Nowcasting China's GDP

Zeming Wang

Australian National University

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This paper presents a novel implementation of nowcasting China's GDP. I show that after transforming the Chinese data to OECD standards, the classical dynamic factor model produces forecast accuracy comparable to that of developed economies. The revision analysis suggests that industrial production is the most important variable in predicting GDP. Furthermore, I show that forecast accuracy is similar even when official GDP growth is replaced by the growth rate implied by night-time light intensity.

1 Introduction

Nowcasting is the practice of analysing real-time data to produce an up-to-date assessment of current economic conditions using automated algorithms. This assessment is typically expressed as a projection of the current quarter's GDP growth rate, which is the most comprehensive indicator of economic conditions. Given that official GDP data are released only on a quarterly basis and with a considerable lag, nowcasting is also understood as inferring quarterly GDP growth from more frequent data releases.

Monitoring economic conditions and continuously updating assessments as new information becomes available is essential for market participants and policymakers. Traditionally, this task has relied on expert judgement. However, with the explosion of data in today's world, there is a pressing need to process it in a scalable and automated way. Giannone et al. (2008) pioneered an econometric framework that meets this need. Automatic nowcasting has since become a standard tool for central banks around the world (Angelini et al., 2011; Matheson, 2010; Aastveit and Trovik, 2012; Yiu and Chow, 2010; Bok et al., 2017; Hayashi and Tachi, 2022).

The nowcasting algorithm exploits the fact that different economic variables tend to move together over business cycles (Burns and Mitchell, 1946; Sargent and Sims, 1977; Stock and Watson, 1989). Moreover, fluctuations in high-frequency series (e.g. survey data, price index, etc.) may indicate similar patterns of movements in low-frequency series (e.g. GDP). The dynamic factor model essentially summarises the co-movements between a large number of time series with a few factors that are continuously updated as new information becomes available. The current GDP figure is then projected from these factors. The process mimics the behaviour of a human expert observing the economy, synthesising a large amount of information into an overall assessment, and continually revising it when new information becomes available. Back-testing results suggest that the automated nowcasting algorithm produces forecasts that are comparable to those made by professionals.

This paper applies the classical nowcast framework to the Chinese economy and contributes to the existing literature in three aspects. First, China's macroeconomic series are usually reported in year-to-date levels or year-over-year growth rates rather than seasonally adjusted monthly or quarterly values, which is the standard practice in OECD countries. In addition, the Chinese time series also have country-specific peculiarities, such as the Lunar New Year effect, which require special treatment. The existing literature applies the nowcasting algorithm with the official data without transformation (Yiu and Chow, 2010; Giannone et al., 2013; Zhang et al., 2018). This treatment is technically unsound and also makes the result less comparable with other economies. In this paper, I transform the Chinese time series into an OECD-consistent format. The model is then back-tested using the most recent data — the existing literature only has back-testing results up to 2013. The results show that the forecast accuracy, as measured by the RMSE, is comparable to that of OECD economies.

The second contribution is to provide in-depth impact analysis of key events, which is missing in the existing literature. Impact analysis, or revision analysis, is crucial for nowcasting applications as it allows us to understand which new pieces of data are driving the revision of GDP projections. I studied two iconic events in recent history: the deleveraging policy in 2018 and the COVID pandemic in 2020. The results show that "soft data", such as the PMI survey, often provide an early sign of the upcoming movement due to their timely release; however, it is the "hard data" that has the biggest impact on the nowcasting revision. In pre-pandemic periods, industrial production is the most important indicator driving nowcast revisions. During the pandemic, mobility indicators, such as air passenger traffic, provide the most valuable information.

Conventionally, the nowcasting model is trained and evaluated against official GDP growth rates. However, several studies have raised concerns about the reliability of China's GDP figures (Wu, 2014; Bernanke and Olson, 2016; Nakamura et al., 2016; Martinez, 2022). In particular, the official growth rates appear to be "too smoothed" compared with other countries. To address this concern, I follow the trending literature and construct an alternative measure of economic growth using night-time light (NTL) intensity (Henderson et al., 2012; Donaldson and Storeygard, 2016; Hu and Yao, 2019; Beyer et al., 2022). NTL intensity is found to be highly correlated with economic activity, thus providing an alternative proxy for economic growth in countries with less reliable statistics. Interestingly, benchmarking against NTL-adjusted growth rates yields a similar forecasting accuracy as official growth rates. Although this exercise does not prove or disprove the reliability of the official GDP figures, it does show that the official GDP growth rate is well aligned with the movements of other economic variables, providing little support for the "over-smoothed" claim about official GDP figures.

Nowcasting of China's GDP has been carried out by various researchers. For example, Yiu and Chow (2010) use 189 indicators to nowcast quarterly GDP growth and find that interest rate is the most important factor driving nowcast revisions, followed by retail trade data and fixed-asset investment. Giannone et al. (2013) apply the classical DFM model to 10 Chinese indicators and find that the nowcast accuracy is comparable to market consensus forecasts, with industrial production being the most important indicator. Zhang et al. (2018) explore the use of the Bayesian method and find it outperforming the classical approach at most time horizons.

More recent studies explore the use of machine learning for nowcasting as opposed to the classical DFM method. Dauphin et al. (2022) and Hopp (2022) compare the performance of various econometric and machine learning models for European countries and the United States and find that machine learning methods can sometimes outperform DFM, though DFM is often among the top-ranked models. This paper sticks to the classical DFM method because it correctly conceptualises how the economy works — the vast majority of economic fluctuations are driven by a few underlying forces. Recent studies have also explored the use of Bayesian methods, which incorporate more flexible model specifications that can withstand rare events such as the pandemic (Antolin-Diaz et al., 2021). However, due to the computational cost of Bayesian MCMC, back-testing with large amounts of data is not feasible on a personal computer.

The rest of the paper is organised as follows. Section 2 reviews the econometric framework for nowcasting. Section 3 discusses the data problem and how the data are transformed. Section 4 reports the basic results and compares the forecast accuracy. Section 5 analyses the impact of major events and assesses the importance of each variable in nowcasting revisions. Section 6 addresses the issue of data reliability by using an alternative measure of economic growth. Section 7 concludes.

2 The Nowcasting Framework

2.1 Real-Time Data Flow

The problem of nowcasting is to generate projections of a target variable with data vintages available over time. A *vintage* is a collection of time series available at a given point in time. The vintages are usually updated at a higher frequency than the target variable. Thus, nowcasting provides an early estimate of the target variable. To fix this idea, let the target variable be the quarterly GDP growth rate, denoted by y_t^Q. And a vintage contains multiple monthly time series, denoted by $\mathbf{\Omega}_v$. The nowcasting exercise is to find $\mathbb{E}[y_t^Q|\mathbf{\Omega}_v]$.

As an illustration, Table 1 is a toy example of real-time data flows with three variables $\boldsymbol{x}_t = \{x_{1,t}, x_{2,t}, x_{3,t}\}$, where $x_{1,t}$ and $x_{2,t}$ are monthly variables and $x_{3,t}$ is quarterly. The time index t is monthly. Quarterly variables are dated by their last month (e.g. 2010 Q1 is dated by $t =$ Mar 2010); the first two months of a quarter are treated as missing values. The time series index t should not be confused with the vintage index v, which tracks data release. v advances as new data arrive. Thus v has a higher frequency and is irregularly spaced. Table 1 shows the data release for the last two observations of 2021. As monthly series are usually released one month later, the values for $t =$ Nov 2021 are released in December. The first release comes in $v =$ 9 Dec 2021, where the last value of x_1 is updated with the new value. x_2 is updated in another release coming in $v =$ 15 Dec 2021. The unsynchronised release of each time series inevitably leaves missing values in this dataset, especially at the end of the sample. This is referred to as the "ragged edge" problem. Methods for dealing with the ragged edge will be discussed in later sections.

Real-life data releases may also contain revisions to previously released values. This

Table 1: Demonstration of Real-Time Data Flow

Reference point t	Vintages (data releases)												
	9/12/2021			15/12/2021			...	12/1/2022			17/1/2022		
	x_1	x_2	x_3	x_1	x_2	x_3		x_1	x_2	x_3	x_1	x_2	x_3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Jan 2010	1.5	1.70	na	1.5	1.70	na	...	1.5	1.70	na	1.5	1.70	na
Feb 2010	-0.1	1.84	na	-0.1	1.84	na	...	-0.1	1.84	na	-0.1	1.84	na
Mar 2010	0.2	1.16	1.93	0.2	1.16	1.93	...	0.2	1.16	1.93	0.2	1.16	1.93
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Nov 2021	0.4	na	na	0.4	1.02	na	...	0.4	1.02	na	0.4	1.02	na
Dec 2021								-0.3	na	na	-0.3	0.04	1.64

Notes: This table demonstrates the real-time data flow with a toy dataset of three variables. x_1, x_2 are monthly variables; x_3 is a quarterly variable. New information contained in each release is highlighted in red. Missing values, due to mixed frequencies or late releases, are represented by 'na'.

paper abstracts from such data revisions and assumes that new observations are the only additional information contained in each release.[1] The nowcasts are revised each time new information becomes available: $\mathbb{E}[y_t^Q|\boldsymbol{\Omega}_v]$, $\mathbb{E}[y_t^Q|\boldsymbol{\Omega}_{v+1}]$, ... Typically, the closer to the final release of the target variable, the more accurate the nowcast becomes. It is of paramount interest to analyse which piece of new information contributes most to the revision of the nowcast. This exercise is called *revision analysis* or *impact analysis*. Specifically, a nowcast can be decomposed as

$$\mathbb{E}[y_t^Q|\boldsymbol{\Omega}_{v+1}] = \mathbb{E}[y_t^Q|\boldsymbol{\Omega}_v] + \mathbb{E}[y_t^Q|\boldsymbol{I}_{v+1}],$$

where $\boldsymbol{I}_{v+1}$ represents the new information content and $\mathbb{E}[y_t^Q|\boldsymbol{I}_{v+1}]$ is the revision. With the example of Table 1, let $v+1$ be the second release in December. Using the properties of orthogonal projection, the new information content can be expressed as

$$I_{v+1} = x_{2,t} - \mathbb{E}[x_{2,t}|\boldsymbol{\Omega}_v].$$

[1] There is no complete record of the original values for each new release. In this paper I construct pseudo-historical vintages from the latest data. Revisions to previously released values cannot be recovered in such pseudo samples.

In other words, it is the "unexpected" part of the data release (the difference between the actual value and the previous expectation) that drives nowcast revisions. This unexpected part is what we call *news*. After parametrising the model, it can be shown that the revision is a linear function of the news. This decomposition allows us to assign a weight to the importance of each variable in a given release.

2.2 The Econometric Model

An econometric model that solves the nowcasting problem must overcome three challenges: (1) it must be able to deal with mixed frequencies; (2) it must be able to handle large numbers of time series; (3) it must properly handle missing values (the "ragged edge" problem). This paper follows Giannone et al. (2008), which offers a solution to these problems with a dynamic factor model cast in a state-space representation.

Let $\boldsymbol{x}_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})'$ be a vector of the monthly time series in the dataset, which are assumed stationary. Assume $\boldsymbol{x}_t$ follows the state-space representation:

$$\boldsymbol{x}_t = \boldsymbol{\mu} + \boldsymbol{\Lambda} \boldsymbol{f}_t + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{P}), \tag{1}$$

$$\boldsymbol{f}_t = \boldsymbol{\Phi}(L) \boldsymbol{f}_t + \boldsymbol{\eta}_t, \qquad \boldsymbol{\eta}_t \sim N(\boldsymbol{0}, \boldsymbol{Q}). \tag{2}$$

$\boldsymbol{f}_t$ is an $r \times 1$ vector of factors with $r << n$. Equation (1) assumes the movement of each series is captured by (1) a handful of common factors that drive the joint dynamics and (2) an idiosyncratic residual that is orthogonal to the factors. The idiosyncratic term $\boldsymbol{\epsilon}_t$ is assumed to be diagonal, i.e. there is no cross-sectional correlation that is not captured by the common factors. Although the model is robust to cross-sectional and serial correlation in the error term (Doz et al., 2012), explicit modelling the serial correlation can improve the performance for small samples.

$$\epsilon_{i,t} = \rho_i \epsilon_{i,t-1} + e_{i,t}, \qquad e_{i,t} \sim N(0, \sigma_i^2),$$

with $\mathbb{E}[e_{i,t}e_{j,s}] = 0$ for $i \neq j$, $t \neq s$. Equation (2) models the dynamics of the factors. It is particularly important to exploit the factor dynamics when the contemporaneous information is sparse (e.g. early releases in a month). Most of the nowcasting literature finds that incorporating one lag into the equation is sufficient to produce satisfactory results.

2.3 Mixed Frequencies

A nowcasting model must deal with mixed frequencies as it is tasked with forecasting low frequency series from high frequency ones. This paper focuses on monthly and quarterly series. The only quarterly variable of concern is the quarterly GDP growth rate, although the framework outlined below can easily be extended to include multiple quarterly variables. Let y_t^Q be the quarterly growth rate. Assume it is associated with a monthly latent variable y_t. Further assume that y_t follows the same factor model as other monthly variables:

$$y_t = \mu_Q + \mathbf{\Lambda}_Q \boldsymbol{f}_t + \epsilon_t^Q.$$

Subscript or superscript Q is used to indicate the coefficient associated with the quarterly variable. Mariano and Murasawa (2003) show that y_t^Q can be approximated by a linear combination of y_t:

$$y_t^Q \approx \frac{1}{3}y_t + \frac{2}{3}y_{t-1} + y_{t-2} + \frac{2}{3}y_{t-3} + \frac{1}{3}y_{t-4}.$$

Therefore, the quarterly growth rate can be expressed by the factor model:

$$y_t^Q = \mu_Q + \sum_{j=0}^{4} \omega_j \mathbf{\Lambda}_Q \boldsymbol{f}_{t-j} + \sum_{j=0}^{4} \omega_j \epsilon_{t-j}^Q,$$

where $\boldsymbol{\omega} = \left(\frac{1}{3}, \frac{2}{3}, 1, \frac{2}{3}, \frac{1}{3}\right)$. The joint state-space model of mixed quarterly and monthly variables is thus given by

$$\ddot{\boldsymbol{x}} = \ddot{\boldsymbol{u}} + \boldsymbol{Z}\boldsymbol{\alpha}_t, \tag{3}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{T}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\xi}_t, \tag{4}$$

where

$$\ddot{\boldsymbol{x}} = \begin{pmatrix} \boldsymbol{x}_t \\ y_t^Q \end{pmatrix}, \ddot{\boldsymbol{u}} = \begin{pmatrix} \boldsymbol{\mu} \\ \mu_Q \end{pmatrix}, \boldsymbol{Z} = \begin{pmatrix} \boldsymbol{\Lambda} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{I}_n & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{3}\boldsymbol{\Lambda}_Q & \frac{2}{3}\boldsymbol{\Lambda}_Q & \boldsymbol{\Lambda}_Q & \frac{2}{3}\boldsymbol{\Lambda}_Q & \frac{1}{3}\boldsymbol{\Lambda}_Q & \boldsymbol{0} & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \end{pmatrix},$$

$$\boldsymbol{\alpha}_t = \begin{pmatrix} \boldsymbol{f}_t \\ \boldsymbol{f}_{t-1} \\ \boldsymbol{f}_{t-2} \\ \boldsymbol{f}_{t-3} \\ \boldsymbol{f}_{t-4} \\ \boldsymbol{\epsilon}_t \\ \epsilon_t^Q \\ \epsilon_{t-1}^Q \\ \epsilon_{t-2}^Q \\ \epsilon_{t-3}^Q \\ \epsilon_{t-4}^Q \end{pmatrix}, \boldsymbol{T} = \begin{pmatrix} \boldsymbol{\Phi}_1 & & & & & & & & & & \\ \boldsymbol{I}_r & & & & & & & & & & \\ & \boldsymbol{I}_r & & & & & & & & & \\ & & \boldsymbol{I}_r & & & & & & & & \\ & & & \boldsymbol{I}_r & & & & & & & \\ & & & & \boldsymbol{0} & \mathrm{diag}(\rho_1, \dots, \rho_n) & & & & & \\ & & & & & & \rho_Q & & & & \\ & & & & & & 1 & & & & \\ & & & & & & & 1 & & & \\ & & & & & & & & 1 & & \\ & & & & & & & & & 1 & \end{pmatrix}, \boldsymbol{\xi}_t = \begin{pmatrix} \boldsymbol{\eta}_t \\ \boldsymbol{0} \\ \boldsymbol{0} \\ \boldsymbol{0} \\ \boldsymbol{0} \\ \boldsymbol{e}_t \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

2.4 Estimation

Two-step procedure If there are no missing values in the data set, the common factors can be estimated consistently by PCA. However, because of the "ragged edge" problem, the estimation method must be able to deal with missing values at the end of the sample. Giannone et al. (2008) and Doz et al. (2011) propose a two-step method to overcome this difficulty. Their method is summarised as follows:

1. Estimate the parameters by OLS on the principal components extracted from a

balanced panel, ignoring any missing values in the data.

2. Apply the Kalman smoother with the estimated parameters to the full (unbalanced) dataset. The entries in the variance-covariance matrix used in Kalman filtering for the missing observations are set to infinity, so that the Kalman filter does not weight the missing observations when updating the factors.

EM procedure The state-space model can also be estimated using likelihood-based methods. Banbura and Modugno (2014) propose an EM (Expectation Maximisation) algorithm that can deal with arbitrary patterns of missing data. Compared to the two-stage method, the EM approach has several advantages: it is efficient with small samples, it can deal with arbitrary missing values, and it is also possible to impose restrictions on the parameters. Since the Chinese data often contain missing values in the middle of the series, this paper adopts the EM algorithm for its flexibility in handling missing values. The algorithm is summarised as follows.

Let $\boldsymbol{X} = [\boldsymbol{x}_1, \ldots, \boldsymbol{x}_T]$ be the set of all observables, and $\boldsymbol{F} = [\boldsymbol{f}_1, \ldots, \boldsymbol{f}_T]$ the set of all factors. Denote the joint likelihood function by $\mathcal{L}(\boldsymbol{Y}, \boldsymbol{F}; \boldsymbol{\Theta})$, where $\boldsymbol{\Theta} = \{\boldsymbol{\Lambda}, \boldsymbol{\Phi}, \boldsymbol{P}, \boldsymbol{Q}\}$ is the set of parameters.

1. Initialise the parameters by OLS regressions on the balanced panel and obtain the initial parameters $\boldsymbol{\Theta}_0$.

2. E-step: Calculate the expectation of the log-likelihood function using the parameters estimated from the previous iteration, $\boldsymbol{\Theta}_j$. This step fills in the missing values for the likelihood function,

$$\mathbb{L}_j(\boldsymbol{\Theta}) = \mathbb{E}_{\boldsymbol{\Theta}_j}[\mathcal{L}(\boldsymbol{Y}, \boldsymbol{F}; \boldsymbol{\Theta})|\boldsymbol{\Omega}].$$

3. M-step: Re-estimate the parameters by maximising the log-likelihood function

with respect to $\boldsymbol{\Theta}$:

$$\boldsymbol{\Theta}_{j+1} = \arg\max_{\boldsymbol{\Theta}} \mathbb{L}_j(\boldsymbol{\Theta}).$$

4. Repeat the above two steps until the likelihood converges within a threshold.

Assuming no serial correlation in the error term, the maximising problem has a nice closed-form solution. The factor loading matrix has an expression similar to an OLS solution:

$$\boldsymbol{\Lambda}_{j+1} = \left(\sum_{t=1}^{T} \mathbb{E}_{\boldsymbol{\Theta}_j}[\boldsymbol{x}_t \boldsymbol{f}_t' | \boldsymbol{\Omega}]\right) \left(\sum_{t=1}^{T} \mathbb{E}_{\boldsymbol{\Theta}_j}[\boldsymbol{f}_t \boldsymbol{f}_t' | \boldsymbol{\Omega}]\right)^{-1}.$$

Missing values can be easily handled with a selection matrix. Let $\boldsymbol{S}_t$ be a selection matrix whose i-th diagonal entry is 0 if $x_{i,t}$ is missing and 1 otherwise. The selection matrix ensures that only non-missing data are used in the calculation. The above equation can be modified to account for missing observations:

$$\mathrm{vec}(\boldsymbol{\Lambda}_{j+1}) = \left(\sum_{t=1}^{T} \mathbb{E}_{\boldsymbol{\Theta}_j}[\boldsymbol{f}_t \boldsymbol{f}_t' | \boldsymbol{\Omega}] \otimes \boldsymbol{S}_t\right)^{-1} \mathrm{vec}\left(\sum_{t=1}^{T} \boldsymbol{S}_t \boldsymbol{x}_t \mathbb{E}_{\boldsymbol{\Theta}_j}[\boldsymbol{f}_t' | \boldsymbol{\Omega}]\right).$$

Details of the EM algorithm can be found in Banbura and Modugno (2014) and Doz et al. (2012).

2.5 Impact Analysis

Impact analysis is the process of analysing how the projected GDP growth is revised by new data releases. Given the parametrisation of Equations (1) and (2), the revision of the nowcast in response to the release of a new observation in the j-th variable is a linear function of the "news":

$$\underbrace{\mathbb{E}[y_t^Q | \Omega_{v+1}] - \mathbb{E}[y_t^Q | \Omega_v]}_{\text{forecast revision}} = w_{j,t} \underbrace{(x_{j,\tau} - \mathbb{E}[x_{j,\tau} | \Omega_v])}_{\text{news}}, \tag{5}$$

where the weight $w_{j,t}$ is the j-th column of the Kalman gain matrix. The magnitude of the revision is determined by the weight given to the variable and how much the new observation deviates from the previous expectation. The product of the weight and the news is what we call the *impact*.[2]

3 The Data Problem

3.1 Data Transformation

Chinese data pose unique challenges for nowcasting as they are often released in different formats than most other economies. Time series models typically require seasonally adjusted level data. However, the Bureau of Statistics of China (NBS) rarely publishes such data. The problem is further complicated by the Lunar New Year. The Spring Festival, the country's most celebrated holiday, is based on a lunar calendar and falls between January and February. This seven-day holiday has an extraordinary impact on the economy as businesses and production pause and billions of people travel home to celebrate with their families. This impact is too large to ignore, and it occurs at irregular dates in a solar calendar, which completely distorts the data in January and February. For these reasons, the NBS opts to publish some of the January and February data together in March, as a sum of the two months' values. This is particularly the case for output-related variables. However, this approach leaves only eleven observations in a year, making standard seasonal adjustment methods inapplicable.

Incorporating the data into a nowcasting framework is challenging in a number of ways. Because the original data are published in different formats, such as year-on-year growth rates, month-on-month growth rates, monthly values, cumulative year-to-date values; some have twelve months of observations, others only eleven. The usual treatment is to convert all series into year-on-year growth rates, as most of the existing literature does.

[2] This assumes the same parameters across vintages. Hayashi and Tachi (2021) extend Equation (5) to include the effect of parameter revision when the model is re-estimated across vintages.

However, using year-on-year growth rates would introduce serial correlation with the previous year's observations, which does not fit standard time series models. Moreover, as nowcasts for other economies are usually made using seasonally adjusted data, it is less convincing to compare China's forecast performance with other countries unless the Chinese data are transformed into a similar format.

The NBS has been publishing official seasonally adjusted month-on-month growth rates since 2011, but only for a handful of variables, such as fixed asset investment and retail sales of consumer goods. Where available, official month-on-month growth rates are used directly. Official seasonally adjusted level data are also available for a few variables, such as the money aggregates M1 and M2. In these cases I simply apply first-order differencing to the seasonally adjusted series. Where official seasonally adjusted data are not available, I make my own seasonal adjustment using the X-13 routine. For series with January and February values reported separately (such as import and export), the distortion of the seasonal pattern due to the Lunar New Year can be adjusted by introducing a regressor in the X-13 procedure to account for the number of holidays falling in each month. For series where January and February values are reported together as a sum (such as industrial production), I split the sum according to the impact of the Lunar New Year holidays and then seasonally adjust the series using X-13. Finally, all series are transformed to stationary by differencing or log-differencing. Table 2 reports the transformation applied to each variable.

This paper includes 27 monthly series for nowcasting, which are the most frequently monitored macro variables by market participants and policy makers. Disaggregated data, such as the components of the CPI or the output of individual industries, are not included because studies have found limited gains in forecasting accuracy by including them (Banbura et al., 2010, 2013). Improvements in nowcasting performance are mostly driven by headline data that "moves" the market. Financial market variables, such as stock prices, are also excluded as they are too volatile and contribute little to nowcasting performance (Banbura et al., 2013).

Table 2: Description of the Dataset

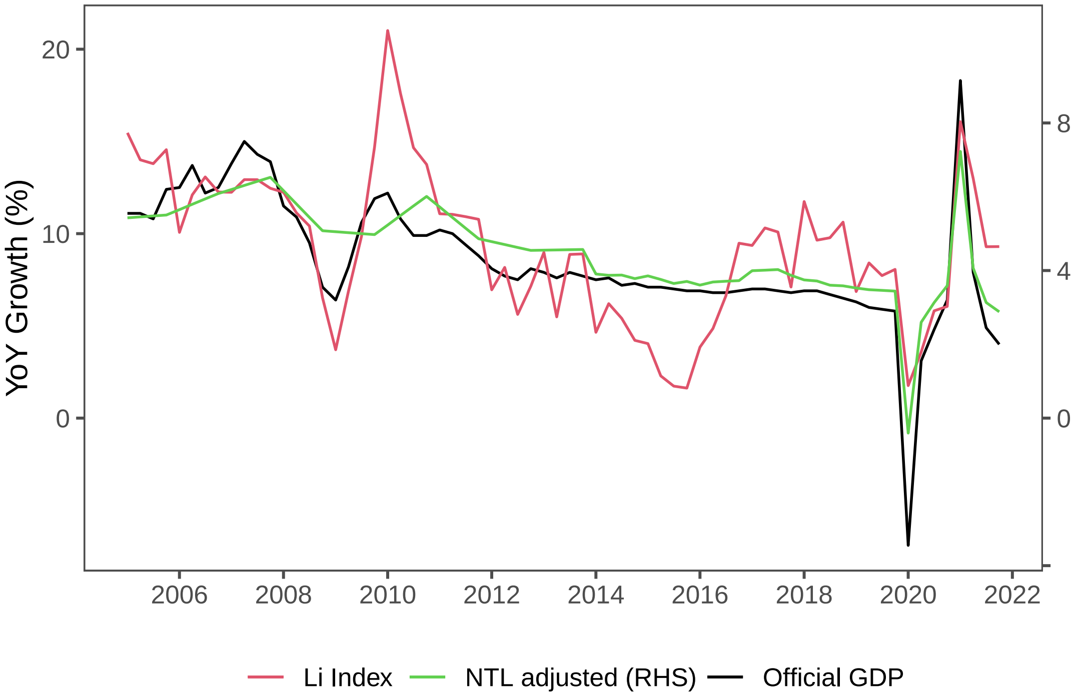
Symbol	Name	Transformation	Group	Release
RSCG	Retail Sales of Consumer Goods	MoM	Consumption	Mid
AUTO	Automobile Sales	Δlog	Durable Consumption	Early
EFOB	Export FOB	Δlog	Import and Export	Early
ICIF	Import CIF	Δlog	Import and Export	Early
STEEL	Steel Product	Δlog	Industrial Production	Early
VAI	Value Added of Industry	MoM	Industrial Production	Mid
FXR	Effective Exchange Rate Index	Δ	Interest and Exchange Rate	Mid
IB7D	Interbank Repo Rate: 7 Day	Δ	Interest and Exchange Rate	Spot
LR5Y	Lending Rate: Over 5 Year	Δ	Interest and Exchange Rate	Spot
TB10Y	Treasury Bond Yield: 10 year	Δ	Interest and Exchange Rate	Spot
FAI	Fixed Asset Investment	MoM	Investment	Mid
FDI	Foreign Direct Investment	Δlog	Investment	Mid
AFNI	Aggregate Financing	Δlog	Money and Finance	Mid
LOAN	Bank Loans	Δlog	Money and Finance	Mid
MSM1	Money Supply M1	Δlog	Money and Finance	Mid
MSM2	Money Supply M2	Δlog	Money and Finance	Mid
CPI	Consumer Price Index	Δ	Price	Early
CPIC	Core Consumer Price Index	Δ	Price	Early
PPI	Producer Price Index	Δ	Price	Early
BLD	Commercial Buildings Sold	Δlog	Real Estate	Mid
REI	Real Estate Investment	Δlog	Real Estate	Mid
CCI	Consumer Confidence Index	Δ	Survey	Late
ICI	Investor Confidence Index	none	Survey	Late
PMIM	PMI: Manufacturing	none	Survey	Spot
PMINM	PMI: Non-Manufacturing	none	Survey	Spot
APT	Air Passenger Traffic	Δlog	Traffic	Late
RFT	Railway Freight Traffic	Δlog	Traffic	Mid

Notes: The third column indicates the methods used to transform the original series into stationary. Δ stands for first order difference; Δ log for logarithmic difference; MoM stands for (official) seasonally adjusted monthly growth rate. The last column indicates the approximate release date of the series in the following month of the reference period. Actual publication dates may differ according to working day arrangements. *Spot* indicates that the series is available right at the end of the reference period. *Early*, *Mid*, *Late* indicates that the series is released early, mid or late in the following month.

3.2 Data Reliability Issue

In the baseline model, I use the official quarterly GDP growth rate as the benchmark. The nowcasting model is thus trained to minimise the difference between the forecasts and the official growth rates. However, several studies have questioned the reliability of Chinese GDP figures. Owyang and Shell (2017) point out that China's official GDP growth is not consistent with indices constructed from other economic variables. For example, Figure 1 shows the comparison of official GDP growth with the Li index, which

Figure 1: Official Economic Growth and Alternatives



Notes: The Li Index (or Keqiang Index) is an index of economic conditions reportedly created by China's Premier Li Keqiang. The index is constructed from three components: railway freight traffic (25%), total bank loans (35%) and electricity consumption (40%). The NTL-adjusted growth rate is constructed from the night-time light intensities described in Section 6. It is the concatenation of two segments: the pre-2013 segment is constructed from annual DMSP and linearly interpolated to quarterly series; the post-2013 segment is constructed from monthly VIIRS observations.

has reportedly been used by China's Premier Li Keqiang to monitor China's economic conditions. The latter shows much more volatility during 2012-2019. Nakamura et al. (2016) use Engel curves to back out inflation and growth, concluding that the official statistics are a smoothed version of reality. Martinez (2022) reports that growth statistics from authoritarian countries are significantly overstated compared to the growth rates implied by night-time light intensities.

Training the model against a biased benchmark would certainly lead to biased parameter estimation. It is particularly concerning if the official growth rates are overly smoothed, since the nature of the dynamic factor model is to exploit the co-movements between variables. To address the reliability issue, I follow the growing literature to construct alternative growth rates from night-time light (NTL) intensities recorded by satellites from outer space (Henderson et al., 2012; Donaldson and Storeygard, 2016; Hu and Yao, 2019; Beyer et al., 2022). Details of constructing the NTL growth rates will be discussed in Section 6.

3.3 Pseudo Real-Time Data Flow

Data flow refers to the flow of information over the days and months leading up to the end of the quarter when quarterly GDP is published. Real-time nowcasting involves continuously updating the growth projection as new information arrives. To back-test the nowcasting model, we need to construct pseudo samples that simulate real-time data flows. Monthly series are usually published one month after the reference period. Although the exact day of a particular release varies depending on working day arrangements, they generally follow a predetermined calendar. In the case of China, the Purchasing Managers' Index (PMI) is usually the earliest released indicator, which is available right at the end of the reference period. Trade balance data from China Customs are usually published a week later. Inflation data is released in the first half of the month (after the reference period), followed by the Central Bank's data on money and finance. The NBS releases most data on production, investment and employment in the middle to late part of the month. Table 2 lists the approximate release times for each variable, divided into four phases: *spot*, *early*, *mid* and *late*, as the exact day of release cannot be precisely identified. Pseudo data streams are constructed to release observations phase by phase over the course of a month.

The training period for this paper starts in 2010 and the pseudo out-of-sample period starts in 2015. China's economy has undergone significant structural change since the Global Financial Crisis. As a result, the parameters estimated before the GFC may not be applicable to the post-GFC era. Therefore, I choose a short training period to ensure the parameters estimated are more relevant to the post-GFC decade.

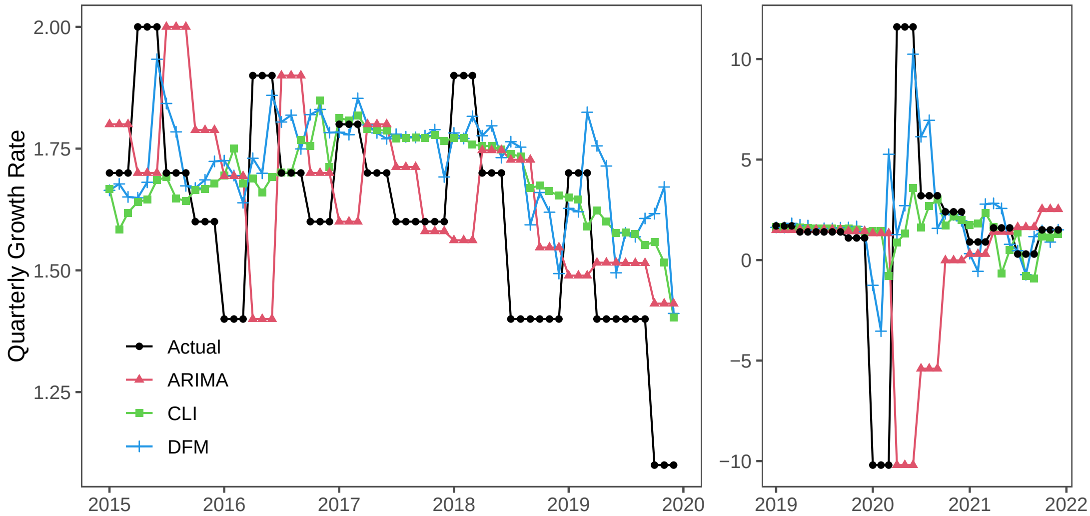
4 Nowcasting Results

This section presents the pseudo out-of-sample nowcasting results from January 2015 to December 2022, conducted on a monthly basis. To assess the overall nowcasting performance, I abstract from the within-month data releases and assume that updates on all variables are released in bulk at the end of a month. The impact of within-month information flows is examined in the following section. The model parameters are re-estimated at the beginning of each quarter to incorporate the latest quarterly GDP growth.

The dynamic factor model is compared with two alternative models, an ARIMA model and a model based on leading indicators. The ARIMA model is a univariate model of quarterly GDP growth whose parameters are automatically chosen by a stepwise algorithm (Hyndman and Khandakar, 2008). The second model is a simple regression that relates a monthly leading index to quarterly growth rates. The leading index used in this paper is the one published by the NBS (hereafter China's Leading Index or CLI).

Figure 2 visualises the nowcasts for the nearest quarter of the three models. The left-hand panel shows results before the pandemic, while the right-hand panel is devoted to the pandemic period, as the pandemic caused unprecedented volatility. The graph is presented on a monthly basis. Thus, the actual (official) growth rates and the ARIMA forecasts are shown as three repeated values for each month in a quarter. As expected, the ARIMA model shows lagged responses. The DFM model generally produces forecasts that are consistent with the fluctuations of the economy. However, the DFM tends to slightly overestimate growth rates. This is because the model does not take full account of the long-term downward trend. The CLI model tends to move in the same direction as the DFM, but in a smoother fashion. The capability of the models is best assessed during the pandemic, the once-in-a-century event that no one can predict in advance.

Figure 2: Nowcasting Results: Current Quarter GDP Growth



Notes: This figure visualises the pseudo out-of-sample nowcasts of GDP growth in the nearest quarter on a monthly basis. The left panel shows the results before the pandemic, and the right panel is for the pandemic period. DFM refers to the baseline dynamic factor model; CLI refers to the forecasts based on China's Leading Index; ARIMA refers to the automated univariate ARIMA model.

The DFM is the first of the three models to identify the recession. It also gives the earliest signal of recovery in the following quarter. The ARIMA model fails to predict the recession. The CLI model gives a signal of recession only in the last month of the first quarter of 2020.

Table 3 compares the forecast accuracy of the three models in terms of RMSE for each month of a quarter. It is noticeable that both CLI and DFM tend to improve their accuracy over time. In the pre-pandemic sample, the CLI model shows better accuracy than the DFM model in the first two months. However, the DFM model makes significant improvements in the third month and eventually outperforms the CLI model. In the pandemic period, the DFM model shows superior performance in the first two months, but the accuracy deteriorates in the third month. This is due to the rebound occurred in March, despite the quarterly growth rate slumps. For the whole sample, the DFM model is the best in the first two months, but less successful in the third month due to the disproportionate impact of the pandemic period.

A comparison of nowcast accuracy with other major economies (pre-pandemic): Banbura et al. (2013) report an RMSE of 0.4-0.5% for the United States. Banbura and Modugno (2014) report an RMSE of only 0.2% for the euro area. The RMSE for Japan, as reported in Hayashi and Tachi (2022), is around 0.7%. Thus, the DFM model applied to Chinese data is as accurate as, if not better than, other major economies. However, we must be cautious when comparing forecast accuracy with other literature. The RMSE reported in Table 3 is based on a relatively short back-testing period compared to, for example, Hayashi and Tachi (2022) who have 20 years in their sample. It is possible that the long-term performance of our model may suffer as the economy undergoes structural changes over time.

Table 3: RMSE Comparison: Nowcasting GDP Growth Rates

	Pre-COVID			COVID			Full Sample		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
DFM	0.231	0.228	0.138	4.966	4.214	5.576	2.661	2.261	2.983
CLI	0.207	0.213	0.178	5.658	5.575	4.440	3.029	2.986	2.378
ARIMA	0.235	0.235	0.235	9.295	9.295	9.295	4.973	4.973	4.973

Notes: The table compares the accuracy of three forecasting methods: (1) Dynamic Factor Model (DFM), (2) China's Leading Index (CLI) and (3) ARIMA model. The target variable is quarterly GDP growth rates. RMSEs are computed for each month of a quarter. The results are reported for three sample periods: the pre-COVID period (2015-2019), the COVID period (2020-2021), and the two periods combined.

5 Impact Analysis

Last section evaluates nowcast performance in terms of RMSE accuracy. However, it does not show what a nowcast looks like in real time, i.e. how the model revises its forecast as new information arrives. This section provides a detailed analysis of the impact of two recent macro events using the pseudo-real-time data constructed in Section 3.3. It mimics the trickling of information within a month. An overall assessment of the importance of each variable is given at the end.

5.1 Deleveraging Policy

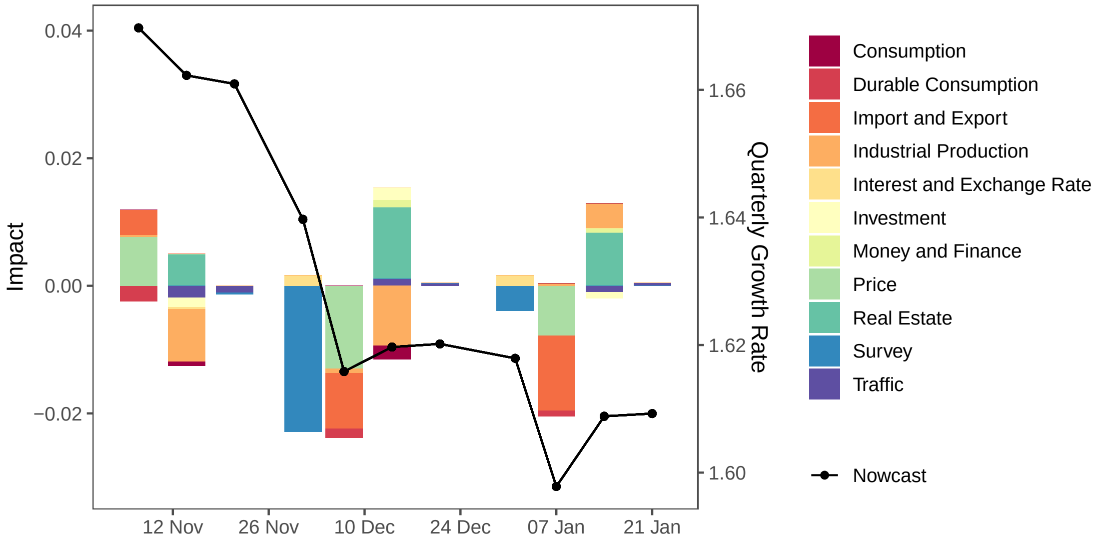
In 2017, Chinese authorities became increasingly concerned about the rising corporate leverage and government debt, prompting them to introduce regulations to curb potential debt risks and deleverage the economy. However, this regulatory tightening turned into an unexpected credit crunch, resulting in the sharpest economic slowdown before the pandemic (Wolf, 2018; Taplin, 2018).

Policy began to tighten in late 2017 and was doubled down in 2018. As a result, year-on-year growth slumped to 6.4% in the fourth quarter of 2018 from 6.7% in the first three quarters of 2018 and 6.9% in 2017. Figure 3 provides an analysis of the nowcast revision for the fourth quarter of 2018. I classify all variables into 11 groups according to Table 2. The impact of each variable is calculated according to Equation (5), and the impact of a group is the sum of the impacts of all variables in that group. The analysis shows that survey data gave the earliest strong signal of a slowdown at the end of November, which was further confirmed by trade and price data released in early December. The nowcast was revised slightly upwards in mid-December, as the housing data remained supportive despite the decline in industrial production. This slowdown was further confirmed by the trade and price data released in January 2019. In the end, the model produced a nowcast of a quarterly growth rate of 1.6% (the official growth rate was 1.4%).

5.2 COVID-19 Lockdown

The COVID-19 pandemic was the most dramatic event in recent history, causing unprecedented economic disruptions. In late January 2020, the Chinese government imposed a citywide lockdown to contain the spread of the virus. The plateauing of new cases in March led to an easing of the lockdown policy, allowing the economy to return to normal. Nevertheless, the halt in production and consumption during the lockdown resulted in a -6.8% year-on-year growth in 2020 Q1, which was the only negative record

Figure 3: Impact Analysis: Deleveraging (2018 Q4)

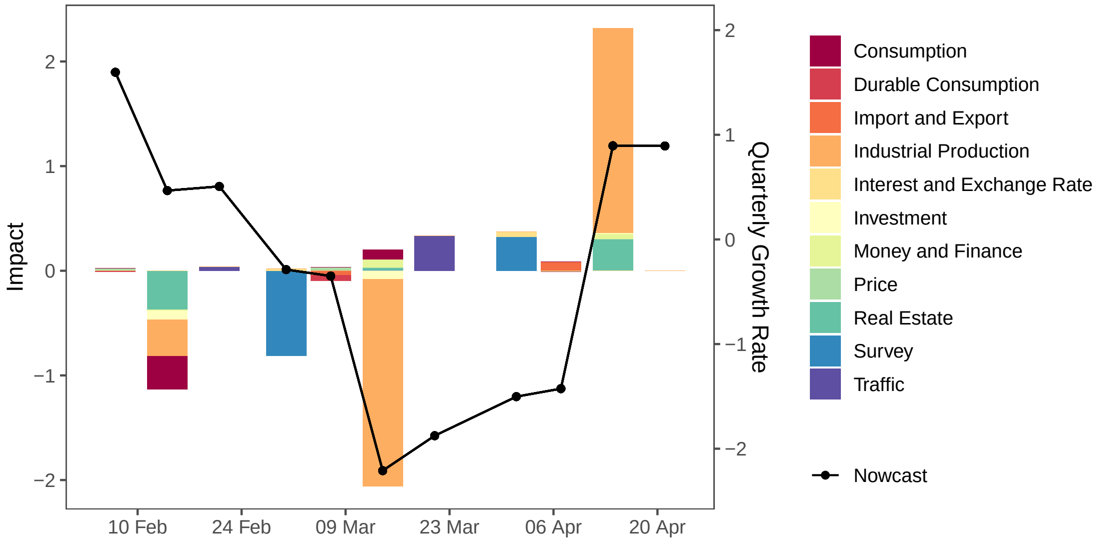


Notes: This figure shows how the nowcasts are revised as new information is released over time. The x axis is the pseudo data release date (one month after the reference period). The left axis is the impact of the news. The right axis is the real time projected growth rates. Variables are grouped according to Table 2.

since 1992.

Figure 4 demonstrates the nowcast revisions through the COVID lockdown period. The first signs of a slowdown were observed in mid-February in the consumption, industrial production and real estate categories. Then a serious alarm came from the survey data released at the end of February. The industrial production in March showed a sharp decline, leading to a substantial downward revision of the nowcast. This was followed by a small upward revision from the traffic data. However, this was a false revision. Because the model was trained using data before the pandemic, the passenger traffic had a small and negative weight. The large reduction in passenger traffic during the lockdown was therefore translated into a positive impact. If the model had been trained using data from the pandemic period, passenger traffic would have had a large negative impact. The April data showed a recovery in industrial production, which led to a positive revision of the nowcast. The final nowcast for the first quarter ended up being 0.9%. This was, of course, far from the actual number -10.2%.

Figure 4: Impact Analysis: COVID-19 (2020 Q1)



Notes: This figure shows how forecasts are revised as new information is released over time. The x axis is the pseudo data release date (one month after the reference period). The left axis is the impact of the news. The right axis is the real time projected growth rates. Variables are grouped according to Table 2.

5.3 Overall Assessment

To provide an overall assessment of the importance of each variable, I run monthly impact analyses over the entire sample to obtain the average impact of each variable. The result is presented in Tables 4 and 5. The *news effect* for each variable is calculated as the standard deviation of the news over all periods, and the associated *weight* is the average of the weights in each release. The *impact* of a variable is then calculated as the product of the *news effect* and its *weight*.

The impact on nowcast revisions is assessed in each month of a quarter respectively. In the pre-pandemic period, GDP growth of the previous quarter has the largest impact in the first month, followed by Producer Price Index (PPI) and Purchasing Managers Index (PMI). In the second month, Producer Price Index (PPI) and Industrial Value-Added (VAI) are the main drivers of nowcast revisions, followed by Imports (ICIF), Exports (EFOB) and Money Supply M1 (MSM1). In the last month, Industrial Value-Added

(VAI) turns out to be the most influential indicator, followed by Import, Export and PPI.

I estimate the model separately for the pandemic period.[3] For the post-pandemic period, in all three months, Air Passenger Traffic (APT) has the largest impact, with a magnitude of a completely different order. This is consistent with the intuition that lockdowns and restricted social mobility were the direct cause of the economic meltdown during the pandemic. Apart from APT, GDP in the previous quarter is still most influential for the first month. In the second month, Vehicle Sales (AUTO) emerge as the second most important variable, which is understandable as it captures the recovery in durable consumption. In the third month, APT and AUTO are still the two most important variables, followed by Steel Production (STEEL), which captures the recovery in industrial activity.

In summary, "soft data", such as surveys, often provide early indicators of changing economic conditions, while "hard data", such as industrial production, are the main drivers of nowcast revisions. During the pandemic, mobility indicators, such as air passenger traffic, are particularly useful for monitoring economic activity.

6 Alternative Measures of Growth

To address concerns about the reliability of China's official GDP growth rates, this section examines the use of alternative growth measures in the nowcasting model. The alleged over-smoothing of the official growth rates is of particular concern, as it would weaken the co-movement between GDP growth rate and other variables (the essence of a dynamic factor model is to exploit this correlation). This section constructs an alternative measure of growth using night-time light (NTL) data observed from space. Two sources of NTL data are commonly used in the literature: the Defence Meteorological

[3] I estimate the model including data from the first quarter of 2020, and start the back-test from the second quarter, so that the parameters are adjusted to reflect the pandemic conditions.

Table 4: Impact Analysis: Contribution from Each Variable (Pre-COVID)

Variable	1st Month	2nd Month	3rd Month	Variable	1st Month	2nd Month	3rd Month
VAI	0.0088	0.0078	0.0073	PMIM	0.0062	0.0045	0.0010
EFOB	0.0032	0.0059	0.0063	AUTO	0.0026	0.0017	0.0010
ICIF	0.0096	0.0070	0.0043	LOAN	0.0059	0.0017	0.0009
PPI	0.0184	0.0127	0.0042	BLD	0.0014	0.0012	0.0006
CPIC	0.0062	0.0054	0.0036	RSCG	0.0013	0.0019	0.0005
REI	0.0090	0.0054	0.0034	FAI	0.0012	0.0008	0.0005
LR5Y	0.0052	0.0051	0.0033	STEEL	0.0010	0.0009	0.0005
MSM1	0.0081	0.0058	0.0025	FDI	0.0003	0.0005	0.0003
RFT	0.0079	0.0041	0.0016	ICI	0.0003	0.0002	0.0000
PMINM	0.0102	0.0051	0.0016	GDP	0.0438	0.0000	0.0000
AFNI	0.0051	0.0026	0.0014	CCI	-0.0001	0.0000	0.0000
MSM2	0.0038	0.0024	0.0012	IB7D	-0.0012	-0.0007	-0.0003
CPI	0.0020	0.0023	0.0011	FXR	-0.0029	-0.0020	-0.0009
TB10Y	0.0047	0.0024	0.0010	APT	-0.0039	-0.0025	-0.0024

Notes: The table reports the impact of each variable averaged from the monthly nowcasts from 2015 to 2019. For each variable, the table reports its impact on the nowcast revision when it is released in the 1st/2nd/3rd month of a quarter. The impact of a variable is calculated as the product of the data revision (the difference between the actual value and the previously forecast value) and its weight (the Kalman gain associated with each variable). Variables are ranked from highest to lowest by their impact in the 3rd month.

Table 5: Impact Analysis: Contribution from Each Variable (Post-COVID)

Variable	1st Month	2nd Month	3rd Month	Variable	1st Month	2nd Month	3rd Month
APT	1.4534	1.5260	0.6950	TB10Y	0.0025	0.0022	0.0010
AUTO	0.0176	0.0574	0.0095	MSM2	0.0019	0.0014	0.0008
STEEL	0.0164	0.0043	0.0062	BLD	0.0048	0.0035	0.0008
EFOB	0.0110	0.0143	0.0054	LOAN	0.0015	0.0012	0.0006
ICIF	0.0068	0.0064	0.0039	PPI	0.0060	0.0029	0.0003
FDI	0.0038	0.0107	0.0034	MSM1	0.0009	0.0007	0.0002
CCI	0.0072	0.0044	0.0034	CPIC	0.0004	0.0003	0.0001
RSCG	0.0022	0.0066	0.0029	LR5Y	0.0000	0.0000	0.0000
RFT	0.0059	0.0050	0.0027	ICI	0.0000	0.0000	0.0000
AFNI	0.0060	0.0044	0.0022	GDP	0.7087	0.0000	0.0000
REI	0.0039	0.0020	0.0021	IB7D	-0.0003	-0.0002	-0.0002
VAI	0.0037	0.0029	0.0021	FXR	-0.0033	-0.0018	-0.0008
PMINM	0.0484	0.0262	0.0014	CPI	-0.0055	-0.0031	-0.0016
PMIM	0.0452	0.0168	0.0012	FAI	0.3709	0.0468	-0.0293

Notes: The table reports the impact of each variable averaged from the monthly nowcasts from 2015 to 2019. For each variable, the table reports its impact on the nowcast revision when it is released in the 1st/2nd/3rd month of a quarter. The impact of a variable is calculated as the product of the data revision (the difference between the actual value and the previously forecast value) and its weight (the Kalman gain associated with each variable). Variables are ranked from highest to lowest by their impact in the 3rd month.

Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIIRS). DMSP covers annual data from 1992 to 2013 and VIIRS covers monthly data from 2013 to 2022. This study uses the VIIRS data, as the nowcasting period falls after 2015.

Although VIIRS is available on a monthly basis, it is not appropriate to construct a time series directly from NTL illumination due to the seasonal nature of solar illumination and cloud cover. To overcome this problem, the monthly NTL intensity is first aggregated to quarterly values and then converted to year-on-year growth rates to reduce the influence of seasonality. The conversion of NTL growth to GDP growth is done by estimating the elasticity between the two. An alternative GDP index is then constructed using the base GDP levels and the growth rate converted from NTL growth. The quarterly growth rates used in nowcast models are derived from this index.

I estimate the elasticity between GDP growth and NTL growth by projecting the former on the latter for a sample of 50 major economies. [4] To preserve the authenticity of the growth rate implied by the NTL, I do not control for any time or country fixed effects. [5] Due to the noisy nature of the satellite data, observations in the tail distribution must be removed to ensure the credibility of the estimation. Following other literature, I construct the NTL-adjusted growth rate as a linear combination of the fitted value and official GDP growth:

$$\bar{y} = (1 - \lambda)y + \lambda\hat{y},$$

where y is official GDP growth, $\hat{y}$ is the projected GDP growth by NTL growth, λ is

[4] National accounts data are taken from the OECD's Quarterly National Accounts (QNA) database: https://stats.oecd.org/Index.aspx?DataSetCode=QNA. As China's official seasonally adjusted GDP is not available before 2011, Higgins and Zha (2015)'s time series data for China's macroeconomy, available from the Federal Reserve Bank of Atlanta, are used instead. https://www.atlantafed.org/cqer/research/china-macroeconomy.aspx?panel=3.

[5] Including time-fixed effects would pick up global common trends in economic growth that may overshadow changes in the night light. Omitting the country fixed effect assumes that the elasticity between GDP growth and NTL growth is the same for all countries, despite their different stages of development, energy consumption peculiarities and so on. This may cause the fitted values to differ from official GDP growth, but it preserves the growth rates implied purely by NTL intensity. For nowcasting purposes, the absolute levels of growth rates are less important than the fluctuations over time.

the weight on NTL projected growth. Beyer et al. (2022) estimated the optimal λ to be around 0.67. In this paper λ is simply set to 0.7.

A comparison between the NTL-adjusted growth and official GDP growth is shown in Figure 1. The graph also includes values before 2013, which are estimated by interpolating annual DMSP observations, although the nowcast only uses values after 2013. By construction, NTL-adjusted growth moves in line with official GDP growth. However, there are also notable differences. NTL-adjusted growth appears to be less volatile, particularly during the pandemic period. There are also periods when the two indicators are not synchronised, such as in 2017. This suggests that NTL-adjusted growth provides additional information about the economy beyond official GDP figures.

I repeat the nowcasting exercise in Section 4, but using NTL-adjusted growth instead of official GDP growth (Table 6). Surprisingly, the back-test reports similar nowcast accuracy as in Table 3. The nowcasts for the first two months are slightly worse than before, while the third month is slightly better. Overall, replacing the official GDP growth with the alternative NTL growth does not seem to make much difference. This does not suggest anything about the accuracy of the absolute value of official GDP growth. However, it does show that the official GDP growth rate is no more or less aligned with other economic variables than the NTL growth rate. Hence, the evidence here does not support the "over-smoothed" claim against official GDP growth.

7 Conclusion

This paper contributes to the existing nowcasting literature on the Chinese economy by back-testing the model with the most recent economic data. After transforming the time series into an OECD-consistent format, the nowcast model delivers an accuracy comparable to other major economies. Impact analysis shows that industrial production is the most important variable driving nowcast revisions before the pandemic. During the pandemic, however, mobility indicators provide the most important signals. Replacing

Table 6: RMSE Comparison: Nowcasting Nightlight Growth Rates

	Pre-COVID			COVID			Full Sample		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
DFM	0.264	0.262	0.108	1.272	1.001	1.793	0.715	0.579	0.963
CLI	0.233	0.231	0.215	1.543	1.469	1.165	0.848	0.809	0.649
ARIMA	0.243	0.243	0.243	1.828	1.828	1.828	0.998	0.998	0.998

Notes: The table compares the accuracy of three forecasting methods: (1) Dynamic Factor Model (DFM), (2) China's Leading Index (CLI) and (3) ARIMA model. The target variable is the quarterly growth rates implied by night-time light intensity, which is an alternative indicator of economic growth. Nowcasts are carried out in the 1st/2nd/3rd month of each quarter. Results are reported for three sample periods: the pre-COVID period (2015-2019), the COVID period (2020-2021) and the full sample period.

official GDP growth rates with night-light-adjusted growth rates does not lead to more accurate forecasts, suggesting that the correlation between various economic variables and official GDP growth is as strong as the correlation with night-light growth, indicating that official GDP growth accurately reflects economic fluctuations.

The results of this paper point to several avenues for further improvement. It has been suggested that incorporating a long-term trend into the model can improve performance, especially in the long run, as China's GDP displays a downward trend over time. It would be useful to include time-varying parameters and stochastic volatility in the model. In addition, the pandemic period poses unique challenges to existing nowcasting models, as none of them are able to provide sufficiently prompt estimates of a recession of this magnitude. It remains an open question how to build a model that can quickly adapt to structural changes and provide more accurate forecasts in extreme events such as the COVID-19 pandemic.

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