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NOWCASTING ITALIAN INDUSTRIAL PRODUCTION: THE PREDICTIVE ROLE OF LUBRICANT OILS

by Marco Fruzzetti* and Tiziano Ropele*

Abstract

This paper examines the potential of industrial lubricant oils as a predictor for nowcasting the index of Italian industrial production. The results show that nowcast accuracy can be significantly enhanced during periods of economic turbulence, such as the 2021-22 energy crisis. Industrial lubricant oils are a more robust economic indicator than other commonly used energy-related timely predictors, such as industrial gas consumption. Furthermore, the findings may prove relevant for nowcasting industrial production in the process of structural changes, such as the ongoing green transition.

JEL Classification: E32, E66.

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1. Introduction[1]

Nowcasting the business cycle, i.e. predicting the current state of the economy, is a critical task for policymakers, businesses, and researchers alike. The accuracy of nowcasting models has a direct impact on the quality of economic decisions and strategies.

Over the past two decades, significant advances in the nowcasting frontier have resulted from both methodological developments (e.g., Dynamic Factor Models, Mixed Data Sampling Models, Bayesian Vector Autoregressive Models) and the use of innovative and timely indicators (e.g., survey indicators, traffic data, payment data, social media information).[2] The ever-changing economic landscape and the increasing complexity of modern economies require continuous assessment, if not re-evaluation, of nowcasting models to ensure highly reliable economic forecasts.

The energy crisis that followed the Covid-19 pandemic, and exacerbated by the Russian invasion of Ukraine in February 2022, unveiled certain weaknesses in macroeconomic nowcasting, and forecasting, models. Models used to nowcast industrial production, a key driver of economic business cycles, typically include predictors related to energy consumption, such as electricity and industrial gas. These variables, which are generally available with minimal time delays, have shown significant explanatory power for tracking and nowcasting industrial production.[3] However, during the 2021-22 energy crisis, when gas and electricity prices surged to record level highs, industrial gas consumption fell sharply in Italy. At the same time, the Italian industrial production index did not decline as much, suggesting a weakening of the correlation between energy use and industrial activity. This evidence may have been the result of firms' adopting more efficient energy utilization practices and/or exploring alternative energy sources (such as renewables).[3]

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[2] For an early review of the literature see Banbura et al. (2013). A more recent survey is Stundziene et al. (2023).

[3] In Italy electricity consumption has been used to nowcast industrial production since the mid-1980s (see Bodo and Signorini, 1987, and the references cited therein); more recent studies include Marchetti and Parigi (2000), Aprigliano (2020) and Galdi et al. (2023). Other studies that explored the properties of electricity consumption include Lewis et al. (2020) for the US, Eraslan and Götz (2021) for Germany, Lourenço and Rua (2021) for Portugal. Fezzi and Fanghella (2021) used electricity consumption to nowcast the decline in economic activity during the first wave of Covid-19 across several European countries.

[3] According to the Invind survey conducted by the Bank of Italy in 2022, about 40 per cent of the industrial firms with at least 50 employees included in the sample reported that they self-produced a significant part (on average

The goal of this paper is to assess the predictive power of a new, timely indicator for the nowcast of Italian industrial production: the consumption of industrial lubricant oils (industrial lubricant consumption, in short). In virtually all manufacturing and processing industries, lubricant oils are used in numerous machines (pumps, compressors, conveyors, hydraulic systems, turbines, etc.) to reduce the friction between mechanical parts, to prevent corrosion and to dissipate heat. Irrespective of the amount and type of energy used in the production process, industrial lubricant consumption maintains a tight link with the actual level of production. It is therefore reasonable to assume that the inclusion of industrial lubricant consumption could improve the prediction accuracy of nowcasting models for industrial production. In Italy, data on industrial lubricant consumption are published with monthly frequency by the Ministry of the Environment and Energy Safety (MASE) in its Petroleum Bulletin.

We employ a series of econometric methods to show that the inclusion of industrial lubricant oils does significantly improve the nowcast accuracy of the monthly growth rate of the Italian industrial production index. Using monthly data from January 2004 to December 2023 we estimate simple univariate regressions in the spirit of Marchetti and Parigi (2000) and compare the nowcast accuracy in two different time windows (during the pre-pandemic and the post-pandemic periods) by conducting a horse race between a *benchmark model* that includes several standard regressors but excludes industrial lubricant consumption and an *augmented model* that instead includes industrial lubricant consumption. The benchmark model comprises the consumption of electricity, the consumption of gas for industrial use (industrial gas consumption, for short) and other predictors related to truck and rail freight traffic volumes, future expected production and temperatures. Common metrics for forecast accuracy, namely the mean absolute error and the root mean squared error, and the results of the Diebold-Mariano test, show a significant improvement in forecast accuracy obtained by incorporating industrial lubricant consumption in the 2021-2022 energy crisis period. However, the benefit of including industrial lubricant consumption in the pre-pandemic period turns out not to be significant.

The predictive role of industrial lubricant consumption during the energy crisis period is confirmed by a number of robustness checks. We address the issue of parameter

30 per cent) of their electricity consumption, primarily through the use of renewable sources. For an analysis of the impact of the energy crisis on Italian industrial firms see Alpino, Citino and Frigo (2023).

instability, given the occurrence of large shocks during the period under consideration, and extend our analysis to a multivariate setting. With regard to the former, we carry out a rolling-window estimation; with regard to the latter, we estimate a Bayesian Vector Autoregressive model with block-specific shrinkages parameters, following the approach outlined in Aprigliano (2020).

Our work fits into two different strands of the literature. First, our research is related to the numerous studies that have explored innovative predictors to improve nowcasting accuracy. This pursuit has been ongoing for much time, but in recent years, especially after the outbreak of the Covid-19 pandemic, there has been a proliferation of new data: transport data (Fornaro, 2020), mobility indices (Furukawa et al., 2022; Delle Monache et al., 2021), financial transaction data (Aastveit et al., 2020; Ardizzi et al., 2019), internet search queries (Götz and Knetsch, 2019), epidemiological data (Aprigliano et al. 2021) and even newspaper articles (Thorsrud, 2020, Aprigliano et al. 2021). Our paper contributes to this literature by proposing a novel indicator, i.e. industrial lubricant consumption, which to our knowledge has not yet been used in any previous nowcasting study.

The second strand of related literature focuses on the impact of the recent energy crisis. Corsello et al. (2023) assess the impact of the abrupt rise in energy prices since 2021 on the Italian industrial sector and find that while producer prices start to rise from the beginning of 2021, especially in energy-intensive industries, industrial production starts to weaken from the spring of 2022. De Santis and Tornese (2021), by using a Bayesian TVAR, find that energy supply shocks have a stronger impact on output in the medium term, with manufacturing being more adversely affected than GDP. Chiacchio et al. (2021) show, for the euro area, that producers in energy-intensive sectors started substituting own production with cheaper imports in early 2022. Our results confirm the view that in 2022 energy variables started to lose adherence with production in Italy.

The paper is organized as follows. Section 2 describes the data and illustrates some preliminary descriptive statistics of key variables. Section 3 presents the econometric strategy and discusses the main results. Section 4 presents some robustness checks and Section 5 concludes.

2. Data

The data cover the period from January 2004 to December 2023. Our target variable is the Italian industrial production index, which is published monthly by the Italian National Institute of Statistics (ISTAT) with a lag of about 40 days with respect to the reference period.[4] Within the set of explanatory variables, we include various predictors commonly used in nowcasting studies of industrial production but we also innovate by introducing a novel variable measuring industrial lubricant consumption. Table 1 shows the full list of explanatory variables.

In Italy, the Ministry of the Environment and Energy Safety (MASE) publishes monthly statistics on the consumption of lubricant oils in its Petroleum Bulletin. These data are collected through surveys that MASE conducts under the National Statistical Program covering, among other things, the import, export and consumption of petroleum products.[6] The survey is carried out using a non-probabilistic sampling design due to the highly concentrated characteristics of the petroleum market and the composition of the sample is periodically updated. For the lubricants sector, given the small quantities of products marketed compared to other petroleum products, the sample includes companies producing and/or importing lubricants regardless of the quantities released for consumption. In the following Sections, we focus on the consumption of lubricant oils for industrial use.[7]

For the purposes of our analysis, the data on the consumption of lubricant oils for industrial use have three important characteristics. Firstly, MASE publishes these data with a lag of only 20 days after the end of the reference month. Secondly, like data related to gas and electricity consumption, data on the consumption of lubricant oils are expressed in physical units (tonnes), thus eliminating the need for deflation. Lastly, as will be discussed in more detail below, the dynamics of lubricant oil consumption exhibit a strong correlation with the industrial production index, even during the recent energy crisis.

The remaining regressors are fairly standard in the literature on the nowcasting of industrial production. We incorporate two predictors related to the monthly consumption of electricity from TERNA (Italy's independent electricity transmission system operator) and the monthly consumption of gas for industrial use from SNAM (Italy's operator for natural gas transportation, dispatching and storage). These data are very timely and virtually available in real time. Given the sensitivity of energy consumption to weather conditions, especially during

[4] For example, the industrial production index for January 2022 is available around the 10th of March 2022. [6] Data must be transmitted by companies on a compulsory basis under both the National Statistical Program and the Legislative Decree No. 249 of December 31, 2012, implementing Directive 2009/119/EC, which establishes the obligation of Member States to maintain minimum stocks of crude oil and/or petroleum products. [7] In particular, the consumption of lubricant oils for vehicles is deducted from the aggregated data.

peak demand periods in the summers and winters for cooling and heating purposes, we include the average monthly temperature in our nowcasting models.

Next, we introduce two predictors that are related to the transport of goods. The rationale for this is that production and transport activities are highly correlated, as produced goods have to be physically delivered to customers. Specifically, we consider the monthly volumes of truck freight and rail freight traffic.

Finally, we include a forward-looking qualitative indicator to capture the possibility of expectation-driven production, thus acknowledging the role of expectations in shaping current production dynamics. To this end we use information from ISTAT's monthly business surveys which are released around the end of the reference month. We focus on two questions. The first question asks firms "*How do you expect your production to develop over the next 3 months? It will….*" followed by a choice of three possible answers: "*increase*", "*remain unchanged*" or "*decrease*". The second question asks "*Do you consider your current stock of finished products to be…?*", with three possible answers: "*too large (above normal)*", "*adequate (normal for the season)*" or "*too small (below normal)*". For both questions, we consider the net balance as the difference between the percentages of respondents giving positive and negative replies and then build a forward-looking indicator as the ratio of the balance for expected production to the balance for current stock of finished goods.

2.1 A preliminary inspection of the data

Figure 1 shows the time series of the Italian industrial production index together with the consumption of electricity, gas and industrial lubricants. The panels in the left-hand column show the unadjusted series, which are characterized by strong seasonal patterns, with noticeable dips in August, due to the summer holidays, and smaller dips in December, due to the winter festivities. The panels in the right-hand column show the series seasonal and calendar adjusted using Tramo-Seats. These adjusted series highlight the significant decline in all indicators following the global financial crisis, the prolonged weakness during the sovereign debt crisis and, more recently, the collapse during the most acute phases of the pandemic in 2020.

As mentioned above, during the recent energy crisis which started in mid-2021 and was then exacerbated by Russia's invasion of Ukraine in February 2022, industrial lubricant consumption maintained a tighter adherence with the industrial production index in particular compared to the consumption of gas for industrial use. Based on seasonal and calendar adjusted data, between July 2021 and December 2022 the industrial production index decreased by 0.3%, while consumption of gas for industrial use plummeted by 25.6% and consumption of electricity (which includes household consumption) fell by 5.1%. In contrast, consumption of lubricant oils for industrial use increased by 1.9%. Using raw data, in the twelve months to December 2022 industrial production fell by 7.2%,[5] accompanied by declines in industrial gas, electricity, and lubricant consumption of 26.8%, 11.7%, and 5.5%, respectively.

In Table 2 we report two matrices of the contemporaneous correlation between the industrial production index[9] and the consumption of industrial lubricants, the consumption of gas for industrial use, and the consumption of electricity.[6] The first matrix (panel (a)) is calculated using raw data, while the second matrix (panel (b)) uses seasonal and calendar adjusted data. The correlations are calculated over two distinct time intervals: the pre-pandemic period from January 2004 to February 2020 (values are reported below the main diagonal) and the recent period of the energy crisis from July 2021 to December 2023 (values are reported above the main diagonal). During the pre-pandemic period, industrial lubricant consumption has the highest correlation (among the variables considered) with the industrial production index: 0.89 based on raw data; and 0.94 for seasonally adjusted data. The correlation is high for the other two energy consumption indicators too (see Table 2). Instead, during the recent energy crisis period, the correlation calculated on the basis of raw data increases for industrial lubricant consumption (to 0.97), while it decreases markedly for industrial gas and electricity consumption (to approximately 0.6 in both cases). The highest correlation of industrial lubricant oil consumption is also confirmed using seasonally adjusted data.

These initial findings suggest that the relationship between the consumption of lubricant oils and industrial production has remained relatively more stable during the energy crisis than other energy consumption indicators. The ability of the latter to accurately signal trends in industrial activity may have been reduced due to energy-saving strategies implemented by companies. Indeed, based on survey-based information collected by the Bank of Italy, in response to the increase in energy costs in the first nine months of 2022, companies

[5] The decline in activity is of a similar magnitude (-5.8%) if only manufacturing activity is considered. [9] Similar results are obtained using the manufacturing production index, which accounts for approximately 90% of the industrial production index.

[6] The construction of correlgrams with lags/leads up to 12 between industrial production and other key indicators (based on seasonal and calendar adjusted series) indicates that the highest correlations are obtained for contemporaneous correlations.

implemented strategies such as diversifying energy sources (e.g., through self-production of energy) and investing in more efficient machinery.

Finally, although the industrial production index is non-stationary, as confirmed by the Augmented Dickey-Fuller test (Dickey and Fuller, 1979), which does not reject the null hypothesis of a unit root in the levels, we express our forecasting models in terms of raw data with monthly fixed effects so as not to have to seasonal and calendar adjust all the variables and then work on first differences.

3. Methodology and estimation results

In this Section, we first describe the benchmark model considered in our analysis and then illustrate the key estimation results.

3.1 A univariate *nowcasting* model

Our benchmark nowcasting model for the (un-adjusted) index of industrial production in period t (IPI_t, henceforth) builds on the following simple univariate specification:

$$\begin{gathered} IPI_t = \beta_0 + \beta_1 GAS_t + \beta_2 ELECT_t + \beta_3 TRUCK_t + \beta_4 RAIL_t + \\ + \beta_5 TEMP_t + \beta_6 (TEMP_t)^2 + \beta_7 PRODEXP_t + \beta_8 LUBR_t + \gamma_m + error_t \end{gathered} \tag{1}$$

where the main explanatory variables are those reported in Table 1, γ_m represents a set of monthly fixed effects to account for seasonality in the data, and $error_t$ is the residual term. Specifications similar to (1) have been used in Bodo and Signorini (1987), Bodo, Cividini, and Signorini (1991) and Bodo, Golinelli, Parigi (2000).[7] The estimation of (1) is carried out using the method of ordinary least squares (OLS) with robust standard errors to heteroscedasticity and autocorrelation in the residuals over three time intervals: (i) the pre-pandemic period (from January 2004 to February 2020), (ii) the pre-energy crisis period (from January 2004 to June 2021), and the entire sample period (from January 2004 to December 2023).

[7] It is worth noting that (1) does not include autoregressive terms. The inclusion of the first lag of the dependent variable turns out to be generally statistically insignificant (likely because the estimation is conducted on raw data), and there are no gains in terms of forecasting accuracy. Including a greater number of lags (up to 12), the predictive performance of the model tends to yield slightly worse results.

3.2 Estimation results

Table 3 presents the results of the OLS estimation of specification (1). For the pre-pandemic period and when excluding the industrial lubricant consumption from the model, the results in column (1) of Table 3 indicate that most of the estimated coefficients are statistically significant and have the expected signs. Focusing on the two energy consumption predictors, the consumption of electricity is statistically significant at the 1% level while the industrial gas consumption is significant at the 5% level. The in-sample fit, as measured by the adjusted R^2, is notably high, likely reflecting the fact that the estimation is conducted on raw data with monthly fixed effects.

Column (2) of Table 2 shows the estimation results obtained by including the industrial lubricant consumption in the specification. Firstly, the estimated coefficient related to this variable is significant at the 5% level and has a positive sign, indicating that an increase in industrial lubricant consumption is associated with an increase in industrial production. Secondly, the inclusion of industrial lubricant consumption in the specification affects the estimated coefficient of industrial gas consumption, reducing it by about half and making it statistically insignificant. This result likely reflects the high correlation between these indicators, as shown in Table 1, which leads to a rejection of their simultaneous inclusion. Instead, the addition of industrial lubricant consumption leaves all other coefficients almost unchanged. Finally, the goodness-of-fit remains virtually identical to that shown in column (1).

Columns (3) and (4) of Table 2 present the estimates derived from the pre-energy crisis period. Two main results are worth stressing. Firstly, the estimated coefficient associated with industrial gas consumption becomes insignificant, even in the specification that excludes the industrial lubricant consumption. This result suggests that the predictive power of industrial gas consumption was markedly reduced during the pandemic crisis. Conversely, the industrial lubricant consumption continues to be a relevant predictor in tracking the evolution of industrial production, albeit with a slight decrease in the statistical significance of the coefficient. Furthermore, the coefficient for electricity consumption maintains its high level of statistical significance.

Finally, columns (5) and (6) present the estimates obtained over the entire sample period. In this case, the coefficient associated with industrial gas consumption is statistically insignificant, indicating a notable decline in the predictive power of this variable in the more recent period. Conversely, industrial lubricant consumption is confirmed as a highly relevant variable: not only does the significance of the coefficient improve, but there is also a marginal increase in the goodness-of-fit for specification (6) compared to (5).

3.3 Nowcasting accuracy evaluation

As previously discussed, the in-sample fit for the various models is notably high. In this Section, we assess the accuracy of the above specifications for nowcasting the industrial production index, with a particular focus on the predictive power of industrial lubricant consumption. More specifically, the nowcasting performance is evaluated with reference to the developments in the seasonal and calendar adjusted series of industrial production in the period from January 2018 to December 2023, excluding the months of 2020 due to the ample fluctuations in activity recorded during the most acute phases of the pandemic, which were largely unrelated to purely economic forces.

Specifically, we proceed in the following way. To begin, we estimate specification (1) in the period from January 2004 to December 2017, first excluding and then including industrial lubricant consumption. This yields two forecasts of the *raw* index of industrial production for January 2018. The extended series, which include the aforementioned forecasts, are then seasonal and calendar adjusted and used to compute the monthly growth rates between December 2017 and January 2018. These predicted growth rates are then compared with the monthly growth rate published by Istat to compute the nowcast error. We then proceed to estimate (1) recursively over the period from January 2004 to January 2018, thereby producing the monthly growth rate of the seasonally adjusted industrial production between January 2018 and February 2018, and so on. These recursive predictions are conducted in pseudo real-time, meaning that in each round of this procedure, the series of industrial production is the one that is made available by Istat at the time of the forecast (i.e., the real-time vintage), while for other predictors we use the values available in the December 2023 vintage as they do exhibit substantial ex-post revisions.

Proceeding along these lines, we obtain two series of nowcast errors from January 2018 to December 2023. On this data we calculate two commonly used prediction accuracy indicators, namely the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) defined as

$$MAE = \frac{\sum_t |g_{IPI,t} - \hat{g}_{IPI,t}|}{T} \quad \text{and} \quad RMSE = \sqrt{\frac{\sum_t \left(g_{IPI,t} - \hat{g}_{IPI,t}\right)^2}{T}}$$

where $g_{IPI,t}$ is the observed monthly growth rate of the industrial production index (published by Istat) at time t=1,…,T and $\hat{g}_{IPI,t}$ is its value as predicted by the nowcasting models.

Table 4 presents the results of the nowcast accuracy calculations conducted over two time periods: from January 2017 to December 2019 and from January 2021 to December 2023. Three main findings emerge from the analysis. Firstly, with regard to the period 2017-19, there appears to be no discernible improvement in the predictive performance resulting from the inclusion of industrial lubricant consumption. In this case, both the MAE and the RMSE marginally decline when industrial lubricant consumption is included: the former, from 1.22 to 1.19; the latter, from 1.52 to 1.49. The fact that the two models produce nowcast accuracy results that are virtually similar is reflected in the Diebold-Mariano test statistics,[8] which turn out not to be statistically significant.

The second result pertains to the predictive performance for the period 2021-23. The inclusion of industrial lubricant consumption into the nowcasting model does improve the predictive performance. The MAE decreases from 1.76 to 1.71, while the RMSE decreases from 2.11 to 2.04. In this case the improvement in the forecast accuracy of the augmented model is statistically significant at the 5% confidence level according to the Diebold-Mariano test statistics.

Finally, we find a significant deterioration in the forecasting performance of both models over the two periods considered, probably due to the fact that in the more recent period the industrial production series have shown greater volatility, also following several shocks to the economy (e.g. the energy crisis, supply-side bottlenecks, uncertainty related to the war in Ukraine), which has made nowcasting a more challenging activity.[9]

[8] The null hypothesis of the Diebold and Mariano (1995) test is that two competing forecasting models have the same prediction accuracy.

[9] We ran the same analysis separately for energy-intensive and non-energy-intensive sectors, recognizing that electricity and gas consumptions might be more relevant predictors for firms heavily reliant on energy inputs in their production processes. The results (available upon request) are largely confirmed: the MAE and RMSE decline substantially in both periods when lubricant oil consumption is included in the regression for the industrial production of energy-intensive sectors. A somewhat smaller improvement in nowcasting activity is obtained for non-energy-intensive sectors during the energy crisis period.

4. Robustness checks

In this Section we present the results of two extensions of our analysis. Firstly, we assess the stability of the coefficients of model (1). Secondly, we generalize our benchmark univariate specification to a multivariate framework by estimating a Bayesian VAR model.

4.1 Stability of coefficients

The entire sample period under scrutiny has been subject to a number of shocks, including the global financial crisis, the sovereign debt crisis, the pandemic and the energy crisis. These shocks could have impacted the stability of the estimated coefficients.

Parameter instability is widely recognized as a crucial factor in forecasting (Stock and Watson, 1996; Rossi, 2013). One way to handle such instability is to use only the most recent observations to estimate the parameters of the forecasting models rather than all available observations, thus implementing the so-called "rolling estimation" method. However, one practical issue with rolling estimation is determining the optimal number of recent observations to use in the estimation. Conventionally, the window size is arbitrarily determined by forecasters or based on past experience. Given the rather eventful sample period we set a short window width, namely 36 months, in order to better adapt to the changing economic landscape.

As shown in Figure 2, the coefficients display a certain degree of instability. Specifically examining industrial gas, electricity, and lubricant oil,[10] it is noteworthy that, in the estimates ending in the most recent months, the estimated coefficient for lubricant oil has generally increased, while the estimated coefficients for the other two energy-related variables have decreased. This observation further supports the fact that during the energy crisis the consumption of gas and electricity has lost adherence with industrial activity.[11]

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[10] Among the other predictors, the estimated coefficients on rail freight traffic volumes and sales have also generally rose (especially the former).

[11] To further address the issue of parameter instability, we also estimate a modified version of specification (1) by postulating the following piecewise linear regression model: $IPI_t = \gamma_0 + \gamma_1 \boldsymbol{X}_t + \gamma_2 \boldsymbol{X}_t DUM_{covid} + \gamma_3 \boldsymbol{X}_t DUM_{energy} + \gamma_m + DUM_{covid} + DUM_{energy} + error_t$ where X includes the same set of predictors that show up in the benchmark specification, where DUM_{covid} represents a dummy variable equal to 1 in the period from March 2020 to June 2021 and 0 elsewhere, and DUM_{energy} a dummy variable equal to 1 in the period from July 2021 to December 2022 and 0 elsewhere. The results (available upon request) show that the estimate for the variable DUM_{energy} is negative for industrial gas and electricity consumption, while it is positive for lubricant consumption. This implies that compared to the pre-pandemic period, lubricant consumption has gained greater significance, while the opposite holds for the other two variables.

We then execute the same nowcasting exercise described in the previous section and compute the nowcasting accuracy metrics. The results are reported in Table 5. First, it is important to note that both the MAE and RMSE are lower compared to those obtained by estimating the model over the entire sample period, as shown in Table 4. This suggests that estimating models over a shorter sample, especially when the full sample period includes significant shocks (such as the global financial crisis or the sovereign debt crisis), can better capture the correlations among variables and thus yield superior results in terms of nowcasting accuracy. Second, while the inclusion of industrial lubricant consumption does marginally worsen the nowcast accuracy in the period 2017-19, it substantially improves it in the second period with a gain of 7.0% for RMSE and 9.0% for MAE.

4.2 A BVAR nowcasting model

As discussed in the Introduction, an extensive body of research in the past few decades has proposed new nowcasting approaches aimed at predicting key macroeconomic variables.

In this Section, we conduct a robust experiment using a multivariate model, specifically a Bayesian vector autoregressive (BVAR) model with block-specific shrinkage parameters as in Aprigliano (2020).[12] BVAR models have several advantages: they can handle large sets of variables, possibly sampled at different frequencies; they do not necessitate data stationarity; and they can effectively account for uncertainties associated with various specification choices (such as the informativeness of prior distributions); furthermore, they are commonly employed by central banks and other policy institutions for forecasting, as well as for constructing narratives about the economic outlook.

By applying Bayesian shrinkage (λ) we are able to handle large dynamic VARs. Bańbura et al. (2010) find that even in a six variables VAR, shrinkage in the VAR can lead to better forecast performance. For $\lambda = 0$ the posterior equals the prior and the data do not influence the estimates while for $\lambda = \infty$ posterior expectations coincide with the ordinary least squares estimates. For a fair comparison, we include in the BVAR the same set of variables used in our previous univariate analyses. The BVAR is estimated in level with seasonal dummies. As in

[12] Bayesian shrinkage in BVAR models is a regularization technique that aids in model selection, improves estimation stability, incorporates prior knowledge, and enhances the overall forecasting performance of the model, especially in situations with high-dimensional data or limited sample sizes. Aprigliano (2020) show a significant improvement in the forecasting performance of Italian industrial production when using block-specific shrinkage parameters compared to the more traditional BVAR based on standard Minnesota priors with a single shrinkage that is equal for all variables.

Aprigliano (2020), we run a 36-month rolling window for the estimation period.[13] As in the previous Sections, the aim of this robustness experiment is to assess the predictive role of lubricant oil consumption for the nowcast of the Italian production index and thus we conduct analyses including and excluding this variable. In addition, and for the sake of comparison, we use a newly calibrated set of shrinkage parameters that are optimally selected to minimize the backcasting errors both for the model that includes lubricants and for the model that does not.[14]

The nowcast accuracy results for the BVAR models are reported in Table 6. Note that the BVAR model shows similar results in term of nowcasting accuracy to those obtained with the rolling-window univariate model for the period 2017-19 (Table 5). The BVAR model achieves significantly better results for the period 2021-23. In this case too, we find that the inclusion of industrial lubricant consumption does improve the accuracy. However, the gain is not statistically significant.

5. Conclusions

The paper has documented the usefulness of industrial lubricant consumption in nowcasting the growth rate of industrial production in Italy in particular during the 2021-22 energy crisis, using state-of-the-art nowcasting models. The 2021-22 energy crisis, which came after the Covid-19 Pandemic and Russia's invasion of Ukraine, together with the ongoing albeit slow-advancing energy transition to a more efficient and sustainable low-carbon future, should lead to refinements in nowcasting models, in particular for industrial production.

Future research could extend our analysis along several dimensions. First, the use of a wider range of econometric tools, including MIDAS models, non-linear approaches such as Markov switching models, and advanced machine learning algorithms, could provide a more robust and refined assessment of the utility of industrial lubricant consumption for nowcasting industrial production. Second, extending the breadth of the analysis to examine other countries and industrial subsectors would provide a more comprehensive understanding of the applicability and generalizability of industrial lubricant consumption as a nowcasting tool across different economic landscapes.

[13] We also tested a longer rolling-window estimation (60-month) and found very similar results.
[14] For this exercise we chose the optimal shrinkage parameters for the model without and with industrial lubricant consumption by minimizing the RMSEs.

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Table 1. Explanatory variables.

Variable	Frequency	Days of delay with respect to the reference month	Source
Consumption of industrial lubricant (LUBR)	Monthly	20	MASE
Consumption of industrial gas (GAS)	Daily	1	SNAM
Consumption of electricity (ELECTR)	Daily	1	TERNA
Road freight traffic (TRUCK)	Weekly	5-10	Private sector
Rail freight traffic (RAIL)	Monthly	15-20	Private sector
Temperature (TEMP)	Daily	1	ISTAT
Production expectations (PRODEXP)	Monthly	0	ISTAT

Notes: Production expectations is given the ratio of firms' expectation about future production to firms' assessment on the current level stock of finished products (see Section 2 for further details). Both expectations and assessments are elicited through the Istat's monthly business surveys. MASE is the Ministry of the Environment and Energetic Safety; SNAM is the operator in natural gas transport; TERNA is the electricity transmission system operator; ISTAT is the Italian National Institute of Statistics.

Table 2. Contemporaneous correlation among selected variables

Panel (a): not seasonally adjusted series

		(1)	(2)	(3)	(4)
Industrial production index	(1)		0.97	0.61	0.65
Industrial lubricant consumption	(2)	0.89		0.62	0.56
Industrial gas consumption	(3)	0.77	0.74		0.58
Consumption of electricity	(4)	0.84	0.73	0.76	

Panel (b): seasonally adjusted

		(1)	(2)	(3)	(4)
Industrial production index	(1)		0.64	0.29	0.39
Industrial lubricant consumption	(2)	0.94		0.46	0.26
Industrial gas consumption	(3)	0.85	0.90		0.68
Consumption of electricity	(4)	0.89	0.83	0.82	

Notes: In each correlation matrix, the numbers reported below (resp. above) the main diagonal are calculated over the period from January 2003 to February 2020 (resp. from July 2021 to December 2023).

Table 3. Estimation results: Univariate nowcasting model

	Sample period:					
	Jan. 2004 –Dec. 2020		Jan. 2004-Jun. 2021		Jan. 2004 –Dec. 2023	
	(1)	(2)	(3)	(4)	(5)	(6)
GAS	0.065**	0.041	0.028	0.0184	0.033	0.0113
	(0.0294)	(0.0287)	(0.0301)	(0.0305)	(0.027)	(0.0270)
ELECT	0.511***	0.471***	0.605***	0.596***	0.546***	0.531***
	(0.0544)	(0.0527)	(0.0564)	(0.0585)	(0.0618)	(0.0624)
TRUCK	0.418***	0.415***	0.383***	0.379***	0.355***	0.348***
	(0.0312)	(0.0308)	(0.0306)	(0.0312)	(0.0230)	(0.0220)
RAIL	0.152***	0.142***	0.150***	0.147***	0.163***	0.153***
	(0.0091)	(0.0104)	(0.0098)	(0.0104)	(0.0094)	(0.0097)
TEMP	-0.957**	-0.855*	-0.994**	-0.966**	-0.790*	-0.739*
	(0.4307)	(0.4364)	(0.42844)	(0.4353)	(0.4363)	(0.4414)
TEMP^2	-0.105**	-0.100*	-0.118**	-0.118**	-0.106**	-0.103*
	(0.0520)	(0.0520)	(0.0552)	(0.0558)	(0.0534)	(0.0547)
PRODEXP	8.171***	6.867**	12.556***	12.394***	9.779***	9.807***
	(2.829)	(2.840)	(2.754)	(2.827)	(2.8612	(2.835)
LUBR		0.0516***		0.0173		0.0425**
		(0.0185)		(0.0202)		(0.0188)
CONSTANT	-21.310***	-15.146**	-33.217***	-31.332***	-26.300***	-22.257***
	(5.888)	(5.876)	(7.179)	(7.796)	(7.451)	(7.922)
Observations	206	206	222	222	252	252
R^2 adjusted	0.986	0.986	0.984	0.984	0.980	0.981

Notes: See Table 1 for the acronyms of explanatory variables. Standard errors are reported in parentheses. Estimates of standard error are robust to the presence of heteroscedasticity and autocorrelation in the residuals. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 4. Nowcasting accuracy: Simple univariate model

	Model excluding lubricants	Model including lubricants	Percentage change: (-) gain / (+) loss
Panel A. Nowcast period: Jan. 2017 –Dec. 2019			
MAE	1.22	1.19	-2.4
RMSE	1.52	1.49	-2.3
Diebold-Mariano test			0.75
Panel B. Nowcast period: Jan. 2021 – Dec. 2023			
MAE	1.76	1.71	-2.9
RMSE	2.11	2.04	-3.5
Diebold-Mariano test statistics			1.88**

Notes: The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are calculated on the monthly growth rates of the seasonally adjusted index of industrial production. The Diebold-Mariano test for the null hypothesis of equal forecast accuracy of two alternative models, namely the model without and with industrial lubricant oils. *, ** and *** indicate rejection of the null hypothesis of equal forecast accuracy at 10%, 5% and 1% significance level.

Table 5. Nowcasting accuracy: 36-month rolling-window estimation.

	Model excluding lubricants	Model including lubricants	Percentage change: (-) gain / (+) loss
Panel A. Nowcast period: Jan. 2017 –Dec. 2019			
MAE	0.79	0.80	1.8
RMSE	1.01	1.05	4.6
Diebold-Mariano test			1.57**
Panel B. Nowcast period: Jan. 2021 – Dec. 2023			
MAE	1.41	1.29	-9.0
RMSE	1.89	1.76	-7.0
Diebold-Mariano test			2.24**

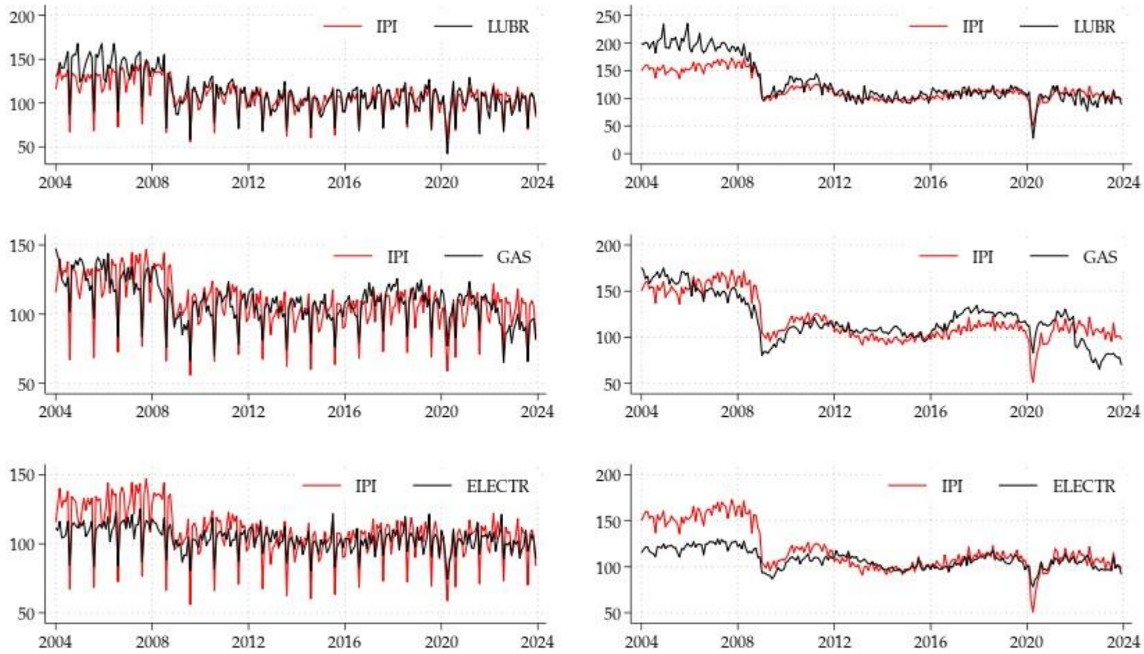
Notes: The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are calculated on the monthly growth rates of the seasonally adjusted index of industrial production. The Diebold-Mariano test for the null hypothesis of equal forecast accuracy of two alternative models, namely the model without and with industrial lubricant oils. *, ** and *** indicate rejection of the null hypothesis of equal forecast accuracy at 10%, 5% and 1% significance level.

Table 6. Nowcasting accuracy: BVAR.

	Model excluding lubricants	Model including lubricants	Percentage change: (-) gain / (+) loss
Panel A. Nowcast period: Jan. 2017 –Dec. 2019			
MAE	0.81	0.79	-2.5
RMSE	0.99	0.98	-0.7
Diebold-Mariano test			0.18
Panel B. Nowcast period: Jan. 2021 – Dec. 2023			
MAE	1.12	1.08	-1.9
RMSE	1.37	1.35	-1.1
Diebold-Mariano test			1.18

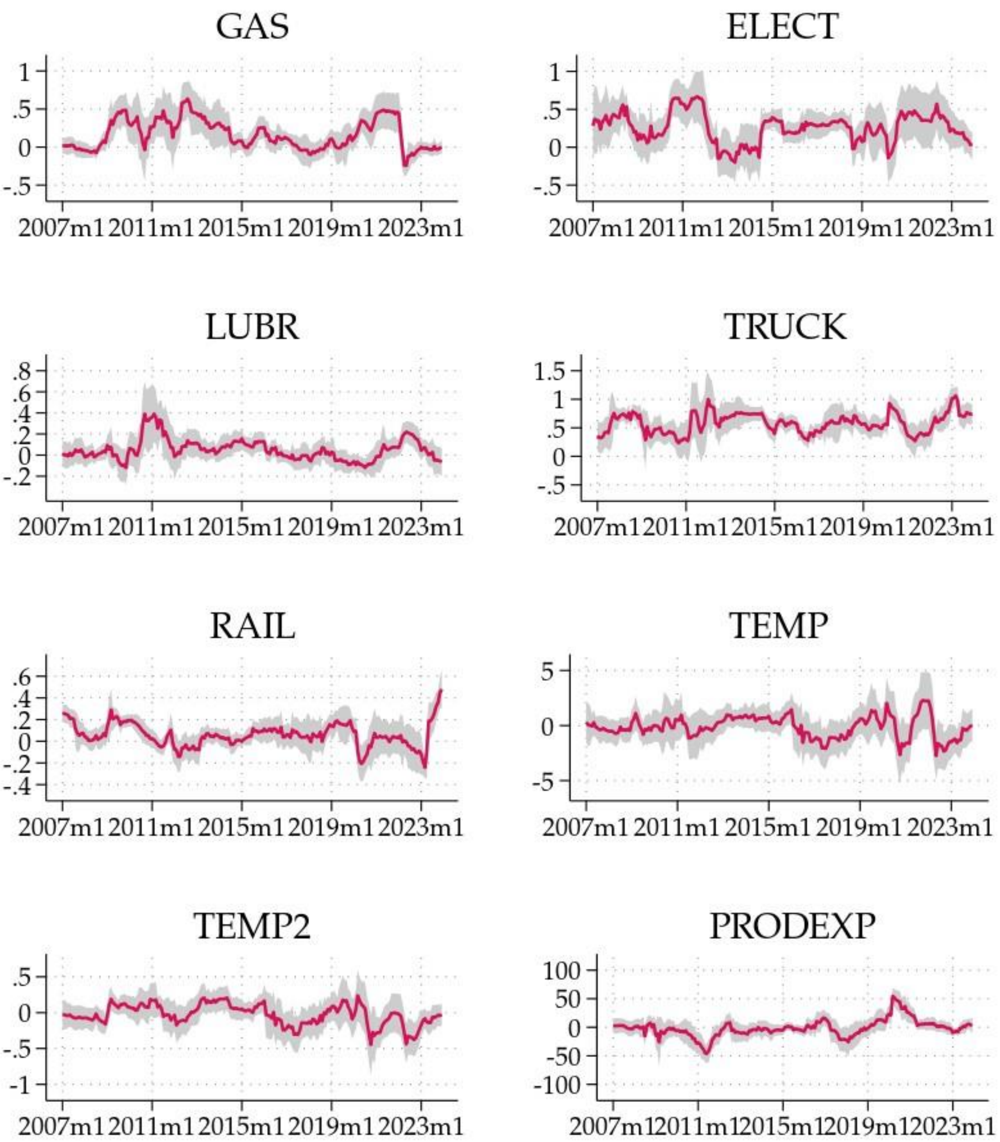
Notes: The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) are calculated on the monthly growth rates of the seasonally adjusted index of industrial production. The Diebold-Mariano test for the null hypothesis of equal forecast accuracy of two alternative models, namely the model without and with industrial lubricant oils. *, ** and *** indicate rejection of the null hypothesis of equal forecast accuracy at 10%, 5% and 1% significance level.

Figure 1. Industrial production, energy and lubricant oil consumption



Notes: On the left-hand side column are reported not seasonally adjusted series while on the right-hand side seasonally and working days adjusted series. IPI is the index of industrial production, LUBR is the index of industrial lubricant consumption, GAS is the index of consumption of gas for industrial use and ELECTR is the index of electricity consumption.

Figure 2. Parameter Stability: 36-month rolling-window estimation



Notes: In this Figure we report the 36-month rolling window estimates of specification (1). Grey shaded areas represent the 90% confidence intervals.