Economic forecasting in Singapore: The Covid-19 experience

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Special Feature B

Economic Forecasting in Singapore: The COVID-19 Experience

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This Special Feature considers how accurately professional forecasters have predicted GDP growth and inflation in Singapore, especially during rare events such as the Global Financial Crisis (GFC) and COVID-19. It also illustrates the value of forecast probability distributions in inferring forecasters' uncertainty when making predictions, and the degree of consensus between projections from different forecasters. The authors find that one-year ahead forecast errors for GDP growth and inflation increased during the GFC and the COVID-19 pandemic. While professional forecasters did not appear to have followed the Government's forecasts when predicting growth during the GFC, they may have exhibited "leader-following" behaviour when forecasting growth and inflation during COVID-19. Similarly, forecasters appear to exhibit herding behaviour during both crises. During the pandemic, moreover, the rise in forecast uncertainty was traced to a more volatile economic policy environment. Collectively, the paper's results suggest that inflation expectations were well-anchored throughout the sample period.

1 Introduction

Even in the best of times, economic forecasting is a challenging endeavour. But the difficulties are accentuated during relatively rare events such as a financial crisis or a pandemic because the past is a less reliable guide to the future. A good example is the GFC of the late 2000s which was triggered by financial market tumult. Alessi *et al.* (2014) found GDP growth forecasts to be markedly overestimated by the European Central Bank and the Federal Reserve Bank of New York during the crisis, with a more than doubling of conventional forecast evaluation statistics compared to pre-GFC levels. Moreover, professional forecasters consistently overestimated economic growth and inflation in the early 2010s (Lewis and Pain, 2015).

Another case in point is the COVID-19 pandemic, which broke out in March 2020 and spread across the world in staggered waves of infection, bringing economic devastation in its wake. The difficulty in making economic forecasts during the pandemic crisis is compounded by the unprecedented nature and scale of the epidemic, as well as the reimposition of movement control measures whenever a new wave of infection occurred. Given this, it would not be surprising should there be widespread forecast failure.[2]

Fundamentally, the forecasting difficulties can be traced to the basic characteristics of an epidemiological outbreak. The SARS pandemic of 2003 which hit Singapore badly was

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[2] Forecast failures refer to larger than usual forecast errors.

quickly found to be a poor template for what was unfolding, since it was confined to Asian countries and rapidly contained. Furthermore, the biological nature of the COVID-19 crisis meant that forecasters could not take their cue from the usual economic indicators and information sources such as business intelligence. Most importantly, the pandemic produced economic disruptions that interacted in unknown ways, unlike in previous recessions or even financial crises when only an aggregate demand or supply shock was at work. In other words, the interplay of macroeconomic forces was exceptionally difficult to grasp and quantify, with indeterminate effects on economic growth and price inflation. The tools that economists employ to generate projections—and the macroeconomic relationships they relied on in the past—may simply be inadequate to the task.

In this Special Feature, a survey of professional forecasters in Singapore collated by the central bank is used to study whether the forecast record during the pandemic is a break from the past. Specifically, the COVID-19 experience is contrasted with that during the GFC with respect to behavioural explanations of forecast failure, consensus and uncertainty among forecasters, and the relationship between subjective and objective uncertainty. Such a study is instructive because it sheds light on how forecasters in Singapore, a small economy that is highly open to trade and investment, dealt with the negative shocks triggered by COVID-19 that originated from abroad and were transmitted domestically. Thus, the local community of forecasters faced the daunting task of predicting the evolving impact of the pandemic on the global economy and its spillover effects onto Singapore, in addition to the consequences of internal infection prevention measures.

To this end, survey forecasts of GDP growth and CPI-All Items inflation were subject to various empirical analyses. Previous studies on assessing the performance of professional forecasters in Singapore had tended to focus on point predictions only (see for instance Monetary Authority of Singapore, 2007, 2014). By contrast, this paper analyses both point forecasts and forecast probability distributions and also extends the sample period of the investigation to include the COVID-19 episode.

2 Data Description

The economic forecasts analysed in this paper are taken from the Monetary Authority of Singapore's (MAS) Survey of Professional Forecasters*,* which provides a rich source of information on the private sector's point forecasts of key macroeconomic variables in Singapore such as real GDP, CPI inflation, the unemployment rate, private consumption, and exports. The first two of these variables are reported with probability distribution forecasts. The central bank's survey began in the last quarter of 1999 and since then, it has regularly polled local forecasters for their short- to medium-term outlook on the economy.

The identities of the 20–30 individuals (or institutions) participating in each survey are confidential, but they consist almost exclusively of professional economists in the Singapore financial sector who work for banks, investment houses and economic consultancies.[3] Each respondent is assigned a unique identification number so that his forecasts can be followed over time (respondents may drop out or new ones added). A standard questionnaire is sent to participants every quarter following the release to the public of the latest official economic data that constitutes a key reference in information sets. Survey findings are announced in

[3] There was academic participation in the survey in the early years.

the first week of the months of March, June, September, and December each year and posted on the MAS website.

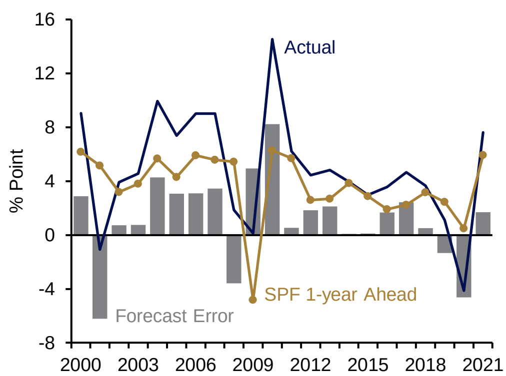
For the purposes of this Feature, attention is focused on the point and probability distribution forecasts of the real GDP year-on-year growth rate and the CPI annual inflation rate, i.e., changes in these two variables from one year to the following year. There are three types of point forecasts with varying time horizons, namely, a rolling horizon forecast for one quarter ahead and two fixed event forecasts. The first fixed event forecast is produced within a given year for the current year's outcome, that is, a projection with a moving time horizon of one quarter to four quarters. The second is a forecast produced within a given year for the next year's outcome, with time horizons of five to eight quarters. As rolling horizon forecasts do not come with probability distributions and are only available for CPI inflation from Q4 2017, the analysis is confined to fixed event forecasts with horizons of one and two years. These are available for the entire sample period Q1 2000–Q4 2021, except for a gap of five years from 2005 to 2009 when the following year's projections were not reported for inflation. The probability distribution forecasts were introduced in Q3 2001 for growth and Q4 2017 for inflation.

The benchmark data against which the accuracy of the professional forecasts is assessed and the behaviour of the forecasters is evaluated are the official statistics published by the Singapore government. In this regard, the use of revised data may yield different conclusions from real-time data as forecasters typically make predictions of the early releases of statistics rather than their final versions (Keane and Runkle, 2018). Although inflation data in Singapore is not revised, GDP data is but its real-time vintages are not available to the public. Consequently, revised data is used in the empirical analyses.

3 Behavioural Explanations of Forecast Failure

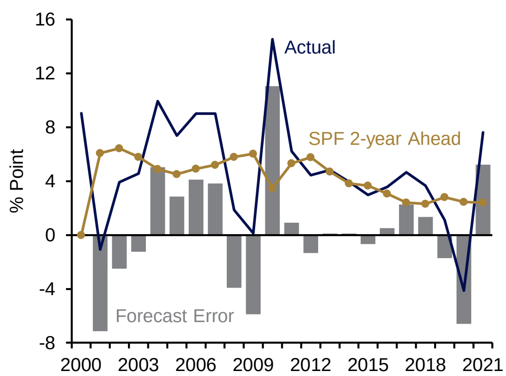
A tentative hypothesis of this study is that forecast failure during the COVID-19 pandemic is worse than in the GFC due to different underlying causes. **Charts 1 and 2** plot the means of the one and two-year ahead forecasts of survey respondents made in the first quarter of each year together with the revised growth and inflation data. The forecast errors computed as realisations minus forecasts are also included in the charts. It can be seen that, in comparison with growth prediction errors, the forecast errors for CPI inflation are smaller in magnitude.

Chart 1a One-year Ahead GDP Growth Forecast



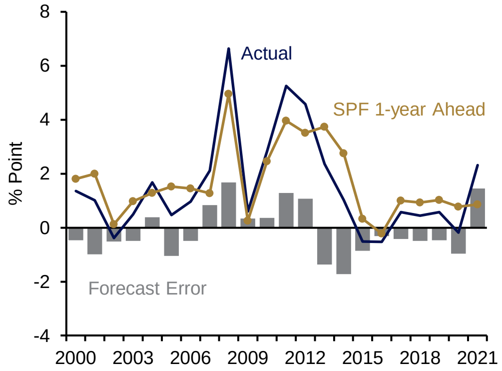
Source: MAS Survey of Professional Forecasters and DOS

Chart 1b Two-year Ahead GDP Growth Forecast



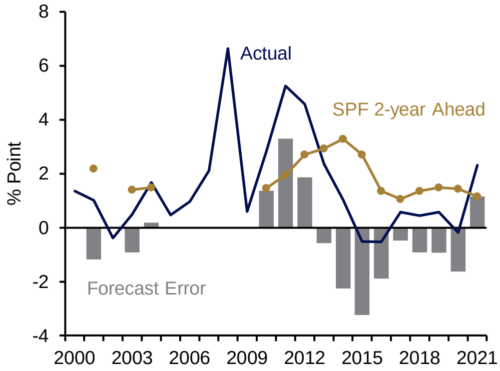
Source: MAS Survey of Professional Forecasters and DOS

Chart 2a One-year Ahead Inflation Forecast



Source: MAS Survey of Professional Forecasters and DOS

Chart 2b Two-year Ahead Inflation Forecast



Source: MAS Survey of Professional Forecasters and DOS

More formally, the root mean square error (RMSE) statistics for the growth and inflation projections at the two time horizons are reported in **Table 1**. These are computed separately for the two crisis episodes and the normal or non-crisis period. The sub-sample periods for the GFC and the COVID-19 pandemic are defined as Q3 2008–Q4 2009 and Q1 2020–Q4 2021 respectively, with the remainder of the sample being the normal period. The table shows that the forecast error in predicting growth during the COVID-19 epidemic exceeds that in normal times but not during the GFC for both time horizons. The situation is less clear-cut for CPI inflation, as the one-year ahead prediction errors during the pandemic are larger than those during the GFC and non-crisis periods but the reverse is true for the two-year ahead forecast errors. Although the lack of observations precludes formal testing of the differences in RMSE for statistical significance, they are indicative of the unparalleled challenges encountered by Singapore's professional forecasters in making predictions during the GFC and the COVID-19 pandemic.

Table 1 Root Mean Square Forecast Errors (% point)

	GDP Growth		CPI Inflation	
Period / Forecast Horizon	One-Year	Two-Year	One-Year	Two-Year
Normal	3.26	3.60	1.01	1.80
GFC	5.03	11.10	0.90	1.62
COVID-19	3.44	5.28	1.28	1.19

Source: Authors' estimates, MAS Survey of Professional Forecasters and DOS

Turning to behavioural explanations, the forecasts made during the two crisis episodes are first tested for evidence of bias, with the implication that survey participants did not use information efficiently. In this regard, an earlier study has shown that GDP growth forecasts tended to be unbiased prior to the GFC, but inflation forecasts were not (Monetary Authority of Singapore, 2007). Following Holden and Peel (1990), the presence of bias during the GFC and COVID-19 is tested by running pooled regressions on the individual forecast errors of survey participants at the one and two-year horizons. The results indicate that forecasters in Singapore produced biased growth forecasts during the GFC, which was also the case in the

OECD countries (Lewis and Pain, 2015). While growth forecasts tended to be too low during the GFC, they turned out to be unbiased during the pandemic. As for inflation forecasts, positive bias was detected by two-tailed *t*-tests at the 5% significance level during both crises, suggesting that forecasters underpredicted inflation.

There are two possible explanations for the biased forecasts made by the MAS survey respondents. First, they could exhibit what the literature has dubbed "leader-following" behaviour. Here, it refers to forecasters being influenced by official forecasts, thereby suppressing private information. In Singapore, official forecasts of current and next year GDP growth and CPI inflation are expressed as ranges of possible values (not to be interpreted as probability density forecasts).[4] Forecasters could choose to locate their point estimates in or out of the ranges, depending on their views—which might or might not coincide with those of the authorities—or the extent to which they were swayed by the government's outlook.

To determine whether there is a tendency for participants to depart from the official forecasts of growth and inflation during the GFC and COVID-19, the number of occasions over each crisis period in which the individual forecasts from the MAS survey fell outside the ranges is counted. Under the null hypothesis that the government's projections did not influence private sector predictions, the conditional probability of overshooting or undershooting the official ranges is 0.5 (Rülke *et al.*, 2016). Combining the current and next year predictions for which official forecasts are available, the computed proportions are recorded in **Table 2**. The results show that the proportion of growth forecasts that were out of the official ranges during the GFC was not significantly different from 0.5 at the 5% significance level although the proportion of inflation forecasts was, implying that survey participants exercised some independence from the government's views. By contrast, there is very strong evidence that the corresponding proportions of growth and inflation forecasts were close to zero during the COVID-19 crisis, indicating the tendency for participants to stay within the official forecast ranges.

Table 2 Test Results for Leader-following Behaviour

	GDP Growth		CPI Inflation	
	Z-test	Proportion	Z-test	Proportion
GFC	1.41	6/8	2.24***	0/5
COVID-19	2.20***	1/9	2.24***	0/5

Source: Authors' estimates, MAS Survey of Professional Forecasters, the Economic Survey of Singapore (GDP growth) and the MAS Macroeconomic Review (CPI Inflation)

Note: *** denotes statistical significance at the 1% level. The numbers in the proportion columns are ratios of forecasters whose predictions are different from official forecasts.

A second explanation of bias on the part of the forecasters is "herding behaviour". Being a relatively small group with professional and social ties, there are pecuniary and reputational incentives for forecasters to influence each other, deviate from their own opinions and follow the crowd. An individual forecaster may do this to avoid making extreme forecasts, or because a wrong forecast may not damage his reputation if other forecasters also delivered poor forecasts (Rülke *et al.*, 2016). However, it is difficult to distinguish between herding

4 The forecasts issued by the government are culled from various issues of the Economic Survey of Singapore (GDP growth) and the MAS Macroeconomic Review (CPI inflation).

behaviour and reliance on a common information set among forecasters which may result in undifferentiated projections. On the other hand, a forecaster may behave in a "contrarian" or anti-herding manner if by doing so, he can enhance his standing in the event his projection turns out to be correct, or to gain publicity (Pons-Novell, 2003). Such a strategic bias has been observed among older and more established practitioners, as compared to novices (Lamont, 2002).

In the context of this study, a reasonable hypothesis will be that participants in the MAS survey tended to herd in times of heightened economic uncertainty such as the GFC and the COVID-19 pandemic. The presence of herding behaviour in fixed event forecasts is investigated using a testing methodology adapted from Pons-Novell (2003), and based on the observed difference between the individual and consensus forecasts made at the start of each year, which should be statistically indistinguishable from zero if a forecaster practised herding behaviour. Due to the small number of observations available for the GFC and COVID-19 periods, the test is carried out by again pooling the predictions of individual forecasters. In both crises and for both growth and inflation, the constant terms in the regressions are statistically insignificant at the 5% level, suggesting that forecasters exhibited herding behaviour.

In summary, it may be concluded that forecast failure during crisis periods can be attributed to bias, with the exception of growth predictions during the COVID-19 pandemic. During the GFC, the bias in growth forecasts may in turn be explained by herding but not leader-following behaviour. However, growth forecasts during the pandemic were unbiased even though the survey participants were leader-following as well as herding. Bias in the one and two-year ahead inflation projections for both the GFC and COVID-19 episodes can be traced to a combination of leader-following and herding behaviour.

4 Consensus and Uncertainty in Crises

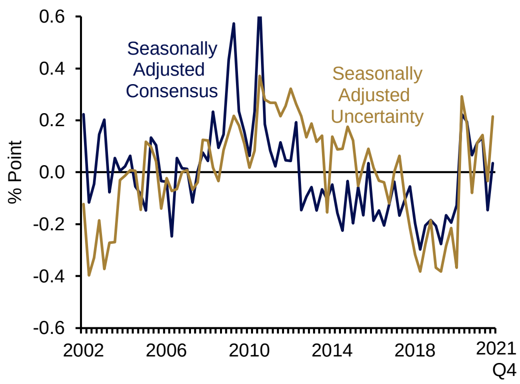
Apart from analysing point forecasts, this Feature also examines probability distribution forecasts to trace the evolution over time of consensus amongst the forecasters as a whole as well as uncertainty in individual forecasts. The probability distribution forecasts for annual GDP growth and CPI inflation returned by respondents in the MAS survey take the form of histograms with pre-assigned intervals and open-ended bins at the lower and upper ends of the distribution. The central tendency and spread of forecaster i's probability distributions are measured respectively by the median $m_{i,t}$ ($y^{(0.5)}$) and the central 68% range r_i ($y^{(0.84)} - y^{(0.16)}$), where $y^{(0.16)}, y^{(0.50)}$and $y^{(0.84)}$ are the 16th, 50th and 84th percentiles respectively. The central 68% range is called the "quasi-standard deviation" by Giordani and Soderlind (2003) and it has the attraction of being twice the standard deviation should the forecast distribution be normal. To compute these percentiles, uniform probabilities within the three bins that the individual percentiles fall into is assumed.

For each survey, the mean of the measure ($\frac{r_{i,t}}{2}$) across the panel of forecasters $i = 1,2,\ldots,n$ represents average forecaster uncertainty $U_t = \frac{1}{n}\sum_i^n \frac{r_{it}}{2}$. Meanwhile, the standard deviation of the $m_{i,t}$ measure across forecasters in each survey serves as a proxy for the lack of consensus among them $C_t = \sqrt{\sum_{i=1}^{n}\left(m_{i,t} - \mu_t^m\right)^2}$ where μ_t^m is the mean of $m_{i,t}$. To trace the changes in consensus and uncertainty, **Charts 3 and 4** present the time profiles of the C_t and U_t measures for GDP growth and inflation forecasts from Q1 2002–Q4 2021, where the series are plotted for all survey dates. To aid interpretation, seasonality in these measures is projected out *a priori* through a regression on seasonal dummy variables.

5 Comparison of COVID-19 and the GFC

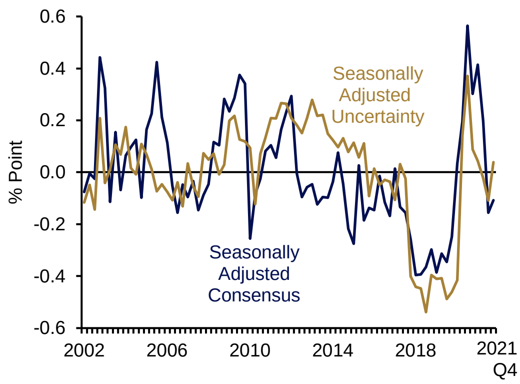
Charts 3a and 3b show that the level of disagreement amongst survey respondents with respect to current and next year growth projections were generally stable except during the two crisis periods. A rising trend in the uncertainty of current year growth projections set in from the start of the GFC until 2012, after which it reversed and uncertainty subsequently declined to low levels in 2018 and 2019. Then COVID-19 struck, whereupon a sudden and sharp increase akin to a trend break occurred. In terms of its level, the uncertainty due to the pandemic was slightly higher than during the GFC but comparable to its aftermath, although the lack of consensus measure was lower.

Chart 3a Current Year (Non-seasonal) Growth Forecast Consensus and Uncertainty



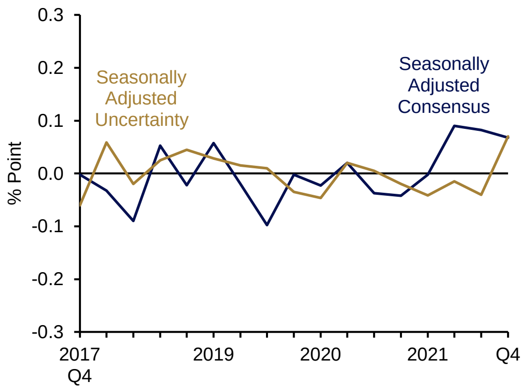
Source: Author's estimates and MAS Survey of Professional Forecasters

Chart 3b Next Year (Non-seasonal) Growth Forecast Consensus and Uncertainty



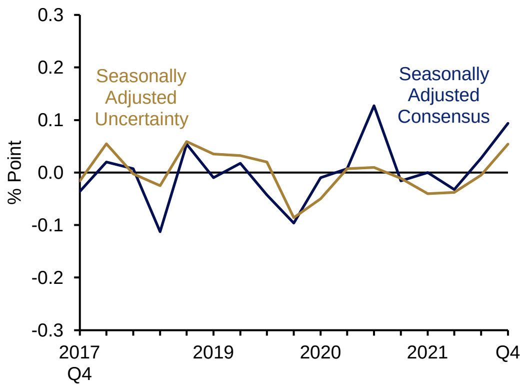
Source: Author's estimates and MAS Survey of Professional Forecasters

Chart 4a Current Year (Non-seasonal) Inflation Forecast Consensus and Uncertainty



Source: Author's estimates and MAS Survey of Professional Forecasters

Chart 4b Next Year (Non-seasonal) Inflation Forecast Consensus and Uncertainty



Source: Author's estimates and MAS Survey of Professional Forecasters

The most surprising feature of the movements in the uncertainty of current year growth forecasts is the further increase seen in 2010 and 2011. This measure was higher after the financial crisis subsided than during the crisis itself, which was likely due to the onset of the Eurozone sovereign debt crisis and the difficulty of forecasting the long-drawn recovery from the financial crisis. The sharp fall in disagreement among forecasters and decline in uncertainty in individual forecasts during 2018 and 2019 for both the one and two-year predictions at first glance seems anomalous given the rise of trade frictions between the US and China. Nevertheless, their depressing effect on global economic activity appeared to have led to lower growth forecasts and narrower official forecast ranges, thereby reducing the disagreement and lowering the uncertainty in survey responses.

Turning to inflation forecasts, **Charts 4a and 4b** show that the lack of consensus statistic and the uncertainty measure were much less variable compared to growth predictions. In fact, the level of uncertainty for both horizons remained rather steady even with the occurrence of the COVID-19 crisis. Similarly, the level of disagreement over current and next year inflation projections were essentially unchanged during the pandemic. It is probably not evident to forecasters that COVID-19 would change the low inflationary environment prior to the crisis, given the curtailment in demand arising from lockdowns and movement restrictions. Indeed, forecasts of inflation during the pandemic were unusually low—below 1% in the current year prediction. It appears that up until the end of 2021, inflationary expectations of the professional forecasters were well-anchored.

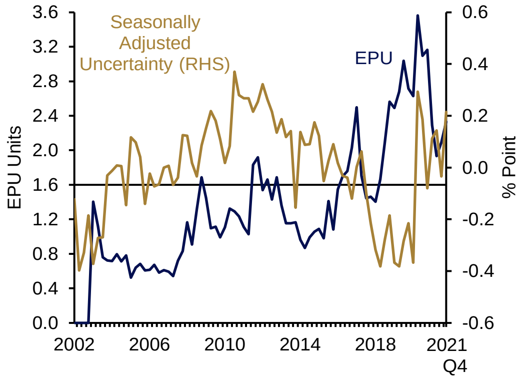
6 Subjective versus Objective Uncertainty

The uncertainty measure extracted from the probability distributions reported in the MAS survey reflects the "subjective" uncertainty of individual forecasters. This measure can be contrasted with a gauge of "objective" uncertainty constructed from observable macroeconomic indicators. Such a measure tailored to Singapore's circumstances has been produced by Baker *et al.* (2009) starting from January 2003. The Singapore Economic Policy Uncertainty Index (EPU) is a weighted average of the monthly economic policy uncertainty indices of 21 countries, i.e., those measuring the relative frequency of own-country newspaper articles which discuss economic policy uncertainty.[5] Time-varying trade weights based on the sum of annual imports and exports between Singapore and each of the 21 countries are used in the computation of the EPU. To link this objective measure of uncertainty to the subjective expectations of professional forecasters, the monthly index is converted to quarterly frequency by taking the average in each quarter and then scaling it by dividing by 100. The resultant index is plotted with the current and next year seasonally adjusted uncertainty series for GDP growth in **Chart 5**.[6]

5 These are Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. Their economic policy uncertainty indexes are normalised to a mean of 100 from 2007 to 2015. For a concise description of the economic policy uncertainty index, see Monetary Authority of Singapore, 2016.

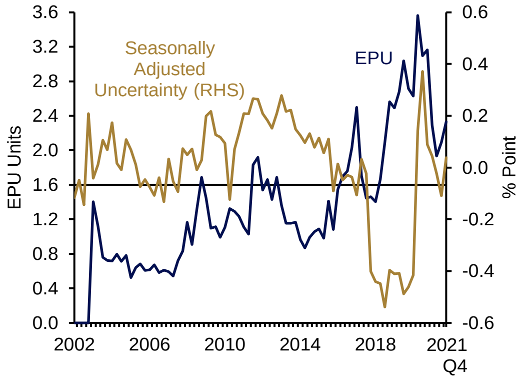
6 The exercise is not carried out for the inflation uncertainty measure given the lack of data observations. In any case, the correlations between it and the EPU index are close to zero.

Chart 5a EPU Index and Current Year Growth Forecast Uncertainty



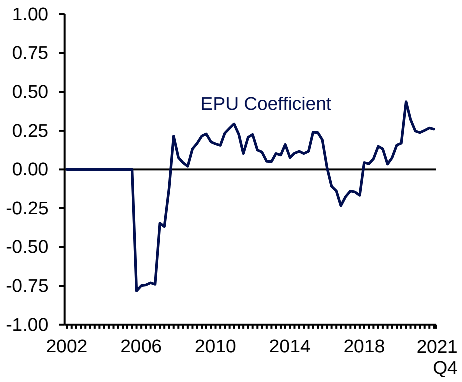
Source: MAS Survey of Professional Forecasters and Singapore Economic Policy Uncertainty Index

Chart 5b EPU Index and Next Year Growth Forecast Uncertainty



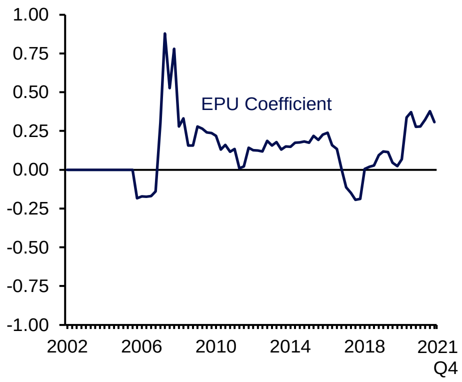
Source: MAS Survey of Professional Forecasters and Singapore Economic Policy Uncertainty Index

Chart 6a Coefficient from Rolling Regression of Current Year Growth Forecast Uncertainty against EPU



Source: Authors' estimates

Chart 6b Coefficient from Rolling Regression of Next Year Growth Forecast Uncertainty against EPU



Source: Authors' estimates

Charts 5a and 5b show that the increase in the subjective uncertainty of forecasters for the current and next year predictions during the COVID-19 pandemic coincided with the rise in the EPU to its highest level in the previous two decades. Similarly, these two measures increased in tandem during the GFC. Conversely, the decline in subjective uncertainty to record lows from 2018 to 2020 was preceded by a drop in objective uncertainty. Forecasters' subjective expectations were therefore empirically grounded in macroeconomic developments.

To verify the visual impressions, the following dynamic rolling regression with a four-year fixed window is estimated separately for current year and next year predictions:

$$GDP_t^u = \beta_0 + \beta_1 GDP_{t-1}^u + \beta_{2t} EPU_t + \delta_1 S_1 + \delta_2 S_2 + \delta_3 S_3 + \varepsilon_t$$

where GDP_t^u denotes the (non-seasonally adjusted) uncertainty measure U_t when forecasting GDP growth and $S_i, i = 1,2,3$ are seasonal dummy variables to capture the periodicity in the uncertainty series for current year forecasts. The lagged dependent variable is included to allow for persistence in the time series. All parameters are assumed to be constant except for the coefficient of EPU_t which is allowed to be time-varying. The plots of the rolling regression coefficient β_{2t} are juxtaposed in **Charts 6a and 6b** and they suggest that the uncertainty measures, after accounting for seasonality, were positively correlated with the EPU most of the time. Moreover, the rolling regression coefficients were larger during the COVID-19 pandemic than in the GFC.

7 Conclusions

Given the nature and scale of the COVID-19 crisis, it is unsurprising that forecast failure occurred in the economic projections of Singapore's professional forecasters. A trend break in subjective uncertainty among forecasters was observed after the occurrence of the pandemic, which coincided with a heightened level of objective uncertainty. This confluence of uncertainty is a possible explanation for the forecasters' tendency not to depart from the official forecast ranges and to exhibit herding behaviour during the pandemic.

The one and two-year ahead forecasts of inflation were unusually low during the pandemic. While forecasters exhibited both "leader-following" and herding behaviour when making these predictions, neither subjective uncertainty nor disagreement over inflation projections showed any increase during the initial phase of the pandemic. Taken together, these results suggest that the short-term inflation expectations of the survey respondents were strongly anchored throughout the sample period.

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