

Forecasting recovery from COVID-19 using financial data: An application to Vietnam

Jesse Lastunen^a, Matteo Richiardi^{b,*}

^a United Nations University World Institute for Development Economics Research (UNU-WIDER), Helsinki, Finland

^b Centre for Microsimulation and Policy Analysis (CeMPA), University of Essex, United Kingdom

ARTICLE INFO

Keywords:
 COVID-19
 Pandemic
 Economic recovery
 Nowcasting
 Financial data
 Vietnam

ABSTRACT

We develop a new methodology to nowcast the effects of the COVID-19 crisis on GDP and forecast its evolution in small, export-oriented countries. To this aim, we exploit variation in financial indexes at the industry level in the early stages of the crisis and relate them to the expected duration of the crisis for each industry, under the assumption that the main shocks to financial prices in 2020 came from COVID-19. Starting from the latest official information available at different stages of the crisis on industry-level trend deviations of GDP, often a few months old, we predict the ensuing recovery trajectories using the most recent financial data available at the time of the prediction. The financial data reflect, among other things, how subsequent waves of infections and information about new vaccines have impacted expectations about the future. We apply our method to Vietnam, one of the most open economies in the world, and obtain predictions that are more optimistic than projections by the International Monetary Fund and other international forecasters, and closer to the realised figures. Our claim is that this better-than-expected performance was visible in stock market data early on but was largely missed by conventional forecasting methods.

1. Introduction

In this paper we develop a new method for projecting recovery from COVID-19 by industry, based on simple, publicly available information. COVID-19 has caused havoc worldwide, in both health and economic terms. During 2020, the world's collective gross domestic product (GDP) fell by 3.4 percent, against an average real growth rate of 3.8 per cent in the period 2000–19. This was the deepest recession since 1945–46 and more than twice as deep as the recession associated with the 2007–09 global financial crisis (World Bank 2020). At the end of 2021, 95 out of 228 countries still had a real GDP lower than in 2019.¹ While there is large national and industry variation, with some countries experiencing far more limited negative outcomes than others and some sectors even benefiting from COVID (generally, everything online, and logistics), there is no doubt that the COVID-19 crisis is a globally defining event that obscured almost everything else that happened in 2020.

One of the many issues on which COVID-19 has found the world unprepared is availability of data. Important decisions on the type and timing of restrictions are based on readily available health data, but their impact on the economy is monitored only with a lag. This implies

that policies to support the economy are also delayed, or implemented under political pressures but not based on clear evidence. Nowcasting, a set of techniques to update older data using more recent external information, has therefore come to the front stage. Nowcasting exploits comovements between economic variables, typically in the form of dynamic factor models, to predict changes in some unobserved variables based on changes in observed ones (Banbura et al. 2013; Stock and Watson 2016). The variables used for prediction typically become available at different frequencies and with different delays—some measured in weeks or months; others, financial variables in particular, almost in real time. Nowcasting is, however, typically used to help predict short-term dynamics, not to forecast the longer-term evolution of the economy (e.g., GDP in the coming months or years). Even financial variables, which are forward-looking by nature and have generally been found useful to improve the accuracy of the predictions (Andreou et al. 2013; Knotek and Zaman, 2019), are rarely exploited for longer-term forecasts.

Yet, particularly in a crisis, policy-makers need projections a few months ahead, as these provide crucial information both on how much support the economy needs and on how sustainable that support is for

* Corresponding author at: Institute for Social and economic Research, University of Essex, Wivenhoe Park, Colchester CO4 3SQ, United Kingdom.

E-mail address: matteo.richiardi@essex.ac.uk (M. Richiardi).

¹ Our computation on World Bank data.

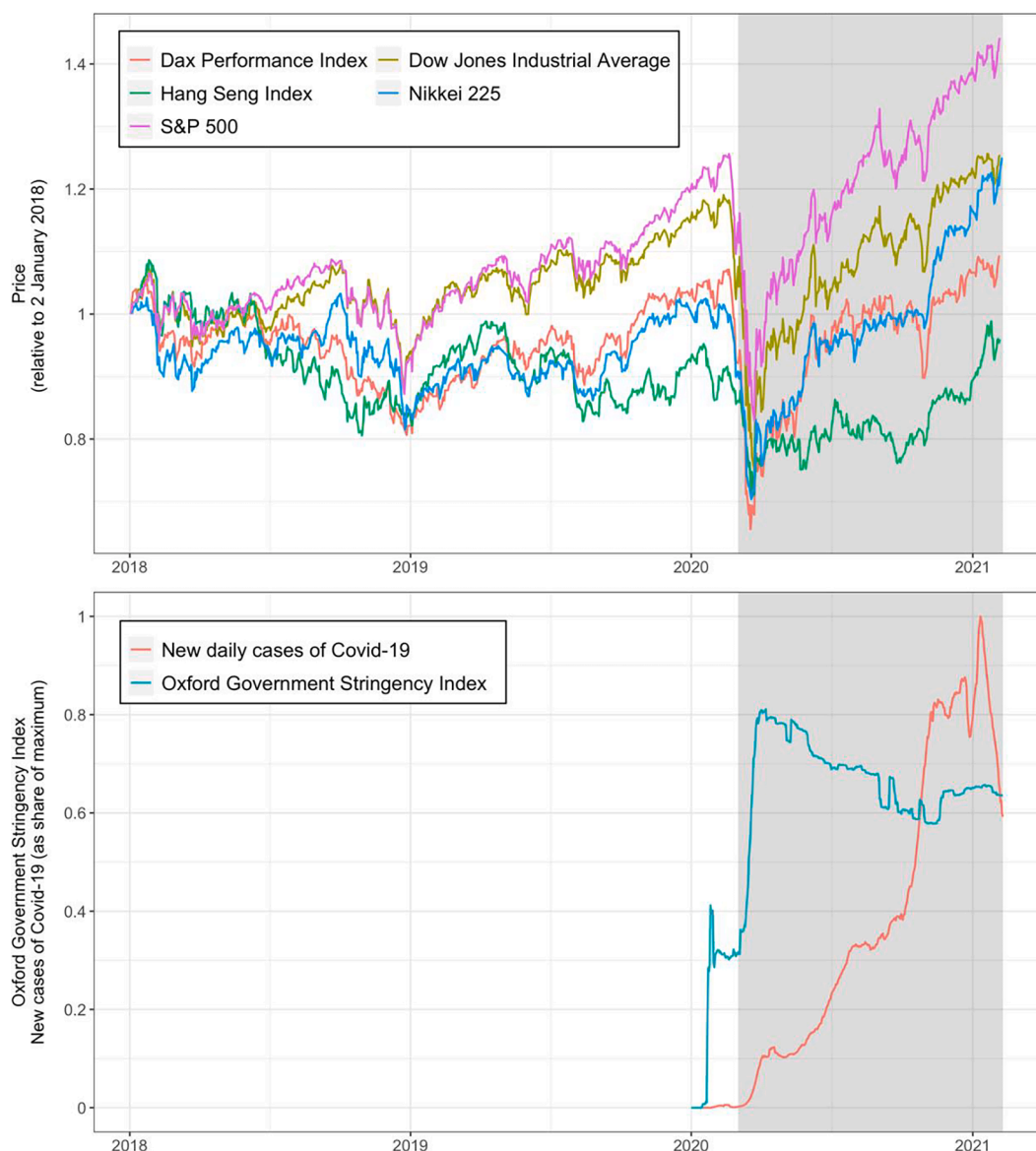


Fig. 1. Evolution of financial performance indexes, January 2018–February 2021, vs new cases of COVID-19. Note: index closing prices are normalised to 1, starting on 2 January 2018 (top); population-weighted Oxford Government Stringency Index and smoothed new cases of COVID-19 around the world as a share of maximum cases (bottom). Source: authors’ computation based on Yahoo Finance (top) and Our World in Data, Johns Hopkins University (bottom).

public finances. The business of forecasting recovery trajectories from crises is generally in the hands of international organisations like the OECD, the World Bank, and the IMF. Governments also engage in independent projections, when they have enough institutional capacity; examples are the Congressional Budget Office (CBO) in the US and the Office for Budget Responsibility (OBR) in the UK. These predictions are based on different methods or combinations thereof, including expert judgement, statistical analysis, and macro-econometric models, although the models used are generally not fully disclosed. The availability of such analyses, and especially the national-level data required to produce them, is particularly limited in low- and middle-income countries.

Our method overcomes these limitations by eliciting expectations about the unfolding of the crisis from financial data. We take inspiration from earlier work by Andreou et al. (2013) and others who argue for the usefulness of financial data in forecasting real variables. Andreou et al. (2013) illustrate the value of daily financial information in providing real-time forecast updates of the current (nowcasting) and future quarters of real GDP growth, relying on a mixed data sampling (MIDAS)

regression model. Their findings point to improvements in quarterly forecasts of U.S. real GDP growth beyond quarterly macroeconomic factors. Applying a similar approach to Mexico, Gómez-Zamudio and Ibarra (2017) find that financial data can improve quarterly forecasts of GDP growth over traditional models that rely on quarterly macroeconomic data. Mitchell (2020) combines daily and weekly financial data with monthly macroeconomic indicators in a mixed frequency probit (MFP) regression to accurately forecast and nowcast U.S. and Canadian recessions.

Our method differs from earlier approaches in its simplicity, more limited data requirements, and longer time horizons for GDP forecasts. We also use industry-level data to develop industry-level forecasts, which can be further aggregated to the level of the national economy. As opposed to general economic forecasts, we focus specifically on recoveries in economic activity from large global shocks such as the COVID-19 pandemic.

In using financial data to elicit expectations about sectoral recovery trajectories during COVID-19, we assume that variations in sectoral indexes in 2020 were driven mainly by news about the pandemic. This

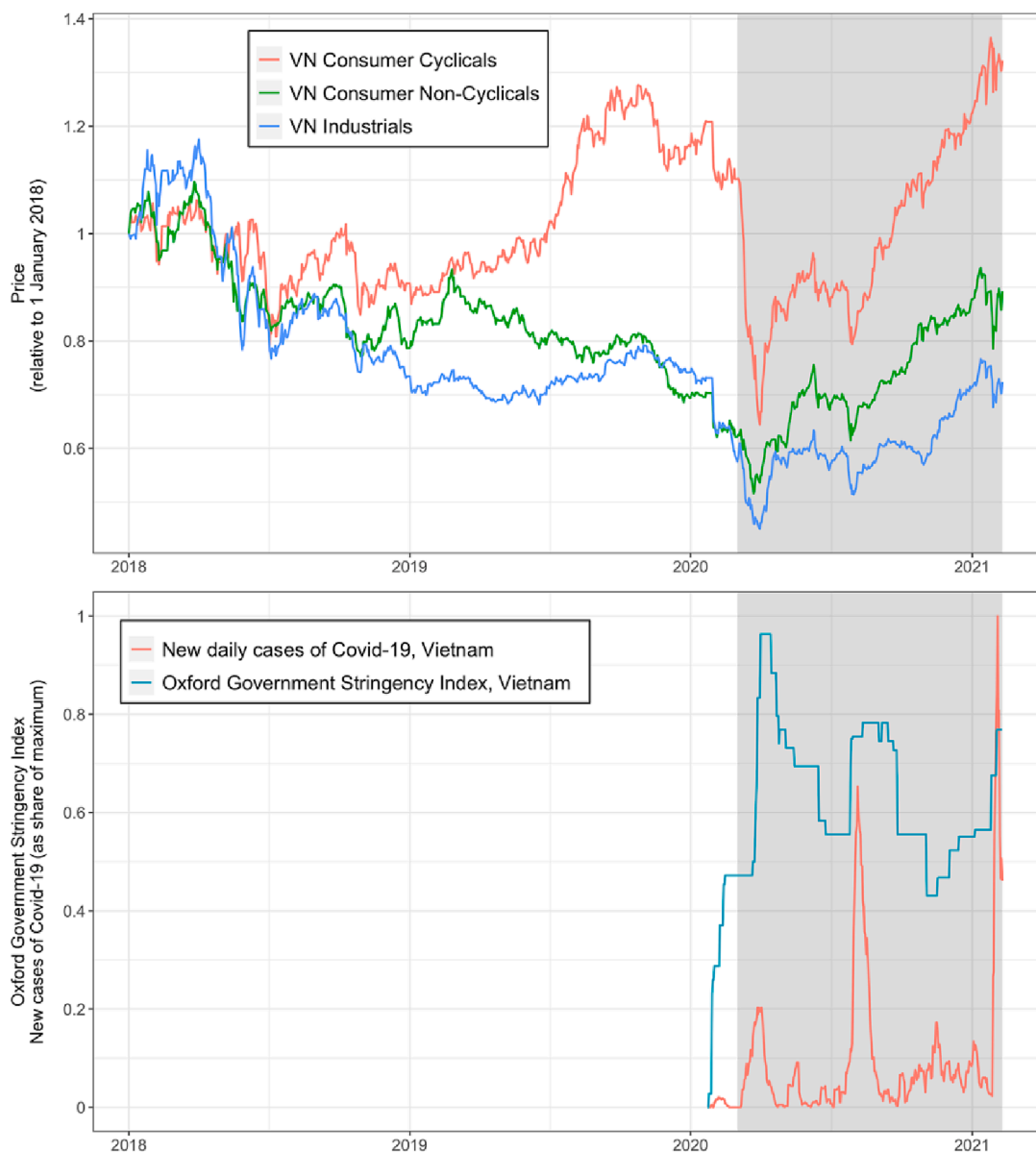


Fig. 2. Evolution of sectoral stock indexes from January 2018 until February 2021 vs new cases of COVID-19. Note: closing prices normalised to 1, starting on 1 January 2018 (top). Oxford Government Stringency Index and smoothed new cases of COVID-19 in Vietnam as a share of maximum cases (bottom). Source: authors’ computation based on Refinitiv Eikon (top) and Our World in Data, Johns Hopkins University (bottom).

sectoral information is then applied to a specific national context by weighting sectors by pre-crisis quarterly GDP shares and starting from initially observed sectoral shocks. The crucial assumption that COVID-19 was a main driver of financial prices in 2020 requires clarification and justification. The fact that financial prices embed expectations about the future is rarely questioned, but these expectations generally compound information on many different events. While singling out one event from all those that might impact on stock prices is in general not a good strategy, we believe that it is valid in this case, given the size and the pervasiveness of the COVID-19 crisis. For instance, when the results of the phase-3 (large-scale) clinical trial of the Pfizer-BioNTech vaccine—the first one to arrive at this stage and file for authorisation—were announced on 18 November 2020 and indicated more than 90 per cent efficacy, energy and travel stocks surged. The S&P 500 Energy Sector index, which had been down more than 50 per cent since the beginning of the crisis, shot up 14.8 per cent in a single trading day, while airlines, down more than 45 per cent, jumped 15.2 per cent.

Fig. 1 shows the three-year evolution of the S&P500, Dow Jones,

Nikkei 225, Hang Seng, and Dax indexes (top) as well as the population-weighted values of the Oxford Government Stringency Index and new cases of COVID-19 around the world as a share of maximum cases.

The area representing time from March 2020, generally accepted as the start of the crisis, onwards is shaded in grey. The second wave of the pandemic is also visible in the figure, with large dents in some financial indexes in the fall of 2020, when new cases surged globally. Fluctuations around the general pattern of a large shock followed by a steady recovery seem minor, in comparison.

The financial reactions to the pandemic are also visible in national figures. Fig. 2 shows the same information as Fig. 1 for Vietnam, using stock market data for three sectoral indexes—Vietnamese industrials, cyclicals, and non-cyclicals. New daily cases have peaked in three distinct waves. Each time government lockdown measures have become more intense, stock prices have plummeted.

Our method distinguishes between domestic and exporting sectors. Expectations about domestic sectors show up mostly in the value of local firms, while expectations about exporting sectors, due to the pressure of

Table 1
Comparing GDP forecasts for Vietnam in 2020 to official data.

Source Release date	Trend reduction in real GDP in 2020	Corresponding growth rate of real GDP in 2020
GSO Vietnam, first official GDP estimate for 2020 2021	-4.0 %	2.5 %
This paper's prediction using Q2/2020 data September 2020	-4.1 %	2.4 %
Government of Vietnam, growth targets September 2020	-4.0 % to -4.5 %	2.0 % to 2.5 %
Atradius November 2020	-4.2 %	2.3 %
ADB September 2020	-4.7 %	1.8 %
IMF October 2020	-4.9 %	1.6 %

Source: GSO (2020); Nikkei Asia (2020); Atradius (2020); Asian Development Bank (2020); IMF (2020).

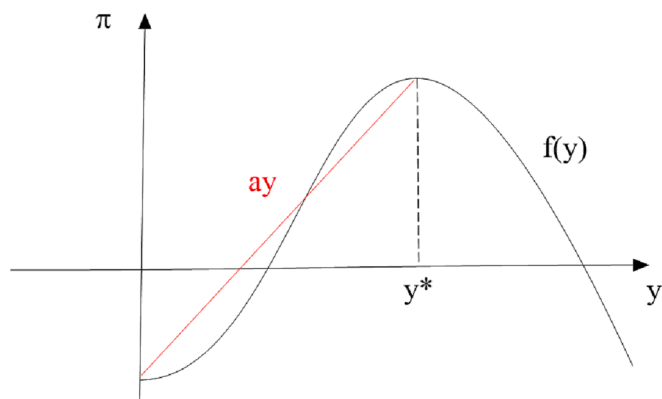


Fig. 3. Approximation of profit function.

international competition, can be elicited by looking at broader aggregates. This helps average out the effects of local information and events that are unrelated to the recovery. For instance, a national government might decide to pay subsidies to domestic companies that have been negatively affected by the crisis. This, ceteris paribus, increases the stock market value of these firms, but does not imply a faster recovery. Said differently, firms operating (mostly) in domestic markets are (more) affected by domestic policies and other domestic factors, potentially unrelated to the country's recovery potential. However, financial indexes computed over thousands of companies located in many different countries and selling to different export markets are broadly unaffected by local policies and affected mainly by expectations about global demand and supply.

This is why we suggest that our method works better for (typically small) exporting countries.

We test our method on Vietnam, which is among the countries least affected by COVID-19. Indeed, in October 2020 its growth rate for the whole year was predicted by the IMF to be 1.6 per cent in real terms, against -3.3 per cent for all emerging economies (IMF 2020). Still, this is significantly below the pre-COVID trend of 6.7 per cent for the average annual growth rate from 2000 to 2019. It is also lower than the average growth rate from 2015 to 2019, 6.8 per cent, which we use as our preferred counterfactual trend for 2020, while also accounting for differential growth rates across sectors.

Our choice of Vietnam as a test case is motivated by its nature as an exporting country. According to World Bank data, with a trade intensity (sum of imports and exports over GDP) of over 200 per cent in 2017, Vietnam is ranked 8th in the world for trade openness, after

Luxembourg, Hong Kong, Singapore, San Marino, Djibouti, Malta, and Ireland.²

Our choice of Vietnam is also motivated by the availability of timely data on GDP at the industry level, which allows us to test the validity of the method by comparing our predictions for Q3/2020 and Q4/2020 based on industry-level data for Q2/2020 with the actual data for those quarters. We also replicate the exercise by updating our predictions using Q3/2020 industry-level data and comparing our forecasts with observed Q4/2020 data. This offers only partial validation, as our predictions are based on elicited expectations, and ex-ante expectations can be (and generally are) different from ex-post realisations. In other words, even the best possible predictions might turn out to be wrong. Full validation of the method would require testing in multiple settings and over multiple timeframes—something that we have to leave for future research.

However, our initial results are encouraging. When Q2/2020 industry-level GDP data were released in September 2020, our method would have predicted—using financial data available at the release date—a -3.5 - 5.2 per cent (point estimate -4.1 per cent) contraction in real GDP for Vietnam in 2020 with respect to trend.³ Feeding the model with Q3/2020 data, and using financial data available until 28 December, brings this estimated annual contraction to -3.8 - 4.0 per cent (point estimate -3.9 per cent). At the time of writing, the General Statistical Office (GSO) of Vietnam has just published its preliminary GDP figures for 2020, which imply a full-year contraction of -4.0 per cent with respect to trend.⁴ This is assuming, as we do in our estimates, that each industry would have grown at its 2015-19 rate (on average 6.8 per cent) in the absence of the pandemic, while stock prices would likewise have followed their sectoral trends from 2015 until the end of 2019.

Our predictions are not only simpler to derive but at least on this occasion more accurate than other prominent projections by international organisations and private companies. In October, the IMF (2020) estimated that real GDP in Vietnam would be 4.9 per cent lower than predicted based on the average growth rate over the past five years (6.8 per cent). Trade credit insurer Atradius (2020) projected a 4.2 per cent drop from trend in November, and estimates from September by the Asian Development Bank (2020) implied a 4.7 per cent trend reduction. The Vietnamese government itself set a GDP growth target in September that corresponded to a 4.0-4.5 per cent trend reduction (Nikkei Asia 2020). Table 1 below lists these estimates, along with the corresponding estimates of the real GDP growth rate, for Vietnam in 2020.

Our estimates are generally more optimistic than other projections—an optimism that was later confirmed in the data. We can explain this with the more positive outlook that was prevalent before the second wave of the pandemic hit the world in the fall of 2020, which is reflected in the financial data but perhaps less so in the big, complicated macroeconomic models used by other forecasters (see Section 2).

The rest of the paper is organised as follows. Section 2 is devoted to reviewing macro-projection methods. Section 3 presents our approach,

² Other candidate countries for our analysis - low and middle income countries with a trade intensity above 100% of GDP - would be Djibouti (trade intensity over 300% in 2019), American Samoa, Marshall Islands, Maldives (all around 150%), North Macedonia, Lesotho (140%), Belarus (130%), Papua New Guinea (130% in 2004), Congo, Bulgaria, Mongolia, Malaysia (125%), Belize, Georgia (120%), Cabo Verde (115%), Mozambique, Serbia, Thailand, Montenegro (110%).

³ We assume that, in the absence of COVID-19, quarterly GDP in each industry would have grown at the average yearly inflation-adjusted rate that it grew over the 2015-19 period.

⁴ A -4.0 per cent trend reduction corresponds to a 2.5 per cent growth rate in 2020. When referring to GDP, we use the total annual output across all sectors in the economy, ignoring taxes and subsidies. Accounting for taxes and subsidies, the full-year trend reduction and real growth rate in GDP from data were roughly the same, -3.6 per cent and 2.9 per cent, respectively.

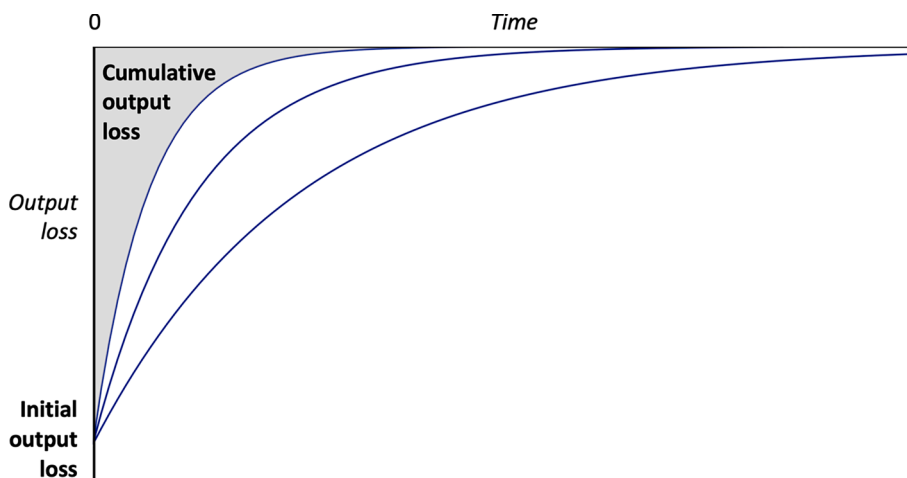


Fig. 4. Recovery trajectories, different values of recovery speed. Note: The area in grey corresponds to the cumulative future output losses due to COVID-19. Note that the output loss at $t = 0$ is $y_0 = -\lambda_0$. Source: authors' construction.

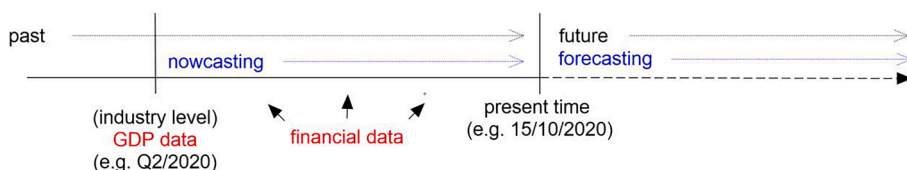


Fig. 5. Recovery trajectories, different values of recovery speed.

while Section 4 describes the data used. Section 5 offers our results, with concluding remarks contained in Section 6.

2. Macro-projection methods

Macro-projection methods by institutional forecasters typically have two characteristics: (i) they are complicated, in an attempt to make the best use of data coming from different sources, integrating different modelling approaches and expert judgements; and (ii) they are seldom fully disclosed, or only partially documented. For instance, the OECD combines ‘expert judgement with a variety of existing and new information relevant to current and prospective developments. These include revised policy settings, recent statistical outturns and conjunctural indicators, combined with analyses based on specific economic and statistical models and analytical techniques.’⁵ The macro-econometric model used by the OECD is the new-Keynesian model NiGEM developed by the British National Institute of Economic and Social Research (NIESR), which, however, offers only a 14-page technical report discussing the theoretical framework and modelling assumptions, with no information on estimation.⁶ Only five references are cited, the most recent dating back to 2006.

Not much is known about the methods employed by the IMF for its World Economic Outlook, except an older paper taking an historical approach (Boughton 1997; see also chapter 5 in Boughton 2001). One problem, of course, is that economies are linked, so that trade patterns also need to be modelled. The specific IMF model for developing

countries—at least until the late 1990s—comprised ‘some two dozen behavioural equations plus around 60 identities’, taking some outputs of a wider model as exogenous inputs (Boughton 1997).

Obviously, these modelling exercises face two very difficult challenges: they have to work in different country contexts, and they have to work at all times, hence predicting growth potentials and not only recoveries from shocks (Cristelli et al. 2017). In the wake of COVID-19, institutional forecasters turned to their models and tried to adapt them to the rapidly changing circumstances. Our claim is that for the sake of predicting recovery trajectories from COVID-19 at an industry level for small exporting countries, a much simpler, easier to understand, and faster to update modelling approach could be at least as effective.

3. Eliciting expectations from financial markets

It is clear that the economic recovery from COVID-19 strongly depends on the health recovery, and the general evolution of the pandemic. These in turn depend crucially on the timing of deployment, coverage, and effectiveness of vaccines. These are hard to predict, with new information often contradicting previous information (for instance, on the planned rollout of vaccination campaigns). In the absence of a crystal ball, we turn to the ‘wisdom of the crowd’ and look at the reaction of financial markets.

Assume that the ‘fundamental’ value of a stock at time t , p_t , is the present value of its future dividends, which in turn are on average equal to future profits π :

$$p_t = \int_t^\infty \pi_\tau \delta^\tau d\tau \tag{1}$$

where δ is the discount factor. The relationship between profits π and output y , $f(y)$, is driven by the maximising behaviour of the firm, with its choices about the use of production factors. As a first-order approximation, we consider it to be linear, for output y in a neighbourhood below the profit-maximising level y^* : $f(y) \approx ay$ (Fig. 3).

⁵ OECD (2011) Forecasting methods and analytical tools. <https://www.oecd.org/economy/outlook/forecastingmethodsandanalyticaltools.htm> (accessed 6 January 2021).

⁶ See <https://nimodel.niesr.ac.uk>. To be fair to NIESR, full documentation would be massive. Each country model, according to the NiGEM website, contains between 80 and 200 variables depending on the data and model structure used. Considering that the model is applied to 44 countries, this makes a total of 6,000 variables and over 10,000 model equations.

Table 2
Industries used.

Industry	GDP share (2019)	Corresponding financial index	Geography of index	Relative trade intensity (2017)
Manufacturing	21 %	Industrial goods	Asia-Pacific	129 %
Agriculture, forestry and fishery	15 %	Applied resources	Asia-Pacific	67 %
Wholesale and retail trade	11 %	Retailers	Asia-Pacific	76 %
Domestic cyclical services	9 %	Consumer cyclicals	Vietnam	19 %
- <i>Administrative and supporting activities</i>				
- <i>Art, entertainment and recreation</i>				
- <i>Real estate</i>				
- <i>Self-employment and self-consumption</i>				
- <i>Other services</i>				
Construction	7 %	Construction materials	Asia-Pacific	50 %
Finance, banking and insurance	7 %	Financials	Asia-Pacific	34 %
Mining and quarrying	6 %	Metals and mining	Asia-Pacific	166 %
Education and public administration	6 %	Consumer non-cyclicals	Vietnam	15 %
- <i>Activities of the Communist Party; socio-political organisations; public administration and defence; compulsory social security</i>				
- <i>Education and training</i>				
Utilities	6 %	Utilities	Asia-Pacific (no domestic index available)	14 %
- <i>Electricity, gas, steam and air-conditioning supply</i>				
- <i>Water supply, sewerage management and waste treatment</i>				
Accommodation and catering services	4 %	Consumer cyclicals	Asia-Pacific	128 %
Transportation and storage	3 %	Transportation	Asia-Pacific	122 %
Technical and professional services	2 %	Industrial and commercial services	Asia-Pacific	36 %
Healthcare and social services	1 %	Healthcare	Asia-Pacific	52 %
Information and communications	1 %	Technology	Asia-Pacific	52 %
Total	100 %			100 %

Note: Column 1: industries used in the analysis; industries in italic type are aggregated into the category above (in roman type). Column 2: corresponding sectoral stock indexes used in the analysis. Column 3: geographical scope of the index (either Vietnam or Asia-Pacific). Column 4: size of sector with respect to Vietnamese GDP in 2019 (GSO 2020). Column 5: relative trade intensity, computed as the ratio of the sectoral trade intensity to economy-wide trade intensity (imports plus exports divided by GDP). For some domestically oriented sectors (e.g. utilities), an Asia-Pacific index is used due to the lack of availability of a domestic index. Source: GSO (2020, columns 1 and 2); Refinitiv Eikon (2020, columns 3 and 4); Asian Development Bank (2018), column 5).

Table 3
Average annual growth rate and deviations of output from trend.

Industry	AAGR, 2015–19	Deviation of output from trend				
		Q1/2020	Q2/2020	Q3/2020	Q4/2020	2020
Manufacturing	12.6 %	-4.9 %	-8.2 %	-7.8 %	-3.6 %	-6.1 %
Agriculture, forestry and fishery	2.5 %	-2.4 %	-0.7 %	0.3 %	2.1 %	0.2 %
Wholesale and retail trade	8.5 %	-2.6 %	-5.1 %	-2.7 %	-1.4 %	-2.7 %
Domestic cyclical services	5.1 %	-1.7 %	-9.8 %	-6.1 %	-4.3 %	-5.5 %
Construction	9.2 %	-4.5 %	-4.2 %	-2.0 %	-0.6 %	-2.3 %
Finance, banking and insurance	8.2 %	-0.7 %	-1.8 %	-1.5 %	-0.9 %	-1.2 %
Mining and quarrying	-3.2 %	-1.0 %	-2.6 %	-2.8 %	-3.0 %	-2.5 %
Education and public administration	6.5 %	-1.0 %	-0.3 %	-0.3 %	0.3 %	-0.3 %
Utilities	9.8 %	-2.3 %	-8.8 %	-5.2 %	-4.6 %	-5.2 %
Accommodation and catering services	7.3 %	-17.1 %	-34.1 %	-16.8 %	-14.3 %	-20.5 %
Transportation and storage	7.8 %	-8.1 %	-16.4 %	-6.6 %	-6.2 %	-9.0 %
Technical and professional services	7.0 %	-0.7 %	-0.2 %	-0.4 %	-0.1 %	-0.3 %
Healthcare and social services	7.3 %	2.5 %	3.1 %	3.2 %	3.5 %	3.1 %
Information and communications	7.7 %	-0.2 %	-0.2 %	-0.5 %	-0.3 %	-0.3 %
All industries	6.8 %	-3.6 %	-6.3 %	-4.2 %	-2.2 %	-4.0 %

Note: Column 1: average annual growth rates in 2015–19, used to derive counterfactual output levels in 2020. Columns 2–6: quarterly and annual output deviations with respect to trend, computed using output levels from official data, and counterfactual levels using the 2015–19 growth rates of column 1. Source: authors' computation based on GSO data.

For $y < y^*$, the current price then becomes:

$$p_t = a \int_t^\infty y_\tau \delta^\tau d\tau \tag{2}$$

The reduction in future profits and hence in stock price due to COVID-19 is then proportional to the reduction in output, which is what we want to measure. We also assume that, at any given point in time, expectations about recovery at a future time t from a shock at time 0 follow a negative exponential trajectory:

$$y_t^e = -\lambda_0 e^{-gt} \tag{3}$$

where detrended real output converges asymptotically to its pre-crisis

level of $y_0 = -\lambda_0$. This implies that real output growth (net of inflation) reverts to its historical average, but the cumulative losses from COVID-19 are never recovered. This assumption, like all subsequent steps in the analysis, are implemented at the level of individual industries.

Fig. 4 depicts alternative recovery trajectories, for different values of g (controlling the speed of recovery), starting from a given initial shock (output loss λ_0). Higher values of g correspond to more V-shaped recoveries, while lower values correspond to more linear recoveries.

If the assumption that profit losses are proportional to output losses is approximately true, the loss in asset value is then proportional to the area above the recovery trajectories, appropriately discounted (this area

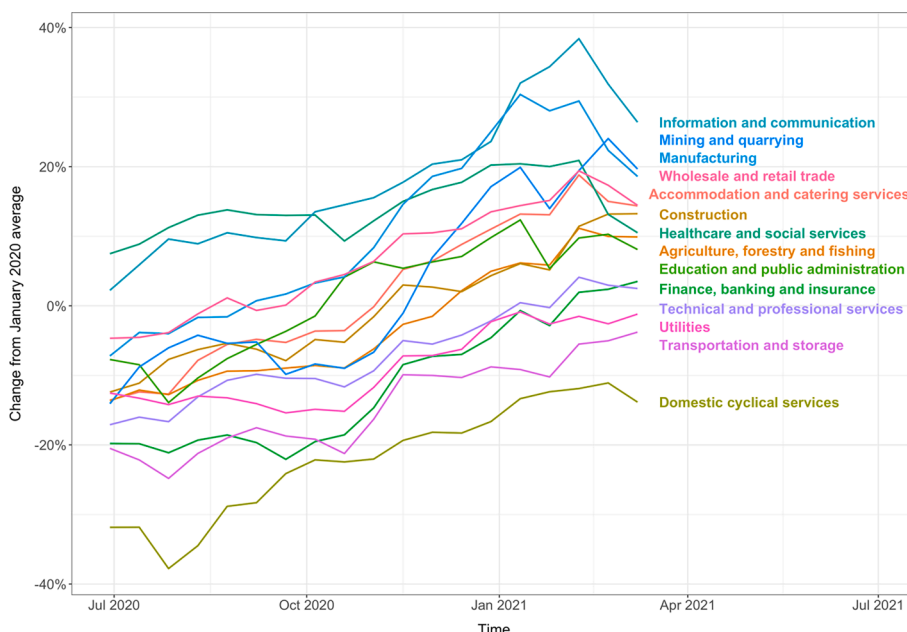


Fig. 6. Evolution of sectoral indexes for Vietnam and the Asia-Pacific region. Note: price levels are biweekly averages as a change from the January 2020 average, de-trended using the average annual growth rate in each index from 2015 until the end of 2019 (see Fig. A1 in Appendix). Source: authors’ computation based on Refinitiv Eikon.

is shadowed in the figure for one specific recovery trajectory).

This corresponds to the present value of the output losses:

$$L_0 = \int_0^\infty -\lambda_0 e^{-g t} \delta^t dt = -\frac{\lambda_0}{g - \ln(\delta)} < 0 \tag{4}$$

where δ is the discount factor (we use $\delta = 0.95$; our findings show little sensitivity to this choice). Knowing the initial output loss $\lambda_0 (> 0)$ and the financial loss $L_0 (< 0)$ allows us to compute g from eq. (3)⁷:

$$g = \ln(\delta) - \frac{\lambda_0}{L_0} > 0 \tag{5}$$

From here, we can calculate the cumulative output loss at any future time t . We also annualize this loss to compare it with the initial shock. Assuming that t corresponds to days (from the start):

$$y_{t, \text{yearly}}^e = \left(\frac{365}{t}\right) \int_0^t -\lambda_0 e^{-g \tau} \delta^\tau d\tau = -\left(\frac{365}{t}\right) \frac{\lambda_0 - \lambda_0 e^{-g t} \delta^t}{g - \ln(\delta)} \tag{6}$$

In our analysis, the initial shock is parameterised by the latest observed shock to output available. In the context of our application to Vietnam, this initial shock, or trend deviation of output, is calculated by comparing quarterly output in Q2/2020 to quarterly output a year earlier, in Q2/2019, appropriately updated by the average annual growth rate (AAGR) of industry-level output before the pandemic, from

⁷ Note that we require $g > \ln(\delta)$ based on formula (3), and hence $\lambda_0 > 0$ and $L_0 < 0$. Equivalently, we need $\lambda_0 < 0$ and $L_0 > 0$ when estimating the output trajectory for sectors with positive initial shocks using a corresponding exponential decay function. This condition is not fulfilled, for instance, when financial losses for a given sector (with initial output loss $\lambda_0 > 0$) become zero or turn into financial gains compared with baseline. In this case, we use an arbitrary threshold level for financial loss, $L_{0, \text{limit}} = -0.005$. This causes the recovery trajectory for output, derived in formula (6), to gradually approach zero. Simply assuming that cumulative output loss becomes zero when financial recovery is achieved leads to unrealistic results; for instance, annualized output shock could turn from -10 per cent to 0 per cent in a single two-week period. In Section 5, we show how estimated recovery trajectories change with different values for the financial loss threshold.

2015 to 2019. When new financial data becomes available, the model can be reparametrized. This is achieved by computing g_t at time t , using the financial loss L_t from the data and the previous output loss $y_t^e = \lambda_t$, estimated by the model. As new data for Q3/2020 become available later in the year, estimates can be updated by also deriving the updated output loss λ_t from data instead of the model.

Summarising the time structure of our model, we have low-frequency industry-level GDP data which give us the starting point for the projections, say in Q2/2020. The projections are made exploiting high-frequency financial data from Q2/2020 to the analysis time point. These projections not only allow us to update industry-level losses up to the moment of the analysis (“nowcasting”) but also make it possible to extrapolate the projections to future dates (“forecasting”). This is shown in Fig. 5 below.

Our projections are updated on a daily basis as new financial data become available. When new (quarterly) industry-data are released, for instance for Q3/2020, we can check the validity of our predictions by comparing our estimated output losses for Q3/2020 with the data, and also further update our projections by revising the realised losses that initialise the model up to Q3/2020.

In the Vietnamese application presented in this paper, the recovery path is updated biweekly.

All variables in the analysis are available or computed for individual industries in Vietnam. This also applies to financial losses, which are parameterised by the percentage change in the biweekly average of daily mean prices of a given sectoral stock index from its January 2020 (pre-COVID) average.⁸

We also use these prices to compute the 95 % confidence interval around the recovery trajectory, assuming, for each stock index, a Gaussian random walk. Accordingly, after the initial shock at $t = 0$, the standard deviation of the biweekly price $p_{t,i}$ is the sum of standard deviations over all previous updates, inclusive of the newest data point at time t . The uncertainty around the stock price trajectory of each index is then converted into uncertainty around output losses following Eqs. (5)

⁸ We de-trend daily stock prices using the average annual growth rate in each sectoral stock index in 2015–2019.

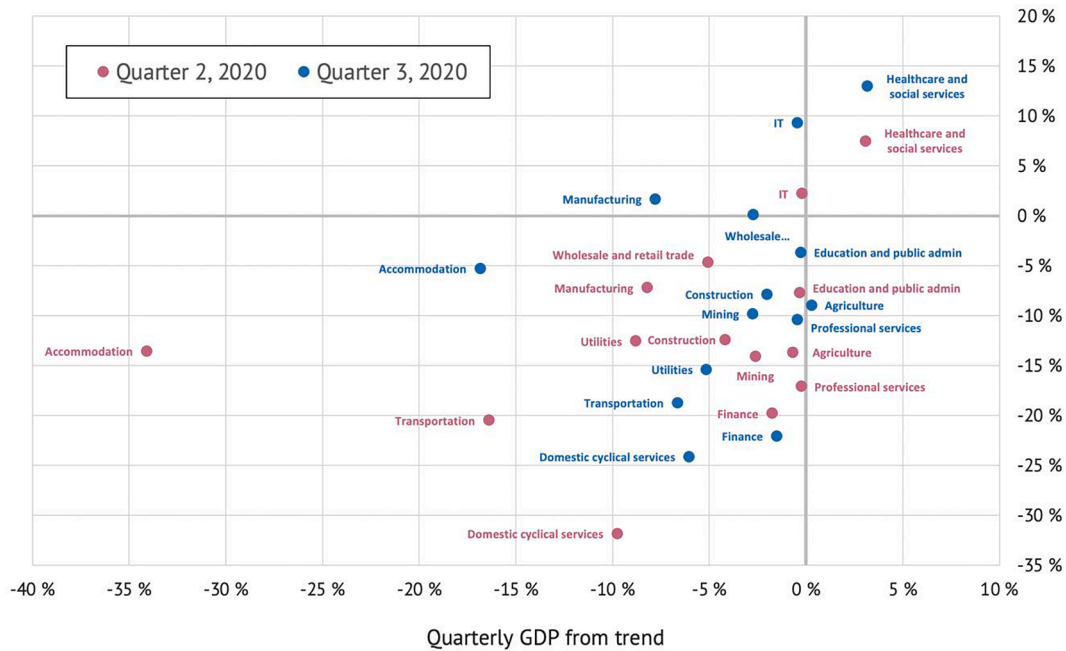


Fig. 7. Financial gains or losses vs trend deviations of output in quarters 2 and 3, 2020. Source: authors' construction based on data from Refinitiv Eikon and GSO.

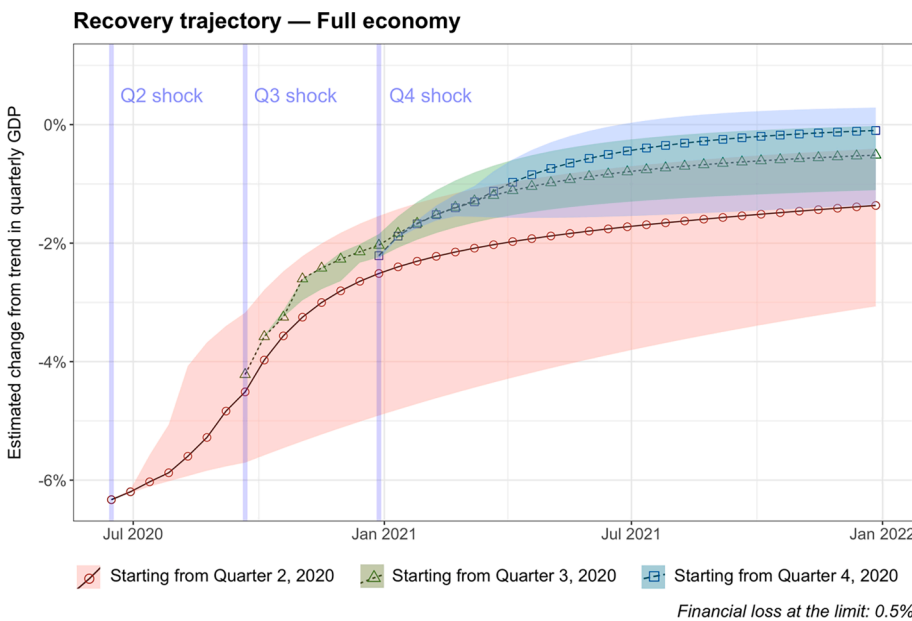


Fig. 8. Estimated recovery paths for Vietnam. Note: chart shows deviations from trend in quarterly GDP, under three sets of data: (1) deviations estimated for Q2/2020 and financial data up to the end of the third quarter (red dots); the red-shaded area measures statistical uncertainty due to financial data volatility; (2) deviations estimated for Q3/2020 and financial data up to the end of the fourth quarter (green triangles), with green-shaded uncertainty; (3) deviations estimated for Q4/2020 and financial data up to 18 March 2021 (blue squares), with blue-shaded uncertainty. The shaded areas show the 95 per cent confidence intervals, estimated using a Gaussian random walk. The financial loss threshold used is -0.5 per cent. Source: authors' construction.

and (6).⁹

Finally note that under the appropriate estimate for the annual GDP loss, y_{2020}^e , is the weighted average of the estimated quarterly GDP realisations $y_{Q_t}^e$, with weights ω_{Q_t} equal to the shares of output produced in each quarter. Under our application focusing on the 2020 calendar year, we use the model-estimated realisations for quarters 3–4 in the calculation of annual GDP loss, while shocks for quarters 1–2 are derived from GDP data. The weights, in turn, are derived from quarterly output shares in 2019 due to the availability of GDP data that is complete for the whole year:

$$y_{2020}^e = \sum_{Q=1}^{Q=4} \omega_{Q_{2019}} y_{Q_{2020}}^e \tag{7}$$

4. Data

4.1. Industry-level GDP

We test our method using data from Vietnam. The quarterly industry-level GDP data, used to derive the output shocks resulting from the pandemic, or the deviations of GDP from trend, come from the General Statistical Office (GSO) of Vietnam.¹⁰ We use information from all 20

⁹ Note that due to the non-linearities in the model, the uncertainty fan around the speed of recovery and estimated output losses is not symmetrically distributed around their respective mean.

¹⁰ General Statistics Office (GSE), Vietnam. Data available at: <https://www.gso.gov.vn/en/data-and-statistics/>.

Table 4
Estimates from model predictions vs data.

Deviation of annual GDP from trend (<i>Model based on Q2 data</i>)	4.1 % [3.5 % – 5.2 %]
Deviation of annual GDP from trend (<i>Model based on Q3 data</i>)	3.9 % [3.8 % – 4.0 %]
Deviation of annual GDP from trend (<i>Actual data</i>)	4.0 %
Deviation of quarterly GDP from trend in Q3 (<i>Model based on Q2 data</i>)	4.5 % [3.2 % – 5.7 %]
Deviation of quarterly GDP from trend in Q3 (<i>Actual data</i>)	4.2 %
Deviation of quarterly GDP from trend in Q4 (<i>Model based on Q2 data</i>)	2.5 % [1.5 % – 4.9 %]
Deviation of quarterly GDP from trend in Q4 (<i>Model based on Q3 data</i>)	2.0 % [1.8 % – 2.2 %]
Deviation of quarterly GDP from trend in Q4 (<i>Actual data</i>)	2.2 %

Note: The estimates reflect reductions in GDP from trend. 95% confidence intervals in brackets.

Source: authors' construction.

Table 5
Estimates from model predictions vs data, with varying values for financial loss threshold.

	Estimates with varying financial loss thresholds		
	(1)	(2)	(3)
	–1.0 %	–0.5 %	–0.1 %
Deviation of annual GDP from trend (<i>Model based on Q2 data</i>)	4.3 % [3.7 % – 5.2 %]	4.1 % [3.5 % – 5.2 %]	3.9 % [3.1 % – 5.2 %]
Deviation of annual GDP from trend (<i>Model based on Q3 data</i>)	4.0 % [4.0 % – 4.1 %]	3.9 % [3.8 % – 4.0 %]	3.7 % [3.5 % – 3.7 %]
Deviation of annual GDP from trend (<i>Actual data</i>)	4.0 %	4.0 %	4.0 %
Deviation of quarterly GDP from trend in Q3 (<i>Model based on Q2 data</i>)	4.7 % [3.8 % – 5.7 %]	4.5 % [3.2 % – 5.7 %]	3.8 % [2.2 % – 5.7 %]
Deviation of quarterly GDP from trend in Q3 (<i>Actual data</i>)	4.2 %	4.2 %	4.2 %
Deviation of quarterly GDP from trend in Q4 (<i>Model based on Q2 data</i>)	2.8 % [1.9 % – 4.9 %]	2.5 % [1.5 % – 4.9 %]	2.4 % [1.2 % – 4.9 %]
Deviation of quarterly GDP from trend in Q4 (<i>Model based on Q3 data</i>)	2.4 % [2.4 % – 2.6 %]	2.0 % [1.8 % – 2.2 %]	1.4 % [0.9 % – 1.5 %]
Deviation of quarterly GDP from trend in Q4 (<i>Actual data</i>)	2.2 %	2.2 %	2.2 %

Note: Growth rates present reductions in GDP from trend. 95% confidence intervals in brackets.

Source: authors' construction.

industries provided in the quarterly data but aggregate them into 14 macro sectors that can be more appropriately matched with financial information from selected stock indexes. The list of industries used is provided in Table 2, along with the corresponding index used in the analysis; the geographical scope of the index; the share of each sector in the Vietnamese GDP in 2019; and its relative trade intensity.

The GDP shares point to each sector's importance for the Vietnamese economy, while the relative trade intensities reflect their openness to international markets. We define relative trade intensity as the ratio of sectoral trade intensity (imports plus exports over GDP) to the overall trade intensity for Vietnam. This measure is reported rather than the absolute trade intensity because sectoral data come from the input–output tables produced by the Asian Development Bank (2018), which are not entirely consistent with the widely used economy-wide World Bank data on trade intensity (see Section 1). Section 4.2. below discusses the financial indexes in greater detail.

Table 3 shows the average annual growth rate in 2015–19 across sectors, used to derive counterfactual output levels in 2020, as well as the quarterly and annual de-trended trend deviations of output for 2020, as measured in the official data in early 2021.¹¹

4.2. Financial data

As already discussed, there is a trade-off to be considered in choosing the financial indexes to use in our model. National indexes are by definition better descriptors of a national economy; however, they might be influenced by specific national policies and other national factors that are unrelated to the recovery potential. More geographically aggregated indexes are less influenced by national policies aimed at supporting businesses during the pandemic; however, they are less representative of the national economy. The disadvantages of a more aggregated index are diminished for more export-led sectors, where performance and output are primarily linked to global rather than domestic demand. This, together with the fact that in the Global South many financial systems remain underdeveloped, and even when they are developed, sectoral indexes are often available only for broad aggregates, motivates our claim that our method is better suited for a small, export-led economy, and contributes to our choice of Vietnam as a testbed, as discussed in Section 1. Sectoral indexes for Vietnamese companies are, moreover, available only for broad aggregates such as consumer cyclicals and consumer non-cyclicals. We use sectoral indexes for the Asia-Pacific region and two Vietnamese indexes as provided by Refinitiv Eikon, a global provider of financial market data and infrastructure. We assume that they are representative, at the industry level, of the Vietnamese export-led economy. Table 2 lists our choice of index and its geographical scope for each sector.

As discussed in Section 3, we use the values of each index in January 2020 as the reference to compute subsequent losses. Fig. 6 shows the evolution of the sectoral indexes, where indexes are denoted by the name of the corresponding sector used in the analysis.

The recovery trajectories differ considerably across sectors. It is notable, however, that the indexes underlying the two industries that account for roughly a third of Vietnam's GDP—manufacturing and trade—have recovered rapidly, both reaching their January 2020 levels by October. In addition, many of the indexes picked up growth in the early fourth quarter. This translates to the rapid recovery in output during this period that is visible in our findings (see Section 4).

Finally, as mentioned briefly in Section 3, our reliance on the negative exponential (and exponential decay) functions means that the model can be used, without additional assumptions, when a sector experiences either (i) financial losses in the presence of a negative output shock, or (ii) financial gains in the presence of a positive output shock. Fig. 7 shows that this condition is generally satisfied in our data. Using industry-level observations from the second and third quarters of 2020, Fig. 7 plots quarterly trend deviations of output (from the five-year trend) against corresponding financial gains or losses (changes in de-trended sectoral stock prices from the January baseline at the end of both quarters). Most of the observations lie broadly along the main diagonal, where financial and output changes are either both positive or both negative. The positive correlation between financial and output changes is also visible in the graph.

5. Results

5.1. Economy-wide results

As discussed above, our decision to apply the method to Vietnam was motivated both by its nature as a small exporting economy and by the

¹¹ Quarterly GDP data for 2021 are available at the time of writing but subject to revisions due to apparent data entry errors in the estimates.

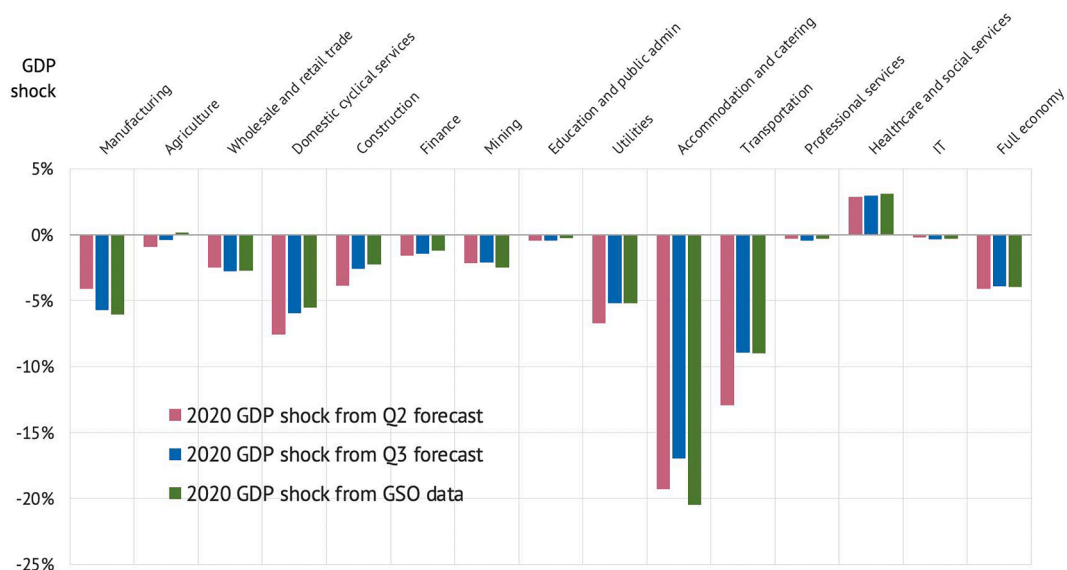


Fig. 9. 2020 GDP growth rates with respect to trend, early model predictions vs GSO data from 2021. Note: all results use a financial loss threshold of -0.5% . Source: authors' construction.

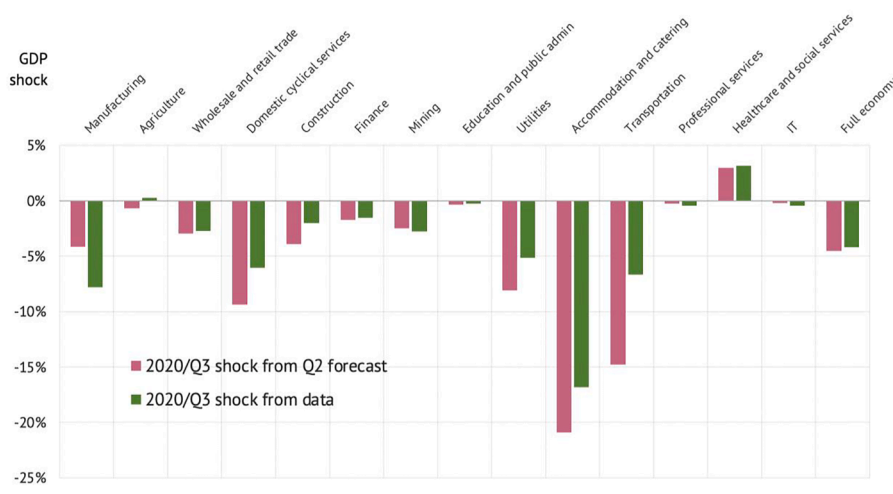


Fig. 10. 2020 Quarter 3 GDP growth rates with respect to trend, early model predictions vs GSO data. Note: all results use financial loss threshold of -0.5% . Source: authors' construction.

availability of quarterly GDP data at the industry level. The detailed and timely GDP data allowed us to test the validity of our method by comparing our predictions for the third and fourth quarters of 2020 with actual data for those periods. We could also acquire new predictions nearly in real time based on biweekly financial data, and evaluate the accuracy of past predictions when new quarterly GDP data were published.

Fig. 8 shows the estimated recovery path for the Vietnamese economy under three sets of data. The first plotted line, starting in July 2020, depicts the change in quarterly GDP from trend based on the initial deviations estimated for Q2/2020 (-6.3 per cent; from GSO's GDP data, blue point) and financial data up to the end of the third quarter. The second line, starting in October 2020, illustrates the change from trend output based on the trend deviations estimated for Q3/2020 (-4.2 per cent; again from GSO's GDP data) and financial data up to late December. Finally, the third line shows the corresponding recovery trajectory that starts from the output deviations estimated for Q4/2020 (-2.2 per cent) and uses financial data up to 18 March 2021.

Error bars show the 95 per cent confidence intervals around each

plotted line, estimated using biweekly standard deviations of sectoral stock prices and a simple Gaussian random walk (see Section 3 for details).

Our estimates for trend reductions from quarterly and annual GDP are summarised in Table 4, and compared with actual data.

Using GDP data from Q2 and financial data up to the end of Q3, our predicted recovery path closely aligns with the recovery path predicted from actual data. Our predictions for deviations of GDP with respect to trend in Q3 and Q4, -4.5 per cent [95 per cent CI: -3.2 per cent to -5.7 per cent] and -2.5 per cent [-1.5 per cent to -4.9 per cent] respectively (in the red-shaded area of the figure), are well aligned with the recent estimates derived from GSO data, -4.2 per cent and -2.2 per cent, respectively.

The recovery path we predict for Q4/2020 using GDP data from Q3 and financial data up to the end of Q4, -2.0 per cent [-1.8 per cent to -2.2 per cent] (in the green-shaded area in the figure) also aligns with the GSO data (-2.2 per cent) and is within the uncertainty bounds using the older set of information.

The quarterly trend deviations for Q2/2020 and financial

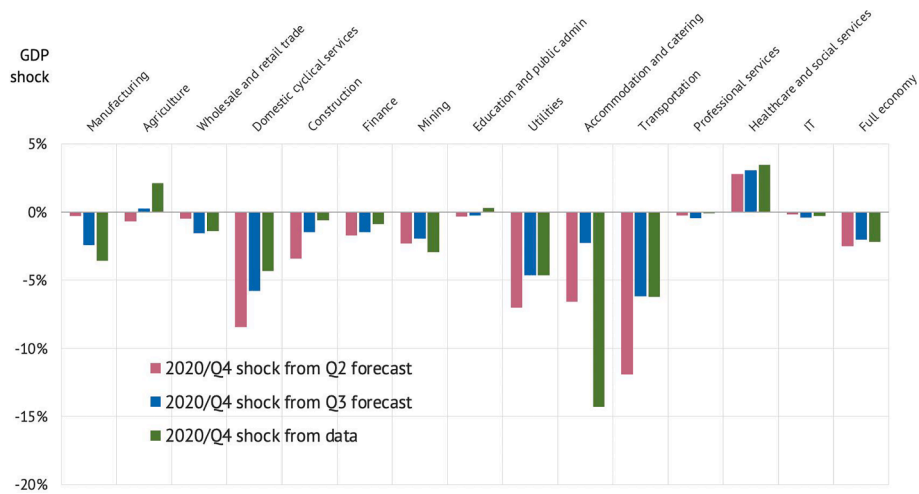


Fig. 11. 2020 Quarter 4 GDP with respect to trend, early model predictions vs GSO data. Note: all results use financial loss threshold of -0.5% . Source: authors' construction.

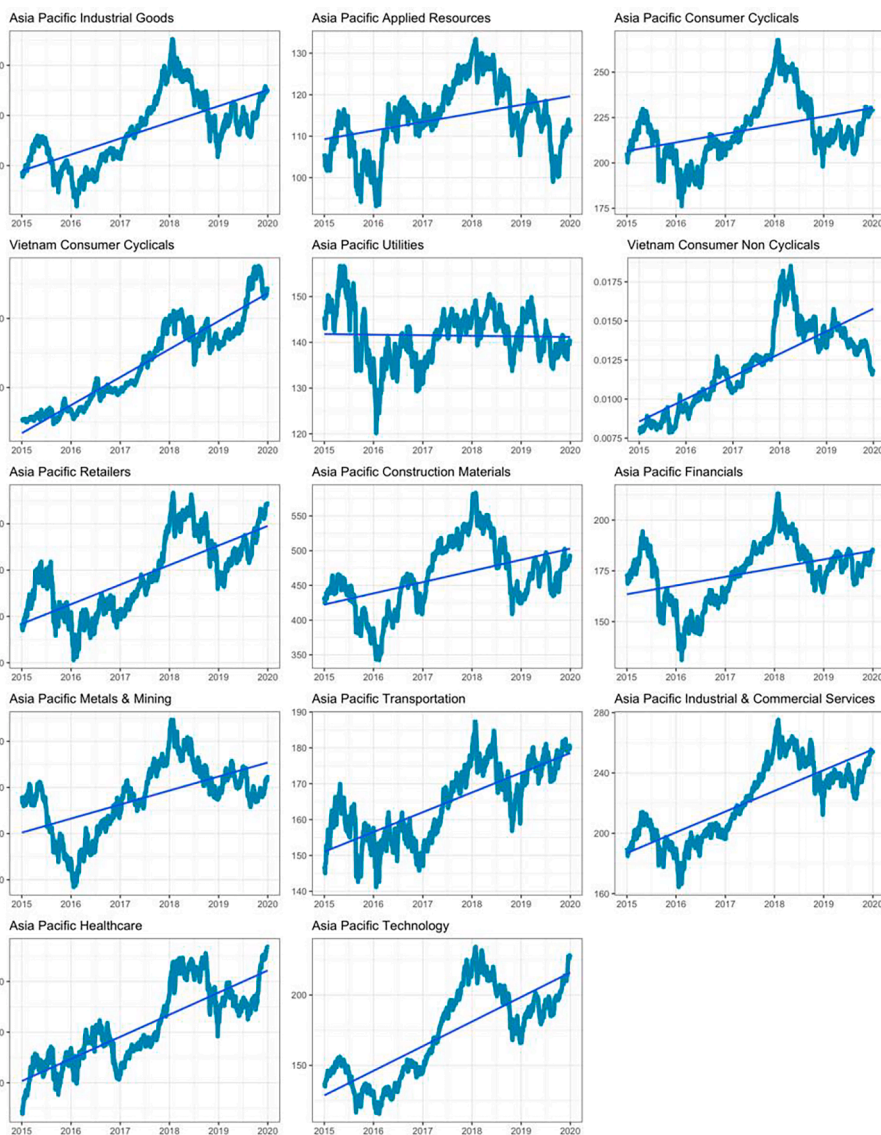


Fig. A1. Prices of sectoral stock indexes from 2015 until the end of 2020.

information up to Q3/2020 imply a yearly contraction of -4.1 per cent [-3.5 per cent to -5.2 per cent] from what would have been expected based GDP growth rates over the 2015–19 period. The updated quarterly deviations for Q3/2020 and financial data up to Q4/2020 imply a contraction of 3.9 per cent [-3.8 per cent to -4.0 per cent]. Our estimates match GDP figures published by the General Statistical Office of Vietnam in early 2021, which imply a 4.0 per cent reduction in 2020 GDP with respect to trend. See Table 1 for corresponding GDP growth estimates.

5.2. Sensitivity analysis

As mentioned in Section 3, the approach, relying on the negative exponential function, requires that for each biweekly update, output and financial changes from baseline are either both negative, or both positive. With full financial sector recovery, the condition is not fulfilled. In these cases, we need to impose a restriction to financial losses at the limit.

Our preferred threshold value for the financial losses is -0.5 per cent, which is large enough to circumvent unrealistically rapid output recoveries in a single two-week period, but small enough to allow financial price variations near the baseline to influence the output trajectory. Table 5 replicates Table 4, but includes results with different assumptions on the financial loss threshold (the second column contains the results for our preferred value for the financial loss threshold of -0.5 per cent). The sensitivity to the different values tested is small.

5.3. Selected industry-level results

In this section, we compare industry-level recovery trajectories and particularly the deviations of output with respect to trend predicted by the model with rates derived from GSO's GDP data. These comparisons are shown in Figs. 9–11. As can be seen in the figures, sectoral predictions are relatively accurate, although understandably less so than the aggregated full economy predictions discussed in the previous section. Notably, the graphs illustrate how predictions tend to improve with newer data.

6. Conclusions

In this paper we have described a new methodology to nowcast the economic effects of the COVID-19 crisis, also applicable to any comparable shocks of global nature. The method can also be used to predict recovery trajectories for economic activity in small, export-oriented countries, both across industries and for entire economies.

The technique relies on two sets of readily available data: observed trend deviations in industry-level GDP, which are typically available only with a delay, and real-time (or near real-time) variation in sectoral financial indexes. The financial indexes are used to update industry-level trend deviations of economic output and extend them into the future.

The application to Vietnam presented in this paper shows that the method can match, if not outperform, more traditional techniques used by government agencies and international organisations; our nowcasted recovery trajectories for Vietnam from fall 2020 are more in line with newest data than those made by reputable organisations such as the IMF.

Vietnam is the only country in the Association of Southeast Asian Nations (ASEAN) and one of few countries in the world that achieved positive nominal GDP growth in 2020 according to recent estimates. Our claim is that its exceptional performance was visible in stock market data early on but was largely missed by conventional forecasters.

At the same time, we acknowledge that this exercise offers only

partial validation for our method. More generally, our predictions are based on elicited expectations, which can be (and generally are) different from ex-post realisations. Full validation of the method requires testing it in multiple settings and over multiple time-frames—something that we have to leave for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Funding

This study was originally published as a UNU-WIDER Working Paper under its Academic excellence project.

Appendix A

Fig. A1 shows the prices of sectoral stock indexes from 2015 until the end of 2019, used for de-trending counterfactual price trends in 2020.

References

- Andreou, E., Ghysels, E., & Kourtellis, A. (2013). Should Macroeconomic Forecasters Use Daily Financial Data and How? *Journal of Business & Economic Statistics*, 31(2), 240–251. <https://doi.org/10.1080/07350015.2013.767199>
- Asian Development Bank (2020). 'Economic Indicators for Viet Nam'. Available at: <https://www.adb.org/countries/viet-nam/economy> (accessed 12 March 2021).
- Asian Development Bank (2018). 'Viet Nam: Input–Output Economic Indicators (2017 table)'. Available at: <https://data.adb.org/dataset/viet-nam-input-output-economic-indicators> (accessed 15 December 2021).
- Atradius (2020). 'Country Report Vietnam 2020'. Available at: <https://group.atradius.com/publications/country-report-asia-vietnam-2020.html> (accessed 12 March 2021).
- Banbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Nowcasting and the Real-Time Dataflow. In G. Elliott, & A. Timmerman (Eds.), *Handbook of Economic Forecasting*. Amsterdam: Elsevier. <https://doi.org/10.1016/B978-0-444-53683-9.00004-9>.
- Boughton, J.M. (1997). 'Modeling the World Economic Outlook at the IMF: a Historical Review'. IMF Working Paper WP/97/48. Washington, DC: International Monetary Fund. <https://doi.org/10.5089/9781451846706.001>.
- Boughton, J. M. (2001). *The Silent Revolution. The International Monetary Fund 1979–1989*. Washington, DC: International Monetary Fund.
- Cristelli, M., A. Tacchella, M. Cader, K. Roster, and L. Pietronero (2017). 'On the Predictability of Growth'. World Bank Policy Research Working Paper 8117. Washington, DC: The World Bank. <https://doi.org/10.1596/1813-9450-8117>.
- Gómez-Zamudio, L. M., & Ibarra, R. (2017). Are Daily Financial Data Useful for Forecasting GDP? Evidence from Mexico. *Economía*, 17(2), 173–203.
- IMF. (2020). *World Economic Outlook, October 2020*. Washington, DC: International Monetary Fund.
- Knotek, E. S., & Zaman, S. (2019). Financial Nowcasts and their Usefulness in Macroeconomic Forecasting. *International Journal of Forecasting*, 35(4), 1708–1724. <https://doi.org/10.1016/j.ijforecast.2018.10.012>
- Mitchell, R. (2020). 'Can Daily Financial Data Help Forecast Economic Downturns'. Unpublished Working Paper, University of Washington.
- Nikkei Asia (2020). 'Vietnam to Halve 2020 GDP Growth Target Due to Pandemic'. Available at: <https://asia.nikkei.com/Economy/Vietnam-to-halve-2020-GDP-growth-target-due-to-pandemic> (accessed 12 March 2021).
- Stock, J. H., & Watson, M. W. (2016). Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. In J. B. Taylor, & H. Uhligin (Eds.), *Handbook of Macroeconomics*, 2 pp. 415–525). Amsterdam: Elsevier. <https://doi.org/10.1016/bs.hesmac.2016.04.002>.
- World Bank (2020). 'Understanding the Depth of the 2020 Global Recession in 5 Charts'. Available at: <https://blogs.worldbank.org/opendata/understanding-depth-2020-global-recession-5-charts#:~:text=The%20COVID%2D19%20recession%20will,2007%2D09%20global%20financial%20crisis> (accessed 5 February 2021).