.

4. Results

We estimate a bivariate model, Model-1, consisting of the transport price index and the consumer price index net of transport to observe how prices of other goods and services determine the transport price. We then specify a multivariate model, Model-2, by adding oil supply to examine how oil shocks impact the transport price index. To identify the most parsimonious model, we start with ordinary least squares (OLS) and subsequently progress to ARMA, GARCH and EGARCH to ascertain the best model fit to the data. Finally, we perform in and out of sample forecasting with the competing models and assess their performances with respect to the real data in both the short and long run to select the appropriate specification.

The results are presented in table 5 and 6. We estimate the mean equations with ordinary least squares after confirming stationarity of the variables. We observe strong autocorrelation in the error terms in both of the OLS regressions. However, the recursive specification rectifies this issue to a large extent.

We utilize the Akaike Information Criteria (AIC) criteria to determine that we can use up to 4 lags within the ARMA model. However, to minimize data loss, we use 2 lags in our analysis. After testing all the possible combinations of autoregressive and moving average lags, we define an ARMA(1,1) model which has the lowest information criteria value with parsimonious specification (see Appendix Tables A2 and A3). From Table 5, we note a positive significant impact of inflation shocks on transportation. It shows that a one inflation point increase in the price level of all other goods and services leads to a 0.15 inflation point increase in the transport price index. The autoregressive (AR) coefficient is below 1, which indicates a stable autoregressive process where any shocks to the transportation price are likely to taper off within a few periods. The diagnostics tests show a well-behaved model with no auto correlation or conditional heteroskedasticity even up to 12 months lags. Despite being a suitable specification for the mean equation, we improve upon the estimations by incorporating variance in the model. By incorporating the prediction errors of the mean equation in the model, it is likely to make an improvement in the estimation and consequently in forecasting. The rationale stems from the fact that the variances are clustered, as in Figure 4. In addition, the square of the prediction errors from the autoregressive moving average estimations also displays volatility clustering (see Appendix Figure A1).

Given the importance of volatility, we specify a generalize autoregressive conditional heteroskedasticity, GARCH(p,q)-M model as illustrated in equation (1.10). The values of p and q are selected by AIC (see Appendix A2). With confirmation that GARCH(1,1) is the best fit to the data, we estimate Model 1 to determine that the coefficients on both the conditional and unconditional variances are less than unity (see Table 5) while the coefficient on moving average (MA) coefficient is no longer significant. The other coefficient estimates remain effectively unchanged from the previous ARMA estimates. While the EGARCH(1,1)-M estimates are similar to those from the GARCH(1,1)-M specification, and there is no asymmetric impact of volatility, as indicated by the insignificant □ in the EGARCH estimations, therefore we determine that both ARMA and GARCH specifications provide the best model fit to the data.

We estimate Model-2 using ARMA and GARCH specifications to observe the impact of oil shocks on TPI. From Table 6, the coefficient estimates on Oil, -0.10 and -0.06 respectively, indicates a negative and significant relationship with the transport price index in the mean equation. Put simply, after controlling the prices of all other goods and services (XCPI), the availability of oil is one of the determining factors for the transportation price in Bangladesh. We see that in both short and long run, volatility is statistically significant with values less than unity indicating a stable volatility process. The higher value of the short run variance coefficient, □=0.53, compared to the long run coefficient, □=0.33, indicates that short run volatility has greater persistence compared to the long run volatility.

Although both ARMA and GARCH models perform well in predicting oil and inflation shocks on transport prices, we still want to compare their forecasting performance in the short and long run. We use in-sample static forecasting technique first, then we compare the performance of the models with out-of-sample prediction by dynamic and static forecasting methods. In static forecasting, we take all the previous actual data points for estimation and predict the next one period based on those estimations. In dynamic forecasting, we include all the foretasted data points in addition to the actual data. Therefore, the errors of the previous forecasting periods will be accumulated in dynamic forecasting while excluded in the static forecast. Static forecasting is limited to one period while in dynamic, there is no limitation for forecasting horizon. From the in-sample static forecasting by ARMA and GARCH models in Figure 6, both models perform similarly in mimicking the actual data in the short run with similar root mean squared errors (RMSE). However, the long run forecast via the GARCH model substantially outperforms the ARMA model with around 30% lower root mean squared errors (RMSE). This indicates that without incorporating variance in the model, we may lose important information necessary to more accurately forecast.

We forecast Model-2 with a GARCH specification to predict out-of-sample data points in both dynamic and static settings. We estimate the first stage with actual data from July 2003 until December 2018. We then forecast the next 24 months and compare the outcomes to actuals data up to December 2020. The short run out-of-sample forecasts are illustrated in Figures 6e and 6f, where we see both static and dynamic forecasts perform similarly with almost similar RMSEs. On the other hand, the long run out-of-sample forecasts display a slightly improved performance in the statistic prediction with a RMSE of 19.24 compared to 21.86 in the dynamic one.

5. Discussion

The study indicates several policy implications for the transportation sector in terms of the transmission of inflation shocks and the impact of oil availability in a small energy constrained economy such as Bangladesh. We find that the short run adjustment of transport prices towards consumer prices net of transport is 2.2% per month, which is very slow. It would take 45 months- almost 4 years- to adjust from any short run disequilibrium to the long run equilibrium trajectory of inflation. The policy objective would be therefore to increase the speed of adjustment by minimizing the length of price disequilibrium periods of transport prices before it reaches the common path of the general prices level in the economy. This can be accomplished through either price support to consumers or cost subsidies to transport suppliers.

Our results describe transmission of downward pressure on transport prices resulting from increasing oil supplies which, in turn, lowers the energy cost to transportation providers and leads to cheaper transport services. Increased oil supplies act as cost support to the transport sector. Both ARMA and GARCH estimations show similar negative marginal impacts of oil on the transport price index in the short run with coefficients ranging from -0.10 to -0.06, implying an additional one million barrels of oil in the economy on average decreases the increment of transport prices by 0.10 to 0.06 inflation points. In Bangladesh, the average oil import is 4.5 million barrels per month with an average increment of only 0.03 million barrels per month. One million barrels of additional oil import is equivalent to an average of 22% increase in oil imports per month. From the environmental point of view, this may have negative repercussions as 65% of the total transportation is dependent on fossil fuel alone. In such a case, fuel switching to renewable energy sources would be more appropriate courses of action.

Apart from the impact of exogenous variation of consumers prices net of transport (XCPI) and oil supply, the transport price index can also be influenced by its own lagged variable, which is evident from the AR(1) coefficient of D.TPI at 0.60 in the GARCH specification. Thus, the current transport price can be predicted by observing the previous period's outcome with significant accuracy. That is to say that the transport price index is bounded and mean reverting thereby implying a better environment for investors as the predictable price ensures lower risk to investment in the transport sector. The variances of TPI are also bounded and predictable, which follows an autoregressive path. The coefficient of the unconditional volatility is below 1, where □=0.53, indicating that a relatively calm period is followed by another calm period, and a more volatile period is followed by more volatility in the short run. In other words, the likelihood of starting an unpredictable volatility clustering in the transport price series in the short run is relatively low as the variances themselves are clustered within specific domains consisting of several time periods. On the other hand, the impact of long run volatility, where □=0.33, is lower that the short run coefficient such that the market reacts less to volatility in the long run than short run. Still, an analyst can have significant insights on contemporaneous long run volatility from the previous clustering. The magnitude of the coefficient below one also assures that the general volatility is not explosive but rather mean reverting and bounded, indicating a stable market.

Finally, we find that the unconditional volatility (coefficient of the variance at mean) does not impact transport prices despite the long and short-term volatility has significant influence. Given that the time varying volatility of transport prices do not impact transport inflation, policy makers should consider intervention in other determining factors of transport prices, such as the supply of oil.

6. Conclusion

The challenges facing Bangladesh regarding energy usage and dependence are like those faced by many other countries. While Bangladesh is likely to follow the world trend toward renewable energy, the transition face by a small energy constrained economy such as Bangladesh from the oil dependent present to the renewable energy future state will depend on the idiosyncratic policy implications on the productive efficiency of alternative energy versus fossil fuels (Barreto, 2018).

This is the first study to examine the relationship between oil supply shocks and transport inflation in Bangladesh from 2003 to 2020. We propose a multivariate framework by including the consumer price index of all goods and services net of transport (XCPI), volume of oil import and transport price index (TPI) in a dynamic recursive time series model. After accounting for the endogeneity between XCPI and TPI by autoregressive distributed lag bounds testing and vector error correction model Granger causality, we estimate the models within autoregressive moving average and generalized autoregressive conditional heteroskedasticity frameworks. We find that the transport price index gravitates toward consumer price index net of transport both in the short run and the long run while XCPI has little or no impact on TPI as such. Estimations indicate that an additional one percent increase in consumer prices net of transport leads to a 0.17 percent increase in transportation prices in the short run. This relationship is, however, reversed for oil since one million barrels of additional oil leads to a decrease in transportation prices by 0.06 inflation points in the short run.

Our results suggest possible policy interventions to reduce the upward pressure on the transportation prices by broadly increasing the supply of energy. While the obvious choice remains importing additional oil, adding additional economy wide renewable energy sources and or improving energy efficiency within the transport sector by shifting toward renewable energy vehicles may have equivalent effects. Furthermore, consumer price supports and or input subsidies to the transport suppliers can serve as intervention tools to improve the business environment. Our volatility modeling of transport price indicates a stable market that is conducive to public and private investment in the transport sector thereby suggesting policy interventions on the price of transport in Bangladesh would necessarily be effective.

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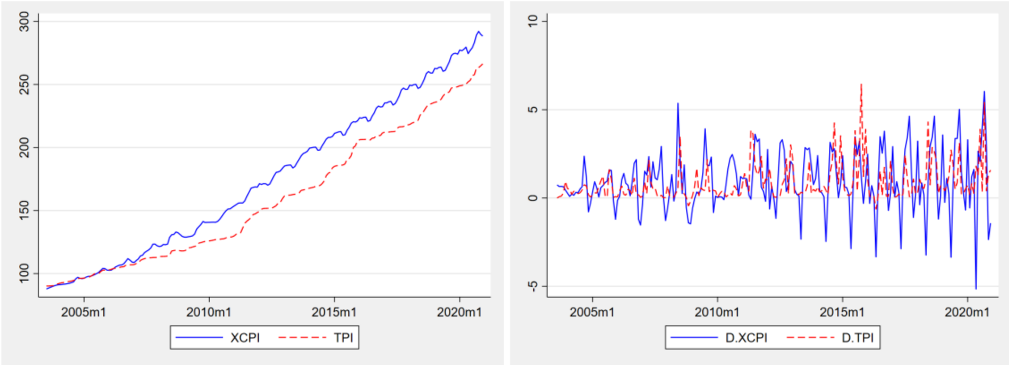
Figure 1: Evolution of CPI and TPI



(A) Level (μ_{tpi} : 159, μ_{xcpi} : 175) (B) Differenced (μ_{tpi} : .84, μ_{xcpi} : .95)

Figure 2: Oil-inflation path diagram

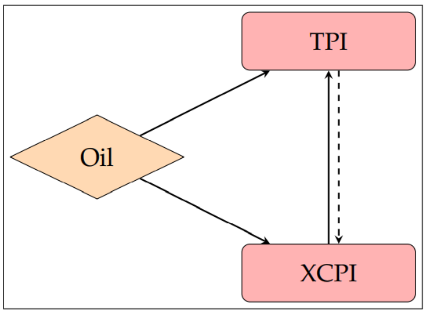
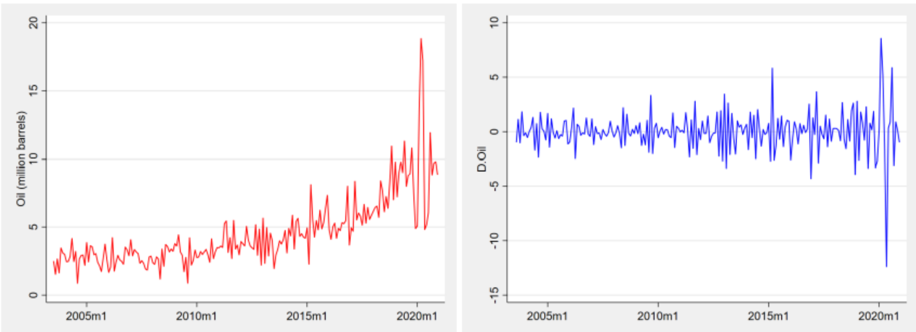
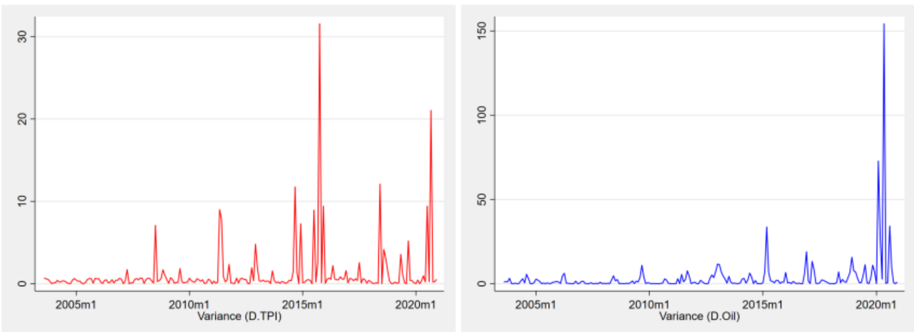


Figure 3: Oil imports per month



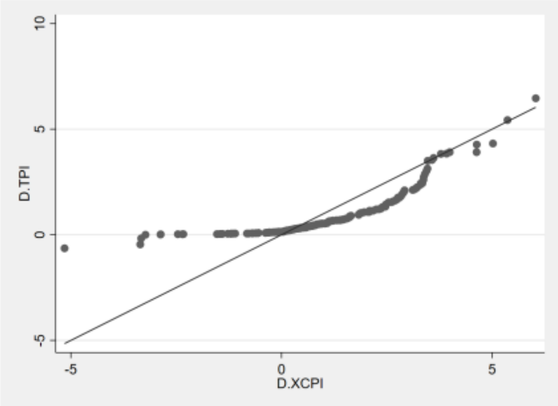
(A) Level (B) 1st differenced

Figure 4: Volatility clustering

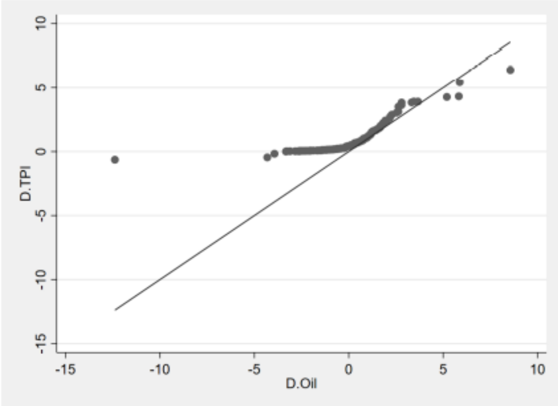


(A) D.TPI (B) D.Oil

Figure 5: Quantile-quantile plots

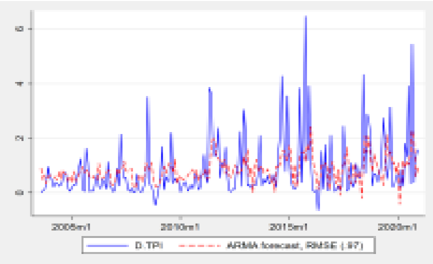


(A) D.TPI and D.XCPI

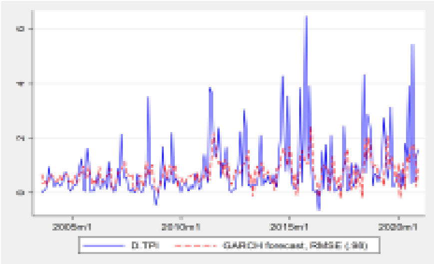


(B) D.TPI and D.Oil

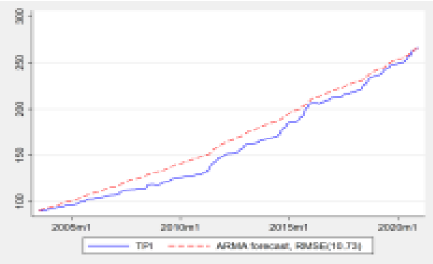
Figure 6: Forecasting comparison of the short run and the long run



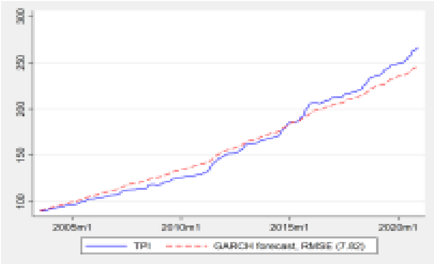
(A) In-sample Static (ARMA-SR)



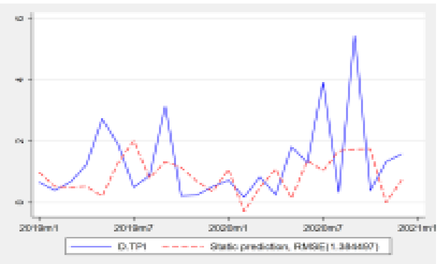
(B) In-sample Static (GARCH-SR)



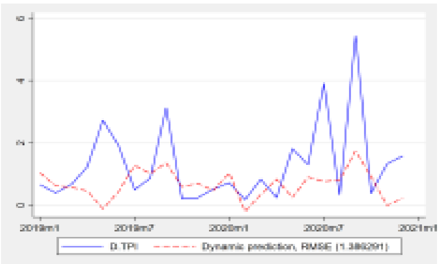
(C) In-Sample Static (ARMA-LR)



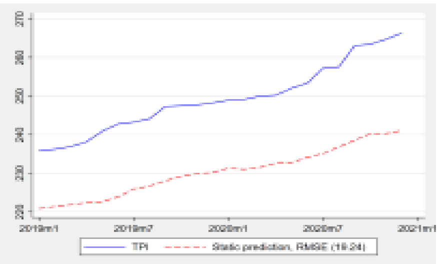
(D) In-sample Static (GARCH-LR)



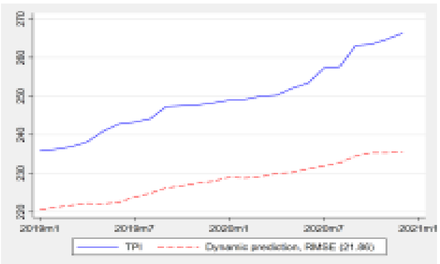
(E) Out-of-sample Static (GARCH-SR)



(F) Out-of-sample Dynamic (GARCH-SR)



(G) Out-of-sample Static (GARCH-LR)



(H) Out-of-sample Dynamic (GARCH-LR)

Table 1: Descriptive statistics

	Level			1st diff.		
	TPI	**XCPI**	**Oil**	**D.TPI**	**D.XCPI**	**D.Oil**
Mean	159.42	176.03	4.54	.84	.96	.03
Standard deviation	52.40	61	2.60	1.07	1.65	1.87
Skewness	.41	.20	2.11	2.23	-.08	-.72
Kurtosis	1.83	1.74	9.69	8.70	4.06	13.69
Correlation matrix						
TPI/D.TPI	1	-	-	1	-	-
XCPI/D.XCPI	.99	1	-	.30	1	-
Oil/D.Oil	.78	.77	1	-.13	.15	1
Autocorrelation (Q-statistic)						
Lag(1)	206.89	207.24	114.38	12.40	21.04	19.23
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Lag(6)	1165.7	1170	522.55	39.25	66.58	62.47
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Lag(12)	2164.7	2181.5	955.16	55.24	242.01	66.46
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
N	210	210	210	209	209	209

Table 2: Unit root tests (t-value)

Variables	**ADF test**		**PP test**		**Decision**
	Level	1st diff.	Level	1st diff.	
TPI_t	2.17	-5.4^{***}	3.29	-11.46^{***}	$I(1)$
$XCPI_t$	2.29	-7.83^{***}	1.44	-9.86^{***}	$I(1)$
Oil_t	-1.00	-10.91^{***}	-4.84^{***}	-27.52^{***}	$I(1)$

*P-value for the levels of significant are $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3: ARDL bounds test

Models	**lags**	**F-stat**	**Adj-R^2**	**D.W. test**
$TPI_t = f(XCPI_t)$	$(3,1)$	5.01^{*}	.17	2.03
$XCPI_t = f(TPI_t)$	$(3,2)$	.65	.19	2.04
Significance	*Lower bounds* $I(0)$		*Upper bounds* $I(1)$	
1% level	6.84		7.84	
5% level	4.94		5.73	
10% level	4.04		4.78	

*P-value for the levels of significant are $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 4: Granger causality tests, χ^2

TABLE 4.4: Granger Causality test, χ^2

	$\sum \Delta TPI_{t-i}$	$\sum \Delta XCPI_{t-i}$
ΔTPI_t	-	5.6 (0.06)
ΔXPI_t	8.46 (0.01)	-

*p-value in the parenthesis

Table 5: Inflation shocks (model 1)

D.TPI	OLS	ARMA(1,1)	GARCH(1,1)-M	EGARCH(1,1)-M
D.XCPI	$.19^{***}$	$.15^{***}$	$.16^{***}$	$.08^{***}$
ar(1)		$.77^{***}$	$.63^{***}$	$.74^{***}$
ma(1)		$-.59^{***}$	-.24	$-.46^{***}$
ξ			-.11	-.86
α			$.65^{***}$	$.50^{***}$
β			$.22^{**}$	$.65^{***}$
γ				-.02
Q-statistics(1)	4.93	.89	2.64	4.55
	(.03)	(.35)	(.10)	**(.03)**
Q-statistics(6)	25.59	8.67	8.14	11.46
	(.00)	(.19)	(.23)	(.08)
Q-statistics(12)	31.67	14.32	12.72	17.68
	(.00)	(.28)	(.39)	(.13)
ARCH-LM(1)	.09	.68	.97	2.83
	(.77)	(.41)	(.32)	(.09)
ARCH-LM(6)	11.43	9.24	8.88	11.68
	(.08)	(.16)	(.18)	(.07)
ARCH-LM(12)	15.46	12.83	13.15	15.94
	(.22)	(.38)	(.36)	(.19)
N	209	209	209	209

*P-value for the levels of significant are $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: Oil shocks (model 2)

D.TPI	OLS	ARMA(1,1)	GARCH(1,1)-M
D.Oil	$-.10^{***}$	$-.10^{***}$	$-.06^{***}$
D.XCPI	$.21^{***}$	$.17^{***}$	$.17^{***}$
ar(1)		$.76^{***}$	$.60^{***}$
ma(1)		$-.56^{***}$	-.22
ξ			-.12
α			$.53^{***}$
β			$.33^{**}$
Q-statistics(1)	7.69	.27	2.18
	(.01)	(.60)	(.14)
Q-statistics(6)	25.32	5.18	7.22
	(.00)	(.52)	(.30)
Q-statistics(12)	30.04	9.38	11.01
	(.00)	(.67)	(.53)
ARCH-LM(1)	.04	.23	.57
	(.84)	(.63)	(.45)
ARCH-LM(6)	11.81	10.76	11.84
	(.07)	(.10)	(.07)
ARCH-LM(12)	16.23	14.75	16.62
	(.18)	(.26)	(.16)
N	209	209	209

*P-value for the levels of significant are $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Appendix

Table A1: Seasonality Testing

Variables	F-Stat. (Month Dummies)	P-value	Decision
TPI	0.02	1.00	No seasonality
XCPI	0.02	1.00	No seasonality
Oil	0.62	0.81	No seasonality

Table A2: ARMA Model Selection

Model: D.TPI=f(D.XCPI)

ARMA(p,q)	IC (AIC)	ARMA(p,q)	IC (AIC)
0,1	607	0,2	601
1,0	605	2,0	601
1,1	599*	1,2	600
2,1	599	2,2	601

*ARMA(1,1) model is elected for lowest IC with parsimonious specification.

Table A3: GARCH-M Model Selection

Model: D.TPI=f(D.XCPI)

GARCH(p,q)-M	IC (AIC)	GARCH(p,q)-M	IC (AIC)
1,0	584	2,0	588
1,1	578*	2,1	585
1,2	579	2,2	590

*GARCH(1,1)-M with ARMA(1,1) model is elected for lowest IC.

Figure A1: Volatility Clustering of ARMA(1,1) Residuals (Model 1)