Annex I. Nowcasting and Forecasting Lebanon's Real GDP Growth

The MIDAS Approach

In line with previous editions of the *Lebanon Economic Monitor*, we nowcast and forecast real GDP growth using Mixed Data Sampling (MIDAS) regressions. A key advantage of MIDAS regressions is that they allow the combination of low frequency GDP data with higher frequency economic activity data.[1]

An exhaustive list of high frequency indicators is employed to nowcast and forecast real GDP growth in 2022 and 2-23. The indicators fall into one of three broad groups: (i) business activity surveys, conducted by the Banque du Liban (BdL), which proxy for business, (ii) real activity indicators, and (iii) financial indicators. While the BdL surveys are available at the quarterly frequency, data on the real activity and financial indicators are available at the monthly frequency. The high frequency indicators that are employed are discussed next.

The (low frequency) variable of interest in the nowcasting or forecasting exercises is

$$y_t^L = (gdpg)$$

where *gdpg* is the annual growth rate in real GDP.

Dynamic Factor Models

Recent advances in the literature demonstrate the success of Dynamic Factor Models (DFMs) in nowcasting economic activity. The important contribution of Giannone, Reichlin and Small (2008) has paved the way for a wide application of DFMs, estimated using the two-step estimation procedure of Doz, Giannone and Reichlin (2011), for nowcasting real GDP. In two contributions to the literature, Banbura, Giannone and Reichlin (2011) and Banbura *et al.* (2012) showcase the ability of DFMs in nowcasting GDP. Because MIDAS regressions are prone to a curse of dimensionality problem and multiple predictors complicate the estimation substantially (Ghysels and Marcellino, 2018), DFMs, which extract the informational content from a large set of predictors, are employed in addition to MIDAS models, to nowcast Lebanon's real GDP in 2022.

Real Activity Indicators

The real economic indicators used are: BdL Coincident Indicator (CI); World Bank Coincident Indicator (WBCI); Cement Deliveries (CD); Cleared Checks in Real Terms (CC); Customs Receipts in Real Terms (CR); Import of Petroleum Derivatives (PI); Incoming Freight at the Port of Beirut (IF); Outgoing Freight at the Port of Beirut (OF); Primary Spending in Real Terms (PRIM), Revenues from the Registration of New Private Vehicles in real terms (CAR), Inflow of Remittances in real terms (REM), Revenues from the Value Added Tax in real terms (VAT), and Imports in real terms (IMP).

The prevalence of cash transactions in the Lebanese economy – the Lebanese economy has turned into a "cash economy" - complicates gauging consumption. The latter four high frequency indicators (CAR, REM, VAT and IMP) are included as indirect – and, admittedly, imperfect - gauges of consumption.

That is, in the MIDAS setup, the vector of high frequency indicators is

[1] Bridge equations have also been widely used by central banks. A comparative assessment of the predictive ability of MIDAS and bridge equations is provided in Schumacher (2016).

$$x_t^H = (ci, wbci, cd, cc, cr, pi, if, of, pf, prim, car, rem, vat, imp)$$

where the lower-case variables denote annual growth rates of their respective upper-case version. The data for the high frequency indicators are available at the monthly frequency.

Financial Indicators

The financial indicators that are used in the nowcasting and forecasting exercises are: non-resident deposits (NR); resident deposits (R); claims on the resident sector (CL) and lines of credit for imports (LC).

That is, in the MIDAS setup, the vector of high frequency indicators is

$$x_t^H = (nr, r, cl, lc)$$

The import constraint is likely not to be binding in 2022, given that imports are financed fully using cash deposits at the banks. Therefore, the nowcasts of real GDP growth obtained from using lines of credit as a high frequency indicator should be interpreted with caution. Further, developments in the financial sector are less likely to be revealing about real economic activity in 2022 and, hence, the results obtained from the financial indicators are de-emphasized, going forward.

Business Surveys

The BdL collects and disseminates business surveys for a host of economic sectors. The surveyed sectors comprise, in broad terms, industry, trade and public works (Jad, 2010). At a more granular level, the retail, construction, services (hotels and restaurants), and the industrial and commercial sectors, defined broadly, are included in the surveys.[2] The BdL business surveys are, in essence, qualitative surveys of the senior managers across the economic sectors. The survey responses are limited to three options: An improvement, no change or a deterioration in business conditions. The results are summarized as "balance of opinions", which are computed as the difference between the proportion of managers reporting an improvement in business conditions and those indicating a deterioration in business conditions (Jad, 2010). The BdL surveys serve as useful gauge of business *sentiment* across the economic sectors.

The following balance of opinions series are employed in the nowcasting exercise: Construction, demand, forecasted sales, sales, general activity, restaurant turnover, hotel turnover, hotel occupancy rates, production, investment, public works, portfolio of projects, inventories of finished goods, registered orders, stock of finished goods, stock of raw materials.

That is, in the MIDAS setup, the vector of high frequency indicators is

$$x_t^H = (const, dem, forsales, sales, ga, resturn, hoturn, occ, prod, inv, pw, pp, invfin, ro, sfg, srw$$

Relative to the previous run, the set of candidate predictors is enlarged significantly and comprises, notably, proxies for consumption and business sentiment. In addition, additional data on the high frequency indicators are collected. Further, DFMs and LSTMs are employed to nowcast economic activity in addition to MIDAS regressions. The latter two models extract the informational content from all of the predictors.

[2] Further details are available from the BdL white paper entitled "Business Surveys".

Forecast Combinations

As noted in Timmermann (2006), combining forecasts is desirable for a number of reasons.[3] First, identifying the best performing model is not a straightforward endeavor. Therefore, combining forecasts provides diversification gains. Second, the combined forecast is more robust to structural breaks in the individual forecasting models. Third, given that every model is likely to be misspecified, combining forecasts will alleviate the effects of misspecification in individual forecasting models (Elliott and Timmermann, 2016). Fourth, Timmermann (2006)'s synthesis of the empirical literature suggests that combining forecasts yields gains in predictive accuracy relative even to the best performing individual forecasting model. The simple mean, the trimmed mean and the median are three simple forecast combination methods that can be applied in this setup. Forecast combination is also undertaken by selecting the predictors in the spirit of Tiffin (2016), using the Least Absolute Shrinkage Selection Operator (LASSO). In addition, the informational content in the predictors is extracted using principal components and the principal components are used in the MIDAS regressions. These models are referred to as factor MIDAS.

The nowcasts of real GDP growth for 2022 are provided in Table 1.

Table 1. Nowcasts of Real GDP Growth using Forecast Combination (or Averaging) and Factor Augmented MIDAS regressions

	GDP Growth for 2022
Mean (Real Indicators)	-2.33%
Median (Real Indicators)	-4.19%
LASSO (Mean)	-3.78%

The nowcast of real GDP growth for 2022 using a DFM are provided in Table 2.

Table 2. Nowcasts of real GDP growth for 2022 obtained from Dynamic Factor Models

Panel of High Frequency Indicators	**Real GDP Growth Forecast for 2022**
Real activity indicators	-3.89%

References

Banbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2012). Nowcasting and the real-time data flow. In G. Elliott & A. Timmermann (Eds.), *Handbook of Economic Forecasting* (Vol. 2A). Amsterdam: Elsevier-North Holland.

Banbura, M., Giannone, D., & Reichlin, L. (2011). Nowcasting. In M. Clements & D. Hendry (Eds.), *The Oxford Handbook of Economic Forecasting*. Oxford: Oxford University Press.

Doz, C., Giannone, D., & Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics*, *164*(1), 180–205.

Elliott, G., & Timmermann, A., (2016). *Economic Forecasting*. Princeton University Press.

Foroni, C., & Marcellino, M. G. (2013). A survey of econometric methods for mixed-frequency data. Working paper, Department of Economics, European University Institute.

Ghysels, E., & Marcellino, M., (2018). Applied Economic Forecasting using Time Series Methods. Oxford University Press.

[3] This discussion is based on Jamali and Yamani (2019).

Ferrara, L., & Marsilli, C., (2019). Nowcasting global economic growth: A factor-augmented mixed-frequency approach. The World Economy, *42*, 846-875.

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

Jad, S. S. (2010). The use of surveys to measure sentiment and expected behaviour of key sectors in the economy: evidence from the business survey conducted by the Central Bank of Lebanon, IFC Bulletin No 34: Initiatives to address data gaps revealed by the financial crisis, Proceedings of the Fifth IFC Conference, Basel, 25–26 August 2010, Bank of International Settlements.

Jamali, I., & Yamani, E. (2019). Out-of-sample exchange rate predictability in emerging markets: Fundamentals versus technical analysis. *Journal of International Financial Markets, Institutions and Money*, *61*, 241-263.

Kuzin, V., Marcellino, M., & Schumacher, C., (2009). Pooling versus model selection for nowcasting with many predictors: An application to German GDP. Department of Economics, European University Institute, EUI working paper ECO 2009/13.

Marcellino, M., & Schumacher, C., (2010). Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. *Oxford Bulletin of Economics and Statistics*, 72(4), 518-550.

Timmermann, A., (2006). Forecast combinations. *Handbook of Economic Forecasting*, *1*, 135-196.

Tiffin, A., (2016). Seeing in the dark: A machine learning approach to nowcasting in Lebanon, IMF working paper WP/16/56, International Monetary Fund, Washington DC.

Annex II. The Exchange Rate Pass-Through in Lebanon

The exchange rate pass through measures the extent to which fluctuations in the exchange rate yield changes in aggregate prices (i.e., inflation). The Exchange Rate Pass Through (EPRT) coefficient is, therefore, akin to an elasticity coefficient in that it measures the sensitivity of the Consumer Price Index (CPI) to the exchange rate.

Estimating the ERPT Coefficient with a VECM

Existing studies commonly employ Vector Autoregressive (VAR) or Vector Error Correction (VECM) models to gauge the degree of the pass through from the exchange rate to inflation (Bhundia, 2002; Ha, Stocker and Yilmazkuday; 2019; McCarthy, 2007; Korhonen and Wachtel, 2006; Korhonen and Wachtel, 2006; Leigh and Rossi, 2002; McCarthy, 2007). All of the latter studies estimate the ERPT coefficient using impulse response analysis from a well-specified model. The extent to which exchange rate (or devaluation/depreciation) shocks drive inflation is also examined using forecast error variance decompositions.

VAR and VECM with Commodity Prices, the Exchange Rate and the CPI

A VAR in log levels comprising in the vector y_t the variables $lcrb_t, ler_t, lcpi_t$, where the latter variables refer to the natural logarithms of commodity research bureau, the BNR and the CPI. Commodity prices are included in the models to account for the surge in energy and wheat prices and their potential effect on inflation in the wake of the Russian war on Ukraine.

The results from estimating the VAR in log levels yield estimates of the ERPT in Table 3.

Table 3. Estimates of ERPT from VAR in log levels

Change in Exchange Rate	Change in Inflation
1%	1.34%
100%	134%

The estimated ERPT coefficient is larger than one suggesting a large degree of pass-through of exchange rate changes to inflation.

Figure 1 provides the Forecast Error Variance Decomposition (FEVD) for inflation. The FEVD provides the proportion of the variation in the CPI that is due to its own shocks as well as to shocks in the other variables in the VAR.

Figure 1. Forecast Error Variance Decomposition for the CPI from VAR in log levels with Commodity Prices, the Exchange Rate and the CPI

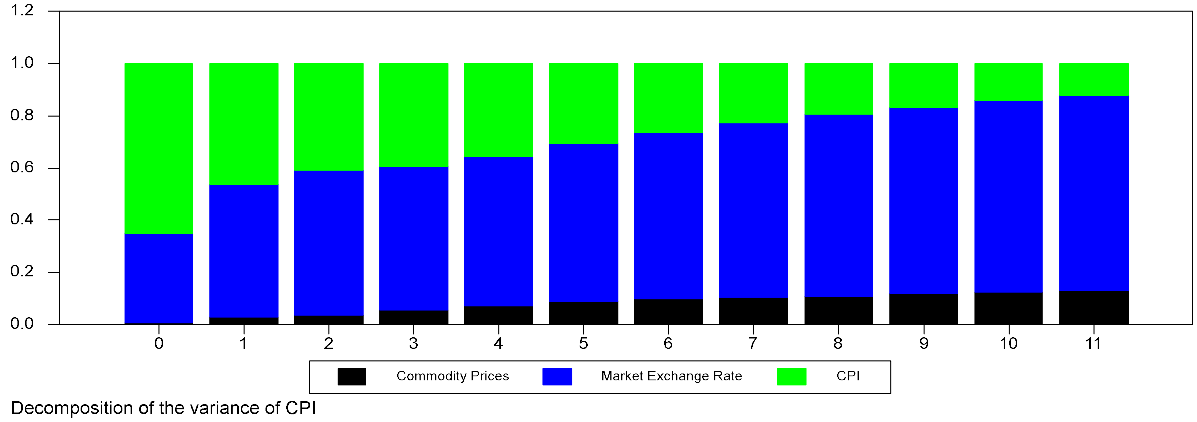


Figure 1 provides evidence that shocks to the exchange rate account for the bulk of the variation in the CPI.

Tests of cointegration using the Johansen (1988) trace statistic as well as the Phillips and Ouliaris (1990) test suggest the existence of a cointegrating relation between the variables. There, a VECM is estimated to account for the cointegrating relation.

The estimate of the ERPT from the VECM is provided in Table 4

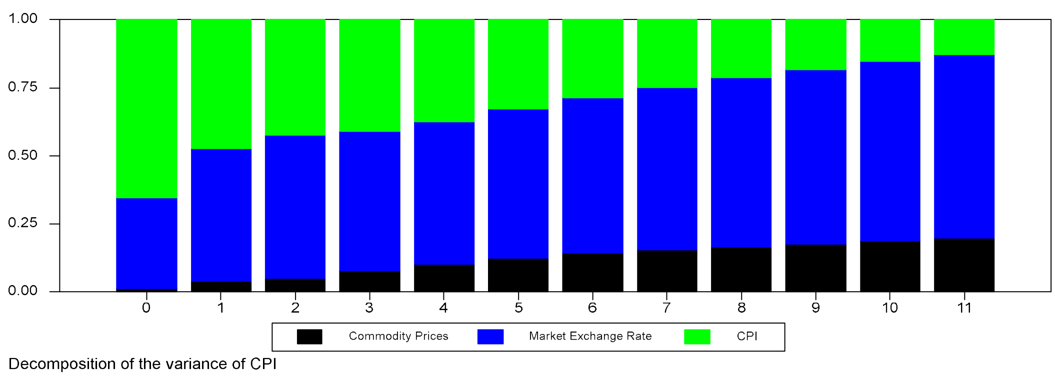
Table 4. Estimates of ERPT from VECM

Change in Exchange Rate	Change in Inflation
1%	1.41%
100%	141%

The estimated ERPT is larger when the cointegrating relation is account for.

Figure 2 provides the FEVD for inflation from the VECM.

Figure 2. Forecast Error Variance Decomposition for the CPI from VECM with Commodity Prices, the Exchange Rate and the CPI



Again, Figure 2 provides evidence that shocks to the exchange rate account for the bulk of the variation in the CPI.

References

Bhundia, A. (2002). An empirical investigation of exchange rate pass-through in South Africa. IMF Working Paper, WP/02/165, International Monetary Fund, Washington DC.

Ha, J., Stocker, M., & Yilmazkuday, H. (2019). *Inflation and exchange rate pass-through.* World Bank Policy Research Paper 8780, World Bank, Washington DC.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, *12*(2-3), 231-254.

Korhonen, I., & Wachtel, P. (2006). A note on exchange rate pass-through in CIS countries. *Research in International Business and Finance*, *20*(2), 215-226.

Leigh, D., & Rossi, M. (2002). Exchange rate pass-through in Turkey. IMF Working Paper WP/02/04, International Monetary Fund, Washington DC.

McCarthy, J. (2007). Pass-through of exchange rates and import prices to domestic inflation in some industrialized economies. *Eastern Economic Journal*, *33*(4), 511-537.

Ortega, E., & Osbat, C. (2020). Exchange rate pass-through in the euro area and EU countries. *European Central Bank, Occasional Paper*.

Phillips, P. C., & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica: journal of the Econometric Society*, 165-193.