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Estimation and Forecasting of Industrial Production Index

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Abstract

It is essential for policy makers to timely consider the cyclical changes in output. Monthly industrial production is one of the most important and commonly used macroeconomic indicators for this purpose. In Pakistan monthly estimates of industrial production are not available. Alternatively, policy makers rely on Large Scale Manufacturing (LSM) index which accounts for only 10% of the GDP. Another limitation of LSM is that it mainly accounts for private sector industry thus leaving out direct public sector presence in industrial production. LSM is relied upon heavily by economic policy makers to gauge economic activity in Pakistan. In this paper, we present a new Industrial Production Index (IPI), which covers whole of industrial sector in Pakistan. The advantage of this IPI index is that it provides additional information that LSM misses out. Post estimation, we built seven econometrics models reflecting conditions in real, financial and external sectors to estimate YoY changes in the proposed Industrial Production Index (IPI). Our results show that the root mean square error of the ARDL model reflecting financial conditions is lowest across all horizons

JEL Classification: L600, C80, C530
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Non-technical Summary

Industrialization leads to economic growth. Most developed economies grew through the process of industrialization. Accordingly, tracking industrial production is key understanding the aggregate fluctuations which affect economic growth. Industrial production has also been seen to closely associate with services sector which tends to be the largest component in national GDP. Major central banks world over- including the Fed in USA and ECB- accord due importance to industrial production for short term economic policy due to its practical advantages. First, industrial production is more frequently available compared to GDP which is available less frequently. Secondly, industrial production leads economic activity thus is a good proxy for overall GDP growth.

In Pakistan, Industry accounts for 23% of the total GDP. Data on industrial production in Pakistan is not available on high frequency. As a proxy of industrial production, policy makers in Pakistan rely on Large Scale Manufacturing (LSM) which is sub-component of total industrial production. Using LSM, to gauge cyclical changes in economy also deprives analysts and policy makers of understanding public-sector induced industrial growth since LSM mainly consists of private sector industry mainly. Thus the need for a broader index accounting for whole of industrial production arises unequivocally.

In this paper we have attempted to compute an Industrial Production Index (IPI) that covers overall value added by Industry in the Pakistan's total GDP. Our proposed index is robust and passes a battery of litmus tests. The advantage of our proposed index is that it provides additional information that LSM misses out. We also provide a range of econometric models which can be used to forecast future industrial production.

1. Introduction

Industrial production is one of the key variables of interest for short term economic policy analysis. This is true despite services sector having the largest share in the GDP. In fact, the industrial sector is important in explaining aggregate fluctuations, also because some of the services activities are closely linked to the industrial ones (Lupi & Bruno, 2004). It is for this reason that economists consider industrial production as a leading indicator of economic activity (Banerjee, 2005). Industrial output has also been found to closely related with level of income (Hemamala et. al 1992). Bean (1946) specifically showed that differences in per capita income were explained by stages[1] and patterns[2] of industrialization across countries.

Accordingly, Industrial production is given due weight in policy analyses by major central banks around the world. Board of Governors of the Federal Reserve System, attaches utmost importance to industrial production in policy analysis. It uses industrial production as an economic indicator to gauge movements in production output and highlight structural developments in the economy[3]. Similarly, researchers and policy makers at ECB also attach utmost due importance to understanding short term changes in the EU's real activity indicated by industrial production (Bodo, 2000).

Industry accounts for 23% of the total GDP at producer's price of Pakistan (See Table-1). Data on industrial production in Pakistan is not available on high frequency basis as Pakistan's GDP is officially available annually. Pakistan Bureau of Statistics (PBS) once provided a series of Industrial production but that series is available since 1999M7. Later PBS discontinued the series in 2012. Arby (2008), Nadim et. al. (2013) and Tahir et. al. (2017) make notable attempts estimating the national accounts on quarterly basis, however, their estimates do not provide series for industrial production as a separate component.

Characteristics of data on industrial production tend to be high-frequency containing cyclical information that is important for economic policy decisions (Bordo, 2000). Yet there has hardly been any effort on measuring industrial production in Pakistan on monthly basis. This has further enhanced the need for availability of monthly estimates on industrial production especially when monetary policy in Pakistan is now conducted on alternate months of every fiscal year. In the absence of complete information on industrial production, policy makers in Pakistan are compelled to make do with proxies such as Large Scale Manufacturing (LSM) which accounts for 10% of the overall industrial production (see Table-1). More importantly, Pakistan Bureau of Statistics (PBS) publishes LSM index with a considerable lag. Rehman et. al. (2018) attempt to address this issue of data delays by providing early estimates of LSM but these are not without limitations since they are early estimates of the actual production. Moreover, the issue of coverage still remains since substantial (about 13%) information on industrial production is not accounted for due to unavailability of an appropriate series. By only relying only on a sub-component (LSM) of overall valued added by industry, the policy makers essentially miss out on crucial information to the tune of PKR 1.6 trillion of GDP (See Table-1) that might influence cyclical changes in the industrial production.

Another short coming of LSM is that it is mostly made up of private sector industry. In Pakistan, public sector has large presence in industrial production. For example, electricity and gas distribution which accounts for nearly 7.4% of total industry. Realizing this need, we have developed a new Industrial Production Index (IPI) for Pakistan which addresses the aforementioned issues.

The contributions of this study are twofold. First, we fill the gap by providing an index of industrial production, which not only enhances the coverage that LSM lacks but is also based on monthly frequency. Secondly, we attempt to forecast the proposed index using a range of econometric models in search of a true model. To this end, we use models to forecast the proposed industrial production index. These models take into account conditions in the real, external and financial sectors. We think

[1] By stage of industrialization, the author meant the proportion of a country's working population engaged in the primary occupations—agriculture, forestry, and fishing.
[2] By pattern of industrialization, Bean meant, the relative importance of secondary occupations (manufacturing, mining, and construction) and relative importance of tertiary occupations (trade and services).
[3] https://fred.stlouisfed.org/series/INDPRO

the forecasts churned out by these models can be useful to stakeholders within and outside of SBP. We have evaluated the forecasting performance of our models to show that they can be useful for policy analysis and economic discussions.

The rest of the paper is organized in seven sections. Section-II covers the literature review. In Section III that followed, we provide the estimation methodology of the IPI for all sectors and sub-sectors of industry which is followed by Section-IV which is dedicated to analyzing and testing the newly estimated IPI. In Section-V we discuss data issues followed by Section-VI which specifies the models used to forecast the IPI. Forecast evaluations are discussed subsequently while the last section provides concluding remarks.

2. Literature Review

It is important to make note of the prior efforts by researchers to make the national income accounts available more frequently. These are helpful to policy makers for analyses of cyclical changes in economic activity. A major contribution in this respect is of Arby (2008) who compiled national accounts of Pakistan. The study provides a thorough account of the relevant literature. The paper also takes note of the earlier studies including Bengaliwala (1995), Kemal & Arby (2004) for their efforts to enhance frequency of national accounts. These authors generate national income accounts using 1980-81 as base year. Similarly, Arby & Batool (2007) quarterised overall gross fixed capital formation. More recently, Hanif, & Iqbal (2013) provided estimates for quarterly private and public sector gross fixed capital formation separately, in addition to estimates of quarterly overall gross fixed capital formation.

These studies have helped made GDP available at higher frequency; their focus was generally on estimating the aggregate national accounts and not the industrial production component despite that fact that it is critical to understand the short term changes in economic activity. Present study fills this gap by providing monthly estimates of industrial production for the period 1990M7:2018M6.

3. Estimation of Monthly Industrial Production Index

Industry accounts for 23% of the total GDP at producer's price released provisionally by PBS (see Table-1) It is sub-divided into four major sectors. Within industry, manufacturing accounts for 56.9% followed by Mining & Quarrying at 11.6% of the industry. Electricity generation & distribution and Gas distribution takes up 7.4% while construction constitutes 11.9% of the total value added industry. Manufacturing within industry is further divided into three sub-sectors namely Large-Scale, Small Scale and Slaughtering which take up 79.6%, 13.8% and 6.5% respectively.

In the following sub-sections, we define the formal set up for obtaining Industrial Production Index (IPI) for each sub-sector within industry. In doing so, we have relied on the methodology proposed by Arby (2008) that was subsequently used by Hanif, Iqbal & Malik (2013) to estimate quarterly GDP of Pakistan using production approach.

The monthly Industrial Production Index is the sum of monthly value added by each sub-sectors given by the following equation.

$$IPI_m = \left[\frac{M\&Q_{m,y}+LSM_{m,y}+SSM_{m,y}+VAS_{m,y}+VAC_{m,y}+VAE_{m,y}}{\frac{1}{12}\sum_{m=1}^{12}(M\&Q_{m,2005-06}+LSM_{m,2005-06}+SSM_{m,2005-06}+VAS_{m,2005-06}+VAC_{m,2005-06}+VAE_{m,2005-06})}\right]*100 \qquad (1)$$

In equation (1) above, M&Q denotes Mining & Quarrying, LSM refers to Large Scale Manufacturing, SSM for Small Scale Manufacturing, VAS &VAC refer to values added by Slaughtering & Cement sectors respectively and VAE is valued added by energy sector. *n* indicates the number of sectors. *m* denotes the valued added by that sector in a given month and *y* indicates the yearly value added by a sector. The methods employed to obtained monthly values for each sector have been discussed below.

3.1 Mining & Quarrying

The first major sub-sector within industry is Quarrying & Mining. This subgroup consists of 33 minerals whose production figures are regularly published in the Monthly Statistical Bulletin published by PBS. For each mineral, we have added the respective production value over the twelve months of each fiscal year. Then we have divided the resultant figure by yearly estimate of Mining & Quarrying (MQ) estimated by Hanif, Iqbal & Malik (2013) to obtain monthly weight of M&Q in industry. We then weighted the yearly figure of Mining & Quarrying (M&Q) of industry available from PBS. Formally, this is expressed as follows

$$M\&Q_{m,y} = \left[w_{m,y} * M\&Q_y\right] \qquad (2)$$

Where $w_{m,y}$ is weighted average of the share of each item in production calculated as follows.

$$W_{m,y} = \sum_{i=1}^{33}\left[\frac{P_{i,m,y}}{\sum_{m=1}^{12} P_{i,y}} * SGVA_i\right] \qquad (3)$$

In the expression above, SGVAi is the share of gross valued added by commodity i in base year 2005-06.

3.2 Manufacturing

Manufacturing is further divided into three sectors. Large-Scale Manufacturing accounts for 79.6% of the total manufacturing, Small Scale takes up about 13.8% while Slaughtering's share is 6.5%. estimation methodology for respective sub-sector is discussed below.

3.2.1 Large Scale Manufacturing (LSM)

The monthly value of LSM is estimated by first estimating the monthly weights of LSM and then multiplying annual LSM production. The weights are determined by using the monthly and annual LSM indices available in Monthly Statistical Bulletin published by PBS. Basically for each month, we divide the monthly LSM index by respective annual LSM index to obtain the weight and then multiply that weight by annual LSM production as expressed in equation (4) below

$$LSM_{m,y} = \left[\frac{LSMI_{m,y}}{\sum_{m=1}^{12} LSMI_{m,y}}\right].LSM\ (Rs.in\ Millions)_y \qquad (4)$$

Where $LSM_{m,y}$ is the value added by LSM in month *m* and fiscal year y and $LSM_{m,y}$ is the monthly index of large scale manufacturing for month *m* in year y.

3.2.2 Small Scale Manufacturing (SSM)

SSM is obtained in the same manner as LSM using the following expression

$$SSM_{m,y} = \left[\frac{LSMI_{m,y}}{\sum_{m=1}^{12} LSM_{m,y}}\right].SSM\ (Rs.in\ Millions)_y \qquad (5)$$

3.3 Slaughtering

We could not have used the aforementioned methods for estimating monthly production of slaughtering since no index is available. Accordingly, we have relied on the quarterly weights of slaughtering estimated in (PBS, 2002a) and linearly decomposed those weights into monthly weights. The respective quarterly weights are 0.18 for Q1, 0.25 for Q2, 0.35 for Q3, 0.22 for Q4. We have implemented these by simply dividing the weights by 3 to obtain monthly weights and multiplying them by annual value added under slaughtering available on PBS to obtain monthly value added under slaughtering using following expression

$$S_{m,y} = w_m.SSM\ (Rs.in\ Millions)_y \qquad (6)$$

Where w_m is the weight for each month of the fiscal year. For m=1,2&3 the respective weight 0.06. For m=4,5,6 the weight applied is 0.083. For m=7,8,9 the weight used is 0.117 and for m=10,11,12 the weight used is 0.073.

3.2.4 Construction

Cement production is the major component of construction. We have used cement production C with 3 months lag to estimate the total value added by construction using following expressions

$$VAC_{m,y} = \left[\frac{PoC_{m,z,y}}{\sum_{m=1}^{12} PoC_{m,z,y}}\right].VAC\ (Rs.in\ Millions)_y \tag{7}$$

Wherein $VAC_{m,y}$ indicates the value added by construction sector for month m of the fiscal year y. $PoC_{m,z,y}$ denotes production of cement for month m for year z. Year z follows year y with a 3-month lag (April to March). VAC_y denotes the value added by construction sector for year y available on PBS.

3.2.5 Energy

Energy accounts for 7.4% of the total industrial production. This component of the industry consists of Electricity Generation & Distribution and Gas Distribution. While PBS provides monthly data of total electricity generation and Gas distribution; the annual value added by these components is provided on a combined basis by PBS. Since the units of two sources of energy are different therefore they could not have been summed up to calculate the monthly weights. This anomaly was dealt with by using the production values of Gas and Electricity expressed in a common unit called TOE available in Energy Year Book for the periods 1999-2017. First for each year, the weights for Gas and Electricity was estimated using the production values of Gas and Electricity for the periods 1999-2017 and averaged over the same period. This results in weights of 0.704 for electricity and 0.296 for gas. In the next step, monthly shares of Gas and Electricity were calculated for each month of the fiscal year for the period of the sample in study and multiplied with respective shares from energy year book to arrive at a common share for each fiscal year in the sample. These weights were then used to estimate monthly value added by energy in the industrial sector using following equation (8)

$$W_{m,y} = \left[\frac{PoE_{m,y}}{\sum_{m=1}^{12} PoE_{m,y}} * SoE_y\right] + \left[\frac{PoG_{m,y}}{\sum_{m=1}^{12} PoG_{m,y}} * SoG_y\right] \tag{8}$$

Where $w_{m,y}$ is weighted average of the share of Electricity & Gas. SoE_y and SoG_y are respective shares of electricity & Gas in total energy in year y. These weights are used to arrive at energy index using the expression below.

$$E\&G_{m,y} = \left[w_{m,y} * E\&G_y\right] \tag{9}$$

4. Analysis and Testing of Estimated IPI

Putting together all the sub-components in equation (1) results in IPI production index whose graph is available in Figure-1. We have carried various statistical and validation tests to lend credence to the calculated IPI.

First, sum of the monthly estimates of value added by industry add up to sectoral value added by industry available in national income accounts. The same can be verified from actual series provided in Appendix-A. Secondly, we plotted our estimated IPI with the IPI once officially published by PBS. This series is available since 1999M7 and was later discontinued in 2012M12. We converted the old PBS series on base year 2005-06 and plotted it with our calculated IPI. The juxtaposed series are available in Figure-2. Both series seem to be highly correlated. The correlation between the two series is high at 0.97 (see Table-2). The results in the same table also show Pearson Correlation Coefficient for testing for zero correlation. The associated p-value show that the strong correlation of 0.97 is statistically significant at 5%.

We test for persistence by estimating the coefficients of both series for the common sample period using ARMA (1,1) models. Results in Table-2 show that the magnitude of two coefficients are nearly same and statistically significant thus indicating strong persistence. We also regressed the YoY changes in old series of PBS on our new IPI index using least squares. The coefficient is a strong 0.95 and statistically significant with model explaining 57% variation.

Overall the computed series strongly correlates with the old series of PBS in the common sample and their AR (1) coefficients are high and statistically significant indicating persistence. The YoY changes in new series also strongly explain the YoY changes in old IPI index of PBS.

5. Modelling and Forecasting of IPI

We identify determinants of industrial production from empirical literature below which were later used to develop specifications for various single and multiple equation econometric models.

5.1 Determinants of Industrial Production

Hettigue, Lucas & Wheeler (1992) find that toxic intensity, environmental regulation and trade policy (quota and tariffs) negatively affect industry. Marchetti & Parigi (2000) use indicators of industrial activity such as electricity consumption[4] to forecast industrial production. Lupi & Burno (2004) use quantity of goods transported by railways and an index developed based on opinions of entrepreneurs about future production prospects to forecast industrial production. Jiranyakul (2006) study impact of international oil prices, real exchange rate and real money supply on Thailand's industrial production. Dutta & Ahmed (2004) show that there exists a unique long-run relationship among the aggregate growth function of industrial value added and its major determinants of the real capital stock, the labor force, real exports, the import tariff collection rate and the secondary school enrolment ratio. Tabak & Feiosta (2010) investigate to see if the term spread presents information that can help predict the path followed by industrial production. Their result suggests that the yield spread contains relevant information for explaining industrial production. Enu & Hagan (2013) identify real petroleum prices and real exchange rate as negatively affecting the industrial production while import of goods & services and government spending as positive factors influencing industrial production. Mohsen, Chua & Sab (2015) argued that industrial output is positively related to capital, manufactured exports, population and agricultural output, but negatively related to the oil price. Jain, Nair & Vishali (2015) find FDI, import, exports, and exports as important determinants of industrial components of India's GDP.

In the case of Pakistan, the literature on industrial production is limited. Perhaps the most relevant study is by Ajmair & Hussain (2017) who attempt to explain industrial production in an ARDL setup with external debt shocks, FDI, GDP, Exports, inflation and personal remittances. They find that trade and personal remittances are positive determinants of IP in Pakistan. Hussain, Hyder & Rehman (2018) uses a range of macroeconomic variables to forecast LSM[5]. Note, however, that their study only takes into account LSM as a proxy of industrial production (a fact they specifically mention), rather than actual industrial production index due to its unavailability. Most of their variables have already been mentioned above. Others include total tax collections, credit, LSM, WPI and interest spreads. Variables which could be important determinants- for which no empirical support was found-may be global GDP and unemployment.

In this study, it is not possible to consider all the variables due to the issue of degrees-of--freedom. Also, population, labor-force participation or unemployment, secondary school enrollment are essentially various proxies of main variable Labor supply. In such situation we have only picked variable that best explains the model or based on behavioral relationships that is most suitable in case of Pakistan. The definitions of variables and classification used along with data sources are available in Table-3. The classification is used to specify different models in later sections.

[4] theoretical rationalization of the use of electricity consumption data along with convincing empirical evidence on their reliability in forecasting industrial production has established (Bodo and Signorini, 1987; Bodo and Signorini, 1991)

[5] LSM is used as a proxy for GDP in Pakistan for both policy and research purposes. It is expected to be closely related to industrial production. Ex ante we expect IPI to strongly correlate with LSM therefore some of the variables considered by authors or the study may also be important determinants of this study.

5.2 Data Issues

Before rushing into specifying models and forecasting, it is important to discuss the issues pertaining to data. In time series econometrics, longer series on high frequency is crucial to better forecasting. With this in mind, all sources and avenues were exhausted to ensure that the maximum data for the period of our estimated index [1990M7:2018M6] was available to ensure accuracy and reliability of the forecasts churned out by models. However, as with any developing country, reliable data in the desired form is not easily available for Pakistan. Accordingly, efforts have been made to ensure that maximum data on all variables used in the estimation is obtained from reliable sources. Where data was not available, proxies have been used to estimate series from certain ancillary information.

5.2.1 External Sector

First, monthly data on exports and imports of goods was taken from International Finance Statistics (IFS) of IMF. For exports we have taken value of goods exported in millions of US $ free on board (FOB) whereas for imports we have taken value of goods imported in millions of US $ inclusive of cost, insurance and freight (CIF). Note that we have excluded import/export of services since the purpose is to explain industrial production. The data on IFS was only available until 2017M9 so the remaining data until 2018M6 has been taken from monthly statistics on external trade published by PBS[6]. For Foreign Direct Investment (FDI) we have considered net flows instead of inflows only since industrial production could be affected by both inward and outward investment flows. On IFS, this data for Pakistan is available on quarterly basis. However, SBP publicly makes available the data on FDI as far back as 1997M7. So we relied on SBP for this data instead. Next, for World Output, the world GDP would be an appropriate indicator but GDP is not available on monthly basis. Therefore, we found it fit to proxy world output by taking the US industrial production index which is readily available for the period 1990M7:2018M6. For commodity prices, we took the average US $/ barrel spot prices of Brent, Dubai Fateh and West Texas Intermediate (WTI) available on World Bank. Data on USD/PKR market exchange rate and Nominal Effective Exchange Rate (NEER) was readily available on IFS-IMF for the whole period of estimated index.

Since first 11 months will be lost as all the variables are YoY growth and data for FDI is available since 1997M7 so the sample for this sector is restricted to 1998M7:2018M6. This meant 240 months of which 228 have been used for estimation while remaining 12 months have been used for forecasting.

5.2.3 Real Sector

For electricity consumption the most relevant indicator is percentage of electricity consumed by industry. Share of industry in total electricity consumption is available in Haver/NEPRA for the period 2004-2017. These shares have been interpolated constantly to arrive at monthly shares. For years prior to 2004, we have simply averaged the annual shares 2004-2007 and applied retrospectively to arrive at monthly shares. These shares are applied to monthly data on electricity consumed by industry in millions KWH available in monthly statistical bulletin from PBS. Using the, 2005-06 as base year, and index of industrial electricity consumption has been calculated for the period 1990M7:2018M6. For monthly investment data we had two options. First, we could have used the quarterly shares used in Hanif et. al (2013) and interpolated them constantly to arrive at monthly investment on right hand side of the GDP side. This data would have been available for 2000M7:2018M6. However, a more suitable proxy for industrial investment is the capital expenditure (CAPEX) incurred by corporates. We estimated CAPEX for industrial sector using annual data of retained earnings, paid up capital and preference shares available on Handbook on Pakistan statistics and Monthly Statistical Bulletin available on SBP's website and used the monthly shares of industry estimated in section three above to arrive at monthly CAPEX data. For proxy of Labour (L) we relied on the data on labor force participation available on annual basis on Haver with source mentioned as PBS/Ministry of Planning, Development & Reforms. To convert this variable to monthly, we used annual share of industry and divided them equally over 12 months of the fiscal year to arrive at monthly shares. These weights were then applied on labor force participation rate to arrive at monthly Labor Force Participation (LFP) for industry. For prices, the relevant indicator is Whole Sale Price Index (WPI) available from SBP for the

[6] http://www.pbs.gov.pk/trade-detail?page=2

period 1991M7:2018M6 on single base year. For income, the best proxy is corporate income. For this, we used the net profit before taxation (in millions PKR) of non-financial corporates available in monthly and annual statistical bulletins available on SBP's website. Since this data was available on annual we used the methodology used for IPI to arrive at monthly estimate. We first estimated the shares of manufacturing, construction and energy (gas and electricity) and used them arrive at weighted monthly shares of each sector. We then applied these shares on the net profit before taxes of non-financial firms to arrive at monthly corporate income. The data on monthly taxes paid by industry was estimated similarly using the total tax provision/expense available in the same source.

As with external sector, first 11 months will be lost since we are interested in YoY growth. Further WPI index is available since 1991M7 so the sample for this sector is restricted to 1992M7:2018M6. This meant 312 months' data of which 300 months' data have been used for estimation while remaining 12 months have been used for forecasting.

5.2.4 Financial Sector

For price of corporate credit, the most relevant indicator is the offer side of the 12-month KIBOR since banks usually use KIBOR as reference rate to price credit to private sector. However, this data is available since 2004M4 only. Alternatively, we could have used auction rate of 12-months t-bills whose data goes back till 1998M7. However, there are 108 instances in which bids were rejected hence the data for that is not available. For data on credit to industry there are two sources. First SBP provides monthly data on private sector credit. However, this is available since 2006M6 only. SBP also provides annual balance sheet data of non-financial firms listed on KSE in its annual as well as monthly statistical bulletin and annual. We relied on this source for two reasons. First, this shows the data from demand side of the credit. Secondly, longer time series is available. The total finance received by industry has been estimated by aggregating the current and non-current liabilities of the non-financial firms adjusted for employees' benefit obligations. To convert into monthly data, we used the methodology used in section-3. Accordingly, the data on finance available to industry is 1990M7:2017M6. Data on money supply (M2) was available from SBP for the period 1990M7:2018M6.

Similar to other two sectors, first 11 months will be lost since we are interested in YoY growth. Further KIBOR is available since 2004M7 so the sample for this sector is restricted to 2005M7:2017M6. This meant 157 months' data of which 145 months' data have been used for estimation while remaining 12 months have been used for forecasting.

The list of final variables used along with their data source is available in Table-3.

6. Methodology for Forecasting IPI

In this section, we discuss specifications of single and multiple equation econometric models capable of forecasting the IPI. These models have been specified based on behavioral relationships between macroeconomic variables identified in the earlier section on "determinants of Industrial Production" our understanding of the empirical evidence of those relationship in Pakistan's economy.

6.1 ARIMA Model

ARIMA Model has been estimated using equation (10) below. The lags of auto-regressive term and moving average have been finalized based on Akaike Information Criterion (AIC). The maximum lag structure has been set at 12 each for auto-regressive and moving average terms. These were then selected using a generalize to specific approach based on lowest AIC. The final estimated model is as follows.

$$IPI_t = \alpha + \sum_{i=1}^{p} \beta_i IPI_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j} + \varepsilon_t \qquad (10)$$

6.2 Auto-Regressive Distributed Lag (ARDL) Models

Since the variables considered in this study could be either integrated of order 0 or 1, therefore, ARDL could be an appropriate model for explaining IPI. We have estimated three models reflective of real, external and financial conditions as affecting the industrial production.

In the real sector, growth in IPI could be explained by a distributed lag component of a set of explanatory variables in the following set up:

$$GIPI_t = c_1 + \alpha_i \sum_{i=1}^{n} GIPI_{t-i} + \phi_i \sum_{i=1}^{n} EC_{t-i} + \beta_j \sum_{j=1}^{n} CAPEX_{t-j} - \gamma_k \sum_{k=1}^{n} P_{t-k} + \delta_l \sum_{l=1}^{n} L_{t-l} - \varphi_l \sum_{l=1}^{n} TX_{t-l} + \varepsilon_{1t} \quad (11)$$

Similarly, IPI growth could also be affected by conditions in the external sector. For this we have run a second ARDL model of the form expressed in equation (12)

$$GIPI_t = c_1 + \alpha_i \sum_{i=1}^{n} GIPI_{t-i} + \rho_i \sum_{i=1}^{n} X_{t-i} + \tau_k \sum_{k=1}^{n} ER_{t-k} + \theta_l \sum_{l=1}^{n} OP_{t-l} + \vartheta_m \sum_{m=1}^{n} FDI_{t-m} + \omega_o \sum_{o=1}^{n} WO_{t-o} + \varepsilon_{2t} \quad (12)$$

Lastly, growth in IPI could also be affected by monetary conditions. For this we estimate the model in equation (13) below.

$$GIPI_t = c_1 - \alpha_i \sum_{i=1}^{n} KIBOR_{t-i} + \beta_j \sum_{j=1}^{n} M2_{t-j} + \gamma_k \sum_{k=1}^{n} Credit_{t-k} + \varepsilon_{3t} \quad (13)$$

In the models above the maximum lag structure has been set at 12 for both dependent and independent variables. The final lags were then selected using a general-to-specific approach based on lowest AIC.

6.3 Vector Autoregressive Model

Sims (1980) criticized the large scale macroeconomic models of the time because of the strong restrictions they imposed. The problem with models of the that time was that they were highly specified with strong assumption about dynamic nature of the relationship between macroeconomic variables. He argued strongly that the models were largely inconsistent with the notion that economic agents take the fact of today's choices on tomorrow's utility into account which later became is a Sims' Critique. The critique basically explained that in a world with rational, forward looking agents, no variable can be deemed as exogenous. Sims proposed VARs as an alternative which allowed to model macroeconomic data without imposing strong restrictions. Since then Vector Auto Regressive (VAR) models have become the mainstay of modern applied macroeconomics, it makes full sense to use the VAR setup for forecasting IPI.

The specification of VARS we have used are not completely free of the theory. The specifications have been developed using empirical literature already discussed. We have estimated three kinds of VAR models which have been specified as follows

6.3.1 Industrial Production and Financial Conditions (VAR-1)

Since industries are capital intensive therefore financial factors will be important. Conducive financial conditions in the form of availably of credit for both working and fixed investment at reasonable interest rates could be precursors to industrial production. Any change in the money supply (MS) will lead to changes in credit supply (CR) which will eventually affect market interest rates (KIBOR). VAR model specifying such financial conditions is modeled as follows.

$$GMS_{t+1} = E_t[GMS_{t+1}] + \varepsilon_{t+1}^{GMS}$$

$$GCR_{t+1} = E_t[GCR_{t+1}] + \alpha_1 \varepsilon_{t+1}^{GMS} + \varepsilon_{t+1}^{GCR}$$

$$KIBOR_{t+1} = E_t[KIBOR_{t+1}] + \alpha_2 \varepsilon_{t+1}^{GMS} + \alpha_3 \varepsilon_{t+1}^{GCR} + \varepsilon_{t+1}^{KIBOR}$$

$$GIPI_{t+1} = E_t[GIPI_{t+1}] + \alpha_4 \varepsilon_{t+1}^{GMS} + \alpha_5 \varepsilon_{t+1}^{GCR} + \alpha_6 \varepsilon_{t+1}^{KIBOR} + \varepsilon_{t+1}^{GIPI}$$

Where E_t is the conditional expectation operator and $\alpha's$ are the impulse response coefficients. VAR of the above form gives us the following recursive structural VAR system:

$$Y_{T+1} = AY_T + B\varepsilon_{t+1} \quad (14)$$

Where $Y = (GMS, GCR, KIBOR)$, $\varepsilon = (\varepsilon^{GMS}, \varepsilon^{GCR}, \varepsilon^{KIBOR}, \varepsilon^{GIPI})$ and $B = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_1 & 1 & 0 & 0 \\ \alpha_2 & \alpha_3 & 1 & 0 \\ \alpha_4 & \alpha_5 & \alpha_6 & 1 \end{bmatrix}$

6.3.2 Industrial Production and External Sector Conditions (VAR-2)

Conditions in the external sector are also expected to affect industrial production. Changes in global oil price (GOP) will affect the growth in global output (GWO) creating investment opportunities (FDI) which in turn will affect exports (X) that will have an effect on equilibrium exchange rate (ER) which eventually will determine industrial production (IPI) Such a VAR model is specified as follows:

$$GOP_{t+1} = E_t[GOP_{t+1}] + \varepsilon_{t+1}^{GOP}$$

$$GWO_{t+1} = E_t[GWO_{t+1}] + \alpha_1\varepsilon_{t+1}^{GOP} + \varepsilon_{t+1}^{GWO}$$

$$GFDI_{t+1} = E_t[GFDI_{t+1}] + \alpha_2\varepsilon_{t+1}^{GOP} + \alpha_3\varepsilon_{t+1}^{GWO} + \varepsilon_{t+1}^{GFDI}$$

$$GX_{t+1} = E_t[GX_{t+1}] + \alpha_4\varepsilon_{t+1}^{GOP} + \alpha_5\varepsilon_{t+1}^{GWO} + \alpha_6\varepsilon_{t+1}^{GFDI} + \varepsilon_{t+1}^{GX}$$

$$GER_{t+1} = E_t[GER_{t+1}] + \alpha_7\varepsilon_{t+1}^{GOP} + \alpha_8\varepsilon_{t+1}^{GWO} + \alpha_9\varepsilon_{t+1}^{GFDI} + \alpha_{10}\varepsilon_{t+1}^{GX} + \varepsilon_{t+1}^{GER}$$

$$GIPI_{t+1} = E_t[IPI_{t+1}] + \alpha_{11}\varepsilon_{t+1}^{GOP} + \alpha_{12}\varepsilon_{t+1}^{GWO} + \alpha_{13}\varepsilon_{t+1}^{GFDI} + \alpha_{14}\varepsilon_{t+1}^{GX} + \alpha_{15}\varepsilon_{t+1}^{GER} + \varepsilon_{t+1}^{IPI}$$

Where E_t is the conditional expectation operator and $\alpha's$ are the impulse response coefficients. VAR of the above form gives us the following recursive structural VAR system:

$$Y_{T+1} = AY_T + B\varepsilon_{t+1} \tag{15}$$

where $Y = (GOP, GWO, GFDI, GM, ER, GIPI)$, $\varepsilon = (\varepsilon^{OP}, \varepsilon^{WO}, \varepsilon^{FDI}, \varepsilon^{X}, \varepsilon^{ER})$

$$B = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ \alpha_1 & 1 & 1 & 0 & 0 & 0 \\ \alpha_2 & \alpha_3 & 1 & 0 & 0 & 0 \\ \alpha_4 & \alpha_5 & \alpha_6 & 1 & 0 & 0 \\ \alpha_7 & \alpha_8 & \alpha_9 & \alpha_{10} & 1 & 0 \\ \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} & 1 \end{bmatrix}$$

6.3.3 Industrial Production and Real Sector Conditions (VAR -3)

This specification takes into account conditions in the real sector of the economy. Variables which are expected to affect industrial production included, tax rate (TX), growth in electricity consumption (GEC), investment growth (GCAPEX), and growth in Whole Sale Price Index (GP). The model is specified as follows.

$$TX_{t+1} = E_t[TX_{t+1}] + \varepsilon_{t+1}^{TX}$$

$$GEC_{t+1} = E_t[GEC_{t+1}] + \alpha_1\varepsilon_{t+1}^{TX} + \varepsilon_{t+1}^{GEC}$$

$$GCAPEX_{t+1} = E_t[GCAPEX_{t+1}] + \alpha_2\varepsilon_{t+1}^{TX} + \alpha_3\varepsilon_{t+1}^{GEC} + \varepsilon_{t+1}^{GCAPEX}$$

$$GP_{t+1} = E_t[P_{t+1}] + \alpha_4\varepsilon_{t+1}^{TX} + \alpha_5\varepsilon_{t+1}^{GEC} + \alpha_6\varepsilon_{t+1}^{GCAPEX} + \varepsilon_{t+1}^{GP}$$

$$GIPI_{t+1} = E_t[GIPI_{t+1}] + \alpha_7\varepsilon_{t+1}^{TX} + \alpha_8\varepsilon_{t+1}^{GEC} + \alpha_9\varepsilon_{t+1}^{GCAPEX} + \alpha_{10}\varepsilon_{t+1}^{GP} + \varepsilon_{t+1}^{GIPI}$$

Where E_t is the conditional expectation operator and $\alpha's$ are the impulse response coefficients. VAR of the above form gives us the following recursive structural VAR system:

$$Y_{T+1} = AY_T + B\varepsilon_{t+1} \tag{16}$$

where $Y = (TX, GEC, GINC, GINV, GP, GIPI)$, $\varepsilon = (\varepsilon^{TX}, \varepsilon^{GEC}, \varepsilon^{GCAPEX}, \varepsilon^{GP}, \varepsilon^{GIPI})$

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_1 & 1 & 0 & 0 & 0 \\ \alpha_2 & \alpha_3 & 1 & 0 & 0 \\ \alpha_4 & \alpha_5 & \alpha_6 & 1 & 0 \\ \alpha_7 & \alpha_8 & \alpha_9 & \alpha_{10} & 1 \end{bmatrix}$$

6.3.4 Bayesian Vector Autoregressive Model

Using the standard VAR model specified in equations (14), (15) and (16), we also run its Bayesian Vector Autoregressive (BVAR) variant for real, external and financial sector. According some discussion on BVAR is warranted here. The difference between standard VAR and BVAR lies in the fact that model parameters in BVAR are treated as random variables and prior probabilities are assigned to them. BVAR methods (Litterman, 1986; Doan, Litterman, & Sims, 1984; Sims & Zha, 1998) have been frequently used to deal with the problem of over-parameterization typical of standard VAR models since Bayesian priors provide a logical and consistent method of imposing parameter restrictions.

The type of prior used in estimation is very important. For our purposes we have used the ubiquitous Littterman/Minnesota prior which specifies hyper-parameters using four scalars μ_1 , λ_1, λ_2, and λ_3. λ_1 is the overall tightness on the variance (of the first lag) and controls the relative importance of sample and prior information. if λ_1 is small, prior information dominates the sample information. λ_2 represents the relative tightness of the variance of other variables. Setting $\lambda_2 = 0$ implies the VAR is collapsed to a vector of univariate models. $\lambda_3 > 0$ represents the relative tightness of the variance of lags.

7. Model Estimation and Forecasting

The first step before estimating any model is a critical overview of the data itself. We have already discussed measurement issues pertaining to the sample in the section on "Data Issues" above. We provide the basic descriptive statistics of data for the sample used is provided in Table-4.

It is also essential to discuss the time-series properties of the sample used in this study. Table-5 provides standard Augmented-Dickey Fuller unit root tests. The test has been carried out on YoY growth in dependent and regressors with a maximum of 13 lags without including trend or intercept. Lag selection is based on SIC. The test has been carried out for the periods of estimation only. Results show that all variables are stationery either at 5% or 10% level of significance.

In Table-6 we have provided diagnostics of all the ten estimated models. First, for AR model the lag length has been finalized using Automatic ARIMA in a general-specific-approach. The system evaluated 169 models and finalized AR (p=9, q=11). The AIC of the final model is a modest 5.7 and model explains about 55% of the variation. We tested for autocorrelation up to selected 9 lags and were unable to reject the null hypothesis that there is no autocorrelation up to 9 lags Note that we have only reported Q-stat at 9th lag.

For ARDL models, the lags of dynamic regressors have been finalized using AIC with a maximum lag of 12 months. The final lags are selected based on AIC using general-to-specific approach. Breusch-Pagan-Godfrey F-Statistics shows that the errors of the estimated models are all homeskadastic except model-2. Similarly, we have also tested for no auto correlation up to final lag using Bruesche-Godfrey Serial Correlation LM Test. Results are acceptable for all models except model-3. Of these the model reflecting financial conditions appears to explain growth in IPI most. It is also the model that best explains the variation in growth in IPI.

For VAR models, the diagnostics are not as strong. However, the critical condition that all variables should be stationery is met comfortably as evident from results in Table-5. As for multivariate normality of errors and serial correlation, the results are less than perfect. For standard VAR specification in model 5 & 6, the LRE-stat shows that there is no autocorrelation up to the final lag used in specification. But for BVAR this condition is not met. Similarly, the condition of hetroskedacitiy appears to have been violated in for both standard and Bayesian VAR models. This may be partly due to specification issues.

7.2 Models' Evaluation

To evaluate models, we performed out-of-sample forecasts by leaving out twelve months of latest data starting 2017M7 till 2018M6 for all the ten models and then calculated their deviations from actual IPI values in that period. The Root Mean Squared Errors (RMSEs) obtained from ten different models estimated for three different horizons: h=3, h=6 and h=12, are provided in Table-7. Generally, ARDL models outperform others in terms of low RMSE. This is true for all three horizons.

Among ARDL models, results show Model-4 outperforms all other models including random walk model. This is true across all horizons. Model-4 takes into account financial conditions in an ARDL setup. The growth in IPI is explained by a distributed lag components of interest rate, monetary growth and credit growth. The model also explains about 66% of the variation (see Table-6)

It is also worth mentioning that, as horizon increases, the forecast accuracy of the models deteriorates generally. This is acceptable since uncertainty increases in distant future. The combined paths of all the forecasts can be seen in Figure-3.

8. Conclusion

Industrial production is a key variables of interest for economic policy analysis. It is important in explaining aggregate fluctuations because of its close association with services sector which is the largest component in national GDP. Major central banks world over- including USA and ECB- accord due importance to industrial production mainly for two reasons. First, industrial production is more frequently available compared to GDP which is available less frequently. Secondly, industrial production leads economic activity thus is a good proxy for overall GDP growth.

In Pakistan, Industry accounts for 23% of the total GDP at producer's price. Data on industrial production in Pakistan is not available on high frequency. As a proxy of industrial production, policy makers in Pakistan rely on Large Scale Manufacturing (LSM) which is sub-component of total industrial production. This is costly in the sense that about 1.6 trillion (See Table-1) worth of production that forms part of industry in Pakistan's GDP is missed out which may contain important cyclical information.

Using LSM to gauge cyclical changes in economy also deprives analysts and policy makers of understanding public-sector induced industrial growth since LSM consists of private sector industry mainly. Thus the need for a broader index accounting for much of industry arises unequivocally.

Note that the problem of lack of coverage is not unusual of developing countries, nevertheless, having a broader index of industrial production can be very useful from the perspective of a practitioners and policy makers. Measuring industrial production is also important because SBP aims to move gradually to inflation targeting and extensive forecasting of economic activity is a key component of inflation targeting regimes. Despite its practical relevance for policy making and analysis; no notable attempt has been made to estimate industrial production in Pakistan. Accordingly, there was a need to develop an index which tracks economic activity as an alternative to GDP which is less frequently available.

In this paper, we have estimated an Industrial Production Index (IPI) that covers overall value added by Industry in the nation's total GDP. Our proposed index closely follows the old Industrial Production Index once disseminated by PBS which has subsequently been discounted in 2012. Their correlation is more than 90%. Our calculated IPI passes a battery of statistical and validation tests thus lending credence to the methodology used. The advantage of our proposed index is that it provides additional information that LSM misses out. Post estimation, we built ten econometric models to forecast growth in estimated IPI. These models have been specified to reflect conditions in key sectors, such as real, financial and external for three months (h=3), six months (h=6) and twelve months (h=12). The RMSE of the ARDL model reflecting financial conditions has the lowest RMSE across all horizons.

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Figure-1: New Industrial Production Index Estimated by Authors

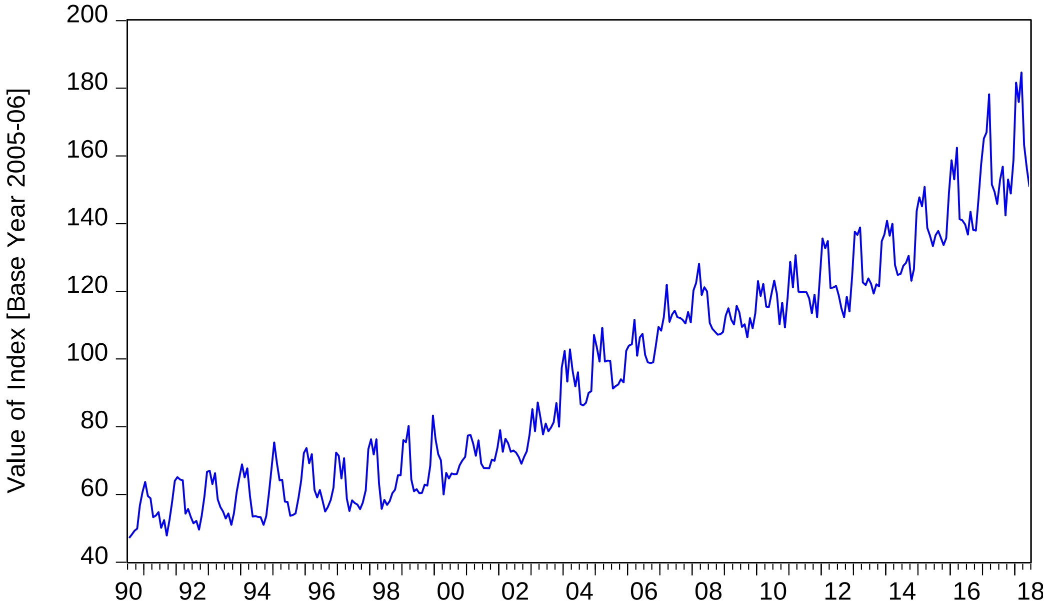

Figure-2: Comparision of PBS IPI and Authors Estimated IPI

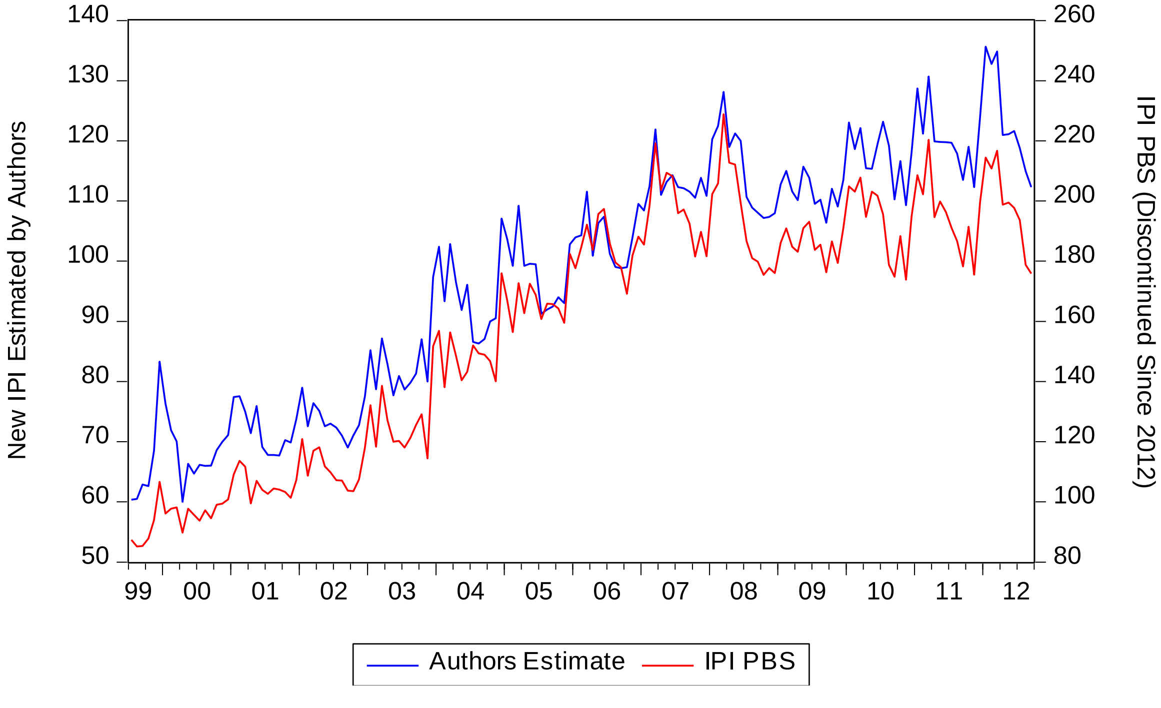

Figure-3: Comparision of 12-Month Moving Avg.of YoY% Growth of Actual and Forecasted IPI using various Models

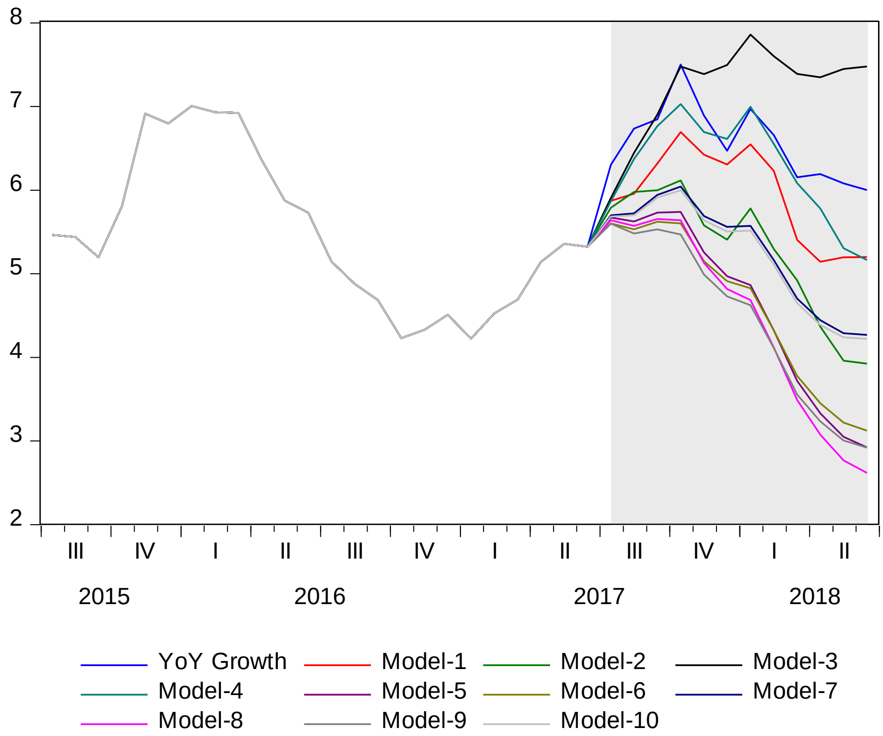

Table-1: Composition of Industry in total GDP of Pakistan 2017-18 (P)

Constant Basic Prices 2005-06,	Rs. Million	as % of Total Industry	as % of Manufacturing
Industry	2,951,336		
M&Q	341,934	11.6%	
Manufacturing	1,680,161	56.9%	
LSM	1,338,010		79.6%
SSM	232,413		13.8%
Slaughtering	109,738		6.5%
Energy	219,463	7.4%	
Construction	349,778	11.9%	
GDP + Tax - Subsidies	13,100,711		
LSM as % of GDP at PP	10.2%		
Industry as % of GDP at PP	23%		

Source: Pakistan Bureau of Statistics

Table-2: Statistical Tests performed on computed IPI

	IPI Estimated by Authors	IPI by PBS	Sample Period
ρ^1	0.975*		1999M7: 2012M9
P-Value	0.000		
Test of Persistence			
AR(1)	0.984*	0.986*	1999M7: 2012M9
MA(1)	-0.251*	-0.273*	1999M7: 2012M9
R^2	0.929	0.940	
Durbin-Watson	2.032	2.038	1999M7: 2012M9

*Indicates Statistical Significance at 5% , [1] Pearson Correlation Coefficient

Table-3: List of variables and sample period

Variable	Definition	Unit	Code	Sample	Source
Real Sector					
Industrial Production	As estimated by authors	Index	IPI	1990M7:2018M6	Authors' Estimation
Electricity Consumption	Electricity consumption index for industry	Index	ECI	1990M7:2018M6	Authors' calculation using PBS
Income	Paid up capital, retaining earnings, preference shares of all listed non-financial corporates.	Millions PKR	CAPEX	1990M7:2018M6	SBP
Tax	Tax provision/expense	Millions PKR	TAX	1990M7:2018M6	SBP
Labor	Labour Force Participation Rate	%	LFP	1990M7:2018M6	Authors' Estimation
Price	Whole Sale Price Index	Index	P	1991M7:2018M6	SBP
External Sector					
Exchange Rate	Monthly Avg. of USD/PKR exchange rate	USD/PKR	ER	1991M7:2018M6	SBP
Foreign Investment	Net figure from financial account of the BOP	Millions USD	FDI	1997M7:2018M6	SBP
Int'l Oil Price	Average of Brent, Dubai & WTI (US$/Barrel)	USD	OP	1997M7:2018M6	Bloomberg
World Output	US Industrial Production: Total index, Index 2012=100, Monthly, Not Seasonally Adjusted	Index	WO	1990M7:2018M6	FRED
Exports	External Trade, Goods, Value of Exports, Free on Board (FOB), US Dollars, Millions	Millions USD	X	1990M7:2018M6	IMF
Financial/Monetary Sector					
Money Supply	Monetary Aggregate M2	Millions PKR	M2	1990M7:2018M6	SBP
Interest Rate	Monthly average of offer side of 12-months tenor	Millions PKR	KIBOR	1990M7:2018M6	SBP
Credit	total finance=current + non-current liabilities (adjusted) on balance sheets of all listed non-financial firms on KSE.	Millions PKR	CR	1990M7:2018M6	SBP

Table-4: Descriptive Statistics on Sample Data starting 1990M7 till 2018M6

Var	Definition	Unit	Mean	Median	Max.	Min.	Std. Dev.	N
CR	Liabilities of the firm	Millions PKR	111,395	63,458	314,667	9,565	89,085	336
ECI	Electricity Consumption	Index	71	68	141	31	23	336
ER	Exchange Rate	PKR/USD	64	60	119	22	27	336
FDI	Net FDI flows from BOP	Millions USD	160	111	1,263	-54	174	252
CAPEX	Capital expenditures	Millions PKR	32,488	25,619	79,654	2,096	24,586	336
P	Whole Sale Price	Index	105	72	234	25	68	324
M2	Money Supply	Millions PKR	4,285,433	2,489,854	15,763,268	340,652	4,165,971	336
KIBOR	Offer side of 12M	%	10	10	16	3	3	171
IPI	Industrial Production Index	Index	95	92	185	47	33	336
TAX	Tax Provision/Expense	Millions PKR	5,061	3,555	16,338	231	4,725	336
OP	Avg. of DF, WTI, Brent	Index	48	35	133	10	32	336
X	Good exported FOB	Millions USD	1,219	1,113	2,613	336	571	336
WO	US Industrial Production	Index	91	95	109	62	13	336
L	Labor Force Participation rate	%	0.52	0.53	0.58	0.46	0.04	300

Table-5: Unit Root Test

G=YoY	ADF Test Statistics	P-Value	Sample
GIPI	-8.85*	0.000	1992M7:2017M6
GKIBOR	-5.26*	0.000	2005M7:2017M6
GCAPEX	-2.72**	0.032	1992M7:2017M6
GECI	-8.31*	0.000	1992M7:2017M6
GCR	-2.79**	0.062	2005M7:2017M6
GFDI	-11.27*	0.000	1998M7:2017M6
GX	-4.04*	0.001	1998M7:2017M6
GP	-1.93**	0.052	1992M7:2017M6
GOP	-3.92*	0.002	1998M7:2017M6
GWO	-4.09*	0.001	1998M7:2017M6
GM2	-2.96	0.040	2005M7:2017M6
GTAX	-4.78*	0.000	1992M7:2017M6
GER	-2.57**	0.100	1998M7:2017M6
GL	-3.61*	0.006	1992M7:2017M6

Null: Variable has Unit Root, Test Statistics: ADF, Lag Length: SIC, *Significant at 5%, **Significant at 10%

Table-6: Time-Series Properties of the Estimated Single and Multiple Equation Time Series Models

#	Model	Regressors	R	Q-Stat[d]	AIC	F-Stat[a]	F-Stat[b]	χ^2	LRE[c]	Sample
1	AR (9,11)	GIPI, MA	0.55	0.39	5.71	-	-	-	-	1991M7:2017M6
2	ARDL (5,0,1,1,0,0)	GIPI, ECI, CAPEX, LFP, TAX, P	0.44	-	5.86	2.50*	2.49*	-	-	1993M7:2017M6
3	ARDL(12,2,0,0,0,3)	GIPI, X, ER, OP, FDI, WO	0.53	-	5.90	1.45**	2.20*	-	-	1998M7:2017M6
4	ARDL (12,5,1,5)	GIPI, KBIOR, M2, CR	0.66	-	5.17	0.96	0.67	-	-	2006M4:2017M6
5	VAR (2,2)	GECI GCAPEX, GP, GTAX^	0.38	-	-	-	-	274.54	17.57	1993M7:2017M6
6	VAR (2,2,2)	GX, GFDI, GER, GWO^, GOP^	0.35	-	-	-	-	255.31	14.47	1998M7:2017M6
7	VAR (2,2,2)	GCR, GM2, GKBIOR	0.48	-	-	-	-	238.53	28.92*	2005M6:2017M6
8	BVAR	GECI GCAPEX, GP, GTAX^	0.36	-	-	-	-	302.91	86.39*	1993M7:2017M6
9	BVAR	GX, GFDI, GER, GWO^, GOP^	0.32	-	-	-	-	253.60	75.80*	1998M7:2017M6
10	BVAR	GCR, GM2, GKBIOR	0.46	-	-	-	-	286.29	66.51*	2005M6:2017M6

*Significant at 5% level, **Significant at 10% level
[d] there is no autocorrelation up to order *k*
[a]Breusch-Pagan-Godfrey F-Statistics with Null: Errors are Homoskedastic
[b] Bruesche-Godfrey Serial Corr. LM Test F**-Statistics with Null: No Serial Correlation up to lag h
[c] LRE-State with Null: No Serial Correlation at lag *h*
χ^2 is the test of VAR residual Heteroskdasticity (with no cross terms)
^ treated exogenous in the model setup

Table-7: Root Mean Square Errors of Estimated Models

No	Model	Specification	h=3	h=6	h=12
1	AR (9,11)	GIPI, MA	4.20	3.96	3.37
2	ARDL (5,0,1,1,0,0)	GIPI, ECI, CAPEX, LFP, TAX, P	3.99	4.07	3.78
3	ARDL(12,2,0,0,0,3)	GIPI,GX, GER, GOP, GFDI, GWO	3.72	4.51	3.49
4	ARDL (12,5,1,5)	GIPI, KBIOR, M2, CR	3.62	3.84	3.28
5	VAR (2,2)	GECI GCAPEX, GP, GTAX^	5.49	5.09	4.55
6	VAR (2,2,2)	GX, GFDI, GER, GWO^, GOP^	5.98	5.50	4.63
7	VAR (2,2,2)	GCR, GM2, GKBIOR	5.11	4.91	4.02
8	BVAR-Real	GECI GCAPEX, GP, GTAX^	5.75	5.27	4.75
9	BVAR-External	GX, GFDI, GER, GWO^, GOP^	6.21	5.71	4.79
10	BVAR-Financial	GCR, GM2, GKBIOR	5.21	4.98	4.06

*treated exogenous in the model setup

Appendix-A: IPI Estimated by Authors' [Base year=2005-06]

FY	July	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
1990	47.13	48.19	49.23	49.85	56.71	60.73	-	-	-	-	-	-
1991	50.13	52.39	47.81	52.33	57.76	64.03	63.70	59.50	58.86	53.30	53.79	54.74
1992	51.44	52.17	49.55	53.75	59.39	66.65	65.10	64.41	64.17	54.29	55.75	53.33
1993	52.88	54.40	51.02	54.46	60.60	64.91	66.97	63.05	66.29	58.52	56.27	54.93
1994	53.33	53.30	50.98	53.62	60.28	67.90	68.92	65.05	67.74	59.51	53.41	53.60
1995	53.67	53.92	54.38	59.02	64.11	72.22	75.38	69.29	64.17	64.30	57.85	57.75
1996	58.22	54.90	56.29	58.38	61.98	72.32	73.68	69.19	71.91	61.29	59.14	61.34
1997	57.43	57.01	55.65	57.51	61.20	73.36	71.41	64.69	70.72	58.80	55.06	58.27
1998	56.93	58.00	60.40	61.44	65.67	65.68	76.31	71.79	76.29	63.17	55.71	58.40
1999	60.36	60.49	62.88	62.60	68.50	83.31	76.06	75.42	80.26	64.36	60.92	61.56
2000	66.18	66.00	66.03	68.58	69.96	71.13	76.32	71.89	70.03	60.01	66.35	64.70
2001	67.78	67.77	67.71	70.29	69.89	73.74	77.43	77.54	75.01	71.43	75.95	69.12
2002	72.36	71.03	69.04	71.06	72.75	77.49	78.96	72.56	76.43	75.14	72.57	72.99
2003	78.66	79.79	81.33	87.00	80.01	97.37	85.20	78.70	87.15	82.86	77.70	80.94
2004	86.59	86.31	87.09	90.00	90.50	107.09	102.42	93.33	102.85	96.49	91.87	96.09
2005	91.28	92.01	92.48	94.06	93.07	102.44	103.67	99.24	109.20	99.23	99.56	99.50
2006	101.22	99.03	98.80	99.00	103.94	109.51	103.98	104.34	111.57	100.94	106.39	107.42
2007	112.30	112.15	111.53	110.53	113.87	110.83	108.40	112.47	121.92	111.01	113.18	114.28
2008	110.68	108.89	108.08	107.18	107.34	107.98	120.28	122.46	128.14	118.97	121.23	120.00
2009	109.50	110.24	106.37	112.05	109.07	113.51	112.78	115.01	111.60	110.16	115.73	113.84
2010	123.18	119.19	110.26	116.63	109.32	118.12	123.06	118.64	122.14	115.43	115.38	119.42
2011	119.69	117.89	113.51	119.03	112.32	123.97	128.70	121.18	130.71	119.89	119.82	119.76
2012	118.78	114.96	112.29	118.41	114.08	124.37	135.64	132.76	134.84	120.96	121.12	121.62
2013	122.24	119.30	122.06	121.47	134.80	136.73	137.58	136.66	138.89	122.67	121.88	123.84
2014	127.52	128.40	130.55	123.09	126.58	143.70	140.84	136.47	139.97	127.75	124.86	125.17
2015	136.61	137.83	135.83	133.70	135.75	148.96	147.77	145.12	150.89	138.70	136.39	133.32
2016	136.74	143.53	138.17	137.89	147.24	157.59	158.74	153.07	162.48	141.31	140.99	139.71
2017	152.97	156.86	142.43	153.05	148.91	158.77	165.13	166.97	178.20	151.55	149.41	145.83
2018	-	-	-	-	-	-	181.66	175.91	184.67	163.21	156.36	150.84