SBP Research Bulletin
Volume 14, Number 1, 2018

Nowcasting LSM Growth in Pakistan

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Abstract: *This paper attempts to nowcast Large-scale Manufacturing (LSM) growth in Pakistan, which is generally used as proxy for economic activity in Pakistan. For this purpose, the dynamic factor and penalized regression models are used to extract the unique information set from a range of variables having close association with LSM. Given high seasonality induced volatility in LSM growth, we have also attempted to nowcast the trend and cycles separately. The estimation results show that the predicted LSM series fairly tracking the actual LSM series. Moreover, penalized regression models perform remarkably well in tracing cycles in LSM growth. However, dynamic factor model is quite successful in tracing the underlying trend growth but not the cycles.*

JEL Classification: C53, E43, E44, O53

Keywords: Nowcasting, Large-scale Manufacturing, Factor Model, Rigid Regressions, Pakistan

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1. Introduction

As actual quarterly or annual GDP date is generally released with a considerable lag, policymakers and analysts keep track of a range of macroeconomic variables to make informed judgments about future state of economic activity. In this context, the policymakers have been putting a lot of efforts to narrow the information gap by tracking a range of indicators. Recently, a number of studies have attempted to get a kind of early estimate for GDP (before its release) using econometric techniques. These techniques use information on macroeconomic variables most related with GDP for which more frequent data is available with a minimum lag to produce early estimates for the target variable.

This technique, similar in nature with leading indicators' approach, is known in the literature as nowcasting. Banbura et al. (2010) and Tiffin (2016) define nowcasting in most simple terms as prediction of the present, near term future, and very recent past. Kliesen and McCracken (2016) called nowcast as "tracking forecasts" as they observed that many central banks track latest information on a range of economic indicators to assess the direction and level of economic activity. The literature shows that use of nowcasting is not limited to forecast GDP, but is also being used as a tool to forecast other macroeconomic variables like inflation, investment, consumption, unemployment, etc. for which data is released with a lag.

Tiffin (2016) records that nowcasting has become a routine at many central banks. Some of the leading central banks including Reserve Bank of New Zeeland, Federal Reserve, Bank of England, Central Bank of Turkey, Bank of Canada, to name a few, use nowcasting to get estimate for quarterly GDP well before its official release. In case of Pakistan, GDP data is not published on quarterly basis. The first estimate of GDP for a fiscal year is released by the close of the same year. Large-scale Manufacturing (LSM) is the only major component of GDP on which data is available on a monthly basis, but with a lag of about two months from the end of reference period. LSM is also often used as proxy for ongoing trends in real GDP during a year.

Therefore, we have chosen LSM as the target variable to start with. To best of our knowledge, this is first such attempt in case of Pakistan. The data on large number of LSM components and other most related variables is usually available within 15 to 20 days after the end of a month. Since LSM is used as a proxy for GDP growth, nowcast or an early estimate for LSM growth could also be used as input for projecting/forecasting other key macroeconomic variables like credit to private sector, tax revenue, trade, inflation, money growth, etc.

We have factor models and penalized regression techniques to nowcast LSM growth in Pakistan. We have chosen 18 data series, either component of LSM or have strong association with LSM. The data spans from first quarter of fiscal year 2000 to the third quarter of fiscal 2017. To filter information from this set of variables to get near term forecast or early estimate for LSM growth, we have used dynamic factor model, ridge, lasso and elastic net methods. The same set of 18 indicators is considered for all the techniques for Nowcasting LSM in Pakistan. The estimates show that all these techniques perform reasonably well in predicting LSM growth (and the cycles and trends separately) in next quarter. However, dynamic factor models almost fail to trace the cyclical part.

The rest of the paper is organized as follows. The section II discusses the estimation methodologies applied in this paper. Section III describes the structure of GDP data, choice of target variable and macroeconomic variables used to nowcast LSM and Section IV concludes the paper.

2. Methodology

Optimal utilization of available information is central to nowcast techniques. However, some variables or groups of variables in the available information set may provide similar conclusions due to strong collinearity within these variables. To address this empirically, while ensuring maximum utilization of all available information, the data series are needed to be filtered to get a unique or a common solution. Factor models and penalized regression methods are the two popular techniques used in the literature for this purpose. These methods help to extract information from a large set of high frequency data having close association with the target variable and are also strongly correlated amongst themselves.

Factor models

There are many techniques in literature to extract common factors. Chamberlain and Rothschild (1983), factor models are most widely used for nowcasting economic variables. In this study, we have followed Stock and Watson (2002), which used principal component (PC) method to extract the factors. The main reasons for choosing PC for estimation of factors are: 1) PC gives consistent estimates of true latent factors, 2) PC based forecasts are asymptotically efficient, and 3) these results are robust.[2]

In view of the fact that we are using a large set of data to nowcast LSM, this can potentially create over-parameterization problem in the model. One of possible ways to solve the problem is to use "factor models". These models transform potential explanatory variables in few unobserved factors which confine the correlation among the data. This method uses these factors instead of original series as explanatory variables in the model.

[2] For more detail, see Stock and Watson (2002).

The most famous method to extract unknown factors from the large set is *principal component (PC) analysis*. This method linearly projects correlation matrix of explanatory variables to orthogonal linear combination of the underlying indicators or principal components. In this procedure, set of explanatory variables, say $\boldsymbol{X_t}$ of dimension m, is transformed into a cross-correlation matrix, say $\boldsymbol{Z}$. Then we find eigenvectors of $\boldsymbol{Z}$, say $\boldsymbol{P}$**.** The Eigen vector matrix $\boldsymbol{P}$ actually transform matrix $\boldsymbol{X_t}$ into orthogonal linear combinations known as principal components:

$$\boldsymbol{P}'.\boldsymbol{X}_t = \boldsymbol{PC_t} \tag{1}$$

Observe that Eq. (1) end up with m Principal components (PCs). Each of the PC has some power to explain the overall set of data. However different PCs have different explanatory power. Their explanatory power can be determined by corresponding eigen values of $\boldsymbol{Z}$. Therefore, sum of eigen values is used as selection criterion for maximum number of PCs that are used in the model. The criterion is defined as follows:

$$sum\ of\ \text{Descending}\ Eigen\ values\ of\ \boldsymbol{Z} \cong 0.9$$

Corresponding to these Eigen values we select Eigen vectors and thereby PCs. In order to relate PCs with LSM growth; Y_t, we need a bridge equation framework. In our case bridge equation has following representation, which we call a factor model.

$$Y_t = \alpha + \boldsymbol{\Lambda}.\boldsymbol{PC_t} + \varepsilon_t; \quad \varepsilon_t \sim i.i.d\ N(0, \textstyle\sum_\varepsilon) \tag{2}$$

In Eq. (2) we have made one innovation. In this innovation we have supposed time variation in factor loadings of $\boldsymbol{PC_t}$. This innovation allows us to incorporate policy impact, internal or external shocks and structural impact. We model time variation of factor loadings as a random walk. Therefore Eq. (2) can be re-written as:

$$Y_t = \alpha + \boldsymbol{\Lambda_t}.\boldsymbol{PC_t} + \varepsilon_t; \quad \varepsilon_t \sim i.i.d\ N(0, \textstyle\sum_\varepsilon) \tag{3}$$

$$\boldsymbol{\Lambda_t} = \boldsymbol{\Lambda_{t-1}} + \nu_t; \quad \nu_t \sim i.i.d\ N(0, \textstyle\sum_\nu) \tag{4}$$

This model is known as *dynamic factor model*. Eq. (3) and Eq. (4) constitute a state space model. Here Eq.(3) is a measurement equation and Eq. (4) is a transition equation. This equation can be estimated by Kalman filter.

Penalized models

Penalized regression methods are estimation techniques used in the environment of high collinear regressors. High correlation among variables forces to consider statistical limitations of the linear regression models, such as co-linearity and over fitting. These limitations might have large influence on out of the sample stability of estimates and in-sample validation of the parameters. The *penalized models* try to reduce the variance of estimates (relative to OLS estimates) by imposing some restrictions on coefficients of predicting series and thereby improve forecasts (see e.g. Tiffin (2016), Elmer (2011), Schneider and Wagner (2008), etc).

Following Tiffin (2016), we have used three penalized regression methods that take care of collinearity problem and dimensionality problem. These include:

1) Lasso regression method,
2) Ridge regression method, and
3) Elastic net regression method.

Let us analyze the collinearity problem in OLS estimation and one among many possible solutions (penalized estimation technique) in more formal way. As we know that OLS estimation technique minimizes residual sum of square (RSS). So minimization results can be written as:

$$B = (\boldsymbol{X}_t{}'\boldsymbol{X}_t)^{-1}\boldsymbol{X}_t{}'Y_t \qquad (5)$$

Since variables in $\boldsymbol{X}_t$ are supposed to be highly collinear, therefore $\boldsymbol{X}_t{}'\boldsymbol{X}_t$ will become nearly singular and making it difficult to invert. Penalized regression adds a positive constant say λ to the diagonal of $\boldsymbol{X}_t{}'\boldsymbol{X}_t$ matrix and make the matrix $\boldsymbol{X}_t{}'\boldsymbol{X}_t$ non-singular. In new setup Eq. (5) can be re-written as:

$$\mathrm{B} = (\boldsymbol{X}_t{}'\boldsymbol{X}_t + \lambda I)^{-1}\boldsymbol{X}_t{}'Y_t \qquad (6)$$

It means that we are basically minimizing following function with respect to B:

$$\binom{\text{Min}}{\mathrm{B}}\ \Gamma = \sum_{t=1}^{T}\left(Y_t - \mathrm{B}_0 - \sum_{i=1}^{n} x_{i,t}\mathrm{B}_\mathrm{i}\right)^2 + \lambda\sum_{i=1}^{n} B_i^2 \qquad (7)$$

Where $x_{i,t}$ are variables in $\boldsymbol{X}_t$ and B_i are parameters in vector B.

Eq. (7) can be rewritten as:

$$\binom{\text{Min}}{\mathrm{B}}\ \Gamma = RSS + \lambda\sum_{i=1}^{n} B_i^2 \ \ ; \quad 0 \le \lambda \le 1 \qquad (8)$$

In more formal form:

$$\binom{\text{Min}}{\mathrm{B}}\ \Gamma = RSS + Penalty\left(\widehat{\mathrm{B}}\right); \quad 0 \le \lambda \le 1; \qquad (9)$$

Here λ is a tuning parameter or penalty term on the sum of squares of parameters B_i. If $\lambda = 0$, the minimization problem reduces to OLS regression analysis, whereas $\lambda > 0$ means more penalty on the parameters for making them non-zero. So values of λ decides between fit of the model, i.e. RSS and size of the parameters. So the question is how to choose the critical value of the parameter λ. This is done by a re-sampling technique known as *cross validation*. In this technique we divide the whole sample into K equal sets. We take one part of the sample and call it validation sample and rest of $(K-1)$ parts as training sets. Now, for given value of $\lambda \in (0\ \ 1)$, we estimate the model for validation sample and then forecast the values in the training sets and estimate forecast errors. This process is repeated for all possible values of

$\lambda \in (0\ \ 1)$ and all validation and training sets. This gives us cross validation curve function. We choose λ, that minimizes this cross validation curve.

The penalty terms in Eq. (9) can be of different nature. It depends upon the objective of the researcher. The penalty term that we have defined in Eq. (8), is known as ridge penalty. [3] In ridge regression, we minimize RSS along with sum of square of parameters.

Penalty term can also be defined as absolute value of the parameters. This penalty is known as Lasso penalty.[4] The Lasso regression problem can be defined as:

$$\binom{\text{Min}}{\text{B}} \ \Gamma = RSS + \lambda \textstyle\sum_{i=1}^{n} |\mathrm{B_i}|; \quad 0 \leq \lambda \leq 1; \tag{10}$$

Ridge regression gives better results when some of the variables with better forecasting ability have values closer to zero. Lasso regression has ability to discard some of non-important variables. So it gives us a parsimonious model. We can combine the virtues of both penalties, in a single model known as *elastic net model*. The structure of the model is as follows:

$$\binom{\text{Min}}{\text{B}} \ \Gamma = RSS + \lambda \textstyle\sum_{i=1}^{n} \left[(1-\alpha)B_i^2 + \alpha|\mathrm{B_i}|\right]; \quad 0 \leq \lambda \leq 1; \alpha > 0; \tag{9}$$

Elastic net model is basically weighted sum of lasso and ridge penalties. We estimate this parameter α i.e. weight parameter of penalties, in cross validation process. We start process for $\alpha = 1$ and perform the k-fold cross validations for all $\lambda \in (0\ \ 1)$. This gives us validation curve function. We repeat this process for $\alpha = 2,3, \ldots \ldots s$; where s is a sufficient large number. The process generates validation curve space. We select those $\alpha's$ and $\lambda's$ that minimizes the validation curve space. Estimation under optimum parameters gives us a parsimonious model which has better predicting properties.

Before using the above methods, we first transformed high frequency data (monthly data) into low frequency data (quarterly data). Since transformation techniques for stock and flow variables are different. Therefore, we have used two different transformation techniques.

Suppose variable, F_t^q, is quarterly counterpart of its monthly variable z_t^m. For the flow variables, like CPI etc., quarterly variable is estimated as:

$$F_t^q = \frac{1}{3} \sum_{k=t-2}^{t} z_k^m$$

Similarly for stock variables

$$S_t^q = \textstyle\sum_{k=t-2}^{t} z_k^m.$$

[3] Ridge regression in the literature is first introduced by Hoerl and Kennard (1970).
[4] The LASSO estimator is first introduced by Tibshirani (1996).

It is here important to note that, after transformation, we seasonally adjusted the series and calculated growth rates.

3. Data and estimation results

Pakistan Bureau of Statistics (PBS) is responsible for compilation and publication of National Income Accounts (NIA) of Pakistan. PBS compiles NIA on annual basis and publishes provisional growth estimates by close of the fiscal year. These estimates are based on the actual data of first nine months of the fiscal year, that is, July-March. The revised full fiscal year data is released with a lag of one year.

Although PBS publishes data on some of the components of GDP on a monthly basis, these are usually available with a considerable lag. For example, data on large-scale manufacturing index is available on monthly basis with a lag of about two months. Similarly, data on production of minerals, oil and gas production and electricity generation is published on monthly basis but is available with a lag of more than two months.

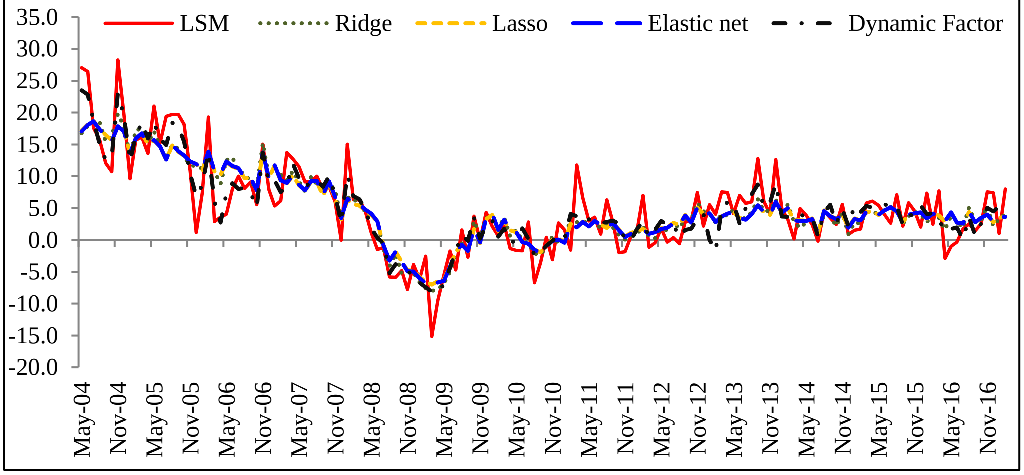
As Pakistan does not have quarterly GDP data, we use quarterly LSM growth as the target variable. We aim to get an estimate for LSM growth for the current month and quarter well before its official release, benefitting from the early release of data on a range of LSM components and those having strong association with the LSM. We include the variables for which data is published by PBS itself or the associations/institutions that provide data to PBS for compilation and releases. We also consider variables that State Bank of Pakistan (SBP) and/or financial markets monitor to assess the state of economic activity. For example, the data on confidence surveys, interest rate spreads, credit, and external sector indicators on which the data is compiled and published by SBP. The list of input variables with frequency and timings of the release is given in Annexure 1.

The timeliest data is on sales variables and financial markets like cement, automobile, and oil sales, interest rate spread, commodity prices and inflation which are available within five to six days from the reference period. The data on imports, export, remittances and private sector credit is available within two to three weeks period from the reference period. The timeline for data on tax collection, an important indicator of LSM performance, is not fixed and its release date varies from a week to three weeks.

Given that some of the series are relatively noisy in Pakistan, LSM being one of them, we have seasonally adjusted these before calculating year-on-year growth rates. All the data series are monthly, starting from July 2004.

The plot of predicted LSM series using dynamic factor model and penalized regression model (lasso, ridge and elastic net) shows that all the technique perform reasonably well in tracking the overall LSM growth (Figure 1).

Figure 1: Overall LSM Growth



With the objective to explore which technique perform better in tracing the underlying trajectory and cyclical part of the LSM, all the estimations are repeated on the trend and cycles of LSM index. As depicted in Figure 2, all models perform better in tracing the LSM growth trajectory. However, dynamic factor models almost fail to trace the cyclical part of the series (Figure 3).

Figure 2: Trend Growth in LSM

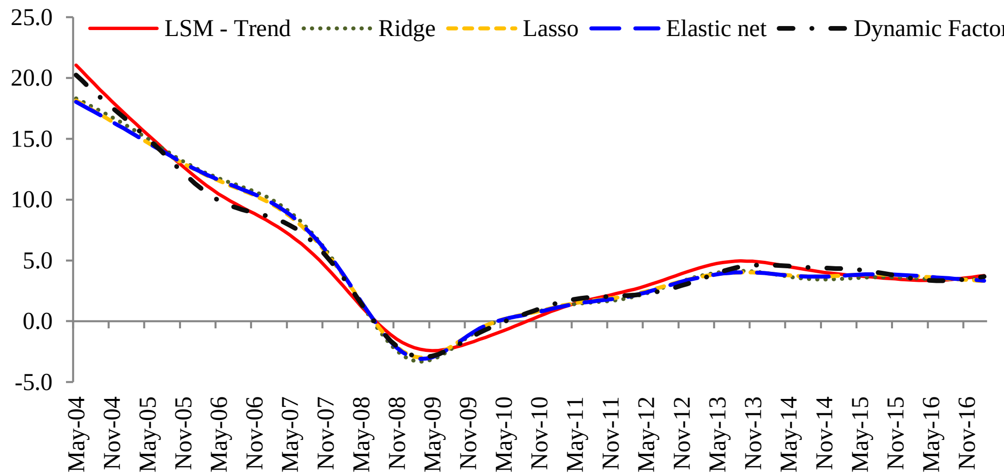
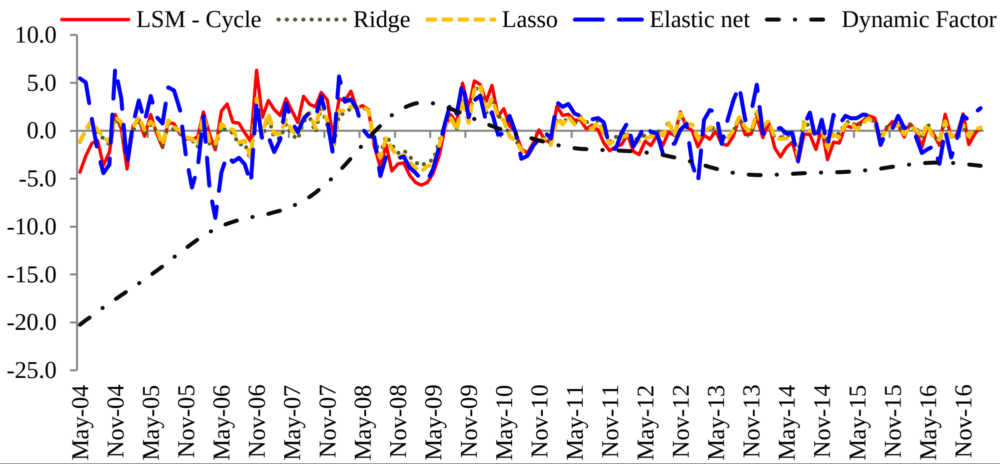


Figure 3: Cycles in LSM Growth



As a robustness check, we have estimated all these models on quarterly data (see Annexure 2). The results are not very different from the estimates based on monthly data.

Performance of the models is evaluated using RMSE criteria, which shows that the dynamic factor models perform the best in case of capturing movement in overall and trend in LSM (Table 1). However, this model fails in tracing the cycles. Lasso technique performs better in tracing the cycle. Regarding the failure of the dynamic factor models to capture the cyclical parts, it is because as Tiffin (2016) described due to the lack of "variable selection", which is done through the penalized models following Tiffin (2016).

Table 1: Root means Square Errors of LSM Nowcasting

	Ridge	Lasso	Elastic net	Dynamic Factor
Overall	42.3	43.9	43.9	31.8
Trends	11.6	11.0	11.5	6.5
Cycle	15.6	13.8	28.9	94.6

4. Conclusion

Nowcasting or near term forecasting is designed to reduce the information lags of data dissemination. Nowcasting is an emerging technique and many central banks are using it in their routine tasks. This paper is an effort to nowcast LSM growth in Pakistan. LSM is available at relatively higher frequency (monthly) than the actual GDP (annual) and is considered best indicator of economic activity. The process of nowcasting starts with the identifying determinants or variables having close association with LSM, which are released earlier than LSM. These determinants include production of important sectors, prices, credit, interest rates and tax collection, external trade and inflows. There is a possibility that these determinants may be highly correlated amongst themselves and may not provide unique set of information. Therefore, conventional forecasting techniques have limited capacity to resolve this issue.

Search for the unique information by filtering collinear information and nowcasting of LSM is carried out by using the dynamic factor model and penalized regression models. Dynamic factor model pre-filter the determinants by using the principal component method and the penalized regression models treat collinearity during the estimation process. These techniques are utilized to nowcast overall LSM growth along with its underlying trend and cycle. Seasonal patterns in production, exogenous and policy induced shocks are main reason for Nowcasting cyclical and trend components of LSM growth. Based on the forecast evaluation indicators, all the techniques perform better in predicting the overall LSM growth. Dynamic factor model performs the best in tracing the underlying trend of LSM growth but it fails in nowcasting the cyclical part. The performance of penalized methods is same in case of trend and cycles.

References

Akkoyun, H. C., & Gunay, M. (2012). *Nowcasting Turkish GDP Growth* (No. 1233).

Alessi, L., Ghysels, E., Onorante, L., Peach, R., & Potter, S. (2014). Central bank macroeconomic forecasting during the global financial crisis: the european central bank and federal reserve bank of new york experiences. *Journal of Business & Economic Statistics*, *32*(4), 483-500.

Aastveit, K. A., Gerdrup, K. R., Jore, A. S., & Thorsrud, L. A. (2014). Nowcasting GDP in real time: A density combination approach. *Journal of Business & Economic Statistics*, *32*(1), 48-68.

Bell, V., Co, L. W., Stone, S., & Wallis, G. (2014). Nowcasting uk gdp growth. *Bank of England Quarterly Bulletin*, Q1.

Bańbura, Marta, Domenico Giannone, and Lucrezia Reichlin (2010). “Nowcasting.” *European Central Bank Working Paper Series,* No 1275.

Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Now-casting and the real-time data flow. In *Handbook of economic forecasting* (Vol. 2, pp. 195-237). Elsevier.

Bragoli, D., & Modugno, M. (2017). A now-casting model for Canada: Do US variables matter?. *International Journal of Forecasting*, *33*(4), 786-800.

Chadwick, M. G., & Sengül, G. (2015). Nowcasting the Unemployment Rate in Turkey: Let's Ask Google. *Central Bank Review*, *15*(3), 15.

Chamberlain, G., & Rothschild, M. (1982). Arbitrage, factor structure, and mean-variance analysis on large asset markets.

D'Agostino, A., McQuinn, K., & O’Brien, D. (2013). Nowcasting Irish GDP. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, *2012*(2), 21-31.

Elmer, S. G. (2011). *Modern statistical methods applied to economic time series* (Doctoral dissertation, ETH Zurich).

Galbraith, J. W., & Tkacz, G. (2015). *Nowcasting GDP with electronic payments data* (No. 10). ECB Statistics Paper.

Giannone, D., Reichlin, L., & Small, D. H. (2006). Nowcasting GDP and inflation: the real-time informational content of macroeconomic data releases.

Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, *55*(4), 665-676.

Granziera, E., Luu, C., & St-Amant, P. (2013). The accuracy of short-term forecast combinations. *Bank of Canada Review*, *2013*(summer), 13-21.

Gálvez-Soriano, O. D. J. (2019). Nowcasting Mexico's Quarterly GDP using Factor Models and Bridge Equations.

Grover, S., Kliesen, K. L., & McCracken, M. W. (2016). A Macroeconomic News Index for Constructing Nowcasts of US Real Gross Domestic Product Growth.

Higgins, P. C. (2014). GDPNow: A Model for GDP' Nowcasting'.

Hoerl, A. E., & Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, *12*(1), 55-67.

Horobeț, V. C. B. A. (2019). Short-term Forecasting Romanian GDP Growth Using a Limited Selection of Monthly Indicators. *The 13th International Days of Statistics and Economics, Prague,* September 5-7. https://msed.vse.cz/msed_2019/article/83-Bulai-Vlad-Cosmin-paper.pdf

Iyer, T., & Gupta, A. S. (2019). Nowcasting Economic Growth in India: The Role of Rainfall.

Koop, G., McIntyre, S., Allan, G., & Smith, P. (2018). Regional nowcasting: an illustration using the Scottish economy. *Sankhya B*, 1-25.

Kuzin, V., Marcellino, M., & Schumacher, C. (2013). Pooling versus model selection for nowcasting GDP with many predictors: Empirical evidence for six industrialized countries. *Journal of Applied Econometrics*, *28*(3), 392-411.

Kuzin, V., Marcellino, M., & Schumacher, C. (2011). MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the euro area. *International Journal of Forecasting*, *27*(2), 529-542.

Modugno, M. (2013). Now-casting inflation using high frequency data. *International Journal of Forecasting*, *29*(4), 664-675.

Nunes, L. C. (2005). Nowcasting quarterly GDP growth in a monthly coincident indicator model. *Journal of Forecasting*, *24*(8), 575-592.

Reserve Bank of New Zealand *Bulletin,* Vol. 72, No. 1, March 2009

Schneider, U., & Wagner, M. (2012). Catching growth determinants with the adaptive lasso. *German Economic Review*, *13*(1), 71-85.

Stock, J. H., & Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. *Journal of the American statistical association*, *97*(460), 1167-1179.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.

Tiffin, A. (2016). Seeing in the dark: a machine-learning approach to nowcasting in Lebanon.

Appendix

Annexure I: List of Data Series – Frequency and Lags

No	Real/nominal	Series	Unit	Frequency	Delays
1	Real	Large-scale manufacturing index	Indices	Monthly	6 to 7 weeks
2	Real	Cement sale	Million tons	Monthly	1 week
3	Real	Automobile sale	Units	Monthly	1 week
4	Nominal	Private sector credit	Billion rupees	Weekly	3 weeks
5	Nominal	Wholesale price index	Indices	Monthly	1 to 2 days
6	Nominal	Imports	Million US$	Monthly	2 weeks
7	Nominal	Exports	Million US$	Monthly	2 weeks
8	Nominal	Consumer price index	Indices	Monthly	1 to 2 days
9	Real	Real effective exchange rate index	Indices	Monthly average	-
10	Nominal	Oil prices	Rupees/bbl	Daily/monthly avg.	1 to 2 days
11	Nominal	Workers' remittances	Million US $	Monthly	2 weeks
12	Nominal	Foreign direct investment	Million US $	Monthly	1 week
13	Nominal	Total tax collection	Billion rupees	Monthly	2 weeks
14	Nominal	Direct taxes	Billion rupees	Monthly	2 weeks
15	Nominal	Indirect taxes	Billion rupees	Monthly	2 weeks
16	Nominal	Sales taxes	Billion rupees	Monthly	2 weeks
17	Nominal	Federal excise duty	Billion rupees	Monthly	2 weeks
18	Nominal	Customs duties	Billion rupees	Monthly	2 weeks
19	Nominal	Interest rate spread (1Y-3M)	Percentage	Monthly	1 day

Annexure 2: Quarterly Nowcast of LSM Growth