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Forecasting recovery from COVID-19 using financial data

An application to Viet Nam

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Abstract: We develop a new methodology to nowcast the effects of the COVID-19 crisis and forecast its evolution in small, export-oriented countries. To this aim, we exploit variation in financial indexes at the industry level and relate them to the expected duration of the crisis for each industry, under the assumption that the main shocks to financial prices in recent months have come from COVID-19. Starting from the latest information available on the size of the shock at the industry level, often a few months old, we predict the ensuing recovery trajectories using the most recent financial data available, monitoring how subsequent waves of infections and information about new vaccines have impacted expectations about the future. We apply our method to Viet Nam, one of the most open economies in the world, and obtain predictions that are close to (though more optimistic than) later projections by the International Monetary Fund and other international forecasters. Our claim is that this better-than-expected performance was visible in stock market data early on but was largely missed by conventional methods. The Vietnamese application hence supports the validity of our method, showing that financial information can be used to accurately nowcast recovery paths following a large economic shock such as a global pandemic.

Key words: COVID-19, pandemic, economic recovery, nowcasting, financial markets, Viet Nam

JEL classification: C53, F47, G01, G17

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1 Introduction

COVID-19 has caused havoc worldwide, in both health and economic terms. In its World Economic Outlook published in October 2020 the International Monetary Fund (IMF) predicted a contraction of -4.4 per cent in global real GDP in 2020, against an average real growth rate of 3.8 per cent in the period 2000–19 (IMF 2020). This will be 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). 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 co-movements 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. 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 et al. 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 public finances. The business of forecasting recovery trajectories from crises is generally in the hands of international organizations 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.

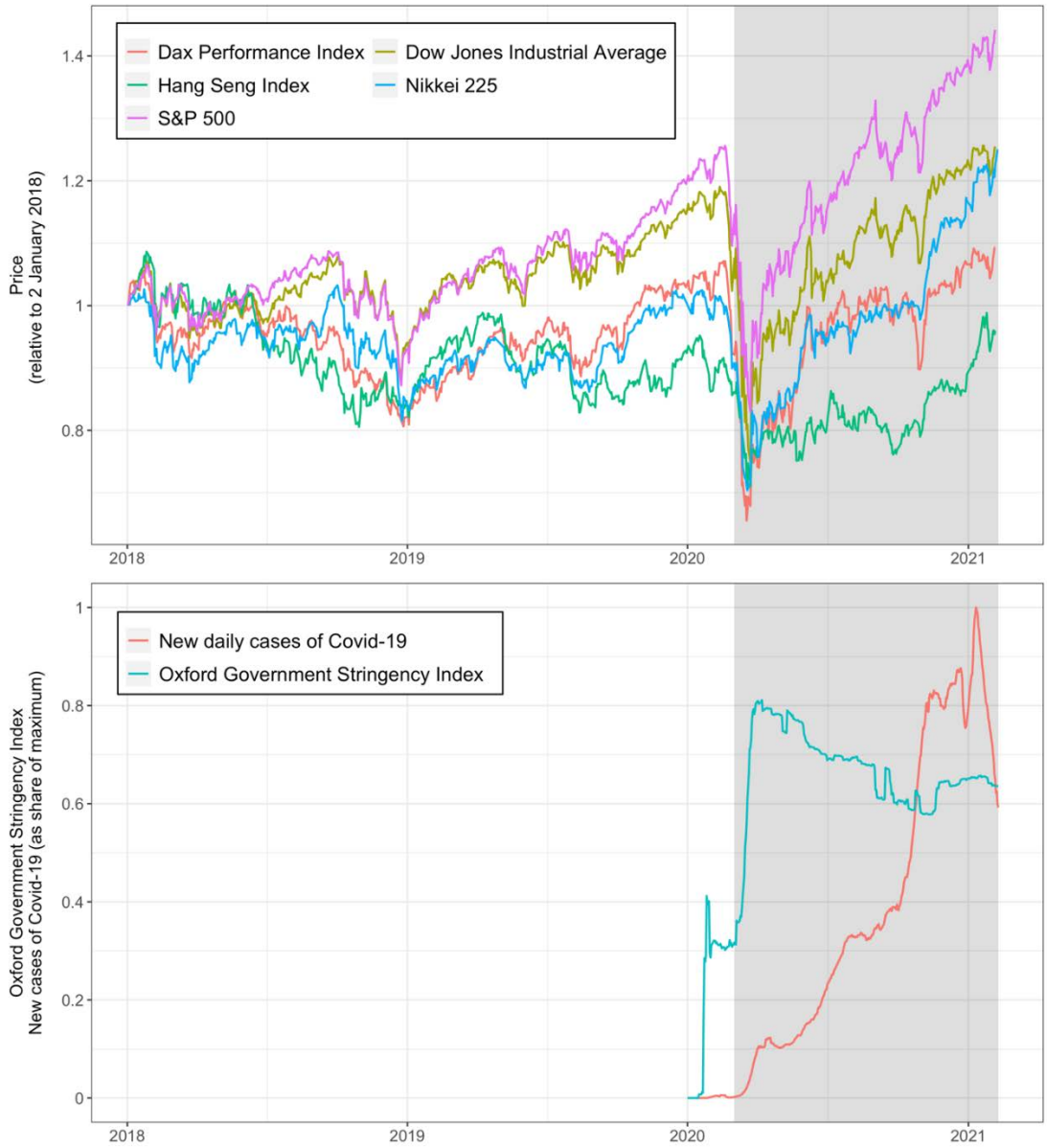
In this paper we develop a new method for projecting recovery from COVID-19 by industry, based on simple, publicly available information. The method elicits expectations about the unfolding of the crisis from financial data, under the assumption that, at a global level, variations in sectoral indexes in 2020 have been mainly driven by news about COVID-19. This 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 authorization—were announced on 18 November 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.

Figure 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.

Figure 1: Evolution of financial performance indexes, January 2018–February 2021, vs. new cases of COVID-19



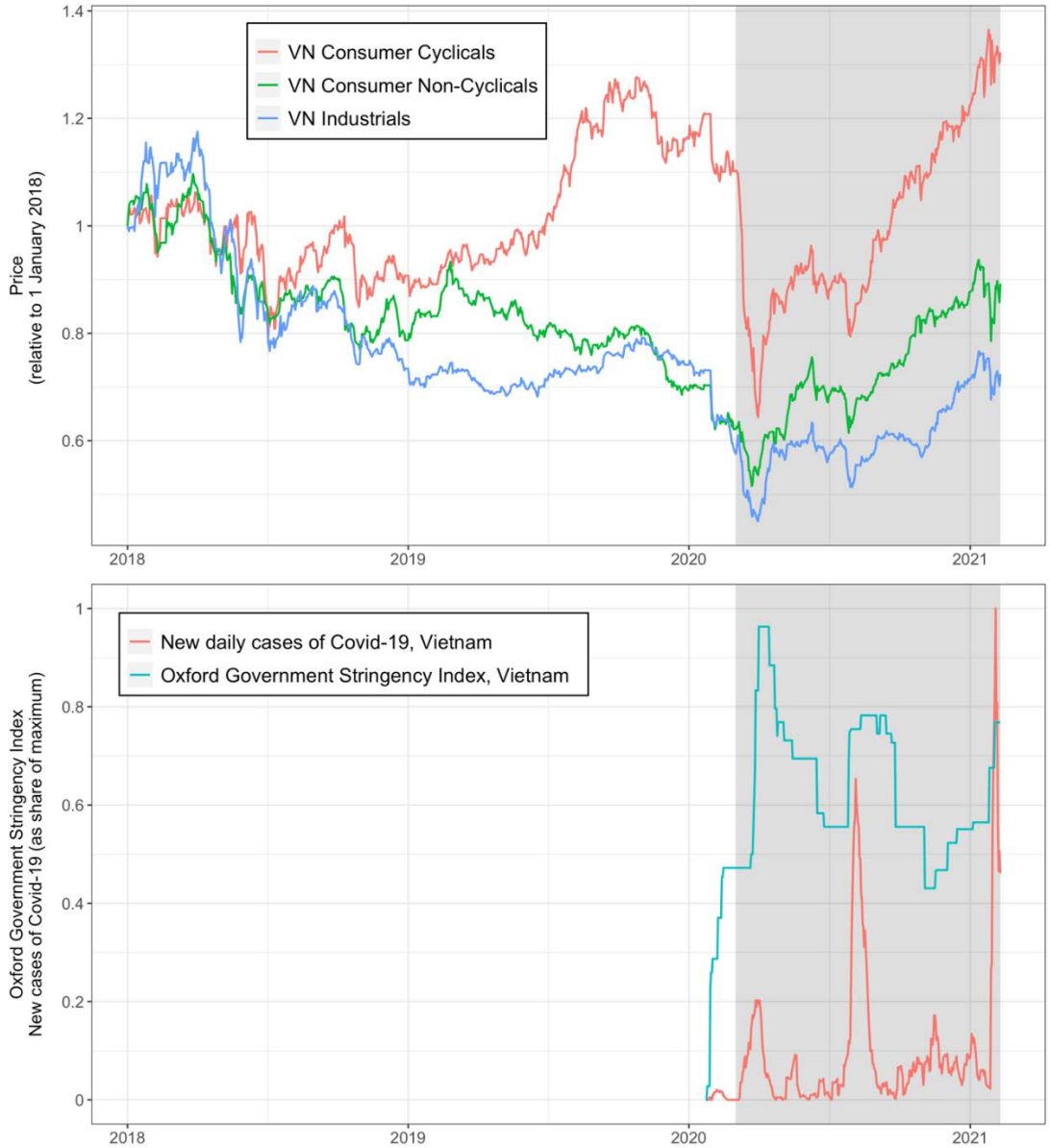
Note: index closing prices are normalized to 1, starting on 2 January 2018 (top); population-weighted Oxford Government Stringency Index and smoothed new cases of COVID-19 around the world as a share of maximum cases (bottom).

Source: authors' computation based on Yahoo Finance (top) and Our World in Data, Johns Hopkins University (bottom).

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. Figure 2 shows the same information as Figure 1 for Viet Nam, 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.

Figure 2: Evolution of sectoral stock indexes from January 2018 until February 2021 vs. new cases of COVID-19



Note: closing prices normalized to 1, starting on 1 January 2018 (top). Oxford Government Stringency Index and smoothed new cases of COVID-19 in Viet Nam as a share of maximum cases (bottom).

Source: authors' computation based on Refinitiv Eikon (top) and Our World in Data, Johns Hopkins University (bottom).

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 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 badly affected by the crisis. This, ceteris paribus, increases the stock market value of these companies, but does not imply a faster recovery. 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 driven 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 Viet Nam. Viet Nam is one of 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 Viet Nam 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 (coming almost exclusively from exports) Viet Nam is ranked 8th in the world for trade openness, after Luxembourg, Hong Kong, Singapore, San Marino, Djibouti, Malta, and Ireland.

Our choice of Viet Nam 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 realizations. 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 Viet Nam in 2020 with respect to trend.[1] Feeding the model with Q3/2020 data, and using financial data available until 28 December, brings this estimated annual shock to -3.8–4.0 per cent (point estimate -3.9 per cent). At the time of writing, the General Statistical Office (GSO) of Viet Nam has just published its preliminary GDP figures for 2020, which imply a full-year contraction of -4.0 per cent with respect to trend.[2] 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,

[1] 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.

[2] A -4.0 per cent trend reduction corresponds to a 2.5 per cent growth rate in 2020. Note that, 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.

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 organizations and private companies. In October, the IMF (2020) estimated that real GDP in Viet Nam 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).[3]

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 organized as follows. Section 2 is devoted to reviewing macro-projection methods. Section 3 presents our approach, 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.'[4] 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.[5] Only five references are cited, the most recent dating back to 2006.

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[3] The various trend reduction and corresponding real growth estimates for GDP in 2020 include: a -4.1 per cent trend change or 2.4 per cent GDP growth (our September 2020 point estimate); -4.0 per cent or 2.5 per cent (official data); -4.9 per cent or 1.6 per cent (IMF, October); -4.2 per cent or 2.3 per cent (Atradius, November); -4.7 per cent or 1.8 per cent (ADB, September); -4.0–4.5 per cent or 2.0–2.5 per cent (government growth targets, September).

[4] OECD (2011) Forecasting methods and analytical tools. www.oecd.org/economy/outlook/forecastingmethodsandanalyticaltools.htm (accessed 6 January 2021).

[5] 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.

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.

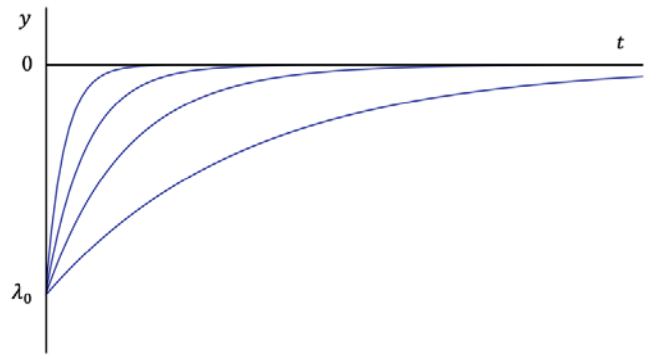
3 Eliciting expectations from financial markets

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. Our starting point is that changes in financial values are proportional to changes in the expected flows of future profits. We make the assumption that the reduction in future profits due to COVID-19 is in turn 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 follow a negative exponential trajectory:

$$y_t^e = -\lambda_0 e^{-gt} \tag{1}$$

where output loss y_t^e is measured against its de-trended pre-crisis level and λ_0 is the level of the initial loss. This assumption, like all subsequent steps in the analysis, is implemented at the level of individual industries; we have omitted the related subscript from the formulas for brevity. Figure 3 depicts alternative recovery trajectories, with different values of g, starting from an initial shock of λ_0. Higher values of g correspond to more V-shaped recoveries, while lower values of g correspond to more linear recoveries.

Figure 3: Recovery trajectories, different values of g



Source: authors' construction.

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, opportunely discounted. This corresponds to the present value of the output losses:

$$L_0 = \int -\lambda_0 e^{-g_i t} \delta^t \, dt = -\frac{\lambda_0}{g - \ln(\delta)} < 0 \tag{2}$$

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 to compute g from (2):[6]

$$g = \ln(\delta) - \frac{\lambda_0}{L_0} > 0 \tag{3}$$

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):

$$y^e_{t,yearly} = \left(\frac{365}{t}\right) \int_{t=0}^{t} -\lambda_0 e^{-gt} \delta^t dt = -\left(\frac{365}{t}\right) \frac{\lambda_0 - \lambda_0 e^{-gt} \delta^t}{g - \ln(\delta)} \tag{4}$$

In (4), the initial shock λ_0 is parameterized by the observed shock to output over the latest time period available, t_0. In the context of our application to Viet Nam, this initial shock is first calculated by comparing quarterly output in Q2/2020 with quarterly output a year earlier, in

[6] Note that we require $g > \ln(\delta)$ based on formula (2), 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, $L_{0,limit} = -0.005$. This causes the recovery trajectory for output, derived in formula (4), to approach zero gradually. 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.

Q2/2019, but uprating the latter by the average annual growth rate of (industry-level) output before the pandemic, $\Delta Y_{preCOVID}$:[7]

$$\lambda_{Q2/2020} = -\frac{Y_{Q2/2020} - Y_{Q2/2019}\,(1+\Delta Y_{preCOVID})}{Y_{Q2/2019}\,(1+\Delta Y_{preCOVID})} > 0 \tag{5}$$

Note that data on output are updated less frequently than financial data, which are available in real time. We can then make the assumption that the recovery in output follows the trajectory predicted by equation (4) and then update our projections using financial data only. The updating procedure is implemented in each subsequent period t (with available financial data) by replacing L_0 in equation (3) with its observed value L_t, and λ_0 in equations (3) and (4) with its latest projected value $\lambda_t = y^e_{t,yearly}$. 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 Viet Nam. This also applies to financial loss $L_{t,i}$ at time t, which is parameterized by the percentage change in the biweekly average of daily mean prices ($p_{t,i}$) of a given sectoral stock index i from its January 2020 average ($\bar{p}_{preCOVID,i}$):

$$L_{t,i} = \frac{p_{t,i} - \bar{p}_{preCOVID,i}}{\bar{p}_{preCOVID,i}} < 0 \tag{6}$$

Daily stock prices are de-trended before these calculations using the average annual growth rate in each sectoral stock index in 2015–19, $\Delta p_{preCOVID,i}$, where the average rate is calculated from the growth trend. The rate used for de-trending a given stock price t days after 1 January 2020, is simply:

$$\rho_{t,i} = (1 + \Delta p_{preCOVID,i})^{\frac{t}{365}} - 1 \tag{7}$$

We also use these prices to compute the 95 per cent confidence interval around the recovery trajectory. This is achieved by first calculating the standard deviation $\sigma_t(p)$ of daily stock prices over each two-week period after $t = 0$. The uncertainty around the longer-term price trajectory, for each stock index, is modelled as a Gaussian random walk. Accordingly, after the initial shock at $t = 0$ (where $\sigma_0(y^e_t) = 0$ and stock data are not required), 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 the trajectory for output loss ($y^e_{t,yearly}$) via equation (3), to derive parameter g at the limits, and then equation (4), to derive output loss at the limits.[8]

Finally, note that, under the application where GDP shocks are updated quarterly, the last prediction for the level of output loss, $y^e_{t,yearly}$, before the next shock update, denotes the estimated reduction in that quarter's GDP from trend. Then, with predictions relying on Q2/2020 GDP and financial data, for instance, we can derive quarterly output shock estimates for Q3/2020,

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[7] In our preferred estimates, $\Delta Y_{preCOVID}$ is the average annual growth rate in a sector over the 2015–19 period. We also calculate the shock to Q2/2020 to compare our predictions from this older data with the more recent, realized, recovery trajectory.

[8] Note that due to the transformation in equation (3), the uncertainty fan around parameter g_t and estimated output loss y^e_t are not symmetric around the mean.

Q4/2020, and beyond. Our estimate for *annual* GDP loss is the weighted average of the estimated quarterly GDP shocks for that year, where weights are the shares of output produced in each quarter of 2019.

In the case illustrated above, the estimated GDP loss from trend for 2020 is the weighted average of shocks in Q1 and Q2 (from GDP data and counterfactual growth trends in stock prices) and Q3 and Q4 (from the model).

Also note that we derive the biweekly shock estimates for the full economy as the weighted average of industry-level shocks, where weights are the GDP shares for different sectors in 2019.

4 Data

4.1 Industry-level GDP

We test our method using data from Viet Nam. The quarterly industry-level GDP data, used to derive the output shocks resulting from the pandemic, come from the General Statistical Office (GSO) of Viet Nam.[9] We use information from all 20 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 1, 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.

Table 1: Industries used

Industry	GDP share (2020)	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	Viet Nam	19%
Administrative and supporting activities				
Art, entertainment and recreation				
Real estate				
Self-employment and self-consumption				
Other services				
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	Viet Nam	15%
Activities of the Communist Party; socio-political organizations; public administration and defence; compulsory social security				
Education and training				

[9] General Statistics Office (GSE), Viet Nam. Data available at: https://www.gso.gov.vn/en/data-and-statistics/.

Utilities *Electricity, gas, steam and air-conditioning supply* *Water supply, sewerage management and waste treatment*	6%	Utilities	Asia-Pacific *(no domestic index available)*	14%
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 Viet Nam 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 4); Refinitiv Eikon (2020, columns 2 and 3); Asian Development Bank (2018, column 5).

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 Viet Nam. 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 2 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 output shocks for 2020, as measured in the official data in early 2021.

Table 2: Average annual growth rate and de-trended output shocks

Industry	**AAGR, 2015–19**	**Output shocks**				
		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 shocks with respect to trend, computed using output levels from official data, and counterfactual levels using the 2015–19 growth rates of Column 1.

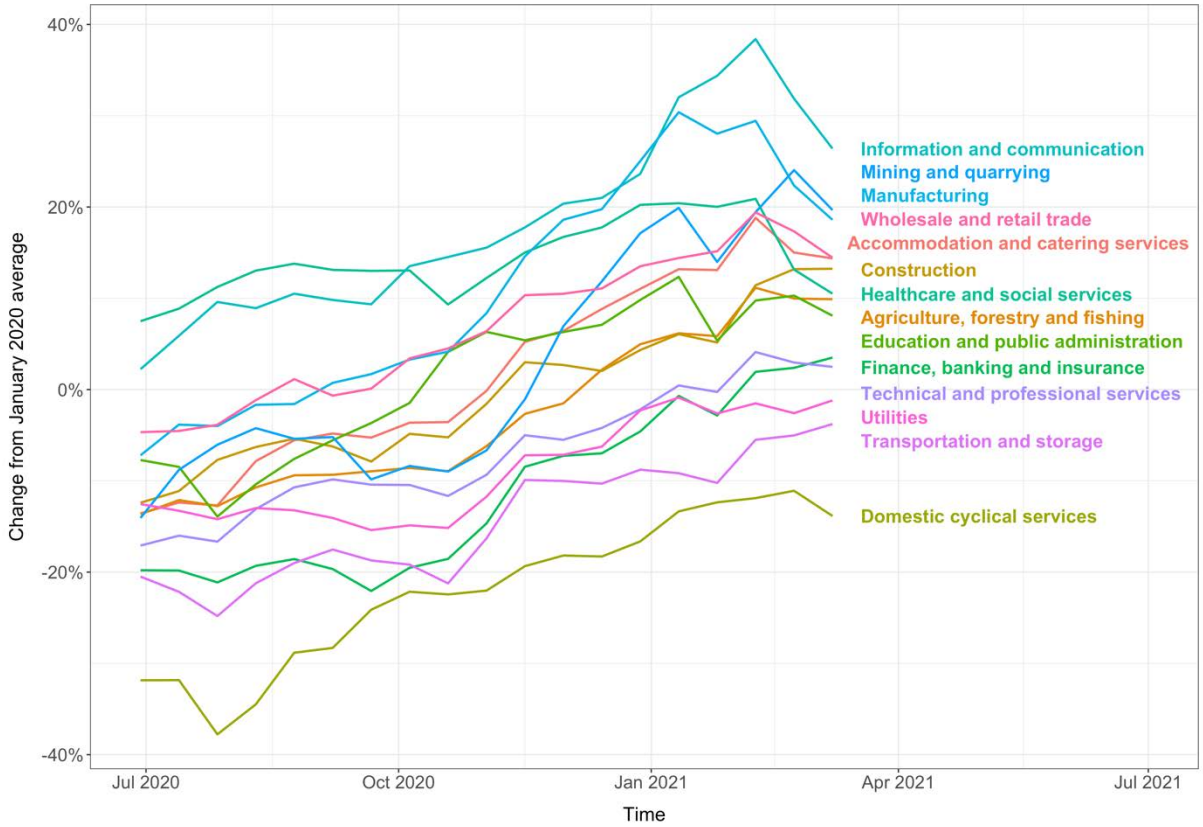
Source: authors' computation based on GSO 2020–21 data.

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 sectoral indexes are available only for broad aggregates for many developing countries, motivates our claim that our method is better suited for a small, export-led economy, and contributes to our choice of Viet Nam 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 1 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. Figure 4 shows the evolution of the sectoral indexes, where indexes are denoted by the name of the corresponding sector used in the analysis.

Figure 4: Evolution of sectoral indexes for Viet Nam and the Asia-Pacific region



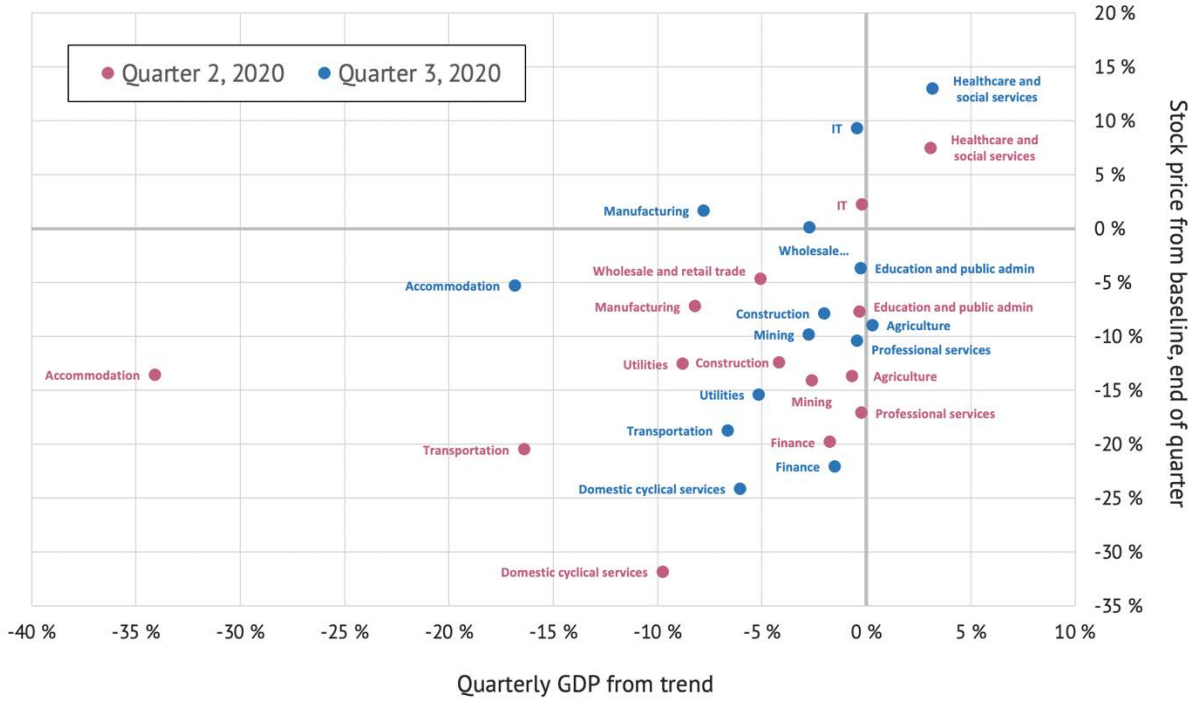
Note: price levels are biweekly averages as a change from the January 2020 average, de-trended using the average annual growth rate in each index from 2015 until the end of 2019 (see Figure A1 in Appendix).

Source: authors' computation based on Refinitiv Eikon.

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 Viet Nam'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. Figure 5 shows that this condition is generally satisfied in our data. Using industry-level observations from the second and third quarters of 2020, Figure 5 plots quarterly output shocks (deviations in 2020 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 in the first and third quadrants, where financial and output shocks are either both positive or both negative. The positive correlation between financial and output shocks is also visible in the graph.

Figure 5: Financial gains or losses vs. output shocks in quarters 2 and 3, 2020



Source: authors' construction based on data from Refinitiv Eikon and GSO.

5 Results

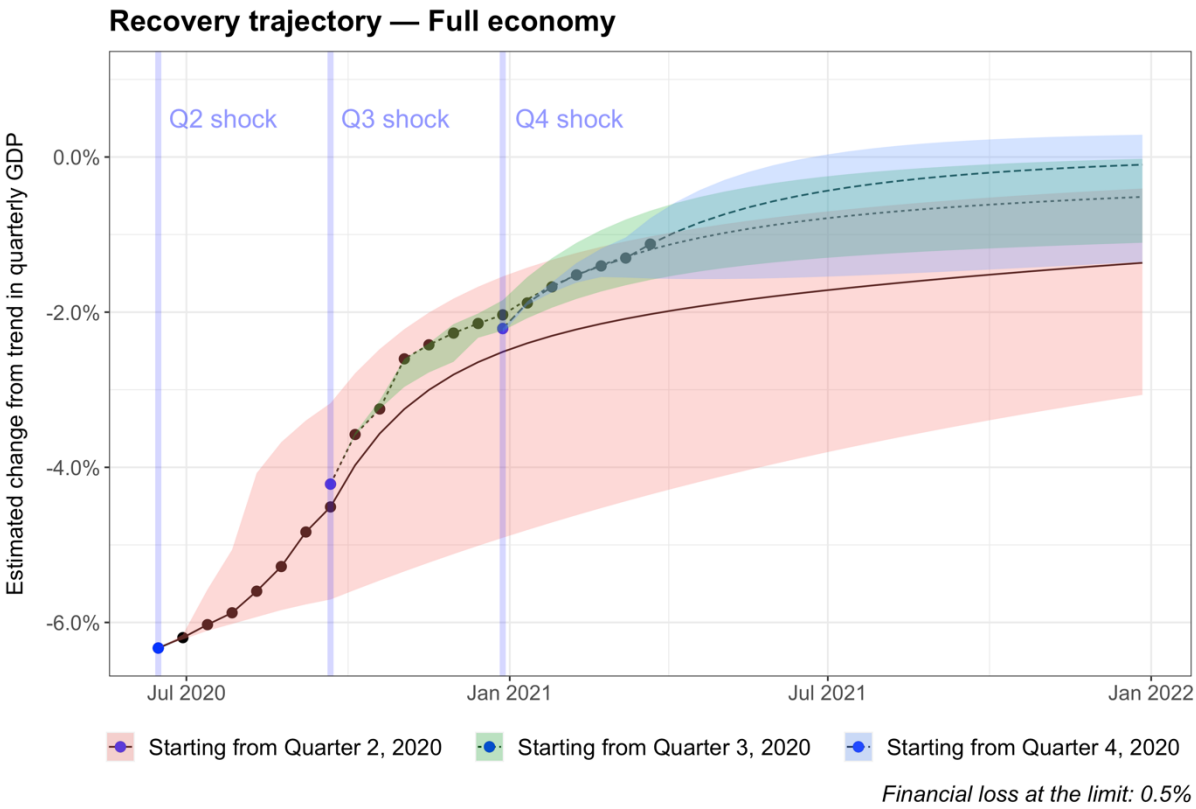
5.1 Economy-wide results

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

Figure 6 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 shock 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 shock 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 shock 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).

Figure 6: Estimated recovery paths for Viet Nam



Note: chart shows deviations from trend in quarterly GDP, under three sets of data: (1) shock estimated for Q2/2020 (blue point) and financial data up to the end of the third quarter; the red-shaded area measures statistical uncertainty due to financial data volatility; (2) shock estimated for Q3/2020 (blue point) and financial data up to the end of the fourth quarter, with green-shaded uncertainty; (3) shock estimated for Q4/2020 (blue point) and financial data up to 18 March 2021, 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.

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 GDP shocks 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 shock for Q2/2020 and financial information up to Q3/2020 imply a yearly contraction of -4.1 per cent [-3.5 per cent to -5.2 per cent] from trend. The updated quarterly shock for Q3/2020 and financial data up to Q4/2020 imply a shock of -3.9 per cent [-3.8 per cent to -4.0 per cent]. Our estimated annual shocks match recent GDP figures published by the General Statistical Office of Viet Nam in early 2021, which show that the actual 2020 GDP shock with respect to trend was -4.0 per cent.

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 ($-\lambda_t < 0$ and $L_t < 0$) or both positive ($-\lambda_t > 0$ and $L_t > 0$). 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, $L_{0,limit} = -0.5\, per\ cent$, 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 3 reports our estimates for trend reductions from quarterly and annual GDP compared with the data, under 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.

Table 3: Model predictions vs. data, with varying values for financial loss threshold

	Estimates with varying financial loss thresholds		
Model prediction or data	**(1)**	**(2)**	**(3)**
Financial loss threshold	*-1.0%*	*-0.5%*	*-0.1%*
Annual GDP shock *(Model based on Q2 data)*	4.3% [3.7%–5.2%]	4.1% [3.5%–5.2%]	3.9% [3.1%–5.2%]
Annual GDP shock *(Model based on Q3 data*)	4.0% [4.0%–4.1%]	3.9% [3.8%–4.0%]	3.7% [3.5%–3.7%]
Annual GDP shock *(Actual data*)	4.0%	4.0%	4.0%
Quarterly GDP shock in Q3 *(Model based on Q2 data*)	4.7% [3.8%–5.7%]	4.5% [3.2%–5.7%]	3.8% [2.2%–5.7%]
Quarterly GDP shock in Q3 *(Actual data*)	4.2%	4.2%	4.2%
Quarterly GDP shock in Q4 *(Model based on Q2 data*)	2.8% [1.9%–4.9%]	2.5% [1.5%–4.9%]	2.4% [1.2%–4.9%]
Quarterly GDP shock in Q4 *(Model based on Q3 data*)	2.4% [2.4%–2.6%]	2.0% [1.8%–2.2%]	1.4% [0.9%–1.5%]
Quarterly GDP shock in Q4 *(Actual data*)	2.2%	2.2%	2.2%

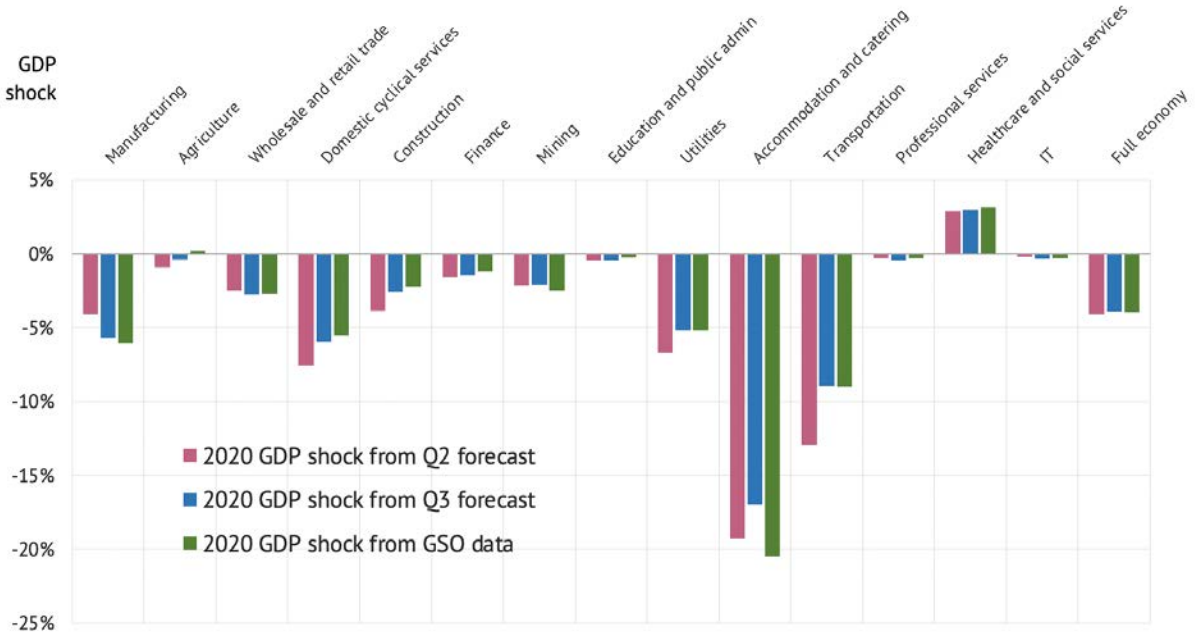
Note: shocks present reductions in GDP from trend. 95% confidence intervals in brackets.

Source: authors' construction.

5.3 Selected industry-level results

In this section, we compare industry-level recovery trajectories and particularly the shocks predicted by the model with shocks derived from GSO's GDP data. These comparisons are shown in Figures 7–9. 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.

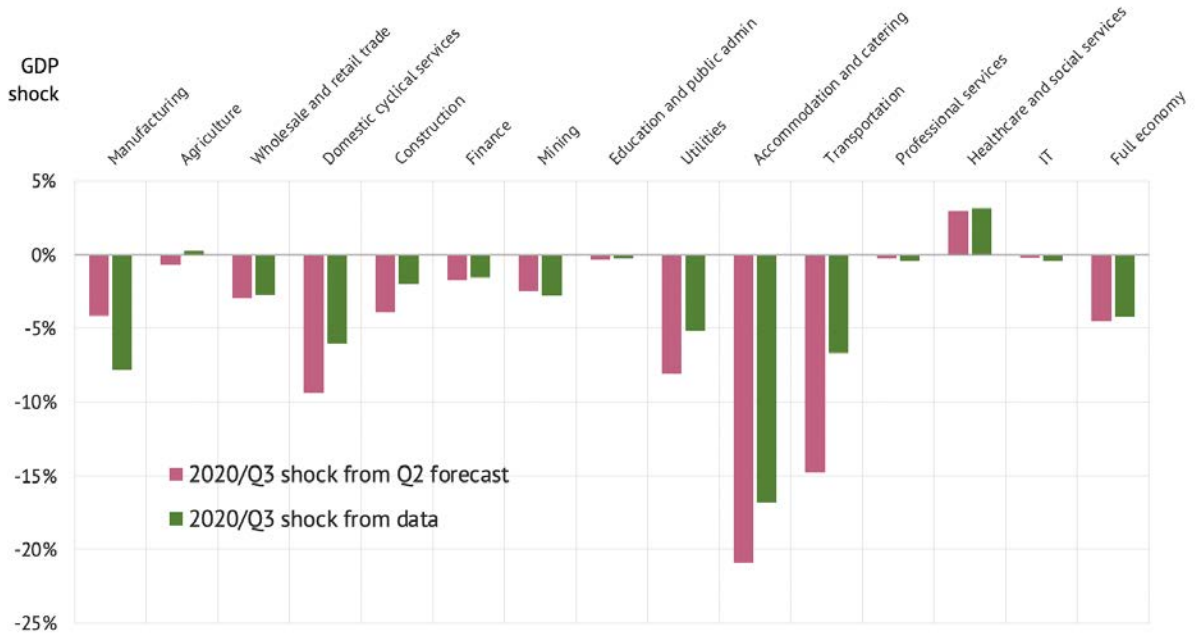
Figure 7: 2020 GDP shocks, early model predictions vs. GSO data from 2021



Note: all results use a financial loss threshold of -0.5%.

Source: authors' construction.

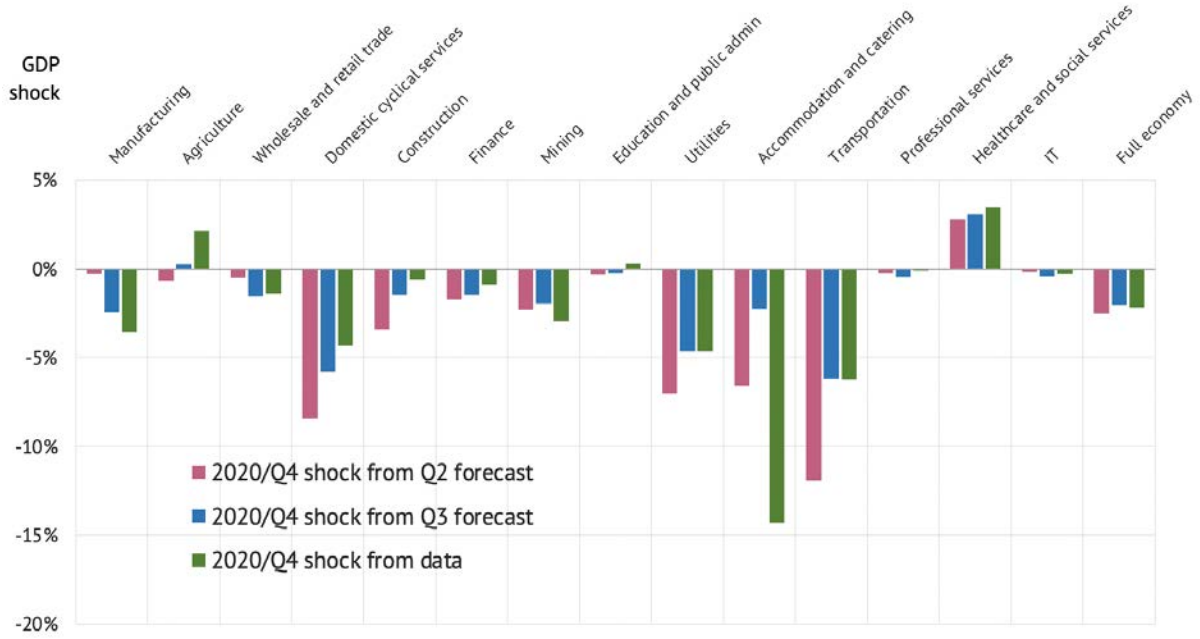
Figure 8: 2020 Quarter 3 GDP shocks, early model predictions vs. GSO data



Note: all results use financial loss threshold of -0.5%.

Source: authors' construction.

Figure 9: 2020 Quarter 4 GDP shocks, early model predictions vs. GSO data



Note: all results use financial loss threshold of -0.5%.

Source: authors' construction.

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 industry-level shocks, 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 shocks in economic output and extend them into the future.

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

Viet Nam 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 realizations. Full validation of the method requires testing it in multiple settings and over multiple timeframes—something that we have to leave for future research.

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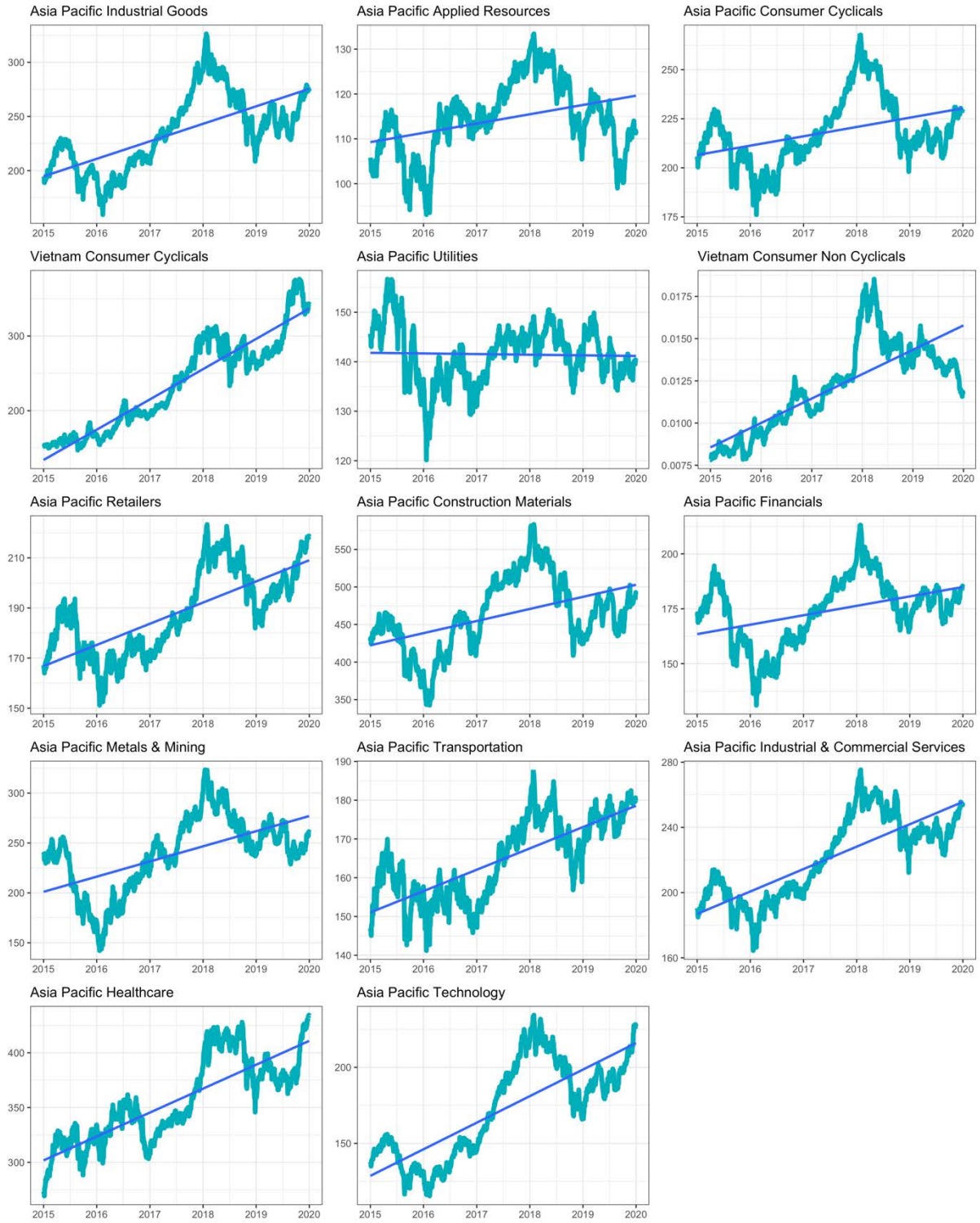
Appendix

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

Figure A1: Prices of sectoral stock indexes from 2015 to the end of 2020



Source: authors' construction.