Nowcasting during the Pandemic: Lessons from Argentina*

Emilio Blanco	Fiorella Dogliolo	Lorena Garegnani
BCRA and UBA	BCRA and UNLP	BCRA and UNLP

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Abstract

We forecast economic activity in Argentina both on a quarterly real-time basis using dynamic factors models (DFM) (Blanco et al. 2018) and evaluate their forecasting performance during the COVID-19 pandemic of 2020. We compare the results of forecasts based on a pre-pandemic estimation of the parameters in the DFM and a re-estimated DFM with updated parameters using the most recent information. Considering the extreme observations that occurred during this particular year, we explore whether including new high frequency indicators (such as energy consumption and mobility) help capture more accurately the severe downturn.

Keywords: Nowcasting, dynamic factor models, Covid-19
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*The opinions expressed in this work are those of the authors, and do not necessarily reflect those of the Central Bank of Argentina or its authorities. Email: emilio.blanco@bcra.gob.ar; fiorella.dogliolo@bcra.gob.ar lgaregnani@bcra.gob.ar

1 Introduction

The pandemic and lockdown of 2020 challenged traditional tools used by monetary authorities and policy-makers. Furthermore it also highlighted the need for adequate and timely economic activity forecasting, given the unprecedented global sudden stop. Typically the assessment of current economic conditions is a crucial ingredient of decision making in central banks and other areas of the government. Moreover, this process has to be conducted in real time based on incomplete information, mainly because GDP -the main source of information on economic activity-is released on a quarterly basis and with an important lag. In the last decade, more timely business cycle indicators providing quantitative information on observed spending decisions (hard indicators) as well as qualitative information provided by different surveys (soft indicators) have become available. Most Central Banks have conducted *nowcasting* exercises using this indicators but the uncertainty surrounding the Covid-19 shock was a giant test for usual forecasting methodologies.

Huber et al. (2020) develop Bayesian econometric methods for posterior inference in non-parametric mixed frequency VARs using additive regression trees. Mixed frequency vector autoregressions (MF-VARs) have been a standard tool for producing timely, high frequency nowcasts of low frequency variables for several years. With the arrival of the COVID-19 pandemic of 2020 the need for such nowcasts has become even more acute. However, conventional linear MF-VARs nowcast poorly during the pandemic due to their inability to effectively deal with the extreme observations that have occurred. Huber et al. (2020) develop Bayesian methods for the mixed frequency version of this model (MF-BAVART) which is a non-parametric model using additive regression trees. They argue that regression tree models are ideally suited for macroeconomic nowcasting in the face of extreme observations, for instance those produced by the COVID-19 pandemic of 2020. This is due to their flexibility and ability to model outliers. In an application involving four major euro area countries, they find substantial improvements in nowcasting performance relative to a linear mixed frequency VAR.

Schorfheide and Song (2020) estimate a mixed-frequency vector autoregression (MF-VAR) developed in Schorfheide and Song (2015) to generate real-time macroeconomic forecasts for the U.S. during the COVID-19 pandemic. They deliberately do not modify the model specification deliberately of the recession induced by the COVID-19 outbreak. Combining eleven time series observed at quarterly and monthly frequency they find that forecasts based on a pre-crisis estimate of the VAR using data up until the end of 2019 appear to be more stable and reasonable than forecasts based on a sequence of recursive estimates that include the most recent observations. Overall, the MF-VAR outlook is quite pessimistic. The estimated MF-VAR implies that level variables are highly persistent, which means that the COVID-19 shock generates a long-lasting reduction in real activity. Finally, they emphasized that time would tell whether this prediction is accurate, or whether it is possible to re-start the economy quickly, shortening the duration of the recessionary effect that the shock has on the economy, and to recover by the end of 2021.

Siliverstovs (2021) presents the results of forecasting the euro area GDP growth over the period from the first quarter of 2006 to the third quarter of 2020, paying a special attention to the models' forecasting performance during the COVID-19 pandemic. Using the data for the pre-COVID period, it shows that ignoring asymmetries in a model's forecasting accuracy across the business cycle phases typically leads to a biased judgement of the model's predictive ability in each phase. Given the dramatic swings in GDP growth rates across a wide range of countries during the coronavirus pandemic, the forecast errors of the econometric forecasting models for these quarters are also highly likely to be extraordinarily large. Undoubtedly, these large forecast errors exert very large leverage on the forecast accuracy metrics based on averages of squared forecast errors and their differentials. In such situations, recursive measures that dissect the models' forecasting ability observation by observation allow to gain detailed insights into the underlying causes of one model's domination over the others. In this paper, Siliverstovs suggests a novel metric referred to as the recursive relative mean squared forecast error and shows how this new metric paired with the cumulated sum of squared forecast error difference of Welch and Goyal (2008) highlights significant differences in the relative forecasting ability of the dynamic factor model and naive univariate benchmark models in expansions and recessions that are typically concealed when only point estimates of relative forecast accuracy are reported.

Ankargren and Lindholm (2021) nowcast Swedish GDP growth using several types of short- term forecasting models. Their results indicate that medium-sized MIDAS regressions and small-scale bridge equation models outperform a dynamic factor model in an evaluation period set to 2010Q1–2019Q4. Among dynamic factor models, they find that a larger set of variables is more appropriate. For the most part, the dynamic factor model's nowcasts are qualitatively similar to the MIDAS and bridge equation models' nowcasts, but the latter models exhibit a larger degree of inertia and less volatility over time. In a closer examination of nowcasting during the COVID-19 pandemic, they find that the dynamic factor model reacted much more forcefully during 2020Q2 and 2020Q3, with nowcasts that to a large degree developed like professional forecasts. They therefore find a clear discrepancy between, on the one hand, better historical forecasting performance, and, on the other hand, usefulness in the pandemic-induced downturn and subsequent recovery in 2020Q2 and 2020Q3. Nevertheless, equal-weighted pooling of forecasts is superior to any single method. Their results reveal a clear divide between, on the one hand, historical forecasting performance in the period between the Great Recession and the COVID-19 pandemic, and, on the other hand, usefulness during the pandemic. Decomposing the revisions of the dynamic factor model's nowcasts into contributions, they find that updated parameters caused large revisions. In comparison with a model that is not re-estimated during the pandemic, however, the re- estimated model's nowcasts are more reasonable and accurate. Finally, they find that incorporating new data sources that measure economic activity at higher frequency does not improve forecasting accuracy historically but amplifies the downturn signal during the peak of the pandemic.

Furthermore, research on activity or price dynamics has been revolutionized by the surge of new types of high-frequency indicators. Internet searches, administrative granular data, credit card transactions, restaurant bookings, electricity consumption, mobility reports, press/news are some examples of new data sources applied recently.[1] In a recent paper, Buell et. al. presents a suite of high frequency and granular country-level indicator tools for Sub-Saharan Africa (SSA) that can be used to nowcast GDP and track changes in economic activity. Using Google search trends and mobile payments and machine learning and parametric factor models, they present nowcast results for 2019Q4 and 2020Q1 GDP for Kenya, Nigeria, South Africa,Uganda, and Ghana, and argue that the methodology might be generalized to nowcast and forecast GDP for other SSA countries with limited data availability and shorter time frames.

In this paper we exploit previous developments (Blanco et al 2017 and 2018) and evaluate the

[1] Regarding the use of original data sources in Argentina, following the seminal paper by Varian and Choi (2011), Blanco (2014) constructs a monthly consumption indicator using Google Trends keywords and categories. Results suggest that including an online research-based index improves forecasting performance.

forecasting performance of a Dymanic Factor Model (DFM) for Argentina's quarterly GDP during the particular year of 2020. The high macroeconomic instability that characterizes the business cycle in Argentina, makes nowcasting a particularly attractive predictive tool, since it is well known that in the context of high volatility and structural breaks, autoregressive models have a poor predictive performance (Bank of England, 2014). Furthermore, given data limitations during the first months of the confinement, we also explore the use of alternative data sources such as such as energy consumption and Google mobility repots.

The paper is organized as follows. In Section 2 we present a general description of the lockdown in Argentina. The methodological approach is developed in the third section. The next segment contains the main results of our nowcasting exercise and the comparison of models in terms of relative predictive ability with a time series benchmark and a pre-pandemic estimate of the DFM parameters. Section 4 discusses if using novel high frequency data sources allows for a better forecasting performance. Finally, section 5 concludes.

2 General Context: Lockdown in Argentina

The world has striven to weather the impact of COVID-19 in the last year and a half, and Argentina has not been an exception. Shortly after the first case of COVID-19 was identified in the country, the National Government implemented containment measures and decreed a social, preventive, and mandatory lockdown on 19 March 2020. As a result, workers other than those considered essential could not attend work, causing economic activities to come to a halt.

The pandemic hit the country during a period of economic and social emergency triggered by the adverse effects of the 2018-2019 balance of payments and debt crises, with an ongoing two years recession —the longest since the 1998-2002 crisis— and record inflation since the early 1990s.

Three distinctive phases could be identified given the epidemiological nature of the shock and the health approach followed by authorities to manage the crisis. The first characterized by strong offer and mobility restrictions, a progressive relaxation later and finally a return to a "new normal".

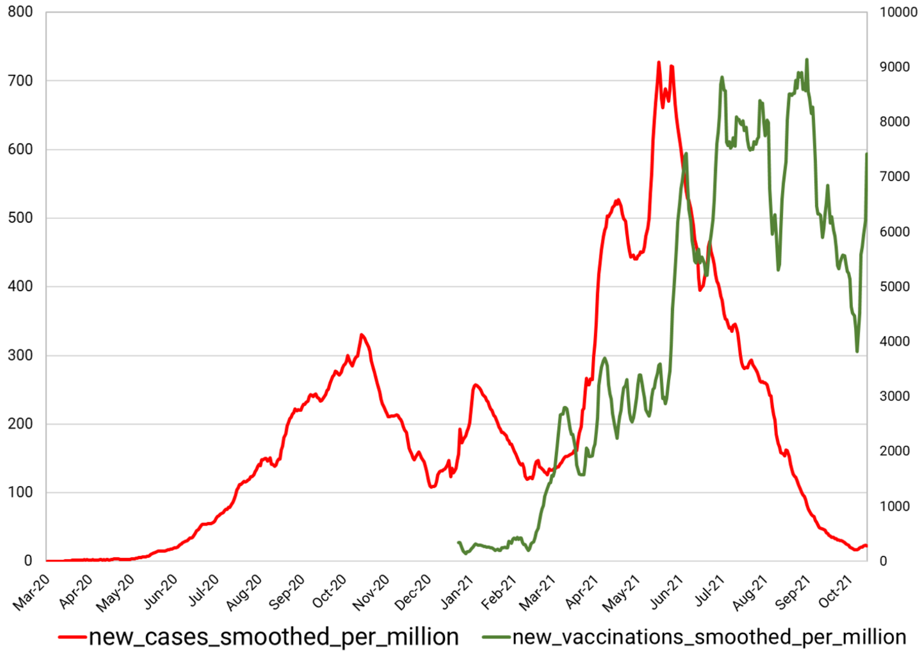
In the first phase, social lockdown measures hampered "non-essential" productive activities and the GDP contracted, despite some easing at geographical and sectorial levels. At this stage, the economic policy was focused on supporting the most vulnerable population (demand) and preserving core productive and financial system.

Argentina began the second phase of the COVID-19 cycle during the second quarter of 2020, when the first signs of recovery emerged after social isolation measures started to be eased gradually. In this second phase, people's mobility is further relieved (however still under strict health regulations), and most activities in most productive sectors are progressively restored with security protocols.

The pandemic spread across Argentina on a heterogeneous basis. The infection rate in the Metropolitan Area of Buenos Aires gradually decreased during the third quarter of 2020, stepping up across the rest of the country until mid-October to decline ever since. The metropolitan area's greater relative share in the GDP shows that the economy recovered in part during the third quarter of 2020, as new activities were resumed in the region. The set of policies developed by the National

Government and the Central Bank since the pandemic was declared in March 2020 attempted to support domestic demand, protecting the most vulnerable segments of the population and aiming at keeping employment level and household income stable.

Figure 1. Argentina. Daily new confirmed COVID-19 cases per million and Number of people vaccinated against COVID-19 per million



Source: ourworldindata.org

One year after the onset of the COVID-19 pandemic, it seem that the Argentine economy was moving slowly towards a gradual recovery as more sectors resumed their activities [2]. The evolution in health care and the adoption of unprecedented fiscal and monetary stimulus enabled an economic recovery process which started in May 2020 and continued all year long. As a result, in December 2020, GDP stood at only 3% in real terms below the pre-pandemic level.

However the epidemiological situation worsened from mid-March 2021 with the onset of the second wave of COVID-19. The National Government implemented new circulation restrictions, less severe than those adopted in 2020. The National Goverment adopted targeted assistance programs for the hardest-hit jurisdictions, focusing its aid programs on the most vulnerable groups of the population and on the assistance to companies.

Economic activity has shown signs of recovery since June 2021, after the curb observed in April and May due to the onset of the second wave of COVID-19 infections. The regularization of the economy is expected to continue in the next months even though, as it is observed in other countries, the circulation of new variants of the virus may postpone such process.

3 Our Nowcast Exercise

Our exercise consists on producing early predictions of GDP growth based on the pandemic and containment sample period 2020:Q1 - 2021:Q2. In Argentina the official GDP figures are released around

[2] implementing health protocols to prevent an acceleration in the virus transmission speed

10 weeks after the end of the quarter. The initial data set comprises 112 business cycle indicators, including *hard* and *soft* business cycle time series, ranging from financial indicators to tax collection data, desegregated data on industrial production, consumer confidence surveys and car sales. The variables comprised in the data set are described in Annex 1. The series were seasonally adjusted (when needed) using X-13 ARIMA-SEATS, detrended or differentiated to make them stationary and finally log transformed.

According to the timing of publication we split the final set of indicators in two groups: those series that are available less than 10 days after the end of each month (Group 1), and series that are published with a delay raging form 10 to 30 days (Group 2). Following this grouping of the series, the Nowcast can be sequentially updated as described in Figure 2.

Figure 2: Sequential updating example

Date	15/05/2017	31/05/2017	15/06/2017	30/06/2017	15/07/2017	31/07/2017	15/08/2017	31/08/2017	15/09/2017
Available data									
Group 1	Apr-17	Apr-17	May-17	May-17	Jun-17	Jun-17	Jul-17	Jul-17	Aug-17
Group 2	Mar-17	Apr-17	Apr-17	May-17	May-17	Jun-17	Jun-17	Jul-17	Jul-17
Nowcast	II 2017	II 2017	II 2017	II 2017	II 2017	II 2017	III 2017	III 2017	III 2017
Official Releases									**Official Release II 2017**

As reported by the aforementioned updating scheme, we can obtain 6 early estimations of the GDP growth within each quarter.Using an initial estimation sample that comprises the period 2016:Q1-2019:Q4, we perform rolling pseudo-real-time one quarter ahead *Nowcast* exercise of GDP growth. Following previous papers results (D'Amato et al 2015, Blanco et al 2018) we consider a smaller group of variables selected according to simple correlations and expert judgment.

3.1 Quarterly Nowcasting approach

Nowcast can be conducted through the estimation of common factors from a large set of monthly data and subsequently using them as regressors for GDP -as proposed by Giannone, Reichlin and Small (2005).The idea behind this approach is that the variables in the set of interest are driven by few unobservable factors.

More concretely, the covariance between a large number of n economic time series with their leads and lags can be represented by a reduced number of unobserved q factors, with $n > q$. Disturbances in such factors could in this context represent shocks to aggregate supply or demand.

Therefore, the vector of n observable variables in the cycle can be explained by the distributed lags of q common factors plus n idiosyncratic disturbances which could eventually be serially correlated, as well as being correlated among i.

A vector X_t of n stationary monthly business cycle indicators $x_t = (x_{1t}, ..., x_{nt})\acute{}$, with $t = 1, ...T$ can be explained by the distributed lags of q common latent factors plus n idiosyncratic disturbances which could eventually be serially correlated. The dynamic factor model (DFM) is therefore:

$$X_t = \lambda(L) f_t + e_t \tag{1}$$

$$f_t = \Psi(L) f_{t-1} + \eta_t \tag{2}$$

Where f_t is a vector $q \times 1$ of unobserved (latent) factors, the lag polynomial matrices $\lambda(L)$ and $\Psi(L)$ are $N \times q$ and $q \times q$, η is a $q \times 1$ vector of (serially uncorrelated) innovations to the factors. The i row of $\lambda(L)$ is called the *dynamic factor loadings* for the ith series, X_{it}, and the e_t are the idiosyncratic disturbances that are assumed to be uncorrelated with the factors in all leads and lags[3], that is to say $E(f_t e_{it}) = 0 \; \forall \; i, s$.

Given a target variable y_t (in our case log GDP growth), the objective would be to estimate $E(y_t|X_t)$

$$y_t = \beta_t X_t + \gamma_t y_{t-1} + \varepsilon_t \tag{3}$$

$$y_t = \beta(L)' f_t + \gamma(L)' y_{t-1} + \varepsilon_t \tag{4}$$

If the lag polynomials $\lambda\,(L)$ in (1) and $\beta\,(L)$ in(4) are of finite order p [4], Stock and Watson (2002a) show that the factors f can be estimated by principal components.

If we define quarterly GDP as the average of monthly latent observations $y_t^Q = 13(y_t + y_{t-1} + y_{t-2})$ and we obtain quarterly factors f_t^Q from these observations, we can use the following equation to obtain early estimates of GDP:

$$\widehat{y_t}^Q = \beta(L)' f_t^Q \tag{5}$$

We follow Banbura et al(2010) and Banbura and Modugno (2014) to estimate the factors. Suppose that the errors idiosyncratic component e_t follows a independent univariate autoregression ($e_{it} = \delta_i(L) e_{it-1} + \nu_{it}$, with $\nu_{it} \sim N(0, \sigma^2_{\nu i})$). Defining θ as a vector that incorporates all the parameters of the model (the λ factors loadings, ε_t and σ_t). Once the joint model is set up in State-Space form, we estimate the parameters θ of the state space form by the Expectation Maximisation (EM) algorithm.[5]

3.2 Evaluating models' relative predictive ability

The criteria for deciding which model is best to nowcast our target variable is predictive ability. To inform this decision, we use the Giacomini and White (2006) test, which allows us to evaluate if the differences in predictive accuracy between models are statistically significant. The Giacomini and White approach differs from that followed by previous tests, as those proposed by Dieblod and Mariano (1995) and West (2003) in that it is based on conditional rather than unconditional expectations. In this regard, the Giacomini and White (GW) approach focuses on finding the best forecast method for the following relevant future. Their methodology is relevant for forecasters who are interested in finding methodologies that improve predictive ability of forecast, rather than testing the validity of a theoretical model.[6]

The test has many advantages: (i) it captures the effect of estimation uncertainty on relative

[3]See Stock and Watson (2016) for cases where e_i is serially correlated

[4]Expressing the DFM in a static (or stacked) form

[5]In a nutshell, this iterative process involves extract the underlying factors using principal components, later estimate the state-space coefficients and finally re-estimate factors with the help of the Kalman filter.

[6]See Pincheira (2006) for a nice description and application of the test.

forecast performance, **(**ii**)** it is useful for forecasts based on both nested and non nested models, **(**iii**)** it allows the forecasts to be produced by general estimation methods, and **(**iv**)** it is quite easy to be computed. Following a two-step decision rule that uses current information, it allows to select the best forecast for the future date of interest.

The testing methodology of Giacomini and White consists on evaluating forecast by conducting an exercise using rolling windows. That is, using the R sample observations available at time t, estimates of y_t are produced and used to generate forecast τ step ahead. The test assumes that there are two methods, f_{Rt} and g_{Rt} to generate forecasts of y_t using the available set of information $\mathcal{F}_t$. Models used are supposed to be parametric.

$$\begin{aligned} f_{Rt} &= f_{Rt}(\widehat{\gamma}_{R,t}) \\ g_{Rt} &= g_{Rt}(\widehat{\theta}_{R,t}) \end{aligned}$$

A total of P_n forecasts which satisfy $R + (P_n - 1) + \tau = T + 1$ are generated. The forecasts are evaluated using a loss function $L_{t+\tau}(y_{t+\tau}, f_{R,t})$, that depends on both, the realization of the data and the forecasts. The hypothesis to be tested is:

$$\begin{aligned} H_0 &: E\left[h_t\left(L_{t+\tau}(y_{t+\tau}, f_{R,t}) - L_{t+\tau}(y_{t+\tau}, g_{R,t})\right) \mid \mathcal{F}_t\right] = 0 \\ & \quad \text{or alternatively} \\ H_0 &: E\left[h_t \Delta L_{t+\tau} \mid \mathcal{F}_t\right] = 0 \ \ \forall\, t \geqslant 0 \end{aligned}$$

for all $\mathcal{F}_t$ -measurable function h_t.

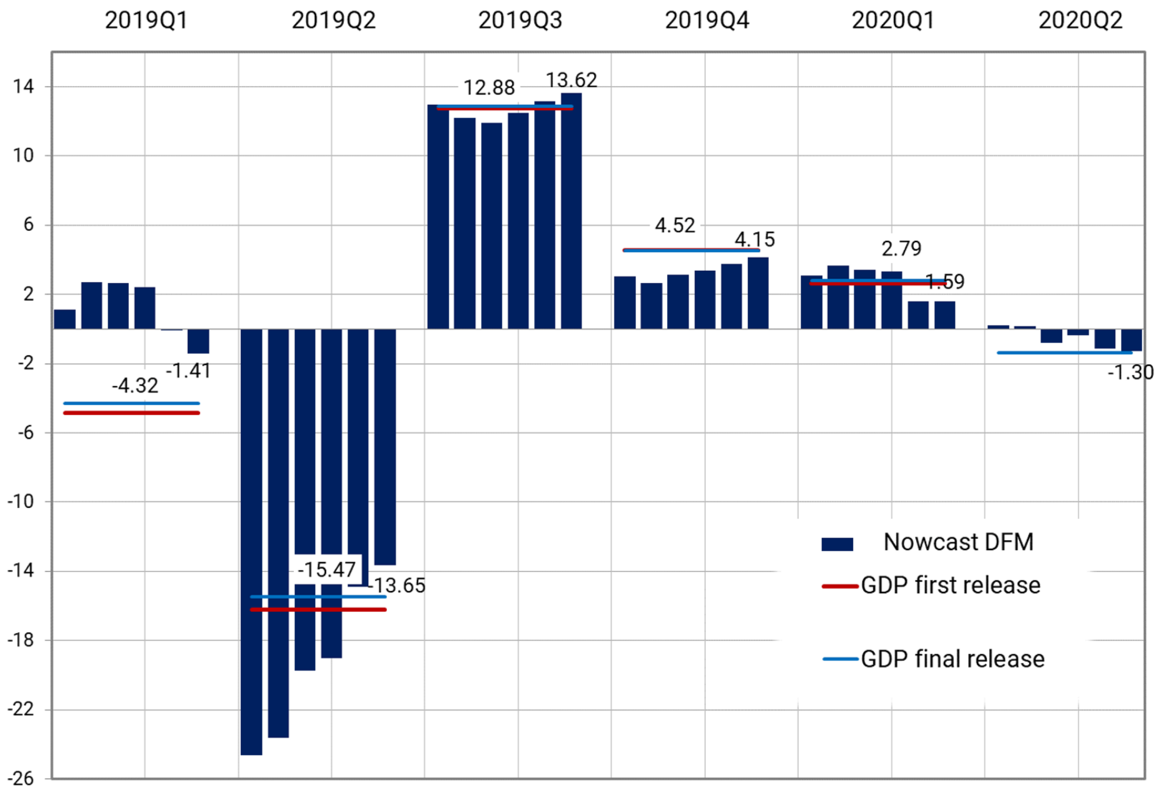
In practice, the test consists on regressing the differences in the loss functions on a constant and evaluating its significance using the t statistic for the null of a 0 coefficient, in the case of $\tau = 1$. When τ is greater than one, standard errors are calculated using the Newey-West covariances estimator, that allows for heteroskedasticity and autocorrelation.

4 Results

The impact of the shock in Argentina's economy was quite significant. The annual fall in GDP was the largest since the 2002 economic crisis. In particular, the downturn of the second quarter of 2020 was the single biggest recorded since national accounts figures are collected.

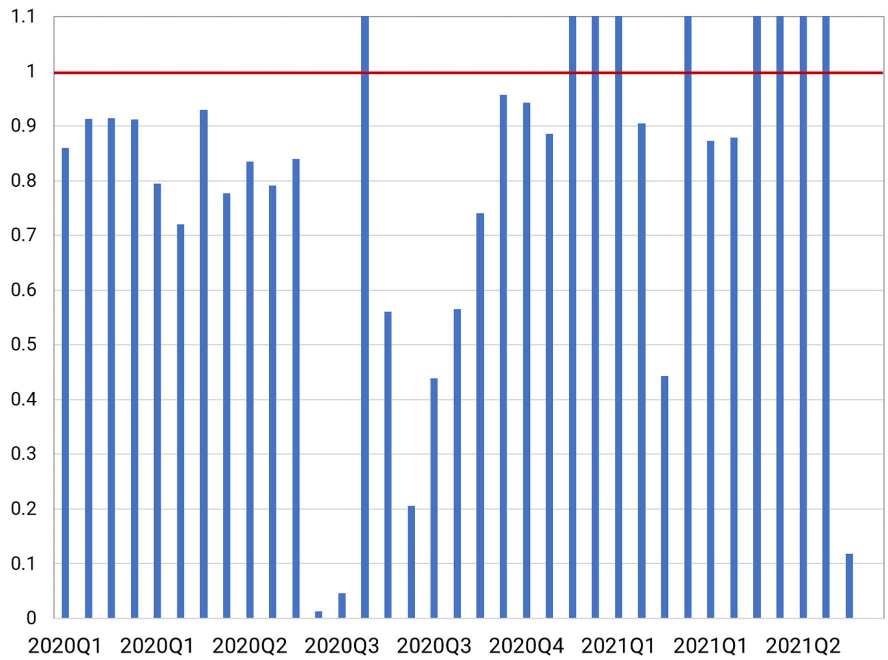
Figure 3 presents the sequential updates of our GDP Nowcasting exercise and official GDP first and final release. Overall, our DFM model seems to capture the sign and in most cases the magnitude of q.o.q s.a. GDP variation. It should be noted that model coefficients are updated on every step, as new information becomes available.

Figure 3. Nowcast Sequential Updates



In order to compare the results, we estimate an autoregressive model as a benchmark. [7] Figure 4 depicts the ratio of RMSE of our DFM nowcast and the AR benchmark when forecasting GDPs first release.

Figure 4. RMSE Nowcast / RMSE AR



Note: A number below 1 indicates that the Nowcast Outperforms the AR Benchmark

[7] The best autorregresive model possible. Estimation results are available upon request.

In 75% of the cases our nowcast overcomes the time series benchmark. To assess whether this result is statistically significant, Table 1 shows the results of the Giacomini and White test. Results indicate that our Nowcast outperforms the AR and that the difference in forecasting capacity is significant at 5%.

Table 1. Results of the Giacomini and White test

RMSE AR- RMSE DFM	
t test	p-value
2.804	0.0101

4.1 Estimation Scheme

So far we have applied a rolling windows estimation scheme where the parameters of the nowcasting model are updated constantly as new data is available. Siliverstovs (2021) finds that the forecasts based on the recursively estimated coefficients proved out to be much closer to the out turns of GDP growth in the second and third quarters of 2020 than the forecasts based on the coefficients frozen at their pre-COVID period values. So a logical question to answer is whether re-estimation during the Covid-19 pandemic lead to better nowcasts in argentina. Table 2 presents the Giacomini and White results comparing both schemes.

Table 2. Results of the Giacomini and White test

RMSE DFMfixed - RMSE DFM	
test t	p-value
0.000004	0.9909

Results indicate that both models are indistinguishable: keeping coefficients constant a priori does not improve forecasting performance. A possible explanation might be that given our country instability history, the model is flexible enough to decently capture the major downturn of 2020.[8]

5 Nowcasting using new data sources

As mentioned before, the never-before-seen shutdown of 2020 posed a challenge in business cycle assessment data collection. Industrial production, a main element of our nowcasting exercise, was one of the main activities affected.[9] In order to give adequate responses to the policy making process and measure the in real time the impact of the crisis, we explored a couple of high frequency indicators: Energy consumption and Google Mobility.

5.1 Energy consumption

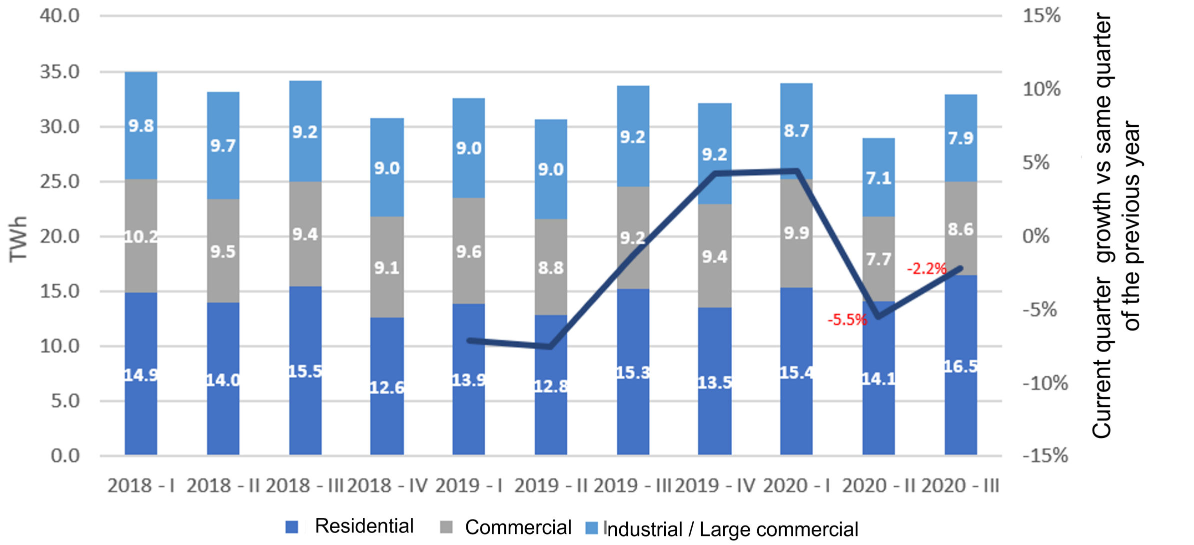
The main data source is Argentine Wholesale Electricity Market Clearing Company (CAMMESA), a private non-profit firm. The data we are considering is daily net demand of the wholesale market, divided by activity (Residential, Commercial and Industrial/Large commercial). As stated in Figure 5, the demand for electricity in Argentina fell during the second and third quarter 2020 on average 5.5% and 2.2%, respectively, in relation to the values observed in the same quarters of 2019. [10]

[8]Further research is oriented in exploring this fact.

[9]Not only data collection was delayed but also during the first months of the lockdown some industries were closed and reported zero production.

[10]IADB, 2020 Demanda y precio Demanda y precio de la energía eléctrica en Argentina: impacto de la pandemia y tendencias

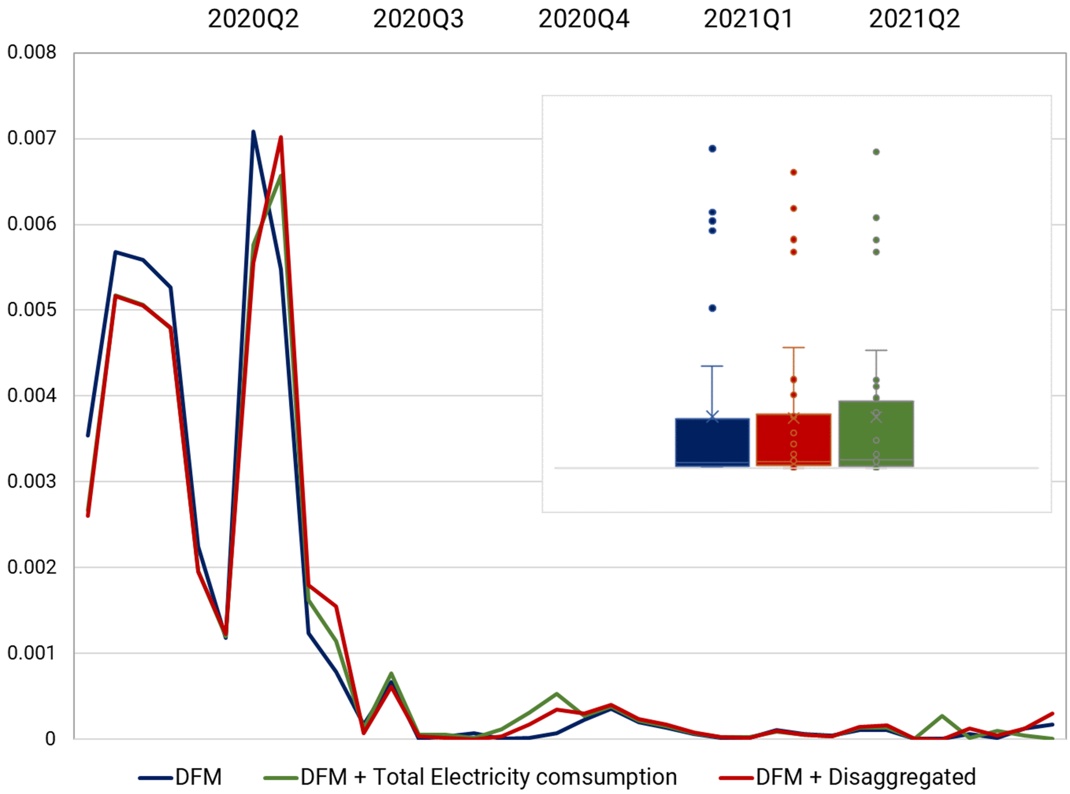
Figure 5. Argentina Energy Consumption



Source: IADB on Cammesa data

We include this indicator in two different ways. First, we add it as an additional variable in the factor model (DFM + Total Energy Consuption), and second as a dissagregated regresor in the nowcasting equation (DFM + Dissagregated Energy Consuption). Given methodological constrains, we have to transform the daily variable to match the frequency of the targeted variable. However, we are currently working on a new version that allows for mixed frequency.

Figure 6. RMSE of the different models



At a glimpse, all of the nowcasts look similar, having the largest error at 2020Q2. When analysing the distribution of the errors, our initial DFM appears to have a lower median error. Nevertheless when we tests the differences in forecasting performance using the Giacomoni and White test, the models that statiscally outperforms the rest is the one that incorporates Energy Consumption as a regressor in (5).

Table 3. Results of the Giacomini and White test

RMSE model in row - RMSE model in columm

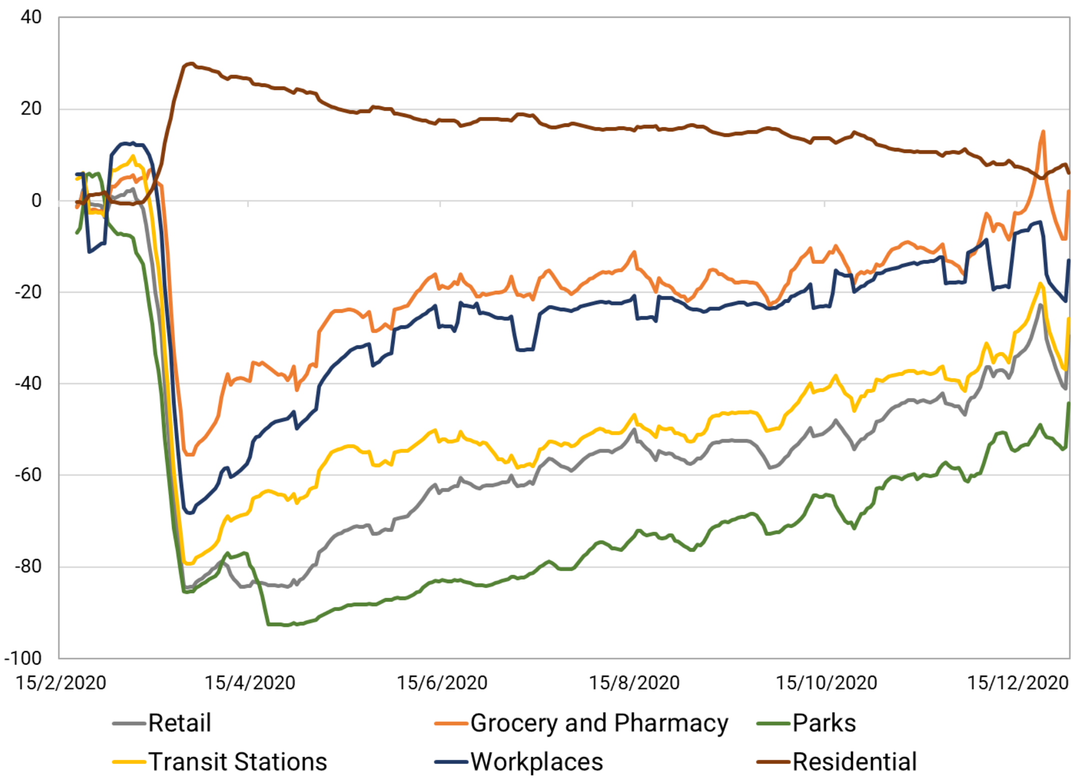
	DFM	DFM+Total Electricity	DFM+Diss. Electricity
DFM		-2.47E-05	1.35E-04
DFM+Total Electricity	2.47E-05		1.10E-04
DFM+Dissagregated Electricity	-1.35E-04	-1.10E-04	

significative at 5% (shaded green)

5.2 Google Mobility

Since the beginning of 2020, Google started sharing their mobility data.[11] The data shows how visits to places, such as grocery stores and parks, are changing in each geographic region compared to a baseline day (i.e. a normal value for that day of the week, set to the median value from the 5-week period Jan 3 – Feb 6, 2020). Figure 7 presents a 7-day moving average of the overall data covered by Google's Report.

Figure 7. Argentina COVID-19 Community Mobility Report 2020
7-day moving average



Source: Google Region Mobility Report (CSVs)

[11]Visit https://support.google.com/covid19-mobility for furhter detail

The precedent figure makes an obvious point: the pattern of mobility shifted significantly after the lockdown was imposed. As restrictions are gradually lifted, mobility tends to look similar to the reference period. Does this fact lead to a better assessment of the business cycle? Once again the new series was transformed in order to match the target frequency. We decided to consider and aggregate mobility measure and incorporate it as a new variable in the estimated factor.[12] We present the results of the GW test in table 4.

Table 4. Results of the Giacomini and White test

RMSE DFM - RMSE DFM+ Google Mob.	
test t	p-value
0.000157	0.6322

Summing up, we find that a nowcasting factor model including the Google Mobility indicator does not significantly outperform our initial DFM.

6 Conclusions

The COVID-19 pandemic and the unprecedented global sudden stop of 2020 posed a mayor challenge for traditional forecasting tools used in many central banks . In this paper, we evaluate a DFM nowcasting tool for Argentina during the lockdown and health crisis of 2020 and 2021 (sample period 2020:Q1 - 2021:Q2).

The impact of the shock in Argentina's economy was quite significant. The annual fall in GDP was the largest since the 2002 economic crises. In particular, the downturn of the second quarter of 2020 was the single biggest recorded since national accounts figures are collected. However, our exercise was able to capture the sing and magnitude of the q.o.q s.a. variation in GDP. It also outperforms an AR benchmark. We also analysed whether working under different estimation schemes improves forecasting capacity. In particular, re-estimation during the Covid-19 pandemic or keeping the models parameters fixed to a pre-pandemic level is indistinguishable in terms of nowcasting ability.

Finally we explore a couple of new high-frequency data sources. Energy consumption added as a separate regressor appears to improve nowcasts, while Google Mobility index do not necessarily lead to a better assessment of the business cycle.

Future research agenda includes exploring other high-frequency variables (i.e. financial data) and working with a methodology that allows for mixed data frequencies.

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[12] The adopted methodology allows for new series despite the length of the sample.

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Annex 1: Complete Data Set

No	Source	Series	Group	
serie1	ADEFA	Automobile national production - units	1	hard
serie2	ADEFA	Automobile exports - units	1	hard
serie3	ADEFA	Automobile sales - units	1	hard
serie4	ADEFA	Automobile national sales - units	1	hard
serie5	AFCP	Portland cement production	1	hard
serie6	MECON	Ganancias (Total)	1	hard
serie7	MECON	Ganancias DGI	1	hard
serie8	MECON	Ganacias DGA	1	hard
serie9	MECON	Total Income revenues	1	hard
serie10	MECON	Income revenues DGI	1	hard
serie11	MERVAL	Income revenues DGA (customs)	1	prices
serie12	MERVAL	Total VAT revenues	1	prices
serie13	BCRA	VAT revenues DGI	1	prices
serie14	BCRA	Interest rate on Time Deposits - Private Banks	1	prices
serie15	CCA	Used Car Sales	1	hard
serie16	UTDT	Consumer Confidence Index - General - BSAS city	1	soft
serie17	UTDT	Consumer Confidence Index - General	1	soft
serie18	UTDT	ICC-DI	1	soft
serie19	UTDT	ICC-SM	1	soft
serie20	UTDT	ICC-SP	1	soft
serie21	UTDT	ICC-Condiciones Presentes	1	soft
serie22	UTDT	ICC-Expectativas	1	soft
serie23	CIS	Hierro Primario	1	hard
serie24	CIS	Acero Crudo	1	hard
serie25	CIS	Lam. Frío	1	hard
serie26	CIS	Lam. En caliente Total No Planos	1	hard
serie27	CIS	Lam. En caliente Planos	1	hard
serie28	FIEL	Industrial production index (IPI) - general level	2	hard
serie29	FIEL	IPI - nondurable consumer goods	2	hard
serie30	FIEL	IPI - durable consumer goods	2	hard

No	Source	Series	Group	
serie31	FIEL	IPI - intermediate goods	2	hard
serie32	FIEL	IPI - capital goods	2	hard
serie33	FIEL	IPI - food and beverages	2	hard
serie34	FIEL	IPI - cigarettes	2	hard
serie35	FIEL	IPI - textiles input	2	hard
serie36	FIEL	IPI - pulp and paper	2	hard
serie37	FIEL	IPI - fuels	2	hard
serie38	FIEL	IPI - chemicals and plastic	2	hard
serie39	FIEL	IPI - nonmetallic minerals	2	hard
serie40	FIEL	IPI - steel	2	hard
serie41	FIEL	IPI - metalworking	2	hard
serie42	FIEL	IPI - automobiles	2	hard
serie43	Gov. BSAS city - CABA	Gross Revenue Tax Collection - City of Buenos Aires	2	hard
serie44	Gov. BSAS Prov. (State)	Gross Revenue Tax Collection - Buenos Aires province	2	hard
serie46	CAME	Sales - General Level	1	hard
serie47	CAME	Sales - FOOD AND DRINKS	1	hard
serie48	CAME	Sales - BAZAAR AND GIFTS	1	hard
serie49	CAME	Sales - Bijouterie	1	hard
serie50	CAME	Sales - Shoes	1	hard
serie51	CAME	Sales - sports	1	hard
serie52	CAME	Sales - Home appliances	1	hard
serie53	CAME	Sales - Pharmacies	1	hard
serie54	CAME	Sales - Hardware store	1	hard
serie55	CAME	Sales - Candy and Soft Drinks	1	hard
serie56	CAME	Sales - Toy stores	1	hard
serie57	CAME	Sales - Leather Goods	1	hard
serie58	CAME	Sales - Electrical Supplies	1	hard
serie59	CAME	Sales - Construction materials	1	hard
serie60	CAME	Sales - Home furniture	1	hard

No	Source	Series	Group	
serie61	CAME	Sales - Office furniture	1	hard
serie62	CAME	Sales - Perfumery	1	hard
serie63	CAME	Sales - Textile - Clothing	1	hard
serie64	CAME	Sales - Textile - White	1	hard
serie65	CONSTRUYA	Construction Companies Activity Index	1	#N/A
serie66	CONSTRUYA	Construction Companies Activity Index SA	1	hard
serie67	INDEC	Exports - General Level	2	hard
serie68	INDEC	Exports - Q Primary Products	2	hard
serie69	INDEC	Exports - Q manufactures of agricultural origin	2	hard
serie70	INDEC	Exports - Q manufactures of industrial origin	2	hard
serie71	INDEC	Exports - Q Fuels and energy	2	hard
serie72	INDEC	Exports - P General level	2	hard
serie73	INDEC	Exports - P Primary Products	2	prices
serie74	INDEC	Exports - P manufactures of agricultural origin	2	prices
serie75	INDEC	Exports - P manufactures of industrial origin	2	prices
serie76	INDEC	Exports - P Fuels and energy	2	prices
serie77	INDEC	Imports - Q General level	2	hard
serie78	INDEC	Imports - Q capital goods	2	hard
serie79	INDEC	Imports - Q intermediate goods	2	hard
serie80	INDEC	Imports - Q Fuels and energy	2	hard
serie81	INDEC	Imports - Q Parts and Accessories	2	hard
serie82	INDEC	Imports - Q consumer goods	2	hard
serie83	INDEC	Imports - vehicles	2	hard
serie84	INDEC	Imports - P General level	2	prices
serie85	INDEC	Imports - P capital goods	2	prices
serie86	INDEC	Imports - P intermediate goods	2	prices
serie87	INDEC	Imports - P Fuel and energy	2	prices
serie88	INDEC	Imports - P Parts and Accessories	2	prices
serie89	INDEC	Imports - P consumer goods	2	prices
serie90	INDEC	Imports - P vehicles	2	prices

No	Source	Series	Group	
serie91	Ministerio de Agroindustria	Soybean milling	2	hard
serie92	Secretaría de Hacienda	Direct real investment + capital transfers to provinces	2	hard
serie93	Secretaría de Hacienda	Direct real investment	2	hard
serie94	Secretaría de Hacienda	Capital transfers to provinces	2	prices
serie95	Tendencias	Dismissals (1986 = 100)	1	soft
serie96	Tendencias	Suspensions (1986 = 100)	1	soft
serie97	EIL - Ministerio de Trabajo de la Nación	Net employment expectancy	2	soft
serie98	EIL - Ministerio de Trabajo de la Nación	Companies that searched for personnel	2	soft
serie99	BCRA	Multilateral nominal exchange rate index (Dec-15=100)	1	prices
serie100	BCRA	Personal Credits	1	prices
serie101	BCRA	Credit Cards	1	prices
serie102	BCRA	Personal + Cards	1	prices
serie103	GCBA	Vehicule Registrations BSAS city	2	hard
serie104	GCBA	Vehicule Registrations Argentina	2	hard
serie105	GCBA	Tolls (collection)	2	hard
serie106	GCBA	Tolls (vehicle ciculation)	2	hard
serie107	GCBA	Tolls (average vehicles)	2	hard
serie108	GCBA	Stamp duty-BSAS city	2	hard
serie109	GCBA	Passengers transported by rail (in thousands)	2	hard
serie110	Banco Central de BRASIL	Brazil Industrial production s.a.	2	hard
serie111	Banco Central de BRASIL	Brazil Industrial production	2	hard
serie112	Banco Central de BRASIL	Brazil Activity indicator s.o.	2	hard
serie113	Banco Central de BRASIL	Brazil Activity indicator s.a.	2	hard
serie114	Secretaria de energía	Asphalt (in tonnes)	2	hard
serie115	Colegio de escribanos Buenos Aires	BSAS city Scriptures	2	hard