Jurnal Nowcasting GDP

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| No | Penulis | Data | Metode | Temuan |
| 1. | Briliana Wellyanti (2019). | 1. Data PDRB Bali Triwulan I th. 2007 s.d. triwulan II th. 2016. | 1. Model ARIMA. | 1. Model ARIMA terbaik yang mampu menggambarkan PDRB Triwulanan Bali dari triwulan I 2007 sampai dengan triwulan II 2016 adalah ARIMA (3,1,0). 2. Hasil ramalan PDRB Bali dari triwulan I 2007 sampai triwulan II 2016 memiliki rata rata perbedaan 8,76 persen dengan PDRB yang sudah di release oleh BPS Provinsi Bali. 3. Ramalan PDRB Bali di triwulan III 2016 adalah sebesar Rp. 36.886.140 dengan laju pertumbuhan sebesar 7,24 persen (jika dibandingkan dengan PDRB hasil release triwulan sebelumnya). |
| 2. | Desy Tresnowati Hardi, Diah Safitri, & Agus Rusgiyono (2019). | 1. Data in sample: Triwulan I 2000 – Triwulan IV 2016. 2. Data out sample: Triwulan I 2017 – Triwulan IV 2018. | 1. Singular Spectrum Analysis (SSA). | 1. Dari proses peramalan yang menggunakan window length sebesar 21 serta terbentuk sebanyak 3 kelompok, diperoleh nilai MAPE sebesar 1,59% dan nilai tracking signal sebesar 2,50. 2. Berdasarkan dari ketentuan kategori MAPE dan tracking signal, keduanya sudah dalam kategori baik sehingga model yang diperoleh dapat menghasilkan peramalan dengan keakuratan tingkat tinggi. Oleh karena itu, metode SSA cocok untuk peramalan data PDB sektor pertanian, kehutanan, dan perikanan. |
| 3. | Nurmalita Oktaviana & Nurisqi Amalia | 1. Data PDRB prov. Kep. Bangka Belitung triwulan I th. 2010 s.d. triwulan IV th. 2017 atas dasar harga konstan 2010 | 1. Kuantitatif trend dg variasi data trend. | 1. Data PDRB Provinsi Bangka Belitung yang dimulai dari tahun 2010 triwulan pertama dan berakhir pada tahun 2017 periode triwulan keempat mengalami kenaikan . 2. Nilai hasil peramalan (forecast) dengan menggunakan trend memiliki jenis data yang berpola trend naik, artinya PDRB Provinsi Bangka Belitung untuk periode lima tahun kedepan ,yakni dari tahun 2018 triwulan pertama dan berakhir pada periode forecast periode triwulan keempat tahun 2022 mengalami kenaikan terus seiring bertambahnya tahun berdasarkan data histories yang tersedia. |
| 4. | Tamara, Novian & Dwi Muchisha, Nadya & Andriansyah, Andriansyah & Soleh, Agus M. (2020) | 1. Dataset periode 2009:Q4 s.d. 2019:Q4 seri referensi pertumbuhan PDB triwulan Indonesia. | 1. Autoregressive model 2. Ridge Regressio 3. Lasso 4. Elastic net 5. Random forest 6. Neural network 7. Support vector machine | 1. Evaluated the performance of several ML algorithms in doing real-time forecast on Indonesia's GDP growth data. 2. All ML models are able to produce more accurate forecasts than AR(1) benchmark. 3. The real-time forecast of GDP growth using the forecast combination method using the Lasso regression provides better results than the other methods used in this study. |
| 5. | Desy Yuliana Dalimunthe. (2017) | 1. Data PDRB prov. Kep. Bangka   Belitung kuartal I th. 2007 s.d. kuartal II th. 2014. | 1. ARIMA | 1. Data PDRB Kepulauan Bangka Belitung yang dimulai dari tahun 2007 kuartal pertama dan berakhir pada tahun 2014 periode kuartal kedua ini memiliki jenis data yang berpola tren naik. 2. Nilai estimasi model ARIMA yang terbaik, maka model estimasi model ARIMA (1,1,0) atau AR(1) ini merupakan jenis model estimasi yang paling signifikan. 3. Nilai hasil peramalan (forecast) pada model AR(1) ini memiliki nilai peramalan yang cenderung membentuk tren naik pula, artinya nilai PDRB Provinsi Kepulauan Bangka Belitung untuk periode kedepan, yakni tahun 2014 kuartal III dan berakhir pada periode forecast pada periode IV tahun 2015. 4. Residual dari model ARIMA (1,1,0) merupakan model yang baik yang dibuktikan dengan plot ACF bahwa tidak ada lag (≥ 1) yang keluar dari garis batas interval. |
| 6. | Kartika Rahayu Tri Prasetyo Sari. (2017) | 1. Data indeks harga saham GDP per kapita Indonesia atas dasar harga konstan, nilai tukar rupiah thd dolar Amerika, harga emas, harga perak, dan harga tembaga pada tahun 1995-2010. | 1. Metode principal component analysis (PCA). 2. Regresi. | 1. Indikator yang paling mempengaruhi besarnya GDP per kapita adalah indeks harga saham. 2. Persamaan regresi linier untuk menghitung besarnya GDP per kapita adalah Nilai GDP per kapita = 6.678.000 + 883,481 x Index Harga Saham. Prediksi besarnya GDP per kapita berdasarkan regresi linier diatas untuk tahun 2017 adalah Rp 10.419.384, 2018 adalah Rp 10.590.365, dan 2019 adalah Rp 10.769.160. |
| 7. | M. Fajar, & Y.G. Winarti. (2021) | 1. Data ekonomi year on year pertumbuhan kuartal 1 tahun 1983 hingga kuartal 3 tahun 2020. | 1. Markov Switching in Mean – Autoregressive. | 1. The Markov Switching in Mean – Autoregressive Model is can be applied to the Indonesian economic growth movement. The model specification is MSM-AR(3). Wald statistic indicates the model is valid, and its transition matrix is irreducible. 2. By using the MSM-AR model (3), it can be predicted that in the 4th quarter of 2020 the economic condition is still experiencing the recession regime due to the impact of the COVID-19 pandemic. In 2021, MSM-AR (3) predicts that the economy will recover, which means economic conditions during the first to fourth quarter will enter an expansion regime. It is indicated by the positive economic growth forecast which shows an increase every quarter, and the probability of a recession regime reach more than 0.5 per quarter. |
| 8. | I Gusti Ngurah Arya Wanayasa, I Putu Eka Nila Kencana, & D.P.E. Nilakusmawati. (2012) | 1. Data PDRB prov. Bali triwulan I 1991 – triwulan IV 2010. | 1. Fuzzy time series. 2. Pemulusan eksponensial Holt-Winter. | 1. peramalan data PDRBP rovinsi Bali Tahun 2011 dengan menggunakan metode Fuzzy Time Series diperoleh hasil ramalan sebesar 30.947.105 dengan persentase kesalahan ramalan sebesar 0,64%. Sedangkan peramalan dengan menggunakan metode Holt-Winter Aditif diperoleh hasil ramalan sebesar 32.960.286 dengan persentase kesalahan ramalan sebesar 7,13%. 2. metode Fuzzy Time Series memiliki tingkat keakuratan yang lebih tinggi dibandingkan dengan metode Holt-Winter Aditif dengan selisih persentase kesalahan ramalan sebesar 6,49%. |
| 9. | Wahyu Dewati, Rama Rahadian Prakasa, Rizki Fitrama, Deasy Ariyanti, Donny Hendri Pratama, Dythia Sendrata, Warsono, & Erwin Syafii. (2018) | 1. Data PDRB tahun 2009 – 2017 wilayah Sumatera.   (Indikator yang merepresentasikan besarnya investasi adalah penjualan semen, Indikator yang terkait dengan kinerja perekonomian  dalam investasi meliputi impor barang modal, total impor, total ekspor, dan  bongkar muat barang (baik melalui pelabuhan domestik maupun  internasional)).   1. Data PDRB tahun 2009 – 2017 wilayah Jawa.   (Indikator yang merepresentasikan besaran konsumsi rumah tangga dan  pandangan konsumen terhadap kondisi perekonomian, seperti indeks keyakinan konsumen (IKK), Indikator yang terkait dengan kinerja perekonomian wilayah, baik di Jawa maupun tingkat nasional meliputi industrial production index (IPI), produksi  kendaraan bermotor roda empat, impor barang konsumsi, ekspor komoditas  makanan dan minuman, inflasi,  indeks harga saham sektoral  dan volume bongkar pelabuhan serta volume muat  Pelabuhan, Indikator yang terkait dengan jasa keuangan atau perbankan ialah suku bunga (DPK, deposito, tabungan, kredit dan kredit konsumsi)).   1. Data PDRB tahun 2011 – 2017 wilayah Kawasan Timur. (Indikator yang merepresentasikan besarnya konsumsi rumah tangga meliputi indeks penjualan riil,nilai tukar petani (NTP), indeks keyakinan konsumen, tingkat inflasi, dan kunjungan wisatawan mancanegara. Indikator yang terkait dengan kinerja perekonomian meliputi data impor, data ekspor, harga komoditas global dan bongkar muat barang di pelabuhan utama. Indiaktor yang terkait dengan perbankan meliputi data kredit, data simpanan (DPK), dan suku Bunga   Dengan pengujian pseudo out of sample memakai data tahun 2018. | 1. Bridge equation 2. Distribusi Lag Model 3. Dengan metode estimasi OLS. | 1. Metode DLM dengan kombinasi indikator NTP, kredit konsumsi, indeks keyakinan konsumen (IKK), harga kopi arabika, dan total DPK menjadi model terbaik dalam memproyeksikan konsumsi rumah tangga pada triwulan berjalan hasil pengujian yang menunjukkan nilai RMSE yang lebih rendah dan adjustred R-squared yang lebih tinggi dibandingkan dengan metode Bridge Model untuk wilayah Sumatera. tingginya kontribusi sektor pertanian dalam PDRB Sumatra, yang mencapai 22%, menjadi sektor terbesar dalam PDRB Sumatra. Kredit konsumsi juga memegang peranan penting besarnya pangsa kredit konsumsi terhadap total kredit di Sumatra yang mencapai 32%.   peran industri kopi dalam perekonomian sebagai salah satu komoditas unggulan ekspor Sumatra. Sumatra juga menjadi sentra utama produsen kopi Indonesia dengan mencapai 70,2% dari total produksi kopi nasional pada tahun 2017. Di wilayah Sumatra investasi bangunan tercatat terus meningkat dibandingkan investasi nonbangunan, dengan pangsa investasi bangunan mencapai 71% pada tahun 2017.   1. Metode DLM dengan kombinasi indikator indeks keyakinan konsumen (IKK), suku bunga deposito, inflasi perumahan, harga listrik; gas; dan air, serta produksi kendaraan roda empat menjadi model terbaik dalam memproyeksikan konsumsi rumah tangga pada triwulan berjalan pada hasil pengujian yang menunjukkan nilai RMSE dan deviasi terhadap realisasi yang lebih rendah dibandingkan dengan metode Bridge Model untuk wilayah Jawa. porsi konsumsi perumahan dan perlengkapan rumah tangga dalam PDRB Jawa yang berkisar pada 12%—14% dalam lima tahun terakhir. impor barang modal, data penjualan semen, produksi mobil nasional, dan juga indeks IHSG untuk sektor perdagangan atau trade. Secara umum, struktur PMTB di Jawa lebih didorong oleh investasi bangunan dengan rata-rata lima tahun terakhir yang mencapai 77%. 2. Metode Bridge Model dengan kombinasi indikator NTP, kredit kendaraan bermotor, 49 dan ekspor barang industri menjadi model terbaik dalam memproyeksikan konsumsi rumah tangga pada triwulan berjalan pada hasil pengujian yang menunjukkan nilai RMSE dan MSE yang lebih rendah dan adjusted R-squared yang lebih tinggi dibandingkan dengan metode DLM untuk wilayah Kawasan Timur Indonesia. pangsa lapangan usaha pertanian pada PDRB KTI yang sebesar 17% secara rata-rata dalam 7 tahun terakhir dan merupakan pangsa lapangan usaha terbesar kedua setelah pertambangan. kredit kepada debitur perseorangan di KTI memiliki pangsa mencapai 60% dari total kredit KTI pada tahun 2017, dengan nominal mencapai 470 triliun rupiah. Ekspor KTI pada tahun 2017 didominasi oleh hasil pertambangan dengan pangsa 67% dan hasil industri dengan pangsa 31%. komponen investasi (PMTB) dalam PDRB KTI memiliki rata-rata pangsa yang cukup signifikan, yaitu sebesar 31,4% selama tiga tahun terakhir. Namun, sepanjang periode observasi pertumbuhan investasi KTI 47 berfluktuasi dalam rentang yang cukup lebar, yaitu 2,47%—11,22% (yoy) dengan rata-rata pertumbuhan sebesar 6,50% (yoy) yang mengindikasikan tingginya volatilitas pertumbuhan serta derajat ketidakpastian pertumbuhan investasi di KTI. |
| 10. | William A. Barnett, Marcelle Chauvet, & Danilo Leiva-Leon. (2014) | 1. Data archives of all available National Income and Product Account (NIPA) series at the monthly frequency, nominal variables from the product side, industrial production and capacity utilization, consumption expenditures, labour market variables, all price indices from the production and consumption sides, and monetary and Önancial series. | 1. Simple-sum Mixed-frequency Naïve Model 2. Mixed frequency dinamic factor model 3. Univariat auroregressive model | 1. Non-linear nowcasting dynamic factor model that includes mixed-frequency and parameter instability that can be helpful in the assessment of current economic conditions. 2. The univariate analysis shows that classical autoregressive models provide poor performance regarding real-time nowcasts of the target variable. 3. Estimate the small-scale non-linear mixed-frequency dynamic factor models. the presence of two breaks in NGDP growth dynamics: the Örst in the late 1980s, associated with the Great Moderation, and the second in the midst of the Great Recession in 2008. 4. The multivariate models that allow parameter instability outperform linear multivariate as well as linear and non-linear univariate specifications, yielding the best nowcasting performance. The best specifications are parsimonious and include economic activity, ináation, monetary indicators and/or interest rates. |
| 11. | Knut Are Aastveit, Karsten R. Gerdrup, & Anne Sofie Jore. (2015) | 1. Consider 120 monthly leading indicators to nowcast quarterly growth in U.S. GDP. The monthly data are mainly collected from the ALFRED (ArchivaL Federal Reserve Economic Data). This database consists of collections of real-time vintages of data for each variable. In addition, several real-time data series are collected from the Federal Reserve Bank of Philadelphia’s Real-Time Data Set for Macroeconomiss. | 1. Bridge equation models 2. factor models (FMs) 3. Mixed-frequency vector autoregressive (MF-VAR) | 1. Combined predictive density nowcast for each of the three different model classes. 2. Log scores for the predictive densities increase almost monotonically, as new information arrives during the quarter. The densities also seem well calibrated. 3. The density combination approach is superior to a simple model selection strategy, and the density combination framework actually performs better, in terms of point forecast evaluation, than standard point forecast combination methods. The results are robust to the choice of benchmark (real-time) vintage. |
| 12. | Su Zhi Fang, Wang Xiang, & He Kai. (2014) | 1. Dataset contains quarterly GDP growth rate and fourteen monthly macro indicators. | 1. MIDAS Model 2. MF-VAR Model | 1. when predicting the quarterly GDP growth in China based on MIDAS and MIDAS-AR, we can obtain that, at horizon h<7, the MIDAS model outperforms than the MF-VAR model, whereas, at horizonhm=8, 9. 2. the results show that, based on the combination of MIDAS and MIDAS-AR, the pooled forecast can protect its performance from the misspecification and parameter instability in single indicator models, besides it can clearly outperform than the MIDAS model and the MIDAS-AR model. 3. the result based on nowcasting and forecasting for China’s quarterly GDP growth highlights that its economy will be rebound in 2012Q3 due to the export picking up gradually, consumer confidence index rising significantly and the fast and stable growing fixed-asset investment. And the quarterly GDP growth forecasts in the following two quarters are 8.2% and 8.5% respectively, which suggests that the economic growth of China will encounter a stable growth period. |
| 13. | Laurent Ferrara. (2016) | 1. data set gathering economic indicators from 37 countries, both advanced and emerging from 1995-2017. | 1. FA-MIDAS | 1. factor‐augmented MIDAS approach enabling to explain the annual global growth by a large database of monthly variables. The targeted variable is the annual global growth estimated by the IMF in its periodic World Economic Outlook assessment. 2. This tool could be fruitfully used by macroeconomists to monitor global economic developments, in addition to the IMF WEO estimates. |
| 14. | W. Jos Jansen, Xiaowen Jin, Jasper M. de Winter. (2015) | 1. monthly dataset consists of 72 monthly time series variables (using harmonized definitions across the countries), which cover the broad range of information that is readily available to economic agents. Period (1996.I-2011.III). | 1. Quarterly models for GDP growth 2. Mixed frequency models 3. Factor and AR augmented models | 1. The largest accuracy gains are for nowcasts and backcasts, suggesting that statistical models are especially helpful when they are able to use information that pertains to the quarter of interest. Moreover, statistical models are generally more efficient at extracting monthly information in volatile periods. Thus, their relative strength is to improve the assessment of the current state of the economy. In contrast, the predictions from statistical models generally incorporate little information at the two-quarter-ahead horizon. 2. The dynamic factor model displays the best forecasting capabilities overall particularly for backcasts and nowcasts. The Bayesian quarterly VAR is the best quarterly model. 3. Factor analysis to summarize the available monthly information clearly delivers better results than the alternative of averaging single-indicator-based forecasts in the case of one-quarter-ahead forecasts and nowcasts. 4. Statistical models differ significantly in the rates at which they are able to absorb monthly information as time goes by. |
| 15. | Daniela Bragolt & Jack Fosten. (2018) | 1. the fully revised real GDP series against the real-time data from 1996 to 2015 | 1. Univariate autoregressive model 2. Univariate bridge model | 1. The factor model improves over benchmark models and professional forecasters only for the final-release GDP series, and not for the first release. 2. Adding in nominal series and, to a lesser extent, international series, yields substantial gains in nowcast accuracy. The addition of international series seems to improve the nowcasts of Indian GDP most markedly during the global crisis period in 2008–9. 3. The factor method improves over a benchmark bridge equation method, potentially as the factors from our expanded dataset are more representative of the Indian economy. 4. Searching for series outside the standard set of variables used in nowcasting studies can improve nowcasts in developing countries such as India. |
| 16. | Oguzhan Cepni, I. Ethem Guney, & Norman R. Swanson. (2019) | 1. set of economic indicators consists of 97, 87, 116, 109, and 102 economic variables for Brazil, Indonesia, Mexico, South Africa, and Turkey, respectively. | 1. Dynamic factor models. 2. dentifying targeted predictors:LASSO-based approaches. 3. Factor-augmented prediction models | 1. New global economic “uncertainty” and macroeconomic data “surprise” factors are indeed useful, in the sense that they contain substantial marginal predictive content for real GDP growth in numerous EM economies, as shown through a series of real-time forecasting experiments. 2. The data shrinkage methods employed in our experiments are found to significantly improve the predictive content of the latent factors used in our DFMs. |
| 17. | Tony Chernis & Rodrigo Sekkel. (2016) | 1. 23 economic predictors for Canada, dataset GDP from 1999-2015. Of the 23 variables that include, 14 are domestic, 6 are USA, and the remaining 3 are the Bank of Canada non-energy commodity price index, WTI oil prices, and Global Purchasing Manager’s Index (PMI). The domestic variables cover most of the standard nowcasting variables: car sales, PMI, merchandise trade, housing variables, and various real activity measures. We also include an indicator from the Bank of Canada’s Business Outlook Survey (BOS). | 1. Bridge models 2. MIDAS regressions | 1. The new model is estimated using a panel of 23 variables and includes a limited factor that takes monthly GDP series into consideration. 2. Dynamic factor model is more accurate than traditional simple benchmarks such as univariate AR models.It outperforms competing MIDAS and bridge models, which take into account extra factors directly. |
| 18. | João C. Claudio, Katja Heinisch, & Oliver Holtemöller. (2019) | 1. For the period 1991–1994. These comprise quarterly GDP as well as gross value added for East German states. 2. For the period 1995–2015, the quarterly shares are based on a bottom-up approach (based on gross value added components). | 1. benchmark AR models. 2. MIDAS models. | 1. Suggests that an ARDL model including a forecast for total Germany is useful to forecast regional GDP. 2. MIDAS forecasting models containing additional (monthly) information on East Germany significantly improve forecasting quarterly East German GDP growth, although only slightly. MIDAS models encompassing the indicators on situation, expectations and climate in manufacturing and retail trade and vacancies provide a reasonable view about quarterly real GDP growth in East Germany. 3. private construction had the largest share in total Eastern German turnover in construction in 2017 (almost 42%), public construction had a share of about 23% and building construction of 35%. |
| 19. | Frederique Bec & Matteo Mognoliani. (2015) | 1. Real-time quarterly GDP series are collected in an upper-triangular matrix spanning the period from 1992Q1 (upper-left corner) to 2012Q4 (lower-right corner). | 1. MIDAS regression | 1. Selected restricted-information models fail to encompass each other. 2. The information pooling strategy dominates the forecast combination strategy in an empirical application involving the nowcasting of French GDP in real-time. |
| 20. | Ard den Reijer, & Andreas Johansson. (2018) | 1. The ragged-edge data set Xtm contains 92 stationary predictor variables. All variables showing an exponential growth are log-transformed, and all nonstationary variables are (moreover) first-differenced. Data set is downloaded in July 2014, and historical revisions of the data are disregarded. | 1. MIDAS regression with few indicators. 2. Factor approaches with large data sets. | 1. on Swedish data that pooled nowcasts outperform the benchmark models very robustly. 2. firstly that pooling of nowcasts gets a lower MSE in comparison with the benchmark (AVG), often significantly so. Especially, the pooled single indicator MIDAS modelsoutperform the original models. 3. Secondly, the pooling shows no significant improvement of nowcast accuracy in the pre-crisis period, while it outperforms the benchmark for most model combinations in the post-crisis period. |
| 21. | Knut Are Aastveit and Tørres Trovik. (2010) | 1. panel of macroeconomic and financial variables for the Norwegian economy. 2. macroeconomic and financial variables for Norway’s main trading partners; the euro area, Sweden, U.K. and the U.S. In total we use a panel of 148 monthly variables. The sample starts in January 1990 and ends in January 2009. | 1. Dynamic Factor model | 1. financial data contribute the most to the precision of the nowcast, in particular data from Oslo Stock Exchange. Hence, financial data provide a valuable contribution in addition to statistically compiled indicators. 2. particular labor market data and industrial production indicators also contribute favorably to the precision of the nowcast. 3. seven sector indices that are included in the data are all close to being equally important. 4. Norway is an open economy this is not surprising as international conditions supposedly have an effect on activity in Norway with a time lag. Even though including international data bring about factors that explain more of the variance among the independent variables, this increased variance in the factors is of a nature that has low correlation to the current quarter GDP growth in Norway, |
| 22. | Alessandro Girardi,  Roberto Golinelli, and  Carmine Pappalardo. (2014) | 1. Short-term economic indicators, mostly for the eurozone and the United States. There are 259 time series in the entire set of indicators, which span from January 1990 to December 2012. | 1. Univariate AR model 2. Benchmark model 3. Factor model | 1. the factor extraction from a subset of targeted indicators to a specific variable, retains the most valuable piece of information to be passed into the FM approach and can deliver substantial gains in terms of forecasting accuracy. 2. Forecasting ability is assessed according two main specific features: the pseudo real-time nature of the information set, and the empirical probability of each indicator to be picked conditional to a screening rule (one hard and 5 soft rules). 3. forecast accuracy of each model (BM, FM, PFM) significantly improves as indicator information increases. 4. by exploiting the moments of the empirical distribution of selected indicators, forecasting ability monotonically increases with the progressive reduction in the number of indicators from the large-panel pool. 5. PFM based on soft rules (PFMsoft) systematically outperform the PFM based on hard-thresholding rule (PFMhard) within all blocks, as the latter retains much more, and less useful, information than the soft ones. 6. PFMsoft at the 90th quantile (PFMsoft90) is the best selected model over all vintages. 7. The best forecast comes from the hierarchical technique at Q = 90th, because it may offset the bias caused by potential misspecification. |
| 23. | Laurent Ferrara, Dominique Guégan And  Patrick Rakotomarolahy. (2010) | 1. The real-time information set starts in January 1990, when possible (exceptions are the confi dence indicator in services, which starts in 1995, and EuroCoin, which starts in 1999) and ends in November 2007. | 1. ARIMA model | 1. The impact of fresh data on short-term projections of Euro area GDP growth quarter-over-quarter is examined in this article. The main contribution is a new way to use non-parametric methods to fill ragged-edge monthly data that emerge in the estimation of quarterly GDP growth. |
| 24. | Pamfili Antipa, Karim Barhoumi, Véronique Brunhes-Lesage, and  Olivier Darné. (2012) | 1. GDP of German period 2002Q1–2008Q4. | 1. Bridge model 2. Dynamic Factor model | 1. changing the BM’s equations by including newly available monthly information provides generally more precise forecasts and is preferable to maintaining the same equation over the exercise’s horizon. 2. forecast errors of the BMs are smaller than those of the DFMs. |
| 25. | William A. Barnett & Biyan Tang. (2016) | 1. 193 macroeconomic series for the Chinese economy, including real variables, such as industrial production and international trade along with financial variables, such as prices, money, and credit aggregates. The data spans from December 1999 to June 2015. The data from 2007 quarter 4 onwards is reserved for the evaluation of out-of-sample nowcasts. | 1. Dynamic factor model | 1. the Chinese money supply declined at the beginning of 2010, after which the growth rates of Divisia M1, M2, M3, and M4 all steadily decreased, reflecting the tightened borrowing conditions in Chinese money. 2. The growth rates of the Divisia monetary aggregates, M1, M2, and M3, began to decrease, while the user-costs of all the Divisia aggregates started to increase rapidly in 2012. 3. Since 2012, the Chinese real annual GDP growth rate settled into a lower steady growth range of within 7 % to 8 %, which is lower than the previous average of 10 % to 11 % during the past decade. These results reflect the fact that the Chinese economy experienced a structural break or regime change in 2012. |
| 26. | Irma Hindrayanto, Siem Jan Koopman, and Jasper de Winter. (2016) | 1. monthly dataset of predictors consists of 52 time  series variables for the euro area and its five largest  countries in terms of GDP contributions (Germany, France, Italy, Spain and The Netherlands). The variables  selected are based on harmonized definitions across the euro area and its countries, and fall into four predefined  categories: production and sales, prices, monetary and  financial indicators, and surveys. | 1. Dynamic factor models | 1. The monthly factors extract information that is valuable for the short-term forecasting of GDP growth. The largest forecast accuracy gains are obtained for nowcasting and backcasting. We conclude that the monthly factors are especially useful for forecasting the corresponding quarter. 2. The gains in forecast accuracy during the Great Recession period are larger than those during the Great Moderation period. This finding underscores the importance of factor models for the forecasting of the GDP growth rate during volatile periods. 3. The collapsed dynamic factor approach of Bräuning and Koopman (2014) has been shown to produce the highest forecast accuracy overall for the euro area and its five largest countries. However, there is a marked contrast between the periods of the Great Moderation and the Great Recession. During the Great Moderation, the model of Bräuning and Koopman (2014) has the highest forecast accuracy for most forecasting horizons and most countries considered. During the Great Recession, the relative forecast accuracy among the factor models considered is much more diversified, although that of Bräuning and Koopman (2014) is still the most competitive one. 4. Interpolating missing values by using an AR(2) model in the Bräuning and Koopman (2014) model improved the forecast accuracy for most countries considered. The inclusion of an autoregressive term of the target variable GDP in the Bańbura and Rünstler (2011) model improves its forecast accuracy slightly, although the gains are generally small. |
| 27. | Hyun Hak Kim & Norman R. Swanson. (2017) | 1. collected real-time Korean GDP beginning with  the vintage available in January 2000 The calendar start date of our dataset is 1970:Q1, and data are collected through June 2014. first-release GDP is announced 28 days after the end of the  quarter, second GDP release is announced 70 days subsequent to the end of the quarter, and the third release is made available 50 days after a calendar year has passed. Finally, a fourth release is made available a full year later. | 1. Factor MIDAS 2. Benchmark models | 1. that only approximately 10% of the forecasting models examined are ‘MSFE-best’ when using VA interpolation instead of AR interpolation. 2. models estimated using rolling data windows are only “MSFE-best” at three forecast horizons, when comparing real-time predictions to “first available” data, and are never “MSFE-best” when comparing predictions to “most recent” data. |
| 28. | Joelle Liebermann. (2014) | 1. Real-time database from 1 January, 1997 to 30 June, 2010 for a panel of US macroeconomic variables which enables us to construct vintages. The panel includes soft data (surveys) and interest rates, which are the timeliest, and hard data such as industrial production, employment, retail sales, housing, income and spending and prices among others. | 1. Dynamic factor model 2. Bridge equation | 1. Analogously to GRS’s pseudo real-time results, we find that as more information on the current quarter is released, the precision of the nowcast increases substantially. 2. The model tracks the strong worsening of growth during the recent recession quite well. The model fares well relative to the SPF at the time of the survey deadline and release dates, which is known to be a tough benchmark. 3. These results highlight the usefulness in real-time of the GRS factor model, an automatic, judgment free, procedure which enables one to incorporate macroeconomic information as soon as it gets released, which is valuable to policy-makers, financial market participants and businesses who need the most up-to-date assessment of the current state of the economy. |
| 29. | Massimiliano Marcellino and Christian Schumacher. (2010) | 1. The dataset contains German quarterly GDP growth from 1992Q1 until 2006Q3 and 111 monthly indicators from 1992M1 until 2006M11 that cover a wide range of economic activity in Germany. | 1. Factor MIDAS 2. Quarterly factor models 3. Benchmarks 4. methods that can handle ragged-edge data: DPCAs with data realignment, static PCA with the EM | 1. mixed-data sampling based on factors, Factor MIDAS, as a nowcasting and forecasting tool that combines methods from the recent literature on large factor models and on mixed-data sampling. 2. Factor MIDAS serves as a projection method that allows for a harmonized comparison of alternative factor estimation methods that can exploit information from a large set of indicators subject to different publication lags that lead to missing values at the end of the multivariate sample, the so-called ragged edge. 3. MIDAS with exponentially distributed lag functions performs similarly to MIDAS with unrestricted lag polynomials. The best performing projection is in many cases a very simple MIDAS with just one lag of the factors. AR dynamics also plays only a minor role in the MIDAS projections. 4. virtually all Factor MIDAS nowcasts can improve over quarterly factor forecasts based on time-aggregated data. Thus, taking into account higher frequency information and exploiting the most recent observations pays off for nowcasting and short-term forecasting. |
| 30. | Biyan Tang, Boniface Yemba & Dongfeng chang. (2020) | 1. Dataset consists of 193 macroeconomic series for US economy, including real variables such as (industrial production and employment), financial variables, prices, wages, money and credit aggregates, surveys from other sources. The span of the data is from January 1982 to October 2019. The data from 2006 onwards is reserved for the evaluation of out-of-sample nowcasts. The dataset is described detailed in appendix and most of the series are monthly, except real GDP growth rate are quarterly. | 1. DFMs 2. The Naïve model 3. Benchmark ARMA (2,2) 4. SPF (survey of professional forcasters) | 1. The DFM works the best for Nowcasting performance over other models when we consider the mean absolute percentage forecast errors (MAPFE) as measure of accuracy of forecast (lowest MAPFE). In fact, the DFM models with Divisia, both Divisia and simple sum monetary aggregates, and simple sum monetary aggregates have the smallest MAPFE (16.2239%, 16.3331% and 16.9998%, respectively). 2. The second best model is the Survey of Professional Forecast (SPF), which is an average of more than 60 models because its MAPFE is 29.1640%. 3. The worst model of forecasting the growth rate of real GDP is the Naïve model which has the highest MAPFE of 52.5016%. 4. However, when consider the Mean Squares Forecast Errors (MSFE) as measure of the accuracy of our forecasts, the Survey of Professional Forecast (SPF), performs slightly better than DFM with Divisia monetary aggregates. 5. Among the DFM models, the one with both Divisia and simple sum monetary aggregates works the better, providing the lowest Mean Squared Forecast Error of 3.1623. The DFM with Divisia monetary aggregates is the second best DFM with MSFE of 3.1924. 6. The worst model to nowcast the growth rate of the US GDP is the Naïve model with a MSFE of 8.2811. |
| 31. | Adam Richardson, Thomas van Florenstein Mulder, & Tugrul Vehbi. (2018) | 1. The data consist of a number of continuous real-time vintages of a range of macroeconomic and financial market statistics. These include: New Zealand business surveys; consumer and producer prices; general domestic activity indicators (e.g. concrete production, milksolids production, spending on electronic cards etc.); domestic trade statistics; international macroeconomic variables and international and domestic financial market variables. The data range from daily to quarterly - with the mean used to aggregate higher frequency data to quarterly for model estimation. The ’global database’ containing 668 series was routinely saved in estimating the Bank’s suite of statistical models. In total, we have a 37 real-time vintages of this dataset, covering the period 2009Q1 to 2018Q1. The data in each vintage begin in 1995Q1. | 1. Autoregressive Model (AR) 2. K Nearest Neighbour Regression (KNN) 3. Least-squares boosting (LSBoost) 4. Lasso, Ridge and Elastic Net (ENET) 5. Support Vector Machine Regression (SVM) 6. Feed Forward Neural Network (NN) 7. Factor Model (FM) 8. Bayesian VAR (BVAR) 9. RBNZ Statistical Suite (RBNZ SS) | 1. The majority of the ML models are able to produce more accurate forecasts than those of the AR and other statistical benchmarks. The results also suggest that there are some gains in combining individual ML forecasts. |
| 32. | Vladimir Kuzin, Massimiliano Marcellinob,& Christian Schumacherc. (2011) | 1. The dataset contains euro area quarterly GDP growth from 1992Q1 until 2008Q1, as well as about 20 monthly indicators until 2008M06. In particular, consider industrial production by sector, a survey on consumer sentiment, and business climate, raw material price indices, car registrations, interest rates, and monetary aggregates. | 1. MIDAS 2. MF-VAR | 1. 1. If we look at selected indicators, we find representatives of both the MIDAS and MF-VAR classes of models that work well relative to the benchmark. However, the relative performances of MIDAS and MF-VAR differ depending on the predictors and forecast horizons, and there seems to be no clear winner in terms of forecasting performance. 2. If we compare all of the models pairwise using the same indicator and compute the average MSE over the whole set of models, we find that AR-MIDAS outperforms MIDAS and MF-VAR at short forecast horizons, up to three months, whereas MF-VAR does better at longer horizons, up to nine months. 3. When the single MIDAS and MF-VAR forecasts are combined, there are advantages over the single indicator models. In addition, pooled MF-VAR forecasts are better at longer horizons (seven to nine months), and pooled MIDAS forecasts are better at shorter horizons. |
| 33. | Dimitra Lamprou. (2016) | 1. Dependent variable is obtained from the, seasonally adjusted, quarterly real GDP series expressed as annual growth rate. As explanatory variables consider the quarterly Gross Capital Formation (GCF), the Gross Fixed Capital Formation (GFCF) and the Exports (EXP) and the monthly economic activity indicators, namely the index of industrial production (IPI), the total turnover of retail sales (RSTOT) and the volume of retail sales (RSVOL).  * The first two are from January 2000 until December 2013 * The data set 3 contains data from January 2000 until Jun 2015 | 1. Bridge models 2. TSFA models | 1. The importance of them and the changes in information content of predictive variables in nowcasting the Greek real growth rate, by exploiting the particular structure of data on the Greek economy. 2. Possible to get reasonably good estimates of current quarterly GDP growth in anticipation of the official release. 3. Suggest that not only do observed large changes in the informational content due to data revisions but the models with highest predictive ability are varying based on both the predictive variables being used and the point in time of the forecast origin. 4. Important to consider an array of models when nowcasting, especially under periods of higher volatility and data revisions, as in the case of Greece. |