

Nowcasting Indonesia

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Abstract We produce predictions of the current state of the Indonesian economy by estimating a dynamic factor model on a dataset of 11 indicators (followed closely by market operators) over the 2002–2014 period. Besides the standard difficulties associated with constructing timely indicators of current economic conditions, Indonesia presents additional challenges typical to emerging market economies where data are often scant and unreliable. By means of a *pseudo*-real-time forecasting exercise, we show that our model outperforms univariate benchmarks, and it does comparably well with predictions of market operators. Finally, we show that when quality of data is low, a careful selection of indicators is crucial for better forecast performance.

Keywords Nowcasting · Dynamic factor models · Emerging market economies

JEL Classification C32 · C53 · E37 · O53

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1 Introduction

It is well known that macroeconomic data are released with a substantial delay. Additionally, in emerging market economies, low-frequency data (i.e., annual national accounts) rely on a smaller array of surveys and indicators than in advanced economies, and provide a partial picture of the economy. However, complete and up-to-date information on the current state of the economy is crucial for policy makers, market participants and public institutions. Indeed, agents periodically update their forecasts, and monitoring economic conditions in real time helps them assess whether the forecasts are on track or need to be revised. Similarly, the process of policymaking often requires long term projections of the economy that heavily rely on accurate initial conditions and forecasts. Therefore, constructing timely “predictions” of current economic conditions, namely *nowcasts*, is of fundamental importance for decision making.

A lot of information is contained in economic indicators that are available on a quarterly, monthly, weekly, and even daily basis, and, in principle, it is possible to use this information to build “predictions” of the current state of the economy. However, high-frequency data in emerging market economies are often scant, noisy, released with a lag, and can have missing observations. This complicates the difficult task of real-time monitoring and decision making as constructing timely indicators on current economic conditions for emerging market economies presents some extra challenges.

In this paper, we focus on Indonesia, the largest economy in Southeast Asia, which is rapidly gaining influence in the world economy. With a number of high-frequency data indicators available and yet facing problems that commonly plague emerging economy datasets, Indonesia provides an interesting training case for developing a nowcasting framework that can be applied to monitor other similar economies in the region.

Two main issues emerge with regard to monitoring in real time: how many and which indicators to select and what econometric model to use to extract information from the data. In this paper, we produce “predictions” of the current state of the Indonesian economy by estimating a Dynamic Factor model on a dataset of 11 indicators (followed closely by market operators) over the 2002–2014 period. Our choice of the model is based on the fact that it is parsimonious, it is able to cope with missing data and mixed frequency indicators, and it can potentially be estimated on a large number of variables. Further, since the seminal paper of [Giannone et al. \(2008\)](#), this model has become a standard tool for monitoring economic activity, as it has proved to be successful in nowcasting several economies, including emerging ones such as China [Giannone et al. \(2014\)](#) and Brazil [Bragoli et al. \(2015\)](#).

The rest of the paper proceeds as follows. Section 2 presents Indonesia’s GDP data, and discusses the problems of having several GDP series with different base years, and no official seasonally adjusted data. Section 3 discusses our nowcasting procedures and is divided in two parts: in the first part we describe the process of choosing a set of indicators that contains useful information on economic activity, and in the second we present the application of a dynamic factor model to Indonesia’s data.

Section 4 presents the evaluation of our model. Several results emerge. First, incorporating high-frequency data in a rigorous framework leads to an improvement in the forecast accuracy of Indonesia’s economy compared with simple univariate



Fig. 1 Gross domestic product series for Indonesia. *Notes* The left plot shows quarterly GDP at constant prices in levels, where the unit of measure is Trillions of Rupiah. The right plot shows the year-on-year growth rate of quarterly GDP at constant prices. In both graphs the *three lines* represent the different base years. There was also an accounting change from SNA 1993 to SNA 2008. *Source:* CEIC Data Company (accessed 30 June 2015); Authors' computation

benchmarks. Second, too many variables are not always optimal for the purpose of monitoring as they can be noisy or uninformative (Bańbura et al. 2013; Luciani 2014b), particularly so when the target variable, namely Indonesia's GDP growth, has limited number of observations. A careful selection of meaningful variables improves the forecast performance. Third, our model does well in predicting quarterly GDP growth when compared with private forecasters such as Bloomberg, and also does well in predicting annual GDP growth when compared with institutional forecasts of the International Monetary Fund and the Asian Development Bank.

Finally, Sect. 5 concludes.

2 Indonesia's GDP data: attens and issues

In this section we present Indonesia's GDP data, and discuss a number of issues in the data that need to be carefully tackled before starting any monitoring process.

The first issue is that there is no single long series for GDP available from official statistical sources. The left plot in Fig. 1 shows the level of quarterly GDP at constant prices in trillions of rupiah from 2000 to 2014, from the national source. The right-hand side plot shows the computed year-on-year (y-o-y) growth rate of quarterly GDP from 2000. The three lines refer to different base years, 1993, 2000 and 2010 respectively. Each line, however, is only available in a limited time span in that 1993 prices is available for 1993–2003, 2000 prices is available for 2000–2014 and the latest 2010 prices is available since 2010 onwards only.¹

The aggregation methodology was common between the 1993 and 2000 base years, but changed from SNA 1993 to SNA 2008 for the 2010 base year.² Base changes are common for GDP data, as they can incorporate changes in the economy's structural

¹ GDP for 2013 and 2014 based on the 2000 base year are preliminary figures projected by the statistical office: <https://www.bps.go.id/linkTabelStatis/view/id/1217>.

² A detailed explanation of the System of National Accounts (SNA) can be found at <http://unstats.un.org/unsd/nationalaccount/sna.asp>.

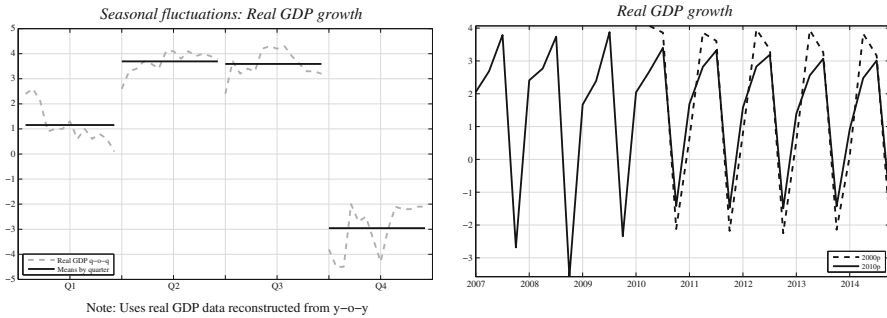


Fig. 2 Quarter-on-quarter growth of real GDP. *Notes* The left plot shows the seasonal fluctuations in q-o-q GDP growth, where real GDP data are reconstructed using y-o-y growth rates. The right plot shows q-o-q growth rates of real GDP series available, based on two different accounting methodologies, SNA 1993 and SNA 2008, and two different base years, 2000 and 2010. *Source:* CEIC Data Company (accessed 30 June 2015); Authors' computation

composition. However, as seen in Fig. 1, growth rates in the few years of overlap between series were also affected.³ Hence the composition of the aggregate series and methodologies used in their construction is brought into question, exacerbated by a lack of publicly available information on procedures used.

The second issue is related to which time span to use in conducting the econometric analysis. Indeed, GDP growth in Indonesia is characterized by large fluctuations due to different crises hitting the economy. In particular, the Asian financial crisis in the late 1990s stands out as a unique episode for Indonesia's growth path with GDP falling more than 15% in 1998 (not shown in Fig. 1). Growth recovered to about 5% in 2000 and stabilized somewhat at this yearly rate with a significantly lower volatility since 2002. Considering this pattern, we exclude the Asian financial crisis years from our sample and use the series only from 2002. This is unavoidable because the evolution of GDP growth over the financial crisis would dominate our estimates if not excluded. It would capture features of the data (i.e., co-movements) that are potentially spurious and misleading for the nowcasting exercise, as the relationships that held during the financial crisis could be different from those that hold during expansions and more moderate recessions.

The third issue with Indonesia's GDP data is that the series exhibits a marked seasonal pattern when we compute quarter-on-quarter (q-o-q) growth rates (Fig. 2). Yet there is no seasonally adjusted GDP series available from official sources, which leaves us with the problem of having to deal with seasonality in the data, particularly when trying to combine series with different base years to obtain coherent and long time series. Indeed, as shown in the right-hand-side panel in Fig. 2, the seasonality in GDP growth data with 2010 base year exhibits a clear departure from the seasonal pattern in the series with 2000 base year. This adds to the complication of splicing the different series together. Suppose we start with the latest available GDP series that is of

³ In fact, even nominal GDP data for the overlapping time periods are not comparable between the different bases for GDP series. Data are available in Table VII.1 at <http://www.bi.go.id/en/statistik/seki/terkini/riil/Contents/Default.aspx>.

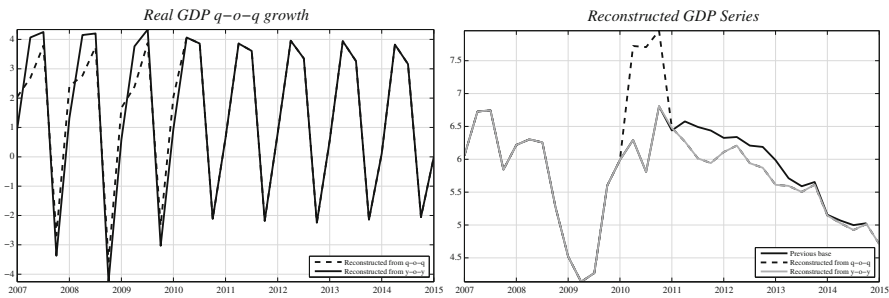


Fig. 3 Reconstructing GDP series using y-o-y growth. *Notes* Since the latest available data starts in 2010, we have to reconstruct a long time series and the left plot displays the growth patterns using q-o-q and y-o-y growth rates. The right plot displays the reconstructed series using different growth rates. *Source:* CEIC Data Company (accessed 30 June 2015); Authors' computation

2010 base, and extend it backwards using the q-o-q growth rates of the previous base series. As seen in the left-hand side plot in Fig. 3, this produces inconsistent seasonal patterns within the spliced series—that is, between the (growth of) actual data and the extended data. On the contrary, the reconstructed series based on y-o-y growth rates instead does not seem to have the same shortcoming.

The right-hand side panel of Fig. 3 plots the constructed long time series for GDP based on the two different splicing methods. It shows that while the series constructed using the y-o-y growth rates has consistent dynamics with that of previous base year, the one generated using the q-o-q growth rates has not. The latter exhibits a jump in GDP during the four quarters when the two shorter series were spliced. For this reason, splicing the series using a y-o-y growth seems to warrant a more consistent long series. Furthermore, we will also continue to use y-o-y growth rates in our analysis going forward.

Finally, we are aware that using y-o-y growth tackles the issue of seasonality and makes series smoother, but it also lags q-o-q growth. However, the alternative of using some standard procedure to seasonally adjust the series, and then evaluating the forecasting performance on the resulting unofficial series would be of little practical use. Not only would it entail defining of a new, somewhat arbitrary target variable, but it would also be of little relevance to policy makers, who focus on the official y-o-y GDP growth. Of course, had the Indonesia Statistics provided official q-o-q seasonally adjusted data, we would have used that as our target for the nowcast.

3 Nowcasting

Typically, GDP data provide the most comprehensive picture of the economy, by aggregating activity of different sectors. Unfortunately, the data come with long delays and are not available on a high-frequency basis. In most cases, data are published quarterly and, in some developing countries, even annually.

For Indonesia, GDP data are reported quarterly with a delay of about 5 weeks. This means that the growth rate of the economy in the first quarter that ends in March is not known until the second week of May. While this is a reasonable delay compared

to most emerging and some advanced economies, it is still insufficient for the purpose of real-time monitoring, as it is not possible to make an assessment of the strength of economic activity for almost 5 months into the year.

To gauge the current state of the Indonesian economy in real time, we need to construct a prediction of GDP growth before the official data are released. This means that at each point in time we want to predict not only the current and next quarter estimates for GDP growth (henceforth *nowcast* and *forecasts*), but also, wherever the official data have not been published yet, the past quarter GDP growth (*backcast*).

Ideally, if the true data sources and compilation methods for GDP were known, we could simply attempt to reverse engineer the process performed quarterly by the Indonesian statistical office but at a higher frequency. Unfortunately, as discussed in Sect. 2, very little information on these methods is available from the statistical agency. This forces us (1) to build an information set that is informative for describing the GDP growth process, possibly by including variables that may be outside the scope of the statistical office but may still contain useful leading information, and (2) to choose an econometric model to build our prediction.

In the next two subsections we address these issues. In particular, in Sect. 3.1, we explain how we construct the database, while in Sect. 3.2 we introduce Dynamic Factor models (DFMs). We choose to use a DFM since it is a parsimonious model, it copes with missing data and mixed frequency, and it can potentially exploit a large information set. Furthermore, being framed in a Kalman filter framework, it allows a formal reading of the news flow coming from successive data releases. Finally, DFMs proved to be very successful in nowcasting several economies, including emerging ones.⁴

3.1 What variables to select?

There is a wide set of potentially useful monthly and quarterly series that could help extract information on the state of the Indonesian economy. However, the limited number of time series observations available for our target quarterly y-o-y GDP growth (see Sect. 2), constrains our choice of both the variables and the model.

In principle, DFMs are consistently estimated when the number of variables is diverging to infinity, and in practice they are usually estimated on relatively large datasets. However, when the time series observation is severely limited, including too many variables is likely to introduce estimation uncertainty, which ultimately worsens the prediction performance. This is a particular source of concern when dealing with Indonesian data, as only few series display a marked comovement with the GDP quarterly dynamics and hence the risk is to introduce excessive noise in the model estimation. Furthermore, the literature on nowcasting with large-dimensional DFMs has reached the conclusion that, unless one needs to monitor the data flow with many

⁴ A non-exhaustive list of countries and papers is: the USA (Bańbura et al. 2011, 2013; Giannone et al. 2008), the Euro Area (Angelini et al. 2011; Bańbura and Rünstler 2011), Germany (Marcellino and Schumacher 2010), France (Barhoumi et al. 2010), Ireland (D'Agostino et al. 2012), Norway (Aastveit and Trovik 2012; Luciani and Ricci 2014), China (Giannone et al. 2014), Brazil (Bragoli et al. 2015), New Zealand (Matheson 2010), the Global Economy (Matheson 2013), and Latin America (Liu et al. 2012).

data releases, there is no gain from too large a database as long as the variables on which the model is estimated are appropriately selected (Bańbura et al. 2013; Luciani 2014a, b). This then leads to questions on how many variables should be selected and on what basis.

A possible strategy to draw from a large pool of variables could be to rely on a purely mechanical statistical selection procedure. For example, Bai and Ng (2008) suggest selecting with the Least Angle Regressions (LARS algorithm) only those variables that are really informative for forecasting the target variable, while Camacho and Perez-Quiros (2010) suggest first selecting a core group of variables and then evaluating if other possible predictors are useful.

An alternative strategy, pioneered by Bańbura et al. (2013) and followed by Luciani and Ricci (2014), Giannone et al. (2014), and Bragoli et al. (2015), is to exploit the “revealed preferences” of professional forecasters who follow the Indonesian economy on the Bloomberg platform. These analysts subscribe to the Bloomberg news alert for specific data releases of the variables that they monitor and use them to form their expectations on current and future fundamentals of Indonesia. As Bloomberg constantly ranks the analysts’ demand for these alerts by constructing a relevance index for each macroeconomic indicator, we can select variables based on this relevance index.⁵

We adopt the latter approach, as the automatic selection approach risks leading to an unstable choice of variables in a real-time scenario.⁶ This instability would not only be difficult to justify from an economic standpoint, but it would also complicate the interpretation of the forecasts’ revisions. Moreover, we also tried the automatic selection approach, and the performance of our model was worse in this case than when we used the revealed preference approach (see Appendix A.1).

It turns out that for Indonesia, only a relatively small number of macroeconomic series are tracked in real time by the markets (see Table 1). On the one hand, there are indicators describing macroeconomic developments (e.g., GDP itself, car sales, exports, imports and manufacturing PMI). Moreover, given their direct influence on the foreign exchange and fixed income markets, analysts also monitor indicators that directly describe the monetary policy stance. These are the central bank reference interest rate as well as key monetary aggregates.

Starting from the set of indicators in Table 1 followed by business analysts we constructed our database as follows:

- (1) We excluded all indicators that either had too few observations, or we could not retrieve. This is the case for PMI, for which data are available only starting in

⁵ The implicit assumption here is that since based on their expectations on future fundamentals analysts allocate their investments, they know which series to monitor to form appropriate expectations on GDP growth.

⁶ As shown by De Mol et al. (2008) since there is a lot of comovement among macroeconomic data, the set of indicators selected with statistical criteria is extremely unstable.

Table 1 Bloomberg calendar: follow the market revealed preference. *Source* Authors' compilation from Bloomberg (accessed 30 June 2015)

Variable	Source	Reference period	Release date	Freq	Rel.
Bank Indonesia reference rate	Bank Indonesia	17-Mar	Mar-17	D	95
CPI y-o-y	Statistics Indonesia	Jan	Mar-6	M	86
Foreign reserves	Bank Indonesia	Dec	Mar-3	M	86
PMI Mfg market	Market	Mar	Apr-4	M	82
GDP y-o-y	Statistics Indonesia	4Q	Feb-2	Q	64
Consumer confidence index	Bank Indonesia	Feb	Mar-4	M	64
GDP q-o-q	Statistics Indonesia	4Q	Feb-2	Q	59
CPI core y-o-y	Statistics Indonesia	Feb	Mar-6	M	55
Local auto sales	Gaikindo	Feb	Mar-16	M	50
Imports y-o-y	Statistics Indonesia	Feb	Mar-15	M	50
Net foreign assets IDR	Bank Indonesia	Feb	Mar-28	M	45
Danareksa consumer confidence	Danareksa	Feb	Mar-5	M	36
Motorcycle sales	Bank Indonesia	Feb	Mar-16	M	32
Money supply: M2 y-o-y	Bank Indonesia	Feb	Mar-28	M	32
Money supply M1 y-o-y	Bank Indonesia	Jan	Mar-28	M	32
CPI NSA m-o-m	Statistics Indonesia	Feb	Mar-6	M	27
Exports y-o-y	Statistics Indonesia	Feb	Mar-15	M	27
Trade balance	Statistics Indonesia	Feb	Mar-15	M	23
BoP current account balance	Bank Indonesia	4Q	Mar-15	Q	14

From left to right: "Variable" reports the name of the variable; "Source" reports the original source of the data; "Reference period" reports the period to which the data that will be released refers to, while "Release date" reports when the data will be released. For example on February 2, 2015, the statistical office released the data for GDP Q4:2014. Note also that both the columns "Reference period" and "Release date" refers to our stylize calendar so that the release date is the same every month/quarter (e.g., GDP Q1 is released on May 2nd). "Freq." reports at which frequency the variable is published. "Rel." is the relevance index in Bloomberg that counts the number of subscribers to the news alert alerting the release of the variable

June 2012, and for Danareksa Consumer Confidence and Motorcycle Sales for which we were not able to retrieve data.⁷

- (2) We screened each of the remaining indicators to understand whether they are followed by analysts because they convey information on the state of the real economy, or they are directly related to the stance of the Central Bank and its balance sheet. Therefore, because the Bank of Indonesia has an inflation target, we discarded CPI, and we also removed Foreign Reserves, and Net Foreign Assets as they are mainly related to the foreign exchange policy. However, we included monetary "instruments" like the bank reference rate and the M2, as proxies for the monetary stance, which itself should be forward-looking.

⁷ As the index compiled by Danareksa was not available to us, we experimented with the household consumer confidence index compiled by the Bank of Indonesia. The latter, however, displays a trending pattern that appears difficult to reconcile with the state of the economy, and we hence discarded it.

Table 2 Data description and data treatment. *Source* Authors' compilation from Bloomberg, CEIC data company, and Haver analytics (all accessed 30 June 2015)

Variable	Freq.	Source	Start	Delay	Trans.
Central Bank policy rate	M	Bank Indonesia	Jan-93	1	
PMI developing economies	M	JP Morgan	Apr-04	4	
Cement, domestic consumption	M	Statistics Indonesia	Jan-94	10	y-o-y
Exports	M	Statistics Indonesia	Jan-93	15	y-o-y
Imports: consumption goods	M	Statistics Indonesia	Mar-01	15	y-o-y
Imports: capital goods	M	Statistics Indonesia	Mar-01	15	y-o-y
Imports: raw materials	M	Statistics Indonesia	Mar-01	15	y-o-y
Car sales	M	PT Astra	Jan-93	16	y-o-y
Gross domestic product	Q	Statistics Indonesia	Q1 1993	36	y-o-y
Business tendency index	Q	Bank Indonesia	Q2 2000	38	
M2	M	Bank Indonesia	Jan-93	59	y-o-y

From left to right: Variable reports the name of the variable; Freq. specifies whether a variable is monthly (*M*) or quarterly (*Q*); Source reports the original source of the data; Start specifies since when a variable is available; Delay reports the release delay expressed in number of days in our stylized calendar; and, finally, Trans specifies whether a variable has been transformed to year-on-year growth rates or it is considered in levels. Data for “PMI developing economies” are produced by JP Morgan and were downloaded from Thomson Reuters, Datastream. Data for “Car sales” are produced by PT Astra data and were downloaded from CEIC Data/ISI Emerging Markets

- (3) We then excluded those variables that are the sum of other variables in the database or are too similar to other series. So we kept Imports and Exports, but we excluded Current Account; and we kept M2, but we discarded M1.
- (4) Finally, we used our “expert judgment” and added a few indicators that we think provide some extra information about the Indonesian economy. To capture information regarding the increasing role of construction activity for the Indonesian economy, we included domestic cement consumption. To account for spillovers from the foreign sector into the domestic economy, we included a variable from the very timely Market PMI manufacturing survey. In particular, we included the aggregate for emerging economies, which is dominated by developments in China as well as countries in Asia. Finally, we also included a sectoral breakdown of the imports series to better capture the possibly different lead/lag characteristics of each of these series with GDP growth.

By following this strategy, we end up with a dataset of 10 macroeconomic indicators plus GDP (see Table 2). While GDP and Business Tendency Index are quarterly series, the remaining are at monthly frequency. The column “Delay” reports the publication delay expressed in number of days in our stylized calendar and shows substantial differences between series in terms of their publication delay. For example, the PMI for developing economies is published just 4 days after the reference month, while data on imports are released a month after the reference month.⁸

⁸ For the policy rate, we adopted the assumption that it is observed the first day of the month following the reference month. For example, the policy rate for January is observed on February 1. Of course this



Fig. 4 Gross domestic product and industrial production. *Notes* The *thick black line* is y-o-y GDP growth rate, while the *thick gray line* is y-o-y growth rate of industrial production index. The *thin horizontal black line* indicates 0. The data for industrial production were converted to quarterly frequency by averaging monthly observations. Note that both variables have been standardized to be mean zero and variance one for comparison purposes, which is why there is no scale in the y axes. *Source*: CEIC data company (accessed 30 June 2015)

A notable exclusion from our database is Industrial Production, particularly so because this variable is often used by analysts to assess high-frequency movements in economic activity in emerging market economies.⁹ The underlying assumption is that movements in the industrial sector are a good approximation of aggregate economic activity. While the assumption may hold well for some economies, in others, the cyclical component of the index is not found to be sufficiently synchronized with GDP (Fulop and Gyomai 2012). The correlation between Indonesia's GDP growth and the y-o-y growth rate of industrial production is in fact relatively weak (standing at 0.35 in the full sample) and displays hardly any comovement since 2010 (see Fig. 4). This is likely related to the decreasing contribution to GDP growth from the manufacturing sector, off-set by other sectors like construction and services, as the share of industrial production has been declining since 2002 and now accounts for about one-third of GDP.

Footnote 8 continued

is an approximation because we know what the policy rate is everyday in January. In principle, we could have accounted for daily observations in the interest rate since DFMs allow us to do so (Modugno 2014). However, Bańbura et al. (2013) have shown that including data at the daily frequency is not particularly useful for nowcasting GDP, so we adopted the convention that the interest rate is monthly and is observed on the first day after the reference month.

⁹ See, for example, Maćkowiak (2007), and Raghavan and Dungey (2015), for applications to a set of emerging economies, and Kasri and Kassim (2009), and Kubo (2009), for Indonesia specifically.

3.2 Dynamic factor models

Factor models are based on the idea that macroeconomic fluctuations are the result of a few macroeconomic shocks that affect *the whole* economy and a number of sectoral/regional shocks that affect *a part of* the economy. Therefore, each variable in the dataset can be decomposed into a common part and an idiosyncratic part, where the common part is assumed to be characterized by a small number of common factors (\mathbf{f}_t) that are time series processes meant to capture the comovement in the data (*i.e.*, the business cycle).

Formally, let x_{it} be the i th stationary variable observed at month t , then

$$x_{it} = \lambda_i \mathbf{f}_t + \xi_{it} \quad i = 1, \dots, n \quad (1)$$

where \mathbf{f}_t is an $r \times 1$ vector (with $r \ll n$) containing the common factors, and ξ_{it} is the i th idiosyncratic component. The vector of common factors evolve over time as a VAR(p) process driven by the common shocks $\mathbf{u}_t \sim \mathcal{N}(0, \mathbf{I}_r)$, while each idiosyncratic component follows an independent AR(1) model driven by the idiosyncratic shocks e_{it} :¹⁰

$$\mathbf{f}_t = \sum_{s=1}^p \mathbf{A}_s \mathbf{f}_{t-s} + \mathbf{u}_t \quad (2)$$

$$\xi_{it} = \rho_i \xi_{it-1} + e_{it} \quad i = 1, \dots, n. \quad (3)$$

Equations (1)–(3) define the DFM used in this paper. This is the model studied in Doz et al. (2011, 2012), which is a special case of the model studied in Forni et al. (2009). In this model, the common shocks and the idiosyncratic shocks are assumed to be uncorrelated at all leads and lags, while the idiosyncratic shocks are allowed to be cross-sectionally correlated, albeit by a limited amount (approximate factor structure). For a formalization of the assumptions and for a more comprehensive treatment of the DFM, we refer the reader to the aforementioned references and to the survey by Luciani (2014b).

Model (1)–(3) can be estimated by Principal Components (Stock and Watson 2002a; Bai 2003), by using a two-step estimator based on the Kalman Filter and Principal Components (Doz et al. 2011), or by maximum likelihood techniques through the EM algorithm (Doz et al. 2012). In this paper, we will use maximum likelihood, and in

¹⁰ It is worth noting here that the use of y-o-y transformations likely add persistence also in the idiosyncratic component so that a higher order autoregressive process might be more appropriate. However, increasing the order of the autoregressive process of the idiosyncratic component from an AR(1) to an AR(2) implies adding eleven extra states to the model. In our case, where we have few time series observations, and the quality of the data is doubtful, adding eleven extra states in the Kalman Filter is feasible, but for sure costly in terms of computation accuracy. In summary, although an AR(1) may be not enough for capturing the whole dynamic in the idiosyncratic process, the cost of adding an extra lag is way higher than the benefits in terms of forecasting accuracy.

particular we will use the EM algorithm proposed by Bańbura and Modugno (2014), which can handle both mixed frequencies and missing data (see Appendix A.2).¹¹

4 Empirics

4.1 The forecasting exercise

To evaluate the performance of our model, we perform a *pseudo* real-time out-of-sample exercise. Predictions of Indonesian GDP growth are produced according to a recursive scheme, where the first sample starts in July 2002 and ends in December 2007, while the last sample starts in July 2002 and ends in December 2014. The model is estimated at the beginning of each quarter using only information available as of the first day of the quarter, and then the parameters are held fixed until the next quarter. For the estimation, we include two factors ($r = 2$) and two lags ($p = 2$) in the VAR model governing the evolution over time of the factors. An extensive discussion of why we included two factors can be found in Appendix A.3.

To perform our exercise we construct real-time vintages by replicating the pattern of data availability implied by the stylized calendar (Table 2), and every time new data are released, we update the prediction based only on information actually available at that time. We label this exercise *pseudo* real time since we do not have access to the actual set of data vintages as they were released over time. As to GDP growth, revisions are very infrequent and relate to changes in national accounts methods rather than to the arrival of more complete information within a year. That is, quarterly figures are treated as the final number until a base change occurs. In those occasions the statistical office can revise substantially the growth profile of GDP, as documented in Sect. 2. Similar changes may occur also for the other variables in our database, but no information regarding the existence of well defined revision schedule is available.

4.2 Comparison against statistical benchmark

To judge the performance of our model and to evaluate the information contained in our dataset, we start by comparing our model with four benchmark univariate models.

Our first benchmark is the *naive* forecast, obtained from the random walk model on GDP growth. Let y_t^Q be the y-o-y GDP growth observed quarterly, that is, at month $t = 3, 6, 9, \dots$, then the random walk model is: $y_t^Q = y_{t-1}^Q + \varepsilon_t$. The second benchmark is a forecast from an autoregressive model of order two on GDP growth: $y_t^Q = \rho_1 y_{t-1}^Q + \rho_2 y_{t-2}^Q + \varepsilon_t$. Given the high persistence in our target series introduced by the y-o-y transformation, these univariate benchmarks are inherently tough competitors to match in our real-time exercise.

¹¹ An alternative to the algorithm proposed by Bańbura and Modugno (2014) is the one proposed by Jungbacker et al. (2011).

Our third benchmark is a bridge model (Parigi and Schlitzer 1995). A Bridge model predicts GDP growth by using past GDP and one or more monthly indicators.¹² Formally, let x_{it} be a monthly variable observed at month t , then the Bridge model is then defined as follows:

$$y_t^Q = \mu + \alpha y_{t-3}^Q + \beta x_t^Q + \varepsilon_t \quad (4)$$

where $x_t^Q = \sum_{j=1}^3 \frac{1}{3} x_{t-j}$ is the monthly indicator aggregated at the quarterly frequency by a simple average. Equation (4) is estimated by OLS.

Our last benchmark is a MIDAS model. MIDAS models (Ghysels et al. 2007; Andreou et al. 2013) are similar to Bridge models, but in MIDAS models, first, the aggregated variables x_t^Q is constructed using a lag polynomial, and, second, for each forecast horizon it is estimated a different model:

$$y_{t+h}^Q = \mu + \beta x_t^Q + \varepsilon_t \quad (5)$$

where $h = \{-3, 0, 3\}$, $x_t^Q = \sum_{m=0}^{11} \gamma(m, \theta) L^m x_t$, and $\gamma(m, \theta) = \frac{\exp(\theta_1 m)}{\sum_m \exp(\theta_1 m)}$. Equation (5) together with the polynomial $\gamma(L, \theta)$ is estimated by nonlinear least squares.

In this paper, the predictions from the Bridge and from the MIDAS models are obtained by first estimating a model for each monthly indicator in the database—with the exception of PMI developing countries that was excluded because there are too few observations for this indicator—and then by averaging the prediction. Furthermore, whenever we have a missing observations in x_t , we filled it by using an AR model.

Table 3 shows the root-mean-squared error (RMSE) at the end of each month of the DFM, an AR(2) model, a Random Walk, and the Bridge and the MIDAS models. The table is divided into three parts: the first part, labeled “Forecast”, reports the RMSE of the prediction of the next quarter; the second, labeled “Nowcast,” reports the RMSE of the prediction of the current quarter; and, the last, labeled “Backcast,” reports the MSE of the prediction of the previous quarter.¹³

As we can see from the fact that the RMSEs in Table 3 are decreasing with each month, the DFM is able to correctly revise its GDP prediction as more data becomes available. Furthermore, compared with the univariate benchmarks, the RMSE of the DFM is consistently lower, up to a maximum reduction at the end of the first month after the reference quarter (i.e., row “backcast” in Table 3) of 55% compared with the Autoregressive model, of 15% compared with the Bridge model, and of 29% compared to the MIDAS model. This is an important finding, as it tells us that there

¹² As pointed out by Baffigi et al. (2004), differently from DFMs, bridge models are not concerned with particular assumption underlying the DGP of the data, but rather, the inclusion of specific explanatory indicators is based on the simple statistical fact that they embody timely updated information about the target GDP growth series.

¹³ Note that the AR(2) and the RW do not update the prediction beyond month 2 of the quarter, but update it between month 1 and month 2 due to the GDP data release. Also, the fact that the RMSE of the AR(2) and the RW in “Backcast” month 1, and “Nowcast” month 2 is different is an artifact due to the fact that when we “Backcast” our target variable is GDP from Q4 2007 to Q3 2014, whereas when we “Nowcast” our target variable is GDP from Q1 2008 to Q4 2014. Of course, had the evaluation period been longer, we would not have this problem.

Table 3 Root-mean-squared error: end of month. *Source* Authors' estimates

	Month	DFM	AR	RW	Bridge	MIDAS
Forecast	1	0.587	0.692*	0.847**	0.623	0.589
	2	0.516	0.612**	0.661	0.541	0.556
	3	0.444	0.612**	0.661**	0.502*	0.527**
Nowcast	1	0.449	0.600**	0.666*	0.484	0.475
	2	0.325	0.443**	0.430	0.359	0.408**
	3	0.287	0.443**	0.430*	0.333	0.374**
Backcast	1	0.288	0.446**	0.459**	0.332	0.372**

This table reports root mean squared error (RMSE) at the end of each month for the dynamic factor model (DFM), an AR(2) model, a random walk (RW), and the Bridge and MIDAS model. The upper panel, labeled “Forecast”, reports the RMSE of the prediction of the next quarter; the middle panel, labeled “Nowcast”, reports the RMSE of the prediction of the current quarter; the bottom panel, labeled as “Backcast”, reports the MSE of the prediction of the previous quarter. Asterisks indicate a rejection of the Diebold and Mariano (1995) test of equal predictive accuracy between each benchmark model and the DFM at 5% (**) or 10% (*) significance levels

is valuable additional information in the Indonesian high-frequency data that can be used to predict GDP growth.

In Table 4, we investigate which data release carries more information for the prediction with the DFM. Identifying such variables is particularly important since it can help policymakers understand which series to track while monitoring the Indonesian economy. More precisely, Table 4 shows the RMSE associated with each data release. We can see that some variables are particularly relevant for correctly updating the prediction of y-o-y GDP growth. Among these, the most important one are exports and imports, which account for the largest reduction in RMSE when the data are released.¹⁴ Other relevant ones are GDP of the previous quarter, and Cement. Notice also that upon the release of some variables the “average” forecasting performance reported in Table 4 appears to deteriorate. Thus, it would be tempting to drop these variables in order to “improve” the overall forecasting performance. However, each of the variables may also improve the estimation of the model by exploiting the commonality in the data and hence make our forecasts more robust to one-off changes in a particular variable.

We conclude this section with a caveat that will apply to most of the empirical exercise. As we argued in Sect. 2, we had to use data only from 2002 onwards, and this has limited us in two ways. First, as discussed in Sect. 3, we had to restrict the number of variables to include in the model. Second, having only forecasts for 28 quarters, the robustness of our RMSE may be an issue. This is even more relevant when we attempt to assess the statistical significance of different forecast performances. To this end, in Table 3 we report Diebold and Mariano (1995) test of equal predictive accuracy. The

¹⁴ The average share of exports to GDP in Indonesia in 2010–2014 was about 20% and even slightly lower for imports (at 19%). Trade data, however, provide information about activity across sectors in the economy, and the results in Table 4 show that this is useful information for predicting GDP.

Table 4 Root-mean-squared error: data flow. *Source* Authors' estimates

	Day	Release	Forecast	Nowcast	Backcast
Month 1	1	Policy rate	0.596	0.443	0.296
	4	PMI	0.603	0.449	0.298
	10	Cement	0.602	0.445	0.295
	15	Exports	0.586	0.448	0.287
	15	Imports ^a	0.586	0.448	0.287
	16	Car sales	0.586	0.448	0.287
	28	M2	0.587	0.449	0.288
	Month 2	1	Policy rate	0.588	0.451
4		PMI	0.593	0.457	0.287
5		GDP	0.584	0.427	
7		BTI ^b	0.583	0.428	
10		Cement	0.576	0.416	
15		Exports	0.513	0.324	
15		Imports ^a	0.513	0.324	
16		Car sales	0.515	0.324	
Month 3	1	Policy rate	0.509	0.325	
	4	PMI	0.514	0.334	
	10	Cement	0.508	0.331	
	15	Exports	0.438	0.286	
	15	Imports ^a	0.438	0.286	
	16	Car sales	0.442	0.286	
	28	M2	0.444	0.287	

This table reports root mean squared error (RMSE) in correspondence of each data releases. Column "Forecast", reports the RMSE of the prediction of the next quarter; column "Nowcast", reports the RMSE of the prediction of the current quarter; column "Backcast", reports the MSE of the prediction of the previous quarter

^a On this day three different series are released: Imports: Consumption Goods, Imports: Capital Goods, and Imports: Raw materials but results are grouped in one variable

^b BTI stands for business tendency index

DM statistics is asymptotically normally distributed, and although we have just 28 predictions, the p values in Table 3 was computed using the normal approximation.

4.3 Comparison against market benchmark

Another way to evaluate the forecasting performance of our model is to compare the prediction obtained with the DFM with the prediction of market operators. In Fig. 5, we compare our predictions with those of the Bloomberg Survey (BS). The BS consists of the median GDP prediction provided independently by a variable number of specialists a few days before GDP is released. Therefore, because the Bloomberg Survey is

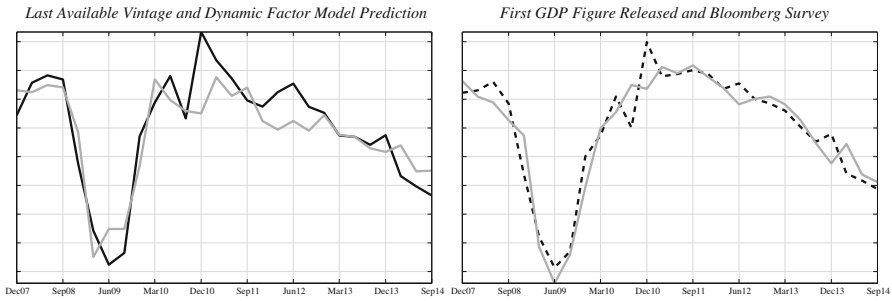


Fig. 5 Prediction of previous quarter GDP. *Notes* in the left plot the *black line* is the last vintage available of the GDP series, and the *gray line* is the prediction obtained with the DFM the last day before GDP is released. In the right plot, the *dashed black line* is the first release of GDP, while the *gray line* is the median prediction from the Bloomberg Survey. Note that for comparison purposes the variables in the *left and the right panel* have been standardized, which is why there is no scale in the y axes. Precisely, the variables in the *left panel* have been standardized using the mean and the variance of GDP final release, while the variables in the *right plot* have been standardized using the mean and the variance of GDP first release. In other words, the *black line* in the left plot, and the *dashed line* in the right plot, have both mean zero and variance one. *Sources:* Authors' estimates; Bloomberg and CEIC data company (both accessed 30 June 2015)

released a few days before previous quarter GDP, according to our terminology the BS prediction is a *backcast*, and we will compare it with our last prediction before GDP is released.

When comparing our prediction with Bloomberg, we have to be careful with respect to data revisions. The black line of the left plot in Fig. 5 represents the last vintage available of the GDP series, while the dashed black line in the right plot of Fig. 5 represents the first release of GDP growth.¹⁵ As discussed in Sect. 2, these two series are quite different due to the fact that the Statistical office has changed both base year and the aggregation method, and, in particular from 2011 onwards the two series differ substantially. This fact is crucial when we attempt to make comparisons with truly historical forecasts. In particular, the analyst interviewed by Bloomberg were targeting the first release GDP growth (right plot), while the DFM has been estimated using—and therefore has been designed to target—the latest release of y-o-y quarterly GDP growth (left plot). Therefore, if we want to understand how good/bad the prediction produced by the DFM are compared to those of Bloomberg, we have to take into account that there is a difference in the target variable.

As we can see from Fig. 5, the Bloomberg Survey is tracking the first release well, with a RMSE of 0.249. Similarly, we can also see that our prediction is good; indeed, our RMSE is 0.287 which is just 15% worse than that of the Bloomberg Survey.

4.4 Comparison against institutional benchmarks

Finally, by following Luciani and Ricci (2014) we can construct predictions for the current annual growth rate and compare them with those published by policy insti-

¹⁵ Note that this is all the “real-time” information that we have available since, as mentioned in Sect. 4.1, we do not have any “real-time” information for the other variables in the dataset.

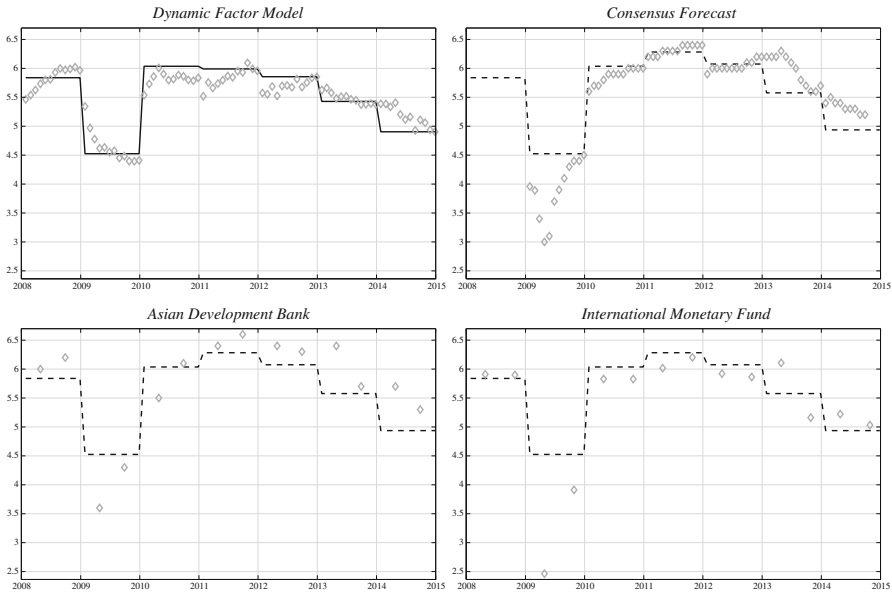


Fig. 6 Prediction of annual GDP growth rate. *Notes* the black line in the northwest plot is annual GDP growth, while the gray diamonds are the prediction obtained at the end of each month with the DFM. In all the other panels, the black line is annual GDP growth computed by using the GDP series released in real time, while the gray diamonds are the prediction of ADB, IMF, and CF. Data for CF are from Consensus Economics Inc. *Source:* Authors’ estimates; Asian Development Bank, Asian Development Outlook database; CEIC Data Company; Consensus Economics, Monthly Consensus Forecasts; and International Monetary Fund, World Economic Outlook database (all accessed 30 June 2015)

tutions.¹⁶ In detail, we compare our predictions with those published by the ADB in the Asian Development Outlook, those published by the IMF in the World Economic Outlook, and the prediction by Consensus Forecast (CF).¹⁷ The ADB publishes its predictions of current annual GDP growth twice a year, in April and in late September, approximately; the IMF also publishes its prediction twice a year but these are released on April and October. Predictions by CF are available each month.

The northwest (NW) panel in Fig. 6 shows annual GDP growth together with the prediction of current annual GDP growth obtained at the end of each month with the DFM. The other panels of Fig. 6 show predictions from ADB, IMF, and CF together with annual GDP growth. Note, however, that the annual GDP growth reported in the

¹⁶ Let $X_q^y = 100 \times \log(\text{GDP}_q^y)$ be GDP of the q th quarter of year y , and let $Z^y = 100 \times \log(\text{GDP}^y)$ be GDP of year y . Then, by definition $x_q^y = X_q^y - X_q^{y-1}$ is the y-o-y growth rate, while $z^y = Z^y - Z^{y-1}$ is the annual growth rate. Following Mariano and Murasawa (2003), we make use of the approximation $Z^y \approx (X_1^y + X_2^y + X_3^y + X_4^y)/4$, which allow us to write the annual growth rate as a function of y-o-y growth rates: $z^y = Z^y - Z^{y-1} \approx (X_1^y + X_2^y + X_3^y + X_4^y)/4 - (X_1^{y-1} + X_2^{y-1} + X_3^{y-1} + X_4^{y-1})/4 = (x_4^y + x_3^y + x_2^y + x_1^y)/4$.

¹⁷ Consensus Economics Inc. forecasts comprise quantitative predictions of private sector forecasters. Each month survey participants are asked for their forecasts of a range of macroeconomic and financial variables for the major economies.

Table 5 Root mean squared error: annual GDP growth. *Source* Authors' estimates

Month	DFM	CF	ADB	IMF
January	0.483	0.438		
February	0.341	0.454		
March	0.264	0.577		
April	0.254	0.722	0.603	0.824
May	0.166	0.655		
June	0.146	0.431		
July	0.161	0.348		
August	0.091	0.237		
September	0.137	0.158	0.262	
October	0.143	0.080		0.306
November	0.129	0.097		
December	0.103	0.096		

This table reports root mean squared error (RMSE) of the prediction of annual GDP growth at the end of each month. The RMSE of the DFM is computed with reference to the last vintage available for the GDP series, while the RMSE for ADB, CF, and IMF, is computed with reference to the last vintage of the old GDP series (2000 basis). Data for CF are from Consensus Economics Inc

NW panel is different from that reported in the other panels. In the NW panel, we are reporting annual growth computed on the basis of the last vintage of available data (and before 2010 reconstructed as described in Sect. 2), while the other panels report annual growth computed on the basis of the real-time release of the GDP series. We do the latter because the ADB, the IMF, and CF predicted the series with this information at hand.

From Fig. 6 and the RMSE values in Table 5, we can see that the DFM is predicting annual GDP growth quite well, and, in particular, it correctly revises its prediction as more data become available during the calendar year. Furthermore, the prediction of the DFM is comparable to that of CF, and slightly superior to that of the ADB and the IMF.

We conclude this section by stressing two caveats on the results just presented: First, by using annual data, we have only 7 predictions, that means that the RMSE reported in Table 5 hinges on very few observations. Second, our exercise is *pseudo* real time in the sense explained in Sect. 4.1, as we avail of a better information set compared to the one exploited in real time by institutional forecasters.

5 Conclusion

In this paper, we have applied state-of-the-art techniques for nowcasting Indonesia's GDP growth. Our approach is based on a Dynamic Factor model, to efficiently exploit monthly and quarterly variables and to properly account for the sequence of macroeconomic data releases.

We find that relying on market "revealed preferences" for certain indicators in the Indonesian economy is an effective guide for choosing what variables to include in

our information set. To this end, we have relied on the Bloomberg platform, which tracks the relevance of each series for its subscribers, and also on our “expert judgment” by including a few indicators that we think provide extra information on the Indonesian economy. Based on this, despite using a relatively narrow set of variables, when focusing on the year-on-year growth rate, the Dynamic Factor model nowcast error falls by 55% compared with the benchmark AR model. Lacking a full time series of GDP revisions as well as for the information set used in the Dynamic Factor model we cannot assess how well our model predictions perform compared with those of experts’ forecast surveyed by Bloomberg. Still, our “pseudo-real-time” forecasting performance is comparable with the one achieved in a truly “real-time” setting by the median Bloomberg survey.

Furthermore, since our model can be used to forecast further ahead, we also compute calendar-year annual growth rates. This exercise allows us to compare the tracking of our Dynamic Factor model forecasts on a smoother and medium-term indicator of Indonesia’s growth, arguably more important for policy decisions than the (potentially erratic) quarterly growth rate. In this case our model compares well with the forecasts produced by the average of private sector expectations (Consensus Forecasts) as well as by the IMF World Economic Outlook.

Finally, our exploration into Indonesia’s data sheds light on a severe lack of valuable high-frequency statistics on economic growth, as well as on possible information gaps in the statistical framework underlying national accounts. Despite such limitations, the Dynamic Factor proposed in this paper constitutes a useful tool for policy makers and private sector experts aiming to nowcast Indonesia’s growth trajectory.

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A Appendix

A.1 Robustness

In this Appendix we show robustness checks with respect to the composition of the dataset.

The first robustness check aims to answer the question “what if we had selected variables in a different way?”. As discussed in Sect. 3.1, we constructed the database by selecting variables from the set of indicators that market analysts are monitoring, however, *a priori* there are other equally valid selection criteria. In particular, in performing this robustness check we considered (a) the option of using all the indicators in Table 1 (labeled Bloomberg selection), and (b) the option of selecting indicators automatically by using a statistical technique (labeled as automatic selection).¹⁸

¹⁸ By using the LARS algorithm as in Bai and Ng (2008), we selected 10 out of all available indicators that were retrieved for Indonesia.

Table 6 Root mean squared error: different model specifications and datasets. *Source* Authors' estimates

	Month	Revealed preferences	Automatic selection	Bloomberg selection	No selection
Forecast	1	0.587	0.916*	0.591	0.828
	2	0.516	0.805**	0.526	0.683
	3	0.444	0.724*	0.531*	0.718
Nowcast	1	0.449	0.725*	0.541**	0.612
	2	0.325	0.541**	0.424**	0.431
	3	0.287	0.483*	0.434**	0.439
Backcast	1	0.288	0.486**	0.409**	0.379

This table reports root mean squared errors for the DFM estimated over database in which the selection process is different than the one explained in Sect. 3.1. The upper panel, labeled “Forecast”, reports the RMSE of the prediction of the next quarter; the middle panel, labeled “Nowcast”, reports the RMSE of the prediction of the current quarter; the bottom panel, labeled as “Backcast”, reports the MSE of the prediction of the previous quarter. Asterisks indicate a rejection of the [Diebold and Mariano \(1995\)](#) test of equal predictive accuracy between each model and the benchmark DFM—i.e., the one estimated by selecting the variable using “Revealed Preferences”—at 5% (***) or 10% (*) significance levels

In [Table 6](#), we show the RMSE for a DFM parameterized as described in [Sect. 4.1](#) but estimated on the two datasets just described. As we can see, our database clearly delivers the best performance, though in forecasting the performance of the DFM estimated over the indicators followed by Bloomberg is comparable. The performance of the DFM is particularly disappointing when the indicators are selected with LARS. We believe that this is a consequence of having too few observations, and some missing values in the time series of our indicators.

The second robustness check aims to answer the question “what if we do not select indicators but include all variables that we are able to retrieve?”. To this end we use a bridge model as in [Eq. \(4\)](#), where the predictor x_t^Q is a factor extracted from a panel of monthly variables by using principal component.¹⁹ The last column of [Table 6](#) reports the RMSE for this model and the results confirm that including all variables does not appear to be a good strategy.

A.2 Technical aspects related to y-o-y transformations

In [Sect. 3.2](#) we mention that to estimate the model we use the EM algorithm proposed by [Bańbura and Modugno \(2014\)](#), which can handle both mixed frequencies and missing data. While we refer the reader to [Bańbura and Modugno \(2014\)](#) and [Bańbura et al. \(2011, 2013\)](#) for detailed information on this algorithm and for a formal treatment,

¹⁹ With the exception of few technical and minor details, this is essentially the same model used by [Giannone et al. \(2008\)](#). In practice, every time we update the prediction we use a balanced panel to estimate the factor with PCA. Then we fit an AR(2) on the estimated factor and use the Kalman Filter to account for missing values at the end of the sample. Finally we estimate [Eq. \(4\)](#) with OLS. An alternative way to perform this exercise would be to use the collapsed dynamic factor model of [Bräuning and Koopman \(2014\)](#).

in this Appendix we provide basic information related to the use of year over year growth rates.

The first issue is to understand what is the relationship between monthly y-o-y growth rates, and quarterly y-o-y growth rates. Let t denotes months, and let Y_t^Q be the log-level of a quarterly variable. The y-o-y growth rate is then equal to $Y_t^Q - Y_{t-12}^Q$ and we will denote it as y_t^Q . Then, let Y_t^M be the monthly log-level of Y , and let $y_t^M = Y_t^M - Y_{t-12}^M$ be the monthly y-o-y growth rate. In order to link y_t^Q and y_t^M we follow [Mariano and Murasawa \(2003\)](#), and we make use of the approximation $Y_t^Q \approx Y_t^M + Y_{t-1}^M + Y_{t-2}^M$ which, after some simple algebra, allows us to write:

$$y_t^Q = y_t^M + y_{t-1}^M + y_{t-2}^M. \tag{6}$$

The second issue is how to write the factor model when we have a vector of monthly and quarterly y-o-y growth rates. [Bańbura and Modugno \(2014\)](#) solved this by treating quarterly series as monthly series with missing observations, and by assigning the quarterly observation to the 3rd month. Suppose for simplicity that we have only one monthly variable y_{1t}^M , one quarterly variable y_{2t}^Q , and one (monthly) factor f_t , then by using (6) we have:

$$\begin{bmatrix} y_{1t}^M \\ y_{2t}^Q \end{bmatrix} = \begin{bmatrix} \lambda_m & 0 & 0 \\ \lambda_q & \lambda_q & \lambda_q \end{bmatrix} \begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \xi_{1t}^M \\ \xi_{2t}^Q \\ \xi_{2t-1}^Q \\ \xi_{2t-2}^Q \end{bmatrix}. \tag{7}$$

A.3 Why two factors?

The literature on factor models has shown that it suffices to include a small number of factors for forecasting (e.g., [Stock and Watson 2002b](#); [Forni et al. 2003](#)). Furthermore, recent literature on small-medium DFMs ([Bańbura et al. 2013](#); [Luciani and Ricci 2014](#); [Giannone et al. 2014](#); [Bragoli et al. 2015](#)) often includes one factor only. Therefore, a natural choice would be to follow the literature and to set $r = 1$.

However, these factor models are estimated for q-o-q growth rates, while we are estimating a model for y-o-y growth rates. So if the model for q-o-q growth rates has one factor, then the corresponding model for y-o-y growth rates has four factors: let X_t be a non-stationary variable in log-levels, and let $x_t^y = X_t - X_{t-4}$ be the y-o-y growth rates and $x_t^q = X_t - X_{t-1}$ be the q-o-q growth rates, so that $x_t^y = x_t^q + x_{t-1}^q + x_{t-2}^q + x_{t-3}^q$. Then, if the true model is $x_t^q = \lambda f_t + e_t$, we have $x_t^y = \lambda(1 + L + L^2 + L^3)f_t + (1 + L + L^2 + L^3)e_t$, which can be rewritten as $x_t^y = \lambda \mathbf{F}_t + (1 + L + L^2 + L^3)e_t$ where \mathbf{F}_t is a 4×1 singular vector.

In light of this, we should set $r = 4$, and, indeed, by looking at the eigenvalues of the covariance matrix of the first subsample (July 2002–December 2007), we can see clearly three/four diverging eigenvalues. However, among these three/four eigenvalues, the first two clearly dominate—the first eigenvalue accounts for 70% of the

total variance, the second for 20%, the third for 5%, and the fourth for 3%—thus suggesting that the other two mainly carry noise, which is why we choose to set $r = 2$. Furthermore, as a robustness check we estimated the DFM by setting either $r = 1$ or $r = 4$, and found (results not shown here) that including two factors proved optimal.

There are at least three possible alternatives to the strategy of setting $r = 2$. The first would be to estimate a model with four common factors driven by only one common shock, so that the vector \mathbf{f}_t in Eq. (2) is 4×1 , while the vector \mathbf{u}_t is 1×1 . A second possibility would be to impose the specific lagged structure described above (see, e.g., Camacho and Perez-Quiros 2010), and a third possibility would be to estimate dynamic factor loadings by using the Dynamic Heterogeneous Factor Models of (D'Agostino et al. 2016).

The reason we prefer to use the model with $r = 2$ to all the alternatives is that we want to keep the model as simple as possible, so that it easy to communicate the prediction obtained with our model to policy makers. Furthermore, all three alternatives complicate the state space representation and in our case where we have few time series observations, and the quality of the data is doubtful, while complicating the Kalman Filter is feasible it is costly in terms of computation accuracy.

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