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Abstract

This paper aims to investigate whether the predictive ability and behaviour of professional forecasters are different during the Covid-19 epidemic as compared with the global financial crisis of 2008 and normal times. To this end, we utilise a survey of professional forecasters in Singapore collated by the central bank to analyse the forecasting record for GDP growth and CPI inflation. We first examine the point forecasts to document the extent of forecast failure in the pandemic crisis and test for behavioural explanations of the possible sources of forecast errors such as leader following and herding behaviour. Using percentile-based summary measures of probability distribution forecasts, we then study how the degree of consensus and subjective uncertainty among forecasters are affected by the heightened economic uncertainty during crises. We found the behaviour of forecasters do not differ much between the two crisis episodes for growth projections despite major differences between the two crises. As for inflation forecasts, our findings suggest forecasters suffer less from forecast inertia when predicting short term one-quarter ahead inflation as compared to longer term one-year and two-year ahead inflation.

Keywords

Survey data, COVID-19, leader following and herding behaviour, disagreement, uncertainty

JEL Classification: D80, E17

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1. Introduction

Even in the best of times, economic forecasting is a challenging endeavour. At business cycle turning points, moreover, the inability of forecasters to recognize the onset of recessions and recoveries is well-known. There is also ample evidence to show that forecast practitioners tend to underestimate both the severity of downturns and the strength of upswings in economic activity (see, inter alia, Zarnowitz (1992)). These deficiencies are accentuated during relatively rarer events such as a financial crisis because the past is a less reliable guide to the future. An illustrative example is provided by the global financial crisis (GFC) of the late 2000s, in the aftermath of which professional forecasters consistently overestimated economic growth and inflation in the early 2010s (see, for instance, Lewis and Pain (2015)).

Such is also the case with 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 owing to its novelty is compounded by the unprecedented nature and scale of the epidemic. The enforced lockdowns, closures of workplaces and shops, and travel restrictions implemented by governments, combined with a general fear of infection, prompted endogenous responses by economic agents with unpredictable effects on the economy. Another complication is the periodical reimposition of movement control measures after they were relaxed whenever a new wave of infection occurs, which makes forecasting all but impossible. Given this, it would not be surprising should there be widespread forecast failure.[1] 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 paper, we utilise a survey of professional forecasters (SPF) in Singapore collated by the central bank to study whether, as the foregoing conjectures suggest, the forecast record during the pandemic is a break from the past. This is unlike past studies of professional forecasters' performance that tended to

[1] We refer to larger than usual forecast errors as a forecast failure.

focus on the advanced economies like the US, UK and Japan.[2] Singapore is a small economy, but it is highly open to trade and investment, which means that the negative shocks triggered by COVID-19 originated partly from abroad and were propagated domestically. Thus, the local community of forecasters faced the daunting task of prognosticating 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. As Singapore hosts a vibrant financial sector, the performance and behaviour of the industry's forecasters in rising to these challenges may be indicative of that experienced by forecasters elsewhere.

The objective of this paper is to investigate whether the predictive ability and behaviour of professional forecasters are different during the Covid-19 epidemic as compared with the GFC and the non-crisis periods. To this end, we subject the survey forecasts of GDP growth and CPI inflation to various empirical analyses, seeking to shed light on the following three questions: (1) Was there forecast failure during the epidemic? (2) What were the behavioural explanations of the possible sources of forecast errors? (3) How did the shock from the Covid-19 outbreak affect the evolution of forecast uncertainty and disagreement among forecasters? Previous studies on assessing the performance of professional forecasters in Singapore had tended to focus on point predictions only (see for instance MAS, 2007 and MAS, 2014). By contrast, this paper analyses both point forecasts and forecast probability distributions, as well as extends the sample period of the analysis to include the Covid-19 epidemic episode.

We first compare the relative magnitudes of the errors incurred by our group of forecasters as a whole during the COVID-19 epidemic, the GFC and the non-crisis periods. There is a strand in the literature on forecast evaluation that analyse forecast errors produced by international organizations with the aim of improving upon forecast accuracy (see, for example, Celasun et al., 2021). However, in this study, the SPF participants are not required to disclose the methodology they relied on to produce the forecasts so that we do not have the requisite information to suggest improvements on their forecast

[2] For instance, Engelberg et al. (2009), Boreo et al., (2015) and Abel et al. (2016) analysed SPF data provided by the US Federal Reserve, Bank of England and ECB respectively.

techniques or procedures. Rather, we follow Pons-Novell (2003) and J. Rülke et. al. (2016) amongst others to investigate the proximate cause of the forecast errors by considering various behavioural explanations. Specifically, we test for biased predictions; the influence of the government's projections on the private sector of forecasters; as well as the fear of deviating from majority opinion.

Finally, we turn the focus of our empirical analysis from point predictions to forecast probability distributions provided by the SPF. These subjective probability distributions convey the central tendency of the survey participants beliefs as well as the uncertainty they feel (see Li and Tay, 2021). More specifically, we examine the changes in the degree of consensus and subjective uncertainty associated with individual forecasts, and how the forecasters' subjective uncertainty relates to an objective measure of uncertainty. Our specific interest is in comparing these measures between the COVID-19 epidemic and the GFC. Even though the two crises are different in terms of trigger, transmission and policy responses, the shock in each episode resulted similarly in a huge spike in uncertainty in the economic environment. Based on non-parametric measures like medians and central ranges of the individual subjective probability distributions, we assess how the forecast uncertainty and disagreement among the forecasters are affected by the elevated economic uncertainty.

The rest of the paper is organised as follows. Section 2 describes the dataset containing the macroeconomic projections of professional forecasters in Singapore from which our evidence is drawn. Section 3 investigates the extent of forecast failure during COVID-19 and the GFC, as well as its possible behavioural causes. Section 4 contrasts the evolution of measures of consensus and uncertainty during the pandemic with the financial crisis and links forecasters' subjective uncertainty to an objective indicator of economic uncertainty. Section 5 concludes.

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 and related 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 participants, which typically numbered between twenty to thirty individuals (or institutions) 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, though there was academic participation in the early years.

Each respondent is assigned a unique identification number so that his forecasts can be followed over time and panel econometric analysis of his behaviour is enabled (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.[3] Survey findings are announced in the first week of the months of March, June, September, and December each year and posted on the MAS website.

The MAS survey questionnaire requests from each respondent his projections of many macroeconomic variables, including real GDP and its sectoral breakdown, CPI inflation, the unemployment rate, private consumption, and exports. For our purposes here, attention is confined to the point and probabilistic 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. We focus on three types of projections with varying time horizons

● A 'rolling horizon' forecast for one quarter ahead. For example, a projection made in March of any given year for the second quarter of that year, or a projection made in December of a given year for the first quarter of the following year.

[3] New questions have been added recently although the older ones were retained.

● A ‘fixed event’ forecast produced within a given year for the current year’s outcome, that is, a projection with a varying effective time horizon of four to one quarter.[4]

● A ‘fixed event’ forecast produced within a given year for the next year’s outcome. In this case, the projection is made with effective time horizons of eight to five quarters.

The predictions made one and two years in advance are available for the entire sample period 2000Q1–2021Q3, except for a hiatus of five years from 2005 to 2009 when the following year’s projections were not reported for inflation. The one-step ahead forecasts only started in 2003Q4 for GDP growth and as late as 2017Q4 for CPI inflation. Another important feature of the MAS survey structure concerns the probability distribution forecasts, which were introduced in 2001Q3 for growth and 2017Q4 for inflation. The set of forecast intervals for each variable that survey respondents are asked to attach probabilities to were decided by MAS and their number and width varied across variables and surveys to take account of prevailing economic developments.

The benchmark data against which the accuracy of the professional forecasts is assessed, and the behaviour of their progenitors are evaluated, are retrieved from the database maintained by the national statistical authority, Singstat. Forecasts issued by the government, on the other hand, are culled from various issues of the *Economic Survey of Singapore* (GDP growth) and of the *Macroeconomic Review* (CPI inflation)—the official publications of the Ministry of Trade and Industry and the MAS, respectively. While the inflation data are not revised, we use revised instead of real-time GDP growth data since real-time vintages of the growth data are not published.

3. This Time is Different: Forecast Failure During Crises

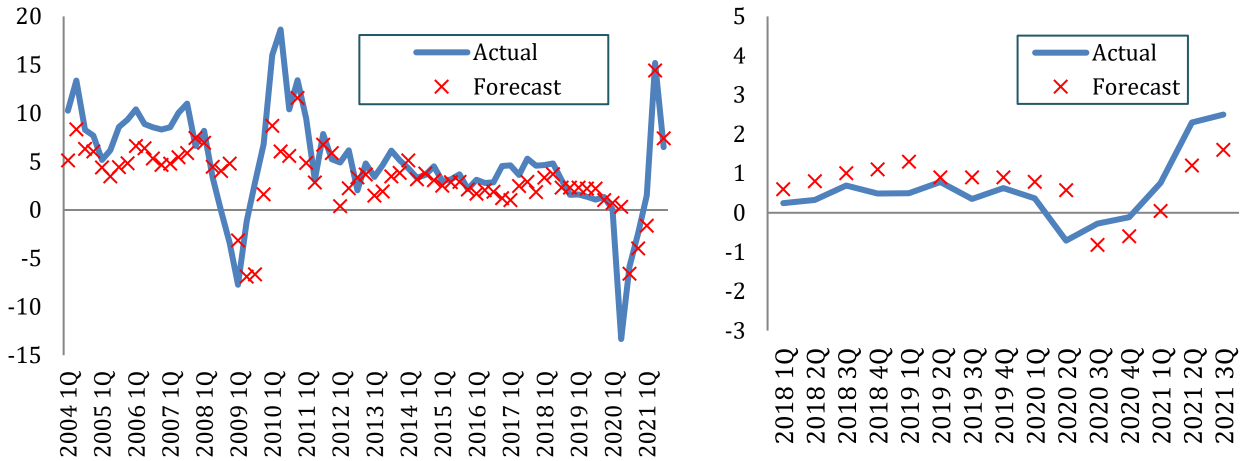
3.1 Forecast Errors

A tentative hypothesis of this paper is that forecast failure during the recent pandemic is worse than in the financial crisis due to different underlying causes. Figures 1a and 1b plot the means of the

[4] The effective horizon is not three quarters because the March forecast was made when no data on the current quarter’s growth was available and only the January inflation rate had been announced.

one-quarter ahead forecasts of survey respondents together with the revised growth and inflation data. The figures bear out the observation that forecasters tend to understate the depth of recessions and the magnitude of recoveries. Apart from over-estimating economic growth at the onset of the pandemic, however, the forecasters appear not to exhibit forecast failure in their one-quarter ahead projections during the pandemic crisis. Meanwhile, the inflation forecasts seem to be systematically biased.

Figure 1: One-quarter Ahead Forecasts for (a) GDP Growth (%) and (b) CPI Inflation (%)



More formally, we report the root mean square error (RMSE) statistics in Table 1 for the aggregated macroeconomic projections at the three time horizons. We define the sub-sample periods for the GFC and the Covid-19 epidemic as 2008Q3 – 2009Q4 and 2020Q1 – 2021Q3 respectively for the rolling one-quarter ahead forecasts. As for the fixed event forecasts, the corresponding periods are 2008 – 2009 and 2020. We see from Table 1 that the forecast error in predicting GDP growth during the COVID-19 pandemic exceeds that in normal times as well as during the GFC for the current and next year projections but not the one-quarter ahead forecasts. The situation is less clear-cut for CPI inflation, as the one-quarter ahead and one-year ahead prediction errors during COVID-19 are larger than those during non-crisis periods but this is not true for the two-year ahead forecasts.[5]

[5] A paucity of observations precludes an analysis of CPI inflation point forecasts during the GFC.

Although the dearth of observations precludes formal testing of the RMSE differences for statistical significance, they are indicative of the unparalleled challenges encountered by Singapore's professional forecasters, as a whole, in making prognostications during the epidemic.

Table 1: Root Mean Square Forecast Errors

	GDP Growth (% point)			CPI Inflation (% point)		
	1-quarter	1-year	2-year	1-quarter	1-year	2-year
Normal	2.75	3.18	3.88	0.48	0.84	1.75
GFC	6.02	4.31	5.01	-	1.21	-
COVID-19	5.36	5.88	7.89	0.83	0.96	1.58

The forecasting difficulties can be traced to the basic characteristics of an epidemiological outbreak. To start with, the economic slump precipitated by the COVID-19 pandemic does not present itself to economists and analysts as a routine business cycle recession or even a financial crisis. In view of the absence of a comparable global epidemic in modern times, there is no precedent to rely on for guidance on how the economy would be affected. The SARS pandemic of 2003 which hit Singapore badly was quickly found to be a poor template for what was transpiring, 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. Instead, they had to depend on pronouncements made by the medical profession, whose members more often than not held divergent views on the future trajectory of the epidemic at any one time.[6]

Most importantly, COVID-19 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 this case, there was a collapse of consumer spending due to lockdowns and movement restrictions but at the same time, interruptions in supply capacity because of factory and shop closures. In other words, the interplay of macroeconomic forces was exceptionally difficult to

[6] The projections in the IMF's *World Economic Outlook* of April and October 2020 furnish good examples of how economists' forecasts depended on epidemiological scenarios.

grasp and quantify, with indeterminate effects on economic growth and price inflation. Consequently, some economic forecasters had to model the dynamics of the epidemic and its impact using explicit and untested assumptions (see for example Eichenbaum et. al., 2021).

3.2 Behavioural Explanations

Turning to behavioural explanations, it is possible that the larger forecast errors incurred during COVID-19 are due to bias on the part of the survey participants, although an earlier study has shown that GDP growth forecasts tend to be unbiased prior to the GFC, but inflation forecasts are not (Monetary Authority of Singapore, 2007). Following Holden and Peel (1990), we retested for the presence of bias during the GFC and COVID-19 episodes by performing pooled regressions on the individual forecast errors of survey participants at all horizons, with the results shown below (the figures in parentheses are heteroscedastic-robust standard errors):

GFC: $$\underset{}{GDP_i - GDP_i^f = \underset{(0.495)}{0.0825}} \qquad n = 160$$

COVID-19: $$GDP_i - GDP_i^f = \underset{(0.390)}{-1.82} \qquad n = 180$$

COVID-19: $$CPI_i - CPI_i^f = \underset{(0.072)}{0.092} \qquad n = 163$$

Unbiasedness implies that forecast errors are zero, on average, so the estimated constant terms ought to be statistically insignificant. The results indicate that forecasters in Singapore continued to produce unbiased growth forecasts during the GFC. In contrast, Lewis and Pain (2015) shows that economic projections are biased during the GFC crisis for the case of OECD countries. Nonetheless, the results suggest they made negatively biased forecasts during COVID-19. We attribute this finding partially to the initial large over-prediction of growth at the outbreak of the pandemic crisis. As for inflation forecasts made during COVID-19, the positive bias evident in Figure 1b is confirmed by an upper-tail t-test at the 10% significance level.

Given the forecasting difficulties mentioned earlier, the MAS survey participants could exhibit what the forecasting literature has dubbed leader following behaviour. This refers to the forecasters being unduly 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). Forecasters can choose to locate their point estimates in or out of the ranges, depending on their views—which may coincide with those of the authorities—or the extent to which they are swayed by the government's outlook.

To determine whether there is a tendency for participants to depart from the official ranges of growth predictions during the GFC and the COVID-19 epidemic, we analyse the projections made by individual forecasters instead of the consensus forecast. The latter is the mean of the point forecasts reported by respondents which we do not used as it is subject to aggregation bias because the heterogeneity amongst forecasters has been averaged away. The conjecture can be investigated by counting the number of occasions over each crisis period in which the individual forecasts from the MAS survey fall outside the ranges. Under the null hypothesis that governmental forecasts do not influence private sector projections, the conditional probability of overshooting or undershooting the official forecast ranges is 0.5 (Rülke et. al., 2016).

We perform the tests only on fixed event forecasts as the one-quarter ahead official forecasts are not publicly available. Combining the current and next year predictions for which official forecasts are available, the computed proportions are recorded in Table 2. The p-values of the lower-tailed tests for these three statistics are 0.5, 0 and 1 respectively. The first and third statistics for growth forecasts are not significantly less than 0.5 at the 5% level, showing that survey participants exercise some independence from official views in both crises. By contrast, we have very strong evidence that the second statistics for inflation forecasts is significantly less than 0.5, indicating the tendency for participants' inflation forecasts to stay within the official forecast ranges during the Covid-19 crisis. In sum, the leader following behaviour of forecasters appear to be present when predicting inflation during the epidemic but is absent for growth projections in both crisis episodes.

Table 2: Tests Results for Behavioural Explanations

	GDP Growth			CPI Inflation		
	Leader Following	*Herding*		*Leader Following*	*Herding*	
	z-test statistic	F-test statistic	t-test	z-test statistic	F-test statistic	t-test
COVID-19	0.47	3.18***	7/24	0.3***	2.37***	6/24
GFC	0.7	1.82**	5/21	-	-	-

Notes: ** and *** denote statistical significance at the 5% and 1% level respectively. The numbers in the t-test columns are the proportion of forecasters whose average forecasts are significantly different from consensus.

Being a relatively small group with professional and social ties, the survey respondents could also exhibit what the forecasting literature has dubbed herding behaviour. This refers to pecuniary or 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 behaviour and reliance on a common information set among forecasters, resulting 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 anticipation 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 postulation will be that participants in the MAS survey tend to herd in times of accentuated economic uncertainty such as the GFC and the COVID-19 epidemic. We investigate the presence of herding behaviour in the one-quarter ahead rolling horizon forecasts and use a testing methodology adapted from Pons-Novell (2003).[7] The test is based on the observed difference between the individual and consensus one-quarter ahead forecasts, which should be statistically indistinguishable from zero if a forecaster practised herding behaviour. Instead of running separate regressions for individual survey respondents as in Pons-Novell (2003),

[7] This test does not require knowledge of the information sets used by forecasters and unlike the previous analysis on detecting leader following behaviour, it is carried out on one-quarter ahead forecasts to increase the degree of freedom in the test.

which is unviable due to the small number of observations available for the GFC and COVID-19 periods, we perform the test in a panel setting. The panel is unbalanced due to dropouts and additions, but also because some forecasters do not submit projections regularly or abstain from predicting some variables. Accordingly, respondents who made fewer than three forecasts are excluded from consideration.

Table 2 records the *F*-statistics for testing the null hypothesis that the individual deviations from the consensus forecasts are all jointly zero. For both periods and both growth and inflation, these produced a rejection at the 5% significance level, suggesting that at least some forecasters do not exhibit herding behaviour. These findings are corroborated by an examination of the individual projections. If herding behaviour is present, the average of a participant's forecasts should not differ from the consensus forecast according to a small-sample *t*-test. The number of forecasters whose average projections deviated significantly from the consensus out of the total number who made the predictions are recorded in Table 2. We observe around a quarter or more of the respondents demonstrated contrarian behaviour in their growth and inflation forecasts during each crisis period.

In summary, the forecasting behaviour of survey participants do not differ much between the two crisis episodes for growth predictions in that they do not exhibit herding nor leader following behaviour in both the GFC and Covid-19 epidemic. The anti-herding tendency is also consistent with the absence of leader following behaviour when the survey participants predict economic growth. It seems the GDP growth projections provided by the professional forecasters do not suffer from much forecast inertia and may still serve as a source of private information during crises. Meanwhile, the presence of leader following behaviour in the current and next year inflation projections contrasts with the lack of herding behaviour in the one-quarter ahead forecasts. While this finding suggests long-term inflation expectation of private sector participants are well anchored in Singapore, they have more diverse views of short-term inflation and thus may respond more readily to newly available information.

4. Consensus and Uncertainty in Crises

4.1 Definitions

In an article three decades ago, Zarnowitz and Lambros (1987) offered seminal definitions of consensus and uncertainty in economic forecasting. They suggested that consensus is best defined as the degree of agreement between the point predictions reported by different forecasters, while uncertainty is properly understood as referring to the diffuseness of the distributions of probabilities that individual forecasters attach to the possible values of a macroeconomic variable. The second definition rules out the commonplace use of a measure of dispersion of individual forecasts around the group average as an indicator of uncertainty. In these instances, it is implicitly assumed that episodes characterized by high (low) dispersion of point forecasts are indicative of a high (low) level of *ex-ante* uncertainty shared by respondents. However, Zarnowitz and Lambros find that this measure tends to understate uncertainty, as compared to their preferred definition.

Boero et. al. (2008) combined the above two definitions in a measure they called “aggregate uncertainty” by considering the variance of the aggregate probability distribution which is computed by summing the individual probabilities reported in survey results, dividing by the number of respondents and normalizing them to add to unity. The mean and variance of the aggregate probability distribution are denoted by μ_A and σ_A^2 respectively. The latter can be expressed in the following equation:

$$\sigma_A^2 = \frac{1}{n}\sum_i^n \sigma_i^2 + \frac{1}{n}\sum_i^n(\mu_i - \mu_A)^2$$

The first component is the average variance of the individual probability distribution (denoted by σ_i^2) with its square root deemed to be a measure of “individual uncertainty”. The second term is the variance of the point estimates which are the means of the individual probability distribution and denoted by μ_i. This variance is used as a proxy for the degree of disagreement among survey participants about their point forecasts (or lack of consensus in the Zarnowitz-Lambros terminology).

In this paper, we define individual forecaster uncertainty in a similar way as the researchers just cited i.e., the dispersion of a survey participant's probability distribution of a macroeconomic variable, but instead of a measure of aggregate uncertainty, we consider the average individual uncertainty in each survey, as in Giordani and Soderlind (2003). The MAS survey reports present aggregate probability distributions by averaging the probabilities from the individual forecasters' histograms, from which a measure of aggregate uncertainty can be constructed. Nevertheless, we eschew the use of this measure due to the arbitrary way in which interpersonal subjective probabilities are combined. We also differ from the cited references by using the dispersion in the median of the individual probability distributions as a proxy for the lack of consensus among forecasters. Our definitions are mutually consistent in that they are based solely on the information contained in the probabilistic forecasts and make no use of point projections.[8]

The probability distribution forecasts of annual GDP growth or CPI inflation divulged 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. As such, it provides a direct measure of subjective forecaster uncertainty, but the problem with the open-ended nature of the intervals needs to be addressed. As in Abel et. al. (2016) and Li and Tay (2021), we resort to the use of percentile-based summary measures instead of moment-based statistics, which have the advantage that they are invariant to how the open intervals are closed, as long as respondents do not place too much probability in either of them. The use of moment-based statistics entails fitting normal density functions to the individual histograms, but we refrain from using this method given that many of the histograms are skewed.

Specifically, the central tendency and spread of the individual probability distributions are measured respectively by the median (y_{50}) and the central 68% range ($y_{84} – y_{16}$), where y_{16}, y_{50} and y_{84} are the

[8] As a robustness check, we compared our measure of lack of consensus with the standard deviation of point forecasts across the panel of respondents and found that they are very close to each other.

16th, 50th and 84th percentiles of the growth and inflation forecast probability distributions. The median of the distributions is preferred to the mean to ensure robustness of the central tendency to asymmetries in the forecast distribution. The chosen range, called the “quasi-standard deviation” by Giordani and Soderlind (2003), has the attraction of being twice the standard deviation should the distribution be normal. To compute these percentiles, we assume uniform probabilities within the three bins that the individual percentiles fall into.

For forecaster *i*, we denote the median and central 68% range of his one-year ahead probability distribution forecasts of growth or inflation surveyed at time *t* as $m_{i,t}$ and $r_{i,t}$ respectively. That is, the time series $r_{i,t}$ traces the evolution of forecaster *i*’s uncertainty over the sample period *t* = 2000Q1, 2000Q2,…, 2021Q3. For each survey, we then calculate the mean of the measure $r_{i,t}$ across the panel of forecasters *i* = 1, 2,…, *n* to represent average forecaster uncertainty:

$$U_t = \frac{1}{n}\sum_i^n r_{it}$$

Next, we compute the standard deviation of the $m_{i,t}$ measure across forecasters in each survey as representing the lack of consensus among forecasters (μ_t^m is the mean of $m_{i,t}$):

$$C_t = \sqrt{\frac{1}{n}\sum_i^n (m_{it} - \mu_t^m)^2}$$

The same computations are repeated for the two-year ahead probability distribution forecasts. In the next section, these measures are tracked over time and comparisons are made between the COVID-19 epidemic and the GFC.

4.2 Comparison of COVID-19 and GFC

It is instructive as an initial step to examine the amount of variation in the spread of professional forecasters’ probability distributions, as revealed by the dispersion of the individual $r_{i,t}$ time series for the first quarter of each year (horizons of four and eight quarters). The natural construct for this purpose is the box-and-whisker plot, shown in Figures 2 and 3.[9] Overall, the response rate that resulted from excluding forecasters who assigned large probabilities to the lower and upper intervals varies from 69% to 83%, with the highest participation for the one-year ahead GDP growth forecasts and the lowest for the two-year ahead CPI inflation predictions. We have also omitted outliers, defined as observations that are more than 1.5 times the interquartile range, from the boxplots.

Figure 2: Boxplots of Growth Forecasts

1-Year Ahead **2-Year Ahead**

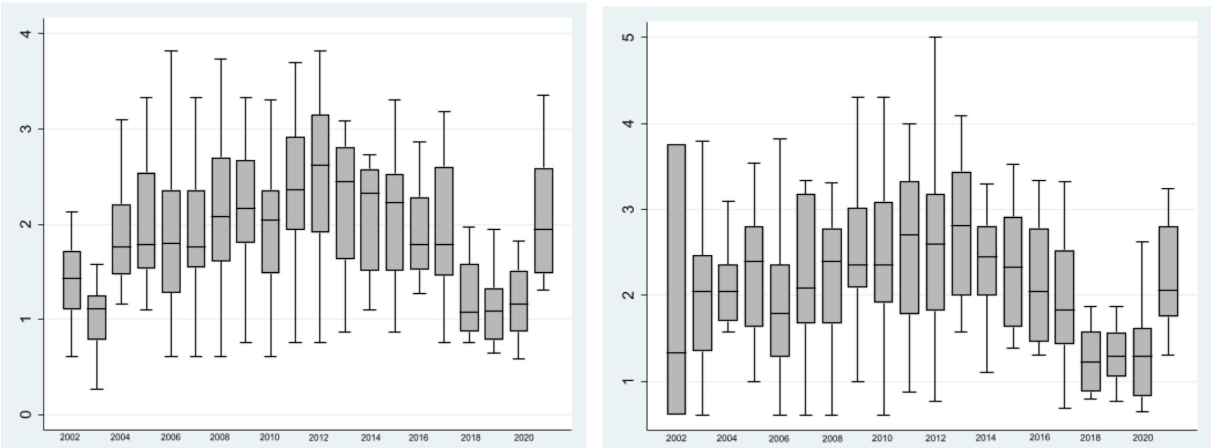
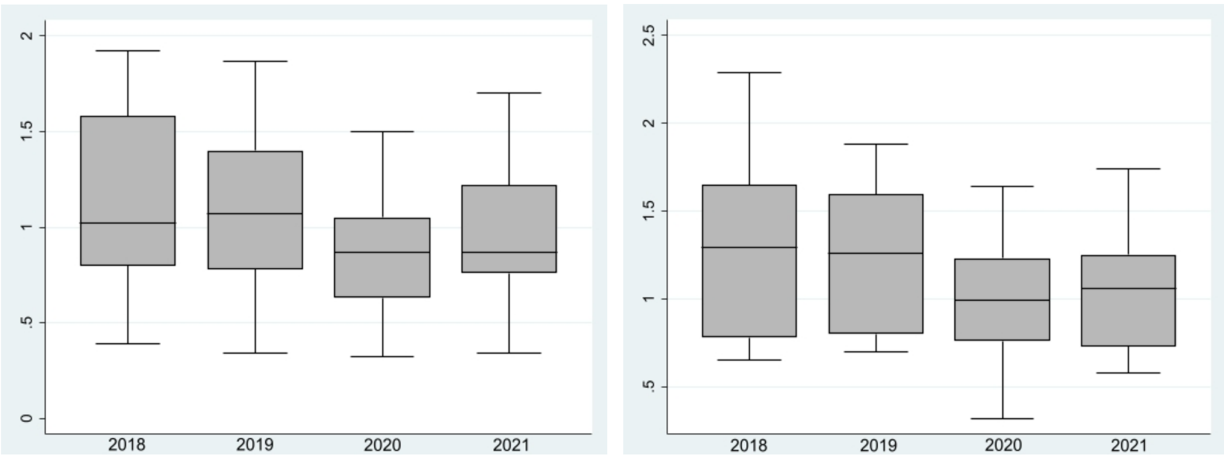


Figure 3: Boxplots of Inflation Forecasts

1-Year Ahead **2-Year Ahead**



[9] In this section, we focus on fixed event forecasts (including those made in quarters other than the first) as probability distribution forecasts are not available for the rolling event predictions.

The horizontal line inside the boxes represents the median level of subjective uncertainty articulated by forecasters (an alternative measure of U_t) while the vertical length of each boxplot including the whiskers is the range or dispersion of individual forecaster uncertainty. A noteworthy observation is that the dispersion in individual uncertainty appears to be greater when the level of uncertainty was heightened. For the one-year ahead GDP growth forecasts, there are discernible jumps in median uncertainty and its dispersion in 2008 and 2021, related to the GFC and COVID-19 epidemic respectively. As forecasters did not realize the severity of the epidemic when it broke out in early 2020, the abrupt increases were delayed for both the one-year and two-year ahead forecasts.

The most surprising feature of the growth boxplots is the further increase in uncertainty and its dispersion across forecasters in 2011 to 2012. Both measures were higher after the financial crisis subsided rather than during the crisis itself, possibly due to the eurozone sovereign debt crisis in 2010/11 and the difficulty of forecasting the long-drawn recovery from the financial crisis. The sharp fall in uncertainty and its dispersion across forecasters from 2017 to 2019 at first glance seems anomalous given the rise of trade frictions between the US and China. Nevertheless, their depressing effect on global economic activity appears to have led to lower growth forecasts and narrower official forecast ranges, which could have influenced private sector predictions. Unlike the case of GDP growth, the level of uncertainty in inflation forecasts for both horizons remained rather stable or even declined slightly with the occurrence of the COVID-19 crisis. Forecasts of inflation during the epidemic were unusually low—below 1% in the one-year ahead prediction.

Moving next to the evolution of consensus and uncertainty, Figures 4 and 5 present the time profiles of the U_t and C_t measures for economic growth forecasts from 2002Q1–2021Q3 and inflation rate predictions from 2017Q4–2021Q3, where the series are plotted for all survey dates. A first feature worth noticing is the general correspondence between the two measures, notwithstanding their different levels. The correlations between the two measures are 0.65 and 0.58 for the one and two-year ahead growth forecasts, respectively, and 0.76 and 0.60 for the inflation forecasts. Since uncertainty is by construction twice the quasi-standard deviation, its mean is higher than the lack of consensus measured by the standard deviation of the median probability forecasts.

Figure 4: Consensus and Uncertainty Measures for Growth Forecasts

1-Year Ahead **2-Year Ahead**

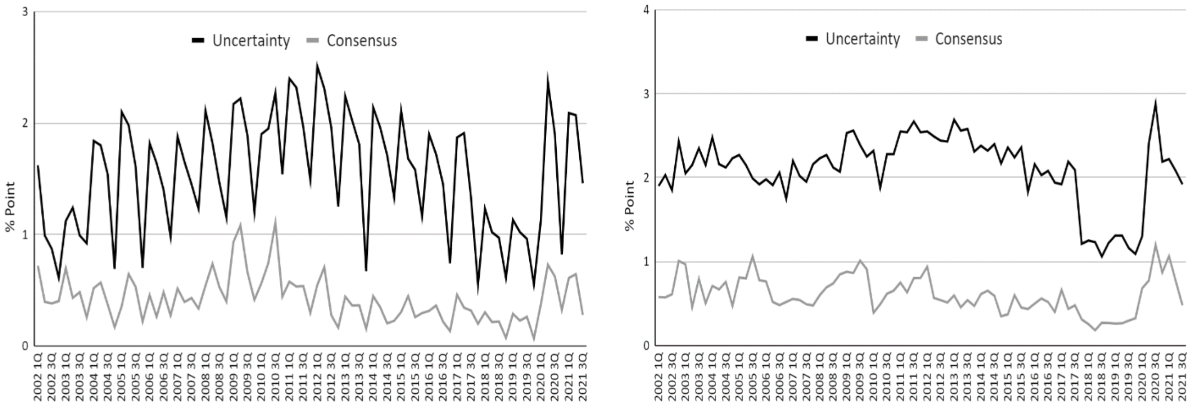
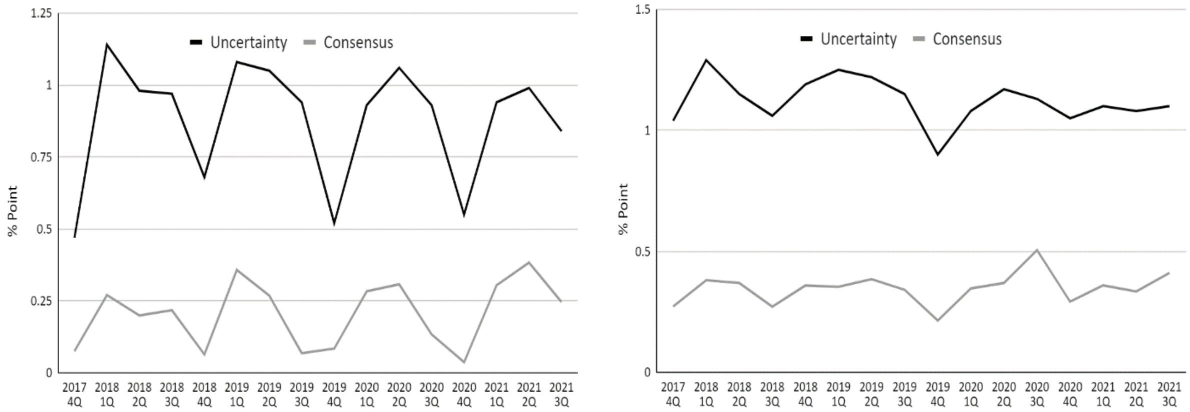


Figure 5: Consensus and Uncertainty Measures for Inflation Forecasts

1-Year Ahead **2-Year Ahead**



Echoing the finding in Zarnowitz and Lambros (1987), the lack of consensus statistic is much less variable and its changes are dampened, compared to the direct uncertainty measure. In both the growth and inflation charts, the seasonal zigzag pattern of the uncertainty series seen especially in the one-year ahead forecasts are expected since with more data being released and fewer quarters to forecast as the fixed event (i.e., this and next year's forecasts) approached, average uncertainty would diminish. The seasonal pattern is more irregular in the lack of consensus series even though in principle, forecasters ought to disagree less on their predictions when there is more information available.

The movements in the one-year ahead growth forecast uncertainty mirror the boxplots: the onset of the GFC saw uncertainty rise and increase further until 2012; the trend reversed after this year and uncertainty declined to low levels in 2018 and 2019, as also observed in the boxplots. Then COVID-19 struck, whereupon a sudden and sharp increase akin to a trend break occurred. In terms of its level, the uncertainty occasioned by the pandemic was slightly higher than during the GFC but comparable to its aftermath. Disagreement amongst survey respondents on their one-year ahead growth forecasts was stable except during the two crisis periods. Corroborating the boxplot results again, neither uncertainty nor disagreement over one-year ahead inflation showed any increase during COVID-19. It is probably not evident to forecasters that the epidemic would change the low inflationary environment prior to the crisis, given the curtailment in demand arising from lockdowns and movement restrictions.

As expected, the average level of uncertainty is higher in the two-year ahead predictions. Their seasonal variation and that of the lack of consensus measure are also less pronounced owing to the absence of information on the target variables at the time the forecasts were made. Both series for the growth forecasts rose to their highest levels during the COVID-19 epidemic, suggesting that longer-term predictions were marked by great uncertainty and more accentuated disagreement amongst forecasters that reflected varied views on how long the pandemic would last. In contrast, the corresponding measures for the two-year ahead inflation projections were essentially unchanged during the epidemic.

4.3 Subjective Versus Objective Uncertainty

Following up on the preceding analysis of uncertainty and consensus during crises, this section poses the question of what causes changes in these measures amongst professional forecasters in

Singapore. We approach the issue by first drawing a clear distinction between two uncertainty concepts: the "subjective" uncertainty measure extracted from the reported probability distributions of individual forecasters versus the "objective" uncertainty metrics constructed from observable macroeconomic developments. Our aim is to assess the relationship between these two types of uncertainty by correlating the survey measure to a recently developed proxy for the level of uncertainty in the macroeconomic and policy environment.

The proxy we use as our measure of objective uncertainty is the news-based Singapore Economic Policy Uncertainty Index (EPU) which starts in January 2003 and is produced by Baker et. al. (2016). The EPU is a weighted average of the monthly economic policy uncertainty indexes of 21 countries.[10] An individual national economic policy uncertainty index measures the relative frequency of own-country newspaper articles which discuss economic policy uncertainty in that month. Time-varying trade weights based on the sum of annual imports and exports between Singapore and each of the 21 countries are used for the computation of EPU. To link this objective measure of uncertainty to our subjective measures extracted from the MAS survey, we first convert the monthly EPU series to quarterly frequency by taking the average in each quarter and then scaling by dividing the index by 100. The EPU index is plotted with the one-year and two-year ahead uncertainty series for GDP growth in the top panel of Figure 6.[11]

The relationship between the uncertainty measures and EPU is not easily discernible from the graphs, so we ran the following dynamic rolling regression with a four-year fixed window:

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

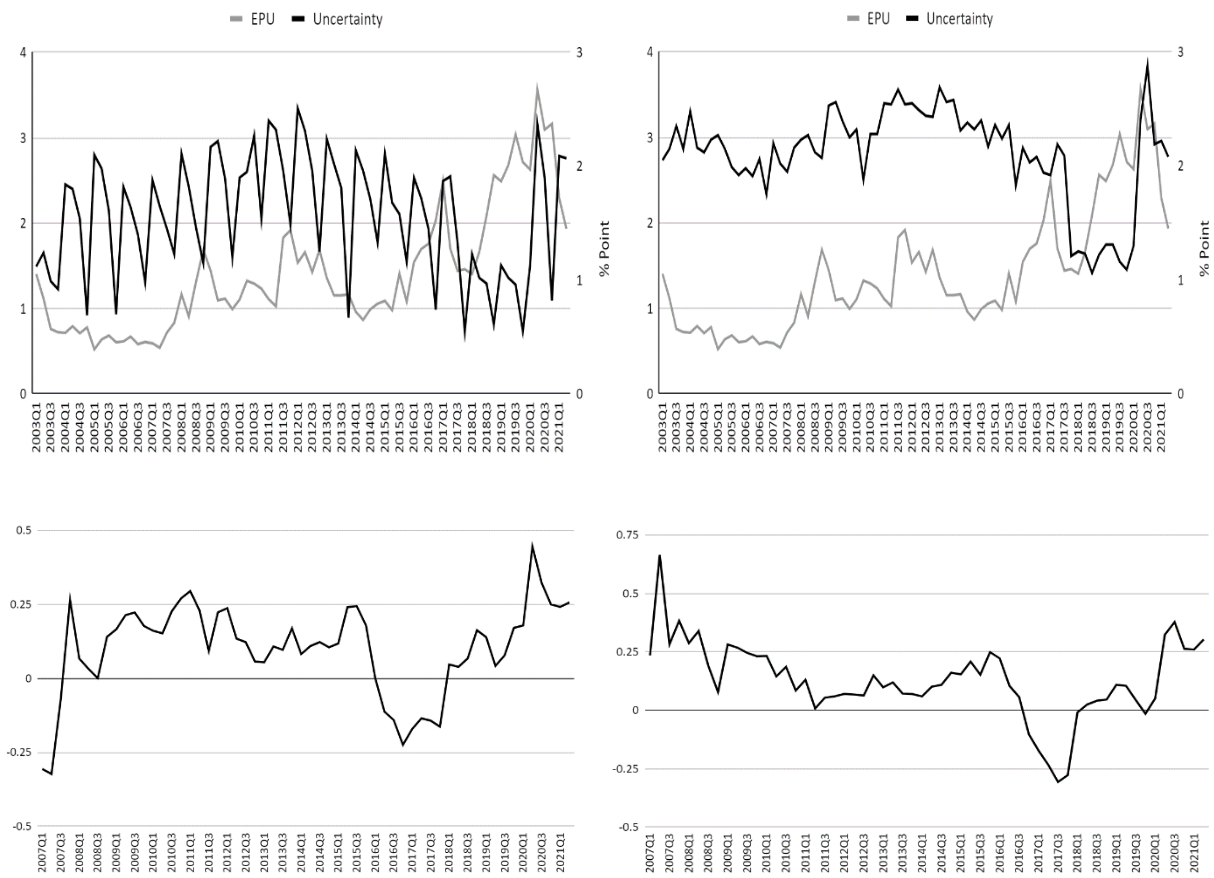
[10] These are Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. Their economic policy uncertainty indexes are normalized to a mean of 100 from 2007 to 2015.

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

where $S_i, i = 1, 2, 3$ are seasonal dummy variables to capture the periodicity in the uncertainty series for the one-year ahead forecasts. We ran the same equation but without the seasonal dummy variables for the two-year ahead forecasts. The lagged dependent variable is included to allow for the persistence in the series. The plots of the rolling regression coefficient β_{2t} are juxtaposed in the lower panel of Figure 6 and they suggest that the uncertainty measures, after accounting for seasonality, are most of the time positively correlated with EPU. Insofar as crises are concerned, the correlation for one-year ahead uncertainty is significantly stronger during the COVID-19 epidemic. In the case of two-year ahead uncertainty, the strength of the correlation with EPU is about equal during the two crises. As noted earlier, there is a significant fall in the uncertainty series in 2016 and 2017. At the same time, this was a period of high uncertainty in the global economy caused by US President Donald Trump's policies. The result is the negatively signed rolling regression coefficients seen in the Figures.

Figure 6: EPU and Uncertainty Measures for Growth Forecasts

1-Year Ahead **2-Year Ahead**



5. Conclusions

Given the nature and scale of the COVID-19 crisis, it would be unsurprising if Singapore's professional forecasters exhibit a break from the past in their economic projections. Indeed, the forecast error in predicting GDP growth during the COVID-19 pandemic not only exceeds that in normal times but also during the GFC, particularly for the current and next year projections. This partly reflects the indeterminacy for growth outcomes of the economic forces unleashed by the pandemic, given its novelty. Unlike the unbiased predictions during the GFC, the GDP growth forecasts made during COVID-19 suffered from a negative bias with forecasters over-estimating economic growth at the onset of the pandemic by expecting too optimistic an epidemiological scenario.

Both the level of subjective uncertainty and the lack of consensus in growth projections shot up during the epidemic. Using percentile-based summary measures of the forecast probability distributions, we observe a trend break in subjective uncertainty and consensus after the occurrence of the epidemic. The two-year ahead uncertainty series also rose to a record high. This was simultaneously matched by a rise in an index that gauges the degree of uncertainty in the economic policy environment to its highest level in the last two decades, thereby demonstrating that the increase in forecasters' subjective uncertainty was empirically grounded. Despite the elevated level of uncertainty, there appears to be a tendency for forecasters to depart from the official ranges and exhibit anti-herding behaviour during the COVID-19 epidemic as is the case during the GFC, suggesting that private information was not suppressed during crises.

Turning to inflation forecasting, forecast failure is not detected particularly for the one-year and two-year projections in spite of the difficulties in making economic forecasts during the epidemic. Forecasts of inflation during the epidemic were unusually low, in view of restriction measures that led to the curtailment in demand. Neither subjective uncertainty nor disagreement over inflation projections showed any increase during COVID-19. Nonetheless, anti-herding tendencies in the one-quarter ahead inflation forecasts are suggestive of short term inflation expectations on the part of the survey respondents may not be strongly anchored. Unfortunately, a paucity of observations precludes a comparative analysis of CPI inflation forecasts between the two crises. In conclusion, we surmise from the paper's findings that professional forecasters in Singapore did not alter their behaviour much in prognosticating growth nor inflation during COVID-19 but the hyper uncertainty arising from the epidemic did lead to a forecast failure in output growth.

Acknowledgements

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