Identifying Aggregate Demand and Supply Shocks in Bangladesh

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Abstract:
This paper explores the relative roles of aggregate demand and supply shocks in affecting the Bangladesh economy. There is a conventional belief that supply-side shocks are the predominant shocks in Bangladesh. Our preliminary analysis of the cyclical behaviour of prices indicates that both demand and supply shocks are relevant in Bangladesh. In an attempt to investigate this issue further, we introduce a Bivariate SVAR model, where the aggregate demand and supply shocks are identified from the VAR residuals using a long run restriction proposed by Blanchard and Quah (1989). The Blanchard-Quah (BQ) approach forces the two shocks to be orthogonal. As argued by Cover et al (2006), this assumption is problematic, as policy actions often cause demand and supply shocks to be correlated each other. Following Cover et al (2006) we thus employ a modification of the standard BQ approach, in which the two shocks are allowed to be correlated. Strong evidence is found for the hypothesis that aggregate demand and supply shocks are interrelated in Bangladesh. Impulse response functions and the variance decompositions indicate a very steep short run aggregate supply curve and suggest that inflation is demand-driven whereas the output level is basically supply-driven. Supply shocks, however, appear to play a greater role in determining inflation in the modified model compared to those in the standard BQ model.

Keywords: Aggregate Demand and Supply Shocks, Structural VAR, Blanchard-Quah Decomposition.

JEL Code: C32, E23, E31
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1. Introduction:

Bangladesh is among the less developed countries of the world. There is a widely held belief that the supply side shocks play dominant role in its economy as natural calamities and political instability often hinder the productive activity. However, in the whole decade of 1990s and in the early 2000s, the Bangladesh economy recorded stable growth performance without experiencing high inflation despite several occurrences of severe natural disaster and frequent political turmoils\(^1\). Bangladesh is one of the first underdeveloped countries to undertake major financial reforms. These reform policies, which were initiated in early 1990s include, among others, deregulation of interest rates and introduction of indirect monetary policy. Since the years when these policies have been initiated, monetary policy became more vital in the Bangladesh economy and thus it is indicative that the demand side shocks via the monetary authorities’ demand management policies might also have played crucial role in achieving output growth and price stability in Bangladesh.

This paper attempts to examine the relative roles of demand and supply shocks in Bangladesh. In particular we endeavour to identify the aggregate demand and supply shocks in the Bivariate SVAR framework and examine the effects of these shocks on output and inflation in Bangladesh. In the wake of recent price hike in Bangladesh, our analysis is of particular significance, in particular from the monetary policy point of view. For the purpose of conducting monetary policy, it is essential for the monetary authority to know the sources of shocks that are affecting the output level and inflation rate. The simple correlation between the price level and output movement can be informative about which shock - demand or supply – is predominant in the economy\(^2\). A positive correlation between the output and price level indicates that demand shocks are

\(^1\) Inflation rate however tends to rise beyond the Central Bank’s implicit target of 5-6 percent in recent months.

\(^2\) An equivalent analysis can be made using inflation instead of the price level.
playing the key role, whereas the negative relation reflects the increased role for the supply shocks. Nevertheless, from a monetary policy perspective, it is also important for the monetary authority to know the individual response of output and inflation to the aggregate demand and supply shocks, in order to use its policy tool effectively.

The rest of this paper proceeds as follows. In Section 2 we examine the cyclical behaviour of the price level in order to get a preliminary idea on which shock is more important in Bangladesh. In Section 3, a general framework for aggregate demand and supply analysis is discussed. We particularly set up an SVAR framework, in which, using the Blanchard-Quah technique, one can identify the aggregate demand and supply shocks and examine their effects on the output level and inflation rate. The results of the Blanchard-Quah decomposition are discussed in Section 4. An alternative identifying method based on the recent paper by Cover, Enders and Hueng (2006) and estimation results of this method are discussed in Section 5. Section 6 concludes this chapter.

2. Cyclical Behaviour of Prices:

Considerable effort has been put towards examining the cyclical properties of the price behaviour in different countries in past decades. In particular, a number of studies focussed on data for the US economy and basically look at the cross-correlation between the cyclical movements of output and prices. One of the main aims of this research is to provide evidence about the types of shocks that are important in generating business cycles. The main idea is that demand shocks cause output and prices to move in the same direction, while supply shocks cause these variables to move in opposite direction. It was initially believed that prices are pro-cyclical (Lucas (1972), Mankiw (1989)); however, results from the more recent studies (as cited before) do not support the idea of a demand driven business cycle. These more recent studies found that although the price-output relationship was positive before the World War II, they mainly became negative or at least non-positive in the post-war era in the USA.

The main purpose of this section is to form a general idea about the types of shocks that are dominant in the Bangladesh economy. We are particularly motivated by the US-based works cited above and we attempt to examine the cyclical relationship between prices and output in a less developed country like Bangladesh. Although the price-output relationship has been extensively studied in the US and other developed economies, only a few studies focus on developing economies. Particularly, we have found only one study (Rahman and Yamagata 2004) that explicitly explores the cyclical properties of prices and other macro variables in Bangladesh. Using Bangladesh data (both quarterly and monthly) that covers the period 1981-1999, this study found very weak support for the pro-cyclical price movements. Here we revisit the same issue by using a more recent dataset; the main aim is to see if there has been any change in the price-output relationship in recent times, especially, after the financial reforms that were initiated in the early 1990s.

Our analysis used quarterly data covering the period 1993:Q3 – 2006:Q1. The primary source of our dataset is the International Statistics online database. Appendix A reports the definition of all data used in this paper. For the general price level, we use consumer price index (P), which is available in quarterly frequency only from 1993Q3. Since real GDP data is not available quarterly, we construct a disaggregated dataset for this purpose. The quarterly real GDP data (Y) is estimated applying a simple disaggregating method that uses simple (quadratic sum) interpolation of annual GDP along with a related annual series, the quarterly data of which is available. The details of this method are explained in Appendix B. Additionally we have also used quarterly Industrial Production Index series (IP) as a proxy for output. All data are in logarithms.

To isolate the cycles from the trends, we apply four alternative methods. Retrieved Cycles in these four methods are labeled here as ‘Detrended’, ‘Log-Differenced’, ‘H-P Filtered’ and ‘B-K Band-pass Filtered’ respectively. The first method (Detrending) involves removing linear deterministic trends from the respective series. The second method (log-differencing), which is based on the assumption of difference-stationarity, simply involves first-differencing of the logged data. As a third method, we use the Hodrick-Prescott Filter (Hodrick and Prescott (1997)) to retrieve the cyclical component.
of a series. We have also used the Baxter-King band-pass filtering method (Baxter and King (1999)). The Baxter-King filter is a kind of Band-pass (frequency) filtering tool which is mainly used to isolate the cyclical component of a time series by specifying a range for its duration. In our analysis, considering our small sample size, we choose 6 to 20 quarters as the range of durations (periodicities) to pass through. Our calculation of moving averages allows 4 lags/leads and this causes us to loose 8 observations.

The figure below plots the cyclical fluctuations of prices and real GDP for the alternative filtering methods. In general, no clear pattern in the relationship between the price and output cycle is visible in these plots. For example, in the ‘detrended’ data, prices increase in some periods of expansion, whereas, in some other such periods, they move in the opposite direction. This is equally true for the plots based on the other three methods.

Figure 2.1: Cyclical movements in Real GDP and Prices
The cross correlations between the output and price cycles are shown in the following table. All four methods show negative contemporaneous correlation; however, none of these figures are significantly different from zero at the 5 percent level. The differenced data shows the strongest negative (although insignificant) relationship, but the figures for the second lags and the second leads in the ‘differenced’ data show a significant positive relationship. The cyclical series obtained from the Hodrick-Prescott and the Baxter-King bandpass filters do not show any significant relationship between the price and output levels. There are thus ambiguities in the relationship between the price level and aggregate output level in Bangladesh. The possible explanation for this may be that the demand and supply shocks offset the effects of each other, which results in the insignificant correlation coefficients.

Table 2.1: Cross Correlation between Real GDP and Lagged Prices

<table>
<thead>
<tr>
<th>Lag/Lead (i)</th>
<th>Detrended data</th>
<th>Differenced data</th>
<th>H-P Filtered data</th>
<th>B-K Band-pass Filtered data</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>0.1931</td>
<td>-0.0311</td>
<td>-0.0240</td>
<td>-0.1037</td>
</tr>
<tr>
<td>-4</td>
<td>0.1145</td>
<td>-0.1920</td>
<td>-0.2261</td>
<td>-0.1820</td>
</tr>
<tr>
<td>-3</td>
<td>0.1327</td>
<td>-0.1499</td>
<td>-0.1156</td>
<td>-0.1111</td>
</tr>
<tr>
<td>-2</td>
<td>0.2396</td>
<td>0.4341**</td>
<td>0.2472</td>
<td>0.0157</td>
</tr>
<tr>
<td>-1</td>
<td>0.0992</td>
<td>0.0134</td>
<td>0.0209</td>
<td>0.0413</td>
</tr>
<tr>
<td>0</td>
<td>-0.0705</td>
<td>-0.2571</td>
<td>-0.2464</td>
<td>-0.0134</td>
</tr>
<tr>
<td>1</td>
<td>-0.0101</td>
<td>-0.1568</td>
<td>-0.1390</td>
<td>-0.0565</td>
</tr>
<tr>
<td>2</td>
<td>-0.0195</td>
<td>0.2835**</td>
<td>0.1273</td>
<td>-0.0505</td>
</tr>
<tr>
<td>3</td>
<td>-0.1097</td>
<td>0.0347</td>
<td>-0.0121</td>
<td>-0.0442</td>
</tr>
<tr>
<td>4</td>
<td>-0.2425</td>
<td>-0.1367</td>
<td>-0.1851</td>
<td>-0.0561</td>
</tr>
<tr>
<td>5</td>
<td>-0.1985</td>
<td>-0.1600</td>
<td>-0.1451</td>
<td>-0.0863</td>
</tr>
</tbody>
</table>

Note: ** shows the significance at 5 percent level. The standard error of our correlation coefficient is $1/\sqrt{N}$, where N is the number of observations.

Figure 2.1 shows the cyclical movements of the Industrial Output Index and price level under different filtering methods. It is evident from the diagram that the fluctuations in the output level are much larger than those in the price level. The direction of the price changes appears to be pro-cyclical; however, we need to look at the corresponding correlation coefficients, which are reported later in this section, to investigate this property.
The contemporaneous correlation figures between cyclical price and industrial output are positive which is consistent with the visual inspection of the graphs. The detrended data shows strong positive (and significant) contemporaneous relationship between output and prices. Although contemporaneous correlation in the ‘differenced’, ‘H-P Filtered’ and ‘Bandpass Filtered’ data are insignificant (marginally) at 5 percent level, the respective coefficients are reasonably high. Industrial output also appears to be somewhat positively correlated with the first lead of the price level as the detrended data shows a significant positive coefficient while the other methods give the moderately large positive values (although insignificant) for the correlation coefficient. Overall, we may conclude that there appears to be a weakly positive relation between the price level and Industrial Output Index.
### Table 2.2: Cross Correlation between Industrial Output and Lagged Prices

<table>
<thead>
<tr>
<th>Lag/Lead (i)</th>
<th>Cross Correlation Between IP&lt;sub&gt;t&lt;/sub&gt; and P&lt;sub&gt;t+i&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Detrended data</td>
</tr>
<tr>
<td>-5</td>
<td>-0.1988</td>
</tr>
<tr>
<td>-4</td>
<td>-0.0191</td>
</tr>
<tr>
<td>-3</td>
<td>0.0811</td>
</tr>
<tr>
<td>-2</td>
<td>0.0702</td>
</tr>
<tr>
<td>-1</td>
<td>0.1141</td>
</tr>
<tr>
<td>0</td>
<td>0.3376**</td>
</tr>
<tr>
<td>1</td>
<td>0.3192**</td>
</tr>
<tr>
<td>2</td>
<td>0.2002</td>
</tr>
<tr>
<td>3</td>
<td>0.1105</td>
</tr>
<tr>
<td>4</td>
<td>0.1867</td>
</tr>
<tr>
<td>5</td>
<td>0.1787</td>
</tr>
</tbody>
</table>

Note: ** shows the significance at 5 percent level. The standard error of our correlation coefficient is $1/\sqrt{N}$, where N is the number of observations.

In addition to the examination of price-output relation, we have examined the cross correlation between output and annualized inflation ($\pi$). As inflation series does not show any linear time trend, we omitted the ‘detrended’ filtering method in this occasion. The relevant cross-correlation figures are shown in table 2.3.

### Table 2.3: Cross Correlation between Industrial Output and Lagged Inflation

<table>
<thead>
<tr>
<th>Lag/Lead (i)</th>
<th>Cross Correlation Between Output(t) and Inflation(t+i)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Differented data</td>
</tr>
<tr>
<td></td>
<td>Y and $\pi$</td>
</tr>
<tr>
<td>-5</td>
<td>-0.0609</td>
</tr>
<tr>
<td>-4</td>
<td>-0.1221</td>
</tr>
<tr>
<td>-3</td>
<td>-0.1559</td>
</tr>
<tr>
<td>-2</td>
<td>0.1320</td>
</tr>
<tr>
<td>-1</td>
<td>0.0314</td>
</tr>
<tr>
<td>0</td>
<td>-0.0457</td>
</tr>
<tr>
<td>1</td>
<td>-0.0863</td>
</tr>
<tr>
<td>2</td>
<td>0.0126</td>
</tr>
<tr>
<td>3</td>
<td>0.0476</td>
</tr>
<tr>
<td>4</td>
<td>0.0069</td>
</tr>
<tr>
<td>5</td>
<td>-0.0437</td>
</tr>
</tbody>
</table>

Note: ** shows the significance at 5 percent level. The standard error of our correlation coefficient is $1/\sqrt{N}$, where N is the number of observations.
In general, the fourth and fifth lags of inflation are found to have negative correlation with output. In particular, the B-K filtering method shows significant negative relation between the output level and the lagged inflation rate. This finding suggests that inflation in Bangladesh may be counter-cyclical and supply shocks may be more important than demand shocks in affecting output and inflation. However, this finding should not be taken guaranteed as other filtering methods do not show any significant correlation between output and inflation. The contemporaneous relations are ambiguous, suggesting demand shocks may be equally important as supply shocks in the short-run.

Overall the analysis of the cyclical behaviour of price and inflation does not provide us any clear indication about which shocks – demand or supply are predominant in Bangladesh. One possibility is that both shocks are equally important in the Bangladesh economy and the observed ambiguities in the cyclical relationships may reflect the offsetting effects of the two shocks. We will explore this issue further in the next sections.

3. AD-AS Model in the SVAR Framework - the Blanchard-Quah Approach:

Although the textbook analysis of aggregate demand and supply (AD-AS) model is quite simple, the empirical analyses are not that straightforward. The main challenge here is to identify the demand and supply shocks, which are not observable. Blanchard and Quah (1989) pioneered the idea of long run identifying restrictions within the SVAR framework and we initially use this Blanchard-Quah (BQ, henceforth) approach to identify the aggregate demand and supply shocks and trace out their dynamic effects on output and inflation in Bangladesh. The BQ technique is extensively used in empirical economic literature, especially to identify the different types of shocks and their effects in different countries. Notable studies include Bayoumi and Eichengreen (1993), Quah and Vahey (1995) and Mio (2002), and our econometric technique applied here, to some extent, is similar to these three works. Bayoumi and Eichengreen (1993) examined the effects of demand and supply shocks in European countries. Quah and Vahey (1995)

4 These three studies used Bivariate SVAR model. Quah and Vahey (1995) include inflation and output, whereas other two papers include prices and output in the VAR model.
apply the BQ technique to identify the core and noncore shocks and to construct a
measure of core inflation for the US economy. Mio (2002) uses the Japanese data to
identify aggregate demand and supply shocks.

To start with, let us assume that the aggregate supply is a positive function and aggregate
demand is a negative function of inflation. Suppose these two functions are represented
by
\[
\Delta y_t^s = \alpha \Delta \pi_t + v_t^s \\
\Delta \pi_t^d = -\beta \Delta y_t + v_t^d
\]
where \( Y \) and \( \pi \) are measures of real output and inflation respectively. The superscripts \( s \)
and \( d \) represent supply and demand, while, \( v_t^s \) and \( v_t^d \) are supply and demand shocks
respectively. The demand and supply shocks are assumed to be uncorrelated. Here \( \alpha \)
is the slope of aggregate supply curve and \( \beta \) is the slope of aggregate demand curve.

Using the equilibrium condition \( y_t^s = y_t^d \), one can now solve for \( \Delta y \) and \( \Delta \pi \), and it is
straightforward to show that
\[
\Delta y_t = \frac{1}{1 + \alpha \beta} v_t^s + \frac{\alpha}{1 + \alpha \beta} v_t^d \\
\Delta \pi_t = -\frac{\beta}{1 + \alpha \beta} v_t^s + \frac{1}{1 + \alpha \beta} v_t^d
\]

For convenience, the two shocks can be further transformed to the unit-variance shocks
\( \epsilon_t^s \) and \( \epsilon_t^d \) by simply assuming that \( v_t^s = h_{11} \epsilon_t^s \) and \( v_t^d = h_{22} \epsilon_t^d \), where \( b_{11} \) and \( b_{22} \) are the
standard deviation of the supply and demand shocks respectively. The contemporaneous
effects of the two shocks (in one standard deviation unit) on output and inflation can thus
be shown as:
\[
\frac{\partial \Delta y_t}{\partial \epsilon_t^s} = \frac{h_{11}}{1 + \alpha \beta} \quad \frac{\partial \Delta y_t}{\partial \epsilon_t^d} = \frac{b_{22} \alpha}{1 + \alpha \beta} \\
\frac{\partial \Delta \pi_t}{\partial \epsilon_t^s} = -\frac{h_{11} \beta}{1 + \alpha \beta} \quad \frac{\partial \Delta \pi_t}{\partial \epsilon_t^d} = \frac{b_{22}}{1 + \alpha \beta}
\]
It is evident that the contemporaneous response of inflation to a demand shock is positive, but that to a supply shock is negative. Output responds positively to both the demand and supply shocks. The magnitudes of the contemporaneous responses of output and inflation to the demand and supply shocks depend on the two slope parameters $\alpha$ and $\beta$. For example, other things being equal, the larger the value of $\alpha$, i.e., the flatter the AS curve, the larger (smaller) will be the effect of a positive aggregate demand (supply) shock on output. On the other hand, the inflation response will be larger (smaller) to a supply (demand) shock, if the short run aggregate supply curve is relatively flatter (larger $\alpha$).

The model described above is a static one and it implies that all adjustments are instantaneous. One may extend this model to capture the dynamic adjustments by introducing lagged values of $\Delta Y$ and $\Delta \pi$ in 3.1 as

$$A_0X_t = A_1(L)X_t + B\varepsilon_t \quad [3.4]$$

where $L$ is the lag operator, $X_t = (\Delta y_t, \Delta \pi_t)$, $A_1(L) = \sum_{i=1}^{q}A_{i1}L^i$, $\varepsilon_t = (\varepsilon'_t, \varepsilon''_t)$ and

$$A_0 = \begin{bmatrix} 1 & -\alpha \\ \beta & 1 \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \quad [3.5]$$

The SVAR system [3.5] can further be transformed to its moving average form as

$$(A_0 - A_1(L))X_t = B\varepsilon_t$$

or

$$X_t = (A_0 - A_1(L))^{-1}B\varepsilon_t \quad [3.6]$$

From equation [3.6] one can trace out the dynamic impacts of the two shocks on inflation and output.

Equation [3.6] implies that we can express $X$ as a function of two shocks as,

$$X_t = D_0\varepsilon_t + D_1\varepsilon_{t-1} + D_2\varepsilon_{t-2} + ... = (D_0 + D_1L + D_2L^2 + ...)\varepsilon_t = D(L)\varepsilon_t \quad [3.7]$$

where all $D_i$'s are 2x2 matrices of coefficients. The two disturbances are assumed to be uncorrelated and their variances are normalized to be one; i.e, $Var(\varepsilon_t) = \mathbf{E}(\varepsilon_t, \varepsilon'_t) = 1$. The

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5 In the next section, we discuss an alternative identifying strategy where the two shocks are allowed to be correlated each other.
main problem with the above model is that the demand and supply disturbances are not observable directly. However, using identifying restriction(s), these disturbances can be identified from the estimated bivariate VAR residuals.

A reduced form VAR model has the following form\(^6\):
\[
X_t = C(L)X_t + e_t
\]
which can be rearranged as:
\[
(I - C(L))X_t = e_t
\]
\[
X_t = (I - C(L))^{-1}e_t
\]
\[
= (I + C(L) + C(L)^2 + ...)e_t
\]
or in more simplified moving average form as
\[
X_t = (I + G_1L + G_2L^2 + ...)e_t = G(L)e_t
\]

Here \(e_t\) is the vector of residuals obtained from the equations in the VAR and the variance of \(e_t\) is \(\Sigma_e = E(e_t e_t')\). Comparing [3.8] and [3.9], we can also write \(G_i = D_o D_o^{-1}\) and \(e_t = D_o^{-1}e_t\).

Knowing \(D(L)\) is essential for our analysis, however, the mapping from the reduced form equation [3.9] to the structure [3.8] is not unique. We need to impose at least one restriction to solve the identification problem. To see this, let us consider the variance-covariance matrix of the VAR residuals:
\[
\Sigma_e = E(e_t e_t')
\]
\[
= E(D_o e_t e_t' D_o)
\]
\[
= D_o D_o E(e_t e_t')
\]
\[
= D_o D_o
\]

The left hand side of [3.10] has three known entries (2 variances plus one covariance), however, in the right hand side we need to estimate 4 unknown elements. Thus for the purpose of unique estimation of the elements of \(D_o\), we need to impose one restriction on the elements of \(D_o\).

\(^6\) A constant term can also be included in the VAR without loss of generality. For the sake of expository ease, here we have omitted the constant.
In order to impose this restriction, here we assume that the aggregate demand shock does not have any long run impact on the output level. Assuming L=1, the long run expression for [3.8] is

\[ X_t = (D_0 + D_1 + D_2 + ...) \epsilon_t = D(1) \epsilon_t \]  

[3.11]

Here \( D(1) \) is a 2x2 matrix, each element of which gives the long run effects of a shock on output or inflation. For \( X = [\Delta y, \Delta \pi] \) and \( \epsilon = [\epsilon^e, \epsilon^d] \), our identification assumption, in terms of the long run expression, \( X_t = D(1) \epsilon_t \) implies

\[
\begin{bmatrix}
\Delta y_t \\
\Delta \pi_t
\end{bmatrix} = 
\begin{bmatrix}
d_{11} & 0 \\
d_{21} & d_{22}
\end{bmatrix}
\begin{bmatrix}
\epsilon^e_t \\
\epsilon^d_t
\end{bmatrix}
\]

with \( D(1) = 
\begin{bmatrix}
d_{11} & 0 \\
d_{21} & d_{22}
\end{bmatrix} \)

This restriction essentially implies imposing a restriction on one element of the matrix \( D_0 \) since \( G(1)D_0 = D(1) \) and \( G(1) \) is known from the VAR estimates. Here \( D_0 \) is a 2x2 matrix, elements of which represent the effects of two shocks on two variables in the impact period. Once we can estimate the elements of \( D_0 \) using the variance-covariance matrix of estimated \( e_t \) and the proposed long run restrictions, we can recover the two structural shocks from the relation \( \epsilon_t = D_0^{-1}e_t \). Also, we will be able to estimate the matrices of all the lag coefficients, \( D_i \) (for \( i = 1, 2, 3,... \)) in [3.1] using \( G_i = D_iD_0^{-1} \).

In summary, our analysis of BQ approach is based on the following procedures: We first estimate a bivariate VAR with \( X = [\Delta y, \Delta \pi] \), and invert it to obtain [3.9]. Imposing the long run restrictions, we then construct the matrix \( D_0 \); and use this to obtain \( \epsilon_t = D_0^{-1}e_t \) and \( D_i = G_iD_0 \). Once we obtain the estimates of \( D_0 \) and \( D_i \), we can use [3.8] to derive the dynamic responses of inflation and output to the demand and supply shocks.
4. Estimation Results of the BQ Model

4.1 Data and their Time Series Properties

Here we have considered two alternative bivariate SVAR models. In the first model we consider the log of quarterly GDP (Y) and inflation rate (π), while the second model uses the log of the industrial production index (IP) and inflation rate (π). Before estimating the VAR, we tested for nonstationarity and cointegration properties of the variables included in the VAR model. The ADF (Dickey and Fuller (1979)) and Phillips-Perron (Phillips and Perron (1988)) unit root results are reported in table 4.1.

Following standard practice, we conduct the tests both with and without including a trend in the test equation. The inclusion of a deterministic trend term in the test equation assists us in differentiating a trend-stationary series from the difference-stationary series. The lag length in the ADF test equation was selected using Schwartz Criterion (for a maximum of 12 lags). In the Phillips-Perron test, the Newey-West bandwidth criterion and the Bartlett Kernel estimation method was applied.

Table 4.1: Unit Root Test Results

<table>
<thead>
<tr>
<th></th>
<th>ADF t Statistic (P-Values)</th>
<th>Phillips-Perron t Statistics (P-Values)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant Only</td>
<td>Constant + Trend</td>
</tr>
<tr>
<td>Y</td>
<td>0.423185 [3] (0.9819)</td>
<td>-2.166483 [3] (0.4965)</td>
</tr>
<tr>
<td>ΔY</td>
<td>-8.382708 [0] (0.0000)</td>
<td>-8.302984 [0] (0.0000)</td>
</tr>
<tr>
<td>IP</td>
<td>-0.015136 [3] (0.9521)</td>
<td>-0.153309 [8] (0.9921)</td>
</tr>
<tr>
<td>ΔIP</td>
<td>-8.552306 [0] (0.0000)</td>
<td>-8.459424 [0] (0.0000)</td>
</tr>
<tr>
<td>π</td>
<td>-1.827782 [0] (0.3628)</td>
<td>-1.795721 [0] (0.6906)</td>
</tr>
<tr>
<td>Δπ</td>
<td>-5.222672 [0] (0.0001)</td>
<td>-5.190342 [0] (0.0006)</td>
</tr>
</tbody>
</table>

Note: Critical values used are from MacKinnon (1996). Figures in the square bracket indicate chosen lag length for ADF test and Bandwidth for the Phillip-Perron test.
The ADF test results suggest that all three series, $Y$, $IP$ and $\pi$, are nonstationary as they indicate that we cannot reject the null of unit root for any of the series in their levels. For the first difference of these series, the unit root hypothesis is strongly rejected. The Phillips-Perron test gives the similar result when the test equations included the constant but not the time trends. However, the hypothesis of a unit root is rejected for $Y$ and $IP$ when time trends are included in the test equations. Here we have conflicting results; the ADF test suggests $Y$ and $IP$ are difference-stationary and differencing the series would make them stationary. But the Phillips-Perron test indicates that $Y$ and $IP$ are trend-stationary, and detrending is the appropriate way to make them stationary. To ensure stationarity, here we choose the first differencing of $Y$ and $IP$. Doing this does not have any interpretational problem, as first differencing of these two variables simply reflect the output growth rate.

If the output and inflation are I(1) (as indicated by the ADF test) and cointegrated with each other, then we must also include that information in the VAR model (as we intend to use first difference of the variables). As such, we need to estimate a structural VECM instead of structural VAR model if the two variables are cointegrated. Thus it is necessary for us to check if there exists any cointegration between the variables in their levels. Here we apply the Johansen Cointegration approach (Johansen 1991, 1995) and the results are reported in table 4.2.

**Table 4.2: Johansen Cointegration Test Result**

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Trace Statistics (P-Values)</th>
<th>Max-Eigen Statistics (P-values)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Cointegration between $Y$ and $\pi$</td>
<td>8.826213 (0.3817)</td>
<td>8.097634 (0.3689)</td>
</tr>
<tr>
<td>No Cointegration between $IP$ and $\pi$</td>
<td>11.76674 (0.1685)</td>
<td>10.68490 (0.1707)</td>
</tr>
</tbody>
</table>

Note: p-values are based on MacKinnon-Haug-Michelis (1999). As indicated by a number of statistical criteria, we use 4 and 3 lags for the first and the second models respectively. Assuming a deterministic trend in the series, we include intercept terms both in the cointegrating equations and the VARs.

Both the Trace and Max-Eigen Statistics suggest that we cannot reject any of the null hypotheses, which implies that there is no cointegration between $Y$ and $\pi$, and $IP$ and $\pi$. Thus we can safely use the first differences of the variables in our SVAR model.
4.2 Response of the Shocks

A reduced form VAR model, which includes $\Delta Y$ and $\Delta \pi$, and uses a lag order of 4, is first estimated using OLS. A constant is included in each equation of the VAR models. The chosen lag order of 4 is basically suggested by AIC, HQ and FPE (for a maximum of 8 lags). We followed the similar procedures for the alternative VAR model that includes $\Delta IP$ instead of $\Delta Y$. For this model, as suggested by different lag selection criteria, a lag order of 3 is chosen.

The elements of the long-run coefficient matrix $D(1)$ are estimated after imposing the identifying restriction that aggregate demand shock does not have any long run impact on the output level. The elements of $D(1) = \begin{bmatrix} d_{11} & 0 \\ d_{21} & d_{22} \end{bmatrix}$ are reported in table 4.3.

It is observed that in the first model (VAR with $\Delta Y$ and $\Delta \pi$), an aggregate supply shock has a significant positive effect on output in the long run ($d_{11} = 0.6490$). The point estimate of the long run effect of the supply shock on inflation is negative ($d_{21} = -0.5787$) but statistically insignificant. The aggregate demand shock appears to have a positive (and significant) effect on inflation in the long run ($d_{22} = 1.2749$).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Standard Error</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{11}$</td>
<td>0.6490**</td>
<td>1.6591112**</td>
<td>.3231</td>
</tr>
<tr>
<td>$d_{21}$</td>
<td>-0.5787</td>
<td>0.762564</td>
<td>.6496</td>
</tr>
<tr>
<td>$d_{22}$</td>
<td>1.2749**</td>
<td>1.680363**</td>
<td>.5046</td>
</tr>
</tbody>
</table>

Note: The standard errors are estimated using Bootstrap technique with 1000 repetition and a random number seed, 9128642. Significance of a coefficient at 5 percent level is shown by **.

Estimates of the second model (VAR with $\Delta IP$ and $\Delta \pi$) show that a positive supply shock is associated with higher output and inflation. As in the first model, the effect of the supply shocks on output ($d_{11}$) is statistically significant. The positive sign of the inflation coefficient ($d_{21}$) is somewhat inconsistent with theory; however, the corresponding standard error figure suggests this coefficient is highly insignificant. In the
second model, the long run effect of the aggregate demand shock on inflation \(d_{22}\) is positive and statistically significant, as expected.

In order to look at the dynamic effects of aggregate demand and supply shocks on output and inflation, we have estimated the relevant impulse response functions for both VAR models. The 95 percent confidence intervals of the responses are also estimated using Bootstrap technique with 1000 repetition.

Figure 4.2: Accumulated Impulse Responses to Structural One S.D. Shocks
(SVAR Model with \(\Delta Y\) and \(\Delta \pi\))

![Impulse response functions](image)

Note: The solid lines give the estimates of the accumulated responses, while the dotted lines represent the bootstrap 95 percent confidence bound.

Figure 4.2 shows the impulse response functions in the first model. We see that the dynamic response of output level to a positive aggregate supply shock is significantly positive. The supply shock permanently increases the level of output. The impulse
response takes about 20 quarters before settling down around its long run value. The negative response of inflation to a supply shock is somewhat consistent with the theory; however, this response does not appear to be significant even in the short-run.

Figure 4.3: Accumulated Impulse Response to Structural One S.D. Shocks
(SVAR Model with $\Delta IP$ and $\Delta \pi$)

![Graphs showing impulse responses to supply and demand shocks](image)

Note: The solid lines give the estimates of the accumulated responses, while the dotted lines represent the bootstrap 95 percent confidence bound.

Figure 4.3 exhibits the impulse response functions obtained from the second model. Compared to the previous model, the only noticeable difference is found in the response of inflation to the supply shock, which is now positive. This is not surprising as the relevant long run coefficient in table 4.3 was positive. The impulse response of inflation, in this case, is however again insignificant, suggesting no impact of supply shock on the inflation rate. Output increases significantly and settles down (at a higher level) after 20 quarters after a one standard deviation supply shock. Output response to the demand
shock is insignificant at any time horizon. Inflation response to the aggregate demand shock is positive and significant, as expected.

To look at the relative contribution of the demand and supply shock in the variation of output and inflation, we have also derived the related variance decompositions, which are shown in the tables below. It is evident that the main source of the variation in output is the aggregate supply shock, whereas most variation in inflation is caused by the aggregate demand shock. However, supply shocks have slightly greater role in changing the output level and inflation rate in the first model, compared to those in the second model. This finding is consistent with our preliminary analysis in the previous section where we showed some weak evidence of pro-cyclical price behaviour, and hence a weakly dominant demand shock, when the Industrial Output was used as a proxy for the aggregate output level.

Table 4.4: Variance Decomposition: SVAR Model with $\Delta Y$ and $\Delta \pi$

<table>
<thead>
<tr>
<th>Period</th>
<th>Variation in $\Delta Y$ due to</th>
<th>Variation in $\Delta \pi$ due to</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Supply shock</td>
<td>Demand Shock</td>
</tr>
<tr>
<td>1</td>
<td>98.14118</td>
<td>1.858823</td>
</tr>
<tr>
<td>2</td>
<td>95.99633</td>
<td>4.003665</td>
</tr>
<tr>
<td>3</td>
<td>91.65452</td>
<td>8.345482</td>
</tr>
<tr>
<td>4</td>
<td>89.81376</td>
<td>10.18624</td>
</tr>
<tr>
<td>5</td>
<td>91.29057</td>
<td>8.709429</td>
</tr>
<tr>
<td>6</td>
<td>91.38592</td>
<td>8.614076</td>
</tr>
<tr>
<td>7</td>
<td>91.32663</td>
<td>8.673373</td>
</tr>
<tr>
<td>8</td>
<td>91.33099</td>
<td>8.669007</td>
</tr>
<tr>
<td>16</td>
<td>91.74643</td>
<td>8.25357</td>
</tr>
<tr>
<td>24</td>
<td>91.78185</td>
<td>8.218149</td>
</tr>
<tr>
<td>32</td>
<td>91.78507</td>
<td>8.214927</td>
</tr>
<tr>
<td>40</td>
<td>91.78538</td>
<td>8.214618</td>
</tr>
</tbody>
</table>
Table 4.5: Variance Decomposition: SVAR Model with \( \Delta P \) and \( \Delta \pi \)

<table>
<thead>
<tr>
<th>Period</th>
<th>Variation in ( \Delta y ) due to Supply Shock</th>
<th>Variation in ( \Delta y ) due to Demand Shock</th>
<th>Variation in ( \Delta \pi ) due to Supply Shock</th>
<th>Variation in ( \Delta \pi ) due to Demand Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>92.22889</td>
<td>7.771107</td>
<td>17.69054</td>
<td>82.30946</td>
</tr>
<tr>
<td>2</td>
<td>92.51491</td>
<td>7.485093</td>
<td>17.82319</td>
<td>82.17681</td>
</tr>
<tr>
<td>3</td>
<td>88.13035</td>
<td>11.86965</td>
<td>16.74981</td>
<td>83.25019</td>
</tr>
<tr>
<td>4</td>
<td>87.93134</td>
<td>12.06866</td>
<td>16.49447</td>
<td>83.50553</td>
</tr>
<tr>
<td>5</td>
<td>88.11211</td>
<td>11.88789</td>
<td>16.50963</td>
<td>83.49037</td>
</tr>
<tr>
<td>6</td>
<td>88.36946</td>
<td>11.63054</td>
<td>16.38986</td>
<td>83.61014</td>
</tr>
<tr>
<td>7</td>
<td>87.44345</td>
<td>12.55655</td>
<td>16.48693</td>
<td>83.51307</td>
</tr>
<tr>
<td>8</td>
<td>87.43883</td>
<td>12.56117</td>
<td>16.493</td>
<td>83.507</td>
</tr>
<tr>
<td>16</td>
<td>87.21022</td>
<td>12.78978</td>
<td>16.52446</td>
<td>83.47554</td>
</tr>
<tr>
<td>24</td>
<td>87.1859</td>
<td>12.8141</td>
<td>16.52626</td>
<td>83.47374</td>
</tr>
<tr>
<td>32</td>
<td>87.18396</td>
<td>12.81604</td>
<td>16.52638</td>
<td>83.47362</td>
</tr>
<tr>
<td>40</td>
<td>87.18377</td>
<td>12.81623</td>
<td>16.52639</td>
<td>83.47361</td>
</tr>
</tbody>
</table>

One important finding of our SVAR analysis of the BQ approach is that a supply shock does not contribute to the inflation rate in Bangladesh. The relevant impulse response functions show no significant role of the supply shocks for inflation. Also, the variance decomposition of the inflation rate shows that only about one fifth of the variation in inflation is caused by the supply shocks.

This finding, however, is somewhat contrary to the conventional belief that supply shocks are the main sources of inflation in a less developed country like Bangladesh. Based on this belief, Bhattacharya, a prominent Economist in Bangladesh suggests that “Given the natures of Bangladesh’s inflation, which is largely supply-driven, ... monetary intervention such as up-scaling the interest rate cannot be an effective tool” (Bhattacharya 2006, p 26). Whether interest rate manipulation can be used as a tool for ensuring price stability needs further study; however, results from our BQ approach suggests that inflation in Bangladesh is typically a demand-driven phenomenon.
5. Alternative Identification

5.1 The Model

In Blanchard-Quah (BQ) approach, the variances of the two shocks are normalized to be ‘one’ and the covariance between the two shocks is assumed to be zero. Recently Cover, Enders and Hueng (2006) argued that the assumption of zero covariance is unrealistic as demand and supply shocks do affect each other in the real world. In the previous section, the BQ model suggests that the AS shock does not have any effect on the inflation rate. As shown in figure 5.1(a) this essentially suggests a horizontal AD curve. A horizontal AD curve means that aggregate spending is very sensitive to the interest rate, which is hard to rationalize for an underdeveloped country like Bangladesh. An alternative explanation for this is shown in figure 5.1(b), which reflects the fact that the aggregate demand curve has shifted rightward in response to a supply shock, causing exactly the same outcome as in figure 5.1(a).

Figure 5.1: Interrelated Demand and Supply Shocks

In terms of the Bangladesh economy, for example, an adverse supply shock stemming from severe crop failure may reduce rural income causing aggregate demand to decline. This type of negative supply shock may lead to an increase of imports of food items and
thereby cause a negative aggregate demand shock. During the adverse supply shock, the monetary authority may also react by initiating a contractionary monetary policy (to counter the cost push inflation), which may also cause the aggregate demand curve shift backward.

On the other hand, the demand shock may also cause a shift of the supply curve. For example, higher export demand of Bangladeshi ready-made garments may make the domestic garments industries hire more workers and produce the higher level of output. The same example is applicable to the domestic demand for goods and services. Firms are able to respond with higher output supply as, due to the abundance of the labour supply in Bangladesh, they can usually hire additional workers without increasing the wage rate. In terms of monetary policy, in an underdeveloped and under-monetized financial system additional money (an AD shock) may imply a more efficient financial system through which domestic resources can be better channelled into the productive activities causing a shift in the supply curve.

Here we closely follow the strategy adopted in Cover, Enders and Hueng (2006), which is based on the following AD-AS model.

\[ y_t^s = E_{t-1}[y_t] + \alpha(\pi_t - E_{t-1}[\pi_t]) + b_{11} \varepsilon_t^s \]
\[ y_t^d + \pi_t = E_{t-1}[y_t^d + \pi_t] + b_{22} \varepsilon_t^d \]
\[ y_t^s = y_t^d \]

Here, as before, \( Y \) and \( \pi \) are measures of real output and inflation respectively, while \( \varepsilon_t^s \) and \( \varepsilon_t^d \) are the one standard deviation supply and demand shocks with \( b_{11} \) and \( b_{22} \) being the standard deviations of the actual supply and demand shocks respectively. \( E_{t-1}[\cdot] \) represents expected value of a variable in period \( t \), given the set of information available at the end of period \( (t-1) \). The superscripts \( s \) and \( d \) represent supply and demand respectively.

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The first equation is based on Lucas’s ‘Monetary Misperception Theory’ and represent the Lucas-type aggregate supply curve (Lucas 1972), where real output depends on its expected value, unanticipated inflation and a random supply shock ($\varepsilon_s^t$). The second equation shows the aggregate demand function which can be derived from some version of the IS-LM model. Here we introduce the simplest version of an AD function, which reflects the fact that the nominal aggregate demand depends on its expected value and a random demand shock ($\varepsilon_d^t$). For the moment, assume that $E_{t-1}[y_t] = y_{t-1}$ and $E_{t-1}[\pi_t] = \pi_{t-1}$. The above model can then be modified to

$$
\Delta y_t = \alpha \Delta \pi_t + b_1 \varepsilon_s^t \\
\Delta \pi_t = -\Delta y_t + b_2 \varepsilon_d^t 
$$

[5.2]

In general, the actual and expected values of output and inflation also depend on the past realization of these variables. We can thus transform the above model as

$$
\Delta y_t = \alpha \Delta \pi_t + \sum_{i=1}^q \phi_{yi} \Delta y_{t-i} + \sum_{i=1}^q \phi_{yi} \Delta \pi_{t-i} + b_1 \varepsilon_s^t \\
\Delta \pi_t = -\Delta y_t + \sum_{i=1}^q \theta_{yi} \Delta y_{t-i} + \sum_{i=1}^q \theta_{yi} \Delta \pi_{t-i} + b_2 \varepsilon_d^t 
$$

[5.3]

which is equivalent to [3.4]. In practice, it is more convenient to work with the reduced form VAR, which can be represented as:

$$
\Delta y_t = \sum_{i=1}^q a_{1i} \Delta y_{t-i} + \sum_{i=1}^q a_{12} \Delta \pi_{t-i} + e_t^{y} \\
\Delta \pi_t = \sum_{i=1}^q a_{2i} \Delta y_{t-i} + \sum_{i=1}^q a_{22} \Delta \pi_{t-i} + e_t^{\pi} 
$$

[5.4]

Following Cover, Enders and Heung (2006), here it is assumed that the slope of AD curve is -1. Our earlier SVAR analysis of Blanchard-Quah approach left this coefficient unrestricted.
Having specified the SVAR and the corresponding reduced form VAR models, it is now straightforward to show the following relationship between the reduced form VAR residuals \((e^v, e^z)\) and the orthogonalized unit variance structural shocks \((\varepsilon^s, \varepsilon^d)\):

\[
\begin{bmatrix}
1 & -\alpha \\
1 & 1
\end{bmatrix}
\begin{bmatrix}
e^v \\
e^z
\end{bmatrix} =
\begin{bmatrix}
b_{11} & 0 \\
0 & b_{22}
\end{bmatrix}
\begin{bmatrix}
\varepsilon^s \\
\varepsilon^d
\end{bmatrix}
\tag{5.5}
\]

In [5.5], it is assumed that the two structural shocks are uncorrelated. Recently Cover, Enders and Hueng (2006) questioned this assumption, and suggested that aggregate demand and supply shocks may be affected by each other. Two alternative situations are considered here; 1.) The supply shock contemporaneously affects the demand shocks, and 2.) The demand shock contemporaneously affects the supply shocks.

**Case 1: The supply shock is causally prior to the demand shock**

If the AD shock is affected by the AS shock, then the aggregate demand shock may be redefined as \(\rho(b_{11}\varepsilon^s_t + b_{22}\varepsilon^d_t)\). That is, the AD shock is the combination of a pure AD shock \((b_{22}\varepsilon^d_t)\) and an induced change from the AS shock \((\rho(b_{11}\varepsilon^s_t))\), where \(\rho\) measures the contemporaneous response of the AD shock to the AS shock. In this case, [5.5] may be rewritten as:

\[
\begin{bmatrix}
1 & -\alpha \\
1 & 1
\end{bmatrix}
\begin{bmatrix}
e^v \\
e^z
\end{bmatrix} =
\begin{bmatrix}
\rho b_{11} & b_{22} \\
\end{bmatrix}
\begin{bmatrix}
\varepsilon^s \\
\varepsilon^d
\end{bmatrix}
\tag{5.6}
\]

We can rearrange terms in [5.6] to write

\[
\begin{bmatrix}
e^v \\
e^z
\end{bmatrix} =
\begin{bmatrix}
1 & -\alpha
\end{bmatrix}^{-1}
\begin{bmatrix}
b_{11} & 0 \\
\rho b_{11} & b_{22}
\end{bmatrix}
\begin{bmatrix}
\varepsilon^s \\
\varepsilon^d
\end{bmatrix}
\]

or

\[
\begin{bmatrix}
e^v \\
e^z
\end{bmatrix} =
\frac{1}{1+\alpha}
\begin{bmatrix}
1 & \alpha
\end{bmatrix}
\begin{bmatrix}
b_{11} & 0 \\
\rho b_{11} & b_{22}
\end{bmatrix}
\begin{bmatrix}
\varepsilon^s \\
\varepsilon^d
\end{bmatrix}
\]

or

\[
\begin{bmatrix}
e^v \\
e^z
\end{bmatrix} =
\frac{1}{1+\alpha}
\begin{bmatrix}
(1+\alpha\rho)b_{11} & \alpha b_{22}
\end{bmatrix}
\begin{bmatrix}
\varepsilon^s \\
\varepsilon^d
\end{bmatrix}
\tag{5.7}
\]
Using [5.7], the matrix representing the contemporaneous effects of the structural shocks can be shown as:

\[
\begin{bmatrix}
    d_{11}^0 & d_{12}^0 \\
    d_{21}^0 & d_{22}^0
\end{bmatrix} = \begin{bmatrix}
    (1 + \alpha \rho) b_{11} & \alpha b_{22} \\
    1 + \alpha & 1 + \alpha \\
    -(1 - \rho) b_{11} & b_{22} \\
    1 + \alpha & 1 + \alpha
\end{bmatrix}
\]  

[5.8]

It can also be shown that equation [5.7] implies

\[
\begin{bmatrix}
    \text{var}(e^y) & \text{cov}(e^y, e^x) \\
    \text{cov}(e^y, e^x) & \text{var}(e^x)
\end{bmatrix} = \begin{bmatrix}
    (1 + \alpha \rho) b_{11} & \alpha b_{22} \\
    1 + \alpha & 1 + \alpha \\
    -(1 - \rho) b_{11} & b_{22} \\
    1 + \alpha & 1 + \alpha
\end{bmatrix}\begin{bmatrix}
    (1 + \alpha \rho) b_{11} & -(1 - \rho) b_{11} \\
    1 + \alpha & 1 + \alpha \\
    \alpha b_{22} & b_{22} \\
    1 + \alpha & 1 + \alpha
\end{bmatrix}
\]  

[5.9]

The left hand side of [5.9] has 3 known elements, which are obtained from the estimation of the reduced form VAR. But in the right hand side we have 4 parameters to be estimated. To identify the model, we must impose another restriction, and this additional restriction comes from the assumption that the AD shock does not have any long run effect on output. This long run neutrality assumption implies:

\[
d_{12}^0 = -\frac{a_{12}(1)}{1 - a_{22}(1)} d_{22}^0
\]

Using [5.8], this can be rewritten as

\[
\alpha = -\frac{a_{12}(1)}{1 - a_{22}(1)}
\]

[5.10]

We can substitute the value of \( \alpha \) in [5.9] to solve for the rest of the parameters in an exactly identified model.

The parameter \( a_{12}(1) \) and \( a_{22}(1) \) can be obtained from the reduced form VAR. Our reduced form VAR estimates give \( a_{12}(1) \) \( = -0.13 \) or \( a_{22}(1) = 0.13 \). This implies that the aggregate supply curve is very steep. For a steeper short run aggregate supply curve, the aggregate demand shock is supposed to have large effect on the inflation rate and little effect on the output level in the short run. In fact, the steeper AS curve is consistent with
our earlier analysis, where we found significant effect of the AD shock on inflation, but none on the output level.

Case 2: The demand shock is causally prior to the supply shock

If the AS shock is affected by the AD shock, then the aggregate supply shock can be redefined as: \( \gamma(b_{22}^d e^d_i) + b_{11}^s e_i^s \). Here \( b_{11}^s e_i^s \) is a pure AS shock, which is uncorrelated with the AD shock and \( \gamma(b_{22}^d e^d_i) \) is the component of AS shock that is induced by the AD shock. In this case [5.5] may be rewritten as:

\[
\begin{bmatrix}
1 & -\alpha \\
1 & 1
\end{bmatrix}
\begin{bmatrix}
e^s \\
e^\pi
\end{bmatrix}
= 
\begin{bmatrix}
b_{11} & \gamma b_{22} \\
0 & b_{22}
\end{bmatrix}
\begin{bmatrix}
e^d \\
e^s
\end{bmatrix}
\]

or

\[
\begin{bmatrix}
e^s \\
e^\pi
\end{bmatrix}
= 
\begin{bmatrix}1 & -\alpha \end{bmatrix}^{-1}
\begin{bmatrix}
b_{11} & \gamma b_{22} \\
0 & b_{22}
\end{bmatrix}
\begin{bmatrix}
e^s \\
e^d
\end{bmatrix}
\]

or

\[
\begin{bmatrix}
e^s \\
e^\pi
\end{bmatrix}
= 
\frac{1}{1+\alpha}
\begin{bmatrix}
b_{11} & (\alpha + \gamma) b_{22} \\
-b_{11} & (1-\gamma) b_{22}
\end{bmatrix}
\begin{bmatrix}
e^s \\
e^d
\end{bmatrix}
\]

Now, we have

\[
\begin{bmatrix}
d_{11}^0 & d_{12}^0 \\
d_{21}^0 & d_{22}^0
\end{bmatrix}
= 
\begin{bmatrix}
b_{11} & (\alpha + \gamma) b_{22} \\
1+\alpha & 1+\alpha \\
-b_{11} & (1-\gamma) b_{22} \\
1+\alpha & 1+\alpha
\end{bmatrix}
\]

The variance-covariance matrix of the reduced form VAR residuals can be defined as

\[
\begin{bmatrix}
\text{var}(e^s) & \text{cov}(e^s, e^\pi) \\
\text{cov}(e^s, e^\pi) & \text{var}(e^\pi)
\end{bmatrix}
= 
\begin{bmatrix}
b_{11} & (\alpha + \gamma) b_{22} \\
1+\alpha & 1+\alpha \\
-b_{11} & (1-\gamma) b_{22} \\
1+\alpha & 1+\alpha
\end{bmatrix}
\]

Again, we need to impose an additional restriction to identify the system [5.14]. Here we assume that the aggregate demand shock does not have any effect on the output level in the long-run as long as it does not shift the AS curve. This assumption essentially gives us the same expression for \( \alpha \) (as in 5.10). As a matter of fact, we are assuming a vertical long-run AS curve, however, we are not ruling out the case in which the long-run AS
curve may shift due to an aggregate demand shock. Now the value of $\alpha$ from [5.10] can be substituted in [5.14] to solve for the remaining three parameters.

5.2 Estimation Results

Table 5.1 reports the estimated coefficients of the structural parameters under three alternative assumptions based on the reduced form VAR with $\Delta Y$ and $\Delta \pi$. The slope of the aggregate supply curve ($\alpha$) is first estimated using [5.10] and the estimated value of 0.13 suggests a very steep short-run aggregate supply curve. One implication of a steeper aggregate supply curve is that in the short-run aggregate demand shock leads to a large change in the inflation rate, but not that much in the output level.

Table 5.1: Estimates of the Structural Parameters under Alternative Assumptions

<table>
<thead>
<tr>
<th>Assumptions</th>
<th>$b_{21}$</th>
<th>$b_{22}$</th>
<th>$\rho$</th>
<th>$\gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>BQ: No Causality across the Shocks (Equation [5.5])</td>
<td>1.291902 (0.140958)</td>
<td>1.534963 (0.167478)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case 1: Causality from Supply to Demand (Equation [5.6])</td>
<td>1.291902 (0.140958)</td>
<td>1.431347 (0.156173)</td>
<td>0.429133 (0.170959)</td>
<td></td>
</tr>
<tr>
<td>Case 2: Causality from Demand to Supply (Equation [5.11])</td>
<td>1.204694 (0.131443)</td>
<td>1.534963 (0.167478)</td>
<td>0.303987 (0.121103)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The slope of the AS curve ($\alpha$) is estimated as 0.13 in all three models. Figures in parentheses are asymptotic standard errors.

The first row reports the standard deviation of two shocks when the shocks are not assumed to be correlated. The standard deviation of the supply and demand shocks are 1.29 and 1.53 respectively and these two figures are statistically significant. When the causality is assumed to run from supply to demand, the standard deviation of the supply shock remains the same, but the standard deviation of the independent demand shock is now a bit lower (1.43). This is expected; as the demand shock is now divided in two components and this independent demand shock is just one component of the entire demand shocks. The contemporaneous response of the demand shock to the supply shock

---

8 We did not estimate the SVAR model with Industrial Production Index ($IP$) as it is evident from the results of the BQ approach that the basic conclusions drawn from the two SVAR models are essentially the same.
(ρ) is positive (0.43), which is reasonably high and statistically significant. This is consistent with our a-priori presumption that the demand shock responds positively to a shock in the aggregate supply.

In opposite case, when the causality is assumed to run from demand to supply, the standard deviation of the supply shock becomes lower (1.2) while that of demand shock remains same as in the Benchmark BQ model. The estimated coefficient of contemporaneous response of the supply shock to the demand shock (γ) is significantly positive (0.30). This is also consistent with the idea that favourable (adverse) supply shocks take place during the period of high (low) aggregate demand.

Figure 5.2: Accumulated Impulse Responses- Causality Running from Supply to Demand

Note: The solid lines give the estimates of the accumulated responses, while the dotted lines represent the bootstrap 95 percent confidence bound.
Figure 5.2 shows the estimated impulse response functions to output and inflation to two independent shocks for the case when aggregate supply shock is assumed to affect the aggregate demand shock. The estimated responses are almost the same as those in the standard BQ model shown in figure 4.2. The variance decompositions of the changes in output and inflation are also similar to those in the standard BQ model reported in table 4.4. Most of the variation in the output level is caused by the supply shock, whereas the variation in the inflation rate is largely demand-driven.

Table 5.2: Variance Decomposition - Causality Running from Supply to Demand

<table>
<thead>
<tr>
<th>Period</th>
<th>Variation in $\Delta y$ due to</th>
<th>Variation in $\Delta \pi$ due to</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Supply shock</td>
<td>Demand Shock</td>
</tr>
<tr>
<td>1</td>
<td>98.17292</td>
<td>1.827075</td>
</tr>
<tr>
<td>2</td>
<td>96.0367</td>
<td>3.963295</td>
</tr>
<tr>
<td>3</td>
<td>91.6715</td>
<td>8.328505</td>
</tr>
<tr>
<td>4</td>
<td>89.82678</td>
<td>10.17322</td>
</tr>
<tr>
<td>5</td>
<td>91.29638</td>
<td>8.703617</td>
</tr>
<tr>
<td>6</td>
<td>91.39362</td>
<td>8.606382</td>
</tr>
<tr>
<td>7</td>
<td>91.33219</td>
<td>8.667810</td>
</tr>
<tr>
<td>8</td>
<td>91.33645</td>
<td>8.663552</td>
</tr>
<tr>
<td>16</td>
<td>91.74928</td>
<td>8.250722</td>
</tr>
<tr>
<td>24</td>
<td>91.78443</td>
<td>8.215574</td>
</tr>
<tr>
<td>32</td>
<td>91.78762</td>
<td>8.21238</td>
</tr>
<tr>
<td>40</td>
<td>91.78793</td>
<td>8.212073</td>
</tr>
</tbody>
</table>

The scenario is, however, quite different when we consider the case of the causality running from demand to supply. The corresponding impulse response functions are shown in figure 5.2. The figure shows that the response of the inflation rate to the supply shock is significantly negative both in the short and long horizon of time. The response of the output level to the demand shock is initially positive although the significant positive effect is very short lived. The response of the output level to the supply shocks and that of the inflation to the demand shocks are both positive and significant throughout the response horizon. One important feature of the AD shock is that it causes larger effects on output and smaller effects on inflation compared to the corresponding effects in standard BQ model (figure 4.3) and the Case 1 above. This is not surprising, as shifting of the AD curve also shifts the AS curve by the proportion of $\gamma$ and hence, final effect on
inflation will be lower and output response will be higher compared to the case where there is no shift in the AS curve due to the demand shock.

Figure 5.3: Accumulated Impulse Responses- Causality Running from Demand to Supply

![Graphs of Accumulated Impulse Responses](image)

Note: The solid lines give the estimates of the accumulated responses, while the dotted lines represent the bootstrap 95 percent confidence bound.

The corresponding variance decompositions also show that a demand shock has higher role for the variation in output growth and lower role for the variation in the changes in inflation. In other words, now supply shocks have lower contribution in changing output and higher contribution in changing inflation. For example, after 40 quarters, the supply shock can explain about 80 percent of the variation in output changes and 57 percent in the changes in inflation. The corresponding figures in the standard BQ model were about 91 percent and 78 percent respectively.
Table 5.3: Variance Decomposition - Causality Running from Supply to Demand

<table>
<thead>
<tr>
<th>Period</th>
<th>Variation in $\Delta y$ due to Supply shock</th>
<th>Variation in $\Delta y$ due to Demand shock</th>
<th>Variation in $\Delta \pi$ due to Supply shock</th>
<th>Variation in $\Delta \pi$ due to Demand shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>76.58312</td>
<td>23.41688</td>
<td>55.9766</td>
<td>44.0234</td>
</tr>
<tr>
<td>2</td>
<td>72.542</td>
<td>27.458</td>
<td>56.03744</td>
<td>43.96256</td>
</tr>
<tr>
<td>3</td>
<td>75.9878</td>
<td>24.0122</td>
<td>56.02414</td>
<td>43.97586</td>
</tr>
<tr>
<td>4</td>
<td>75.75087</td>
<td>24.24913</td>
<td>56.55627</td>
<td>43.44373</td>
</tr>
<tr>
<td>5</td>
<td>78.89616</td>
<td>21.10384</td>
<td>56.85325</td>
<td>43.14675</td>
</tr>
<tr>
<td>6</td>
<td>78.43122</td>
<td>21.56878</td>
<td>56.72803</td>
<td>43.27197</td>
</tr>
<tr>
<td>7</td>
<td>78.99379</td>
<td>21.00621</td>
<td>56.51025</td>
<td>43.48975</td>
</tr>
<tr>
<td>8</td>
<td>79.02787</td>
<td>20.97213</td>
<td>56.52534</td>
<td>43.47466</td>
</tr>
<tr>
<td>16</td>
<td>80.07748</td>
<td>19.92252</td>
<td>56.61929</td>
<td>43.38071</td>
</tr>
<tr>
<td>24</td>
<td>80.18129</td>
<td>19.81871</td>
<td>56.61881</td>
<td>43.38119</td>
</tr>
<tr>
<td>32</td>
<td>80.19157</td>
<td>19.80843</td>
<td>56.61873</td>
<td>43.38127</td>
</tr>
<tr>
<td>40</td>
<td>80.19258</td>
<td>19.80742</td>
<td>56.61874</td>
<td>43.38126</td>
</tr>
</tbody>
</table>

6. Summary and Conclusion

In this paper we basically tried to analyse the roles of aggregate demand and supply shocks in affecting inflation and output. We started with examining the cyclical behaviour of the price level and inflation in order to have an indication about which shocks – demand or supply – are predominant in Bangladesh. The finding is ambiguous. This may be an indication of the fact that neither the demand nor the supply shocks are predominant in Bangladesh and they are mostly cancelling out the effects of each other.

We then attempted to identify the aggregate demand and supply shocks from a bivariate SVAR model. The shocks are identified from the VAR residuals using a long run restriction proposed by Blanchard and Quah. The estimation of impulse response functions and the variance decompositions indicates a very steep short run aggregate supply curve and also suggest that inflation is mainly demand-driven whereas the output level is basically supply-driven.

One limitation of the Blanchard-Quah model is that this is based on the assumption that demand and supply shocks are uncorrelated. In an attempt to overcome this limitation,
following Cover et al (2006), we introduce a simple AD-AS model and estimate corresponding SVAR system. We particularly consider two different cases; the first of which assumes that the supply shock is causally prior to the demand shock, whereas the second one assumes that the demand shock is causally prior to the supply shock. We have found strong empirical support for both cases. Model based on the first case shows that the demand shock accommodates about 42 percent of the supply shocks in the contemporaneous period. In the second case we found that the supply shock accommodates about 30 percent of the demand shocks in the same quarter. We have also estimated the impulse response functions and variance decompositions for each of these two cases.

The impulse response functions and the variance decompositions in the first case (supply shock shifts the AD curve) are almost similar to the standard BQ case. The second model (demand shock shifts the AS curve), however, shows some noticeable difference. Most important feature of this model is that supply shock appears to have greater role for inflation, which was absent in the standard BQ model. However, the response of the inflation to the demand shock is found significant at all time horizons and the demand shock can still explain about 43 percent of the variation in inflation in the long run.

The results of this paper have important implication for the monetary policy of Bangladesh. Monetary policy is typically a demand management policy, and the finding that the demand shock significantly affects inflation indicates that in Bangladesh tightening of monetary policy can be used effectively in the fight against inflation. However, as it is evident that demand shocks significantly shifts the aggregate supply curve outwards, tightening of policy may lead to having an adverse effect on the long-run growth potentials.
References


APPENDIX A

Data and Their Sources

Our analysis uses the quarterly data that covers the periods 1993:Q3 – 2006:Q1. The definitions of the variables that are used throughout this chapter are given below.

\[ Y = \log \text{ of real GDP.} \] The original real GDP series is at 2000 Price (in Million Taka). Quarterly series is estimated from annual data applying a simple disaggregation method, which is explained in Appendix B. Source: IMF (International Financial Statistics Online Database).

\[ \Delta Y = \text{The first difference of } Y, \text{ which is generated from the } Y \text{ series as} \]
\[ \Delta Y = (Y_t - Y_{t-1}) \times 100 \]

\[ IP = \log \text{ of Industrial Production Index. (Base = 2000). Source: IMF (International Financial Statistics Online Database).} \]

\[ \Delta IP = \text{The first difference of } IP, \text{ which is generated from the } IP \text{ series as} \]
\[ \Delta IP_t = (IP_t - IP_{t-1}) \times 100 \]

\[ p = \log \text{ of Consumer Price Index (CPI) (Base = 2000). Source: IMF (International Financial Statistics Online Database).} \]

\[ \pi = \text{Annualized inflation rate. This is calculated from the CPI series as} \]
\[ (p_t - p_{t-4}) \times 100. \] Source: IMF (International Financial Statistics Online Database).

\[ \Delta \pi = \text{The first difference of } \pi, \text{ which is generated from the } \pi \text{ series as} \]
\[ \Delta \pi = (\pi_t - \pi_{t-1}). \]
APPENDIX B
Disaggregation of Real GDP Data

The idea of our disaggregation method is quite simple\(^9\). Suppose we want to disaggregate the series \(Y\). \(X\) is another series closely related to series \(Y\). In our analysis \(Y\) is the real GDP (in local currency), \(X = \) total volume (in local currency) of trade (total import plus export) and we want to estimate the quarterly real GDP. In annual frequency, the trade series is found highly correlated \((r = .97)\) with real GDP. It may be noted that data on \(X\) is available both in annual and quarterly basis and here we denote the actual quarterly series of \(X\) by \(X_q\).

The technique applied here is quite simple. It basically involves following steps:

**Step 1**: Regress \(Y\) on \(X\) using OLS: \(Y = a + bX\) to get an estimate of \(b\).

**Step 2**: Interpolate (using quadratic sum) \(Y\) and \(X\) to get the quarterly interpolated series \(Y^*\) and \(X^*\).

**Step 3**: Calculate the quarterly real GDP as \(Y_q = Y^* + b(X_q - X^*)\)

We, however, made some modification over this procedure. Since both \(Y\) and \(X\) are nonstationary, the estimates in step 1 may not be consistent unless the residuals are stationary. Thus we use the annual differences of each series (one year difference for annual data and four-quarter difference for quarterly data) in step 1 – 3 above.

Here we needed an additional step to recover the final quarterly series in level \((Y_{qt})\) from the series expressed in 4-quarter difference \((\Delta^4Y_{qt})\) as follows:

\[
Y_{qt} = Y_{q0} + \sum_{t} \Delta^4Y_{qt}
\]

The source of all the data used in this disaggregation method is the International Financial Statistics Online database. We use the annual series of real GDP and total trade covering the period 1974-2005. Using Quadratic-Sum Interpolation technique, we

\(^9\) The basic idea of this method is described as Vangrevelinghe’s Method in Ginsburgh (1971).
construct the quarterly interpolated Output ($Y^*$) and Trade ($X^*$) series that runs from 1974Q3 to 2006Q1. The actual quarterly Trade series is also available for these periods. Since we used differenced data, our interpolation of data begins in the year of 1975. Our estimated quarterly GDP data essentially ranges from 1975:Q3 to 2006:Q1.