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Probabilistic forecasts using expert judgement: the road to recovery from COVID-19

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April 2021

Working Paper 1/21

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We are thankful to Tourism Research Australia, particularly David Smith and George Chen, for providing data and support. We are also thankful to the Australian Tourism Industry Council and the Australian Tourism Export Council for distributing the survey.

26 April 2021

JEL classification: C10,C53,Z32

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Abstract

The COVID-19 pandemic has had a devastating effect on many industries around the world including tourism and policy makers are interested in mapping out what the recovery path will look like. We propose a novel statistical methodology for generating scenario-based probabilistic forecasts based on a large survey of 443 tourism experts. The scenarios map out pessimistic, most-likely and optimistic paths to recovery. Taking advantage of the natural aggregation structure of tourism data due to geographical locations and purposes of travel, we propose combining forecast reconciliation and forecast combinations implemented to historical data to generate robust COVID-free counterfactual forecasts, to contrast against. Our empirical application focuses on Australia, analysing international arrivals and domestic flows. Both sectors have been severely affected by travel restrictions in the form of international and interstate border closures and regional lockdowns. The two sets of forecasts, allow policy makers to map out the road to recovery and also estimate the expected effect of the pandemic.

Keywords: Forecasting, judgemental, probabilistic, scenarios, survey.

1 Background

Tourism around the world has seen tremendous growth over the last few decades. The World Tourism Barometer January 2020 report (UNWTO 2020) had the headline “Growth in international tourist arrivals continues to outpace the economy”, predicting a 3 to 4% growth in international arrivals worldwide in 2020. Similarly, Tourism Research Australia (TRA) reported that for 2017–2018 “Tourism Gross Domestic Product grew at 5.0% in real terms, much faster than the 2.8% growth reported for the economy as a whole.” (Tourism Research Australia 2019).

The COVID-19 pandemic hit in late 2019 with several devastating effects. Immediate responses from governments were the partial or complete lockdown of cities, regions or even entire countries with international borders largely closed. Travel restrictions were also placed on borders within countries; such was the case for Australia with strict state border closures in place for many months during 2020. Airlines were grounded and airports faced financial disaster (Maneenop & Kotcharin 2020; Forsyth, Guiomard & Niemeier 2020), hotels and the hospitality sector went into survival mode (Gursoy & Chi 2020), cafes and restaurants opted for either a delivery service or a complete shutdown, and many businesses relied on extended government support. News headlines such as “International border closures push businesses to the brink of collapse” became a regular feature, with the immediate future looking grim for many within the industry (Yang, Fang & Mantesso 2020).

From a statistical modelling and forecasting perspective, these disruptions cause unique challenges. The pandemic has meant that we cannot extrapolate the strong and persistent signals observed in historical tourism time series. The structural break is deep and the path to recovery remains extremely uncertain. Figure 1 shows the latest data (at the time of writing) for Australia. It highlights the devastating effect on inbound travel with international arrivals dropping to around 3,000 passengers per month (all Australian nationals returning to Australia) beginning from April 2020, down from a peak of 1.1 million international travellers in December 2019.

[Please insert Figure 1 here]

Similar situations have been witnessed around the world (e.g., Airports Council International (ACI) Europe 2020; Richter 2020). Unlike many previous well-studied disruptions to tourism (for a comprehensive list see Bausch, Gartner & Ortanderl 2020), the COVID-19 pandemic has caused a simultaneous global disruption. This has meant that much of the existing literature on modelling and forecasting tourism demand is not applicable (see Song, Qiu & Park 2019, for the latest review). Even the literature that involves judgement is of limited assistance (e.g., Song, Gao & Lin 2013; Lin, Goodwin & Song 2014) as it focuses on integrating statistical forecasts with judgement (Petropoulos, Fildes & Goodwin 2016; Arvan et al. 2019). The aim is to complement statistical forecasts with the domain knowledge of the experts via judgemental adjustments. However, at this stage the statistical signal for many components of tourism has been completely washed out.

To the best of our knowledge this paper is the first to generate probabilistic scenario-based judgemental forecasts. We use a large survey from diverse experts and stakeholders, proposing a novel methodology to produce forecasts. Using survey responses from experts we generate scenario-based probabilistic forecasts for Australian tourism. We concentrate on the two largest sectors of the Australian tourism industry: international arrivals and domestic tourism flows. The survey responses come from tourism experts within the industry drawing on first-hand experience and knowledge. We have designed the survey in order to cover market segments that are of interest to the policy maker and are expected to show diverse behaviour. The expectation is that the various segments of tourism will be affected differentially and will recover at different rates.

Using historical data up to the end of 2019, we generate counterfactual “COVID-free” forecasts. In order to generate coherent and robust forecasts we combine to the concepts of forecast combinations and forecast reconciliation. The accuracy of these forecasts is evaluated against historical data. These set a baseline expectation for what would have been had COVID-19 not occurred.

The remainder of the paper is structured as follows. Section 2 provides a detailed literature review on judgemental forecasting within and outside the field of tourism. Section 3 presents the proposed innovative statistical methodology for generating scenario-based judgemental probabilistic forecasts accounting for the onset of the COVID-19 pandemic; as well as methodology for producing robust counterfactual forecasts based on historical pre-COVID-19 data by combining the notions of forecast reconciliation and forecast combinations. Section 4 presents the experimental design, exploring historical data and generating and evaluating the robustness of COVID-free counterfactual forecasts. Section 5 presents details of the survey design, the survey participants and the detailed analysis of the results together with a post-survey real time evaluation. Some discussion and conclusions follow in Section 6.

2 Literature review on judgemental forecasting

Judgemental forecasting is widely used when there is lack of reliable data to build quantitative models, or there is contextual information that is unaccounted for in models. Judgement can be used to produce forecasts directly, or adjust existing forecasts, with both approaches having received substantial attention in the literature (see recent reviews of the area by Arvan et al. 2019; Perera et al. 2019). Given the context of the COVID-19 pandemic and its dramatic

effect on tourism, we focus on direct judgemental forecasts, as there is very limited data to generate model-based forecasts (Zhang et al. 2021; Kourentzes et al. 2021). Our objective in this section is to provide an overview of judgemental forecasting approaches in the context of their usability to support our forecasting task. The reader is pointed to Lawrence et al. (2006) and Ord, Fildes & Kourentzes (2017, Chapter 11) for details on the different methods.

There are several considerations in the generation of judgemental forecasts, such as the use of a single or multiple humans, the nature of the forecast that could be a point prediction, scenarios, intervals, or a probabilistic forecast, and the use of domain experts or not. Humans benefit from the ability to use unstructured domain knowledge, but at the same time suffer from various cognitive biases (Fildes et al. 2009). Relevant examples are the availability bias (overly rely on easily available or memorable information), the representativeness heuristic (matching to a previous similar observation, ignoring the frequency of occurrence), the anchoring bias (the forecaster ‘anchors’ to an initial estimate and does not consider substantially different values, e.g., the last observation), the over-optimism or motivational biases (motivated to forecast towards a preferred state), and overconfidence in own forecasting abilities (Ord, Fildes & Kourentzes 2017, p. 386). This makes the use of single forecasters for obtaining predictions problematic, with performance varying substantially, as well as being difficult to identify consistently well-performing forecasters (Schoemaker & Tetlock 2016). Instead, many judgemental forecasting methods rely on the use of multiple individuals, to counter both this inconsistency, but also attempt to negate judgemental biases.

When using a jury of experts, the literature suggests avoiding face-to-face interactions (Armstrong 2006), as influential individuals may herd forecasts to a particular preference. A structured approach to overcome this is the Delphi method (for details see Rowe et al. 2007). The Delphi method organises the process by asking a group of experts to provide their forecasts, who do not interact with each other directly. In contrast to many other methods, experts are asked to provide the reasoning behind their predictions. Together with the forecasts, these are collected, summarised and communicated anonymously to the panel of experts, who are asked to revise their predictions in light of the new information. Kauko & Palmroos (2014) provide insights into how the experts converge to a consensus over different rounds, reporting changes towards a more accurate consensus, but with changes being relatively small in magnitude. This iterative process can be repeated until there is adequate convergence between the forecasts. Lin & Song (2015, and references therein) provide a review of the Delphi

method in the tourism forecasting literature, reporting that it is one of the most popular judgemental forecasting methods. However, its usefulness for generating forecasts remains contentious. For example, Song, Gao & Lin (2013) and Lin, Goodwin & Song (2014) report that Delphi was beneficial for the accuracy of tourism forecasts, however, in these experiments participants were asked to adjust statistical forecasts. Kauko & Palmroos (2014) and Graefe & Armstrong (2011) provide evidence that the Delphi method did not result in significantly more accurate predictions than face-to-face meetings, although such findings often point to the weakness of the application, rather than of the method itself (Ord, Fildes & Kourentzes 2017).

An alternative to the Delphi method is the use of the so-called prediction markets. With prediction markets participants are asked to trade 'shares' that correspond to a particular forecast outcome. As the market develops, the favoured outcome by the participants is revealed. Prediction markets can be described as emulating simplified stock-markets, and therefore participants have a strong incentive to be accurate (Tziralis & Tatsiopoulos 2007; Miles et al. 2008). Armstrong (2008) contrast the Delphi method with prediction markets and suggests that the Delphi method has the advantages that the reasoning behind forecasts is revealed, increasing confidence and that it can provide quicker predictions.

Notwithstanding, in both cases, as well as with the jury of experts, the selection of the participants is crucial. This relates to both the number of participants, as well as their domain knowledge. Tetlock (2017) provides multiple examples where experts have been unable to forecast major events. Ord, Fildes & Kourentzes (2017) argue that experts may not represent a wide enough sample, quoting examples from the UK Brexit vote, but also because experts may operate on a similarly incomplete set of information. O'Leary (2017) investigates the accuracy of the wisdom of the crowd, going beyond experts, finding that a broad group of participants has a positive effect on accuracy. Petropoulos et al. (2018) find that the wisdom of the crowd can outperform statistical methods in identifying the best forecast, and although both generic crowds and domain experts performed well, the latter could achieve better performance with smaller groups of participants.

The literature has explored extensively the elicitation of the uncertainty in judgemental forecasts, or equivalently generating probabilistic judgemental forecasts (Lawrence et al. 2006). This task can take many forms, such as asking participants to provide probabilities to events, probabilities to specific values, provide prediction intervals, and so on. Although there is no

consensus, the majority of the literature suggests that such forecasts suffer from overconfidence (see extensive discussion by Lawrence et al. 2006). The task format appears to affect the level of overconfidence, with a higher tendency when the forecaster has to assign probabilities to pre-selected values (Ronis & Yates 1987). Schoemaker (2004) connects overconfidence to psychological factors, such as the feeling of control, information distortions, and challenges in weighting probabilities. Kahneman & Lovallo (1993) suggest that forecasters who double as decision-makers often are influenced by their stakes in the decision, resulting in overly optimistic and confident predictions. We take this as a further argument in using a larger and wider group of forecasters. Interestingly increasing the information content of the task is correlated with overconfidence (Davis, Lohse & Kottemann 1994), a finding that has many parallels with the arguments of Fildes, Goodwin & Önköl (2019), who also find that forecasters act on information without being able to correctly assess its relevance to the task. Furthermore, Goodwin et al. (2019) show that when contrasting scenarios are offered as context, then forecasters' confidence increases. Another interpretation of overconfidence for probabilistic forecasts is offered by Jørgensen & Sjøberg (2003) suggesting that when a point forecast is available forecasters anchor to it. The expertise of the forecasters does not seem to provide a consistent connection with performance (Lawrence et al. 2006). There is limited evidence that when asking participants to assign values to optimistic and pessimistic projections these correspond to extremes of the predictive distribution (5% and 95% respectively, Ord, Fildes & Kourentzes 2017, p. 403).

The literature has explored ways to support the generation of judgemental forecasts. Decomposition aims to do that by breaking the task into smaller sub-tasks (MacGregor 2001). These sub-tasks are not only simpler to resolve, but further permit controlling the flow of information to reduce cognitive overload, as well as potential overconfidence. Edmundson (1990) finds that breaking a forecast in its constituents (e.g., trend, season) increased accuracy over providing a holistic forecast. Petropoulos et al. (2018) conclude the same effect when asking participants to identify the best forecast. Webby, O'Connor & Edmundson (2005) observe the same when tasking forecasters to predict special events with different effects acting simultaneously. Tackling each effect separately increased the accuracy of the forecasts. Nonetheless, Goodwin & Wright (1993) warn that excessive decomposition may lengthen the task to the extent that mental fatigue may have adverse effects.

Similarly, in a judgemental forecasting task asking for very detailed or numerous estimates can degrade the accuracy of the forecasts (Miller et al. 2011; Ord, Fildes & Kourentzes 2017). Therefore, care must be taken in the design of the task, so as to not overload the participants.

(Cook 2006) suggests structuring knowledge into schemas and increasing the working memory capacity by using both visual and verbal information as other ways to reduce cognitive load, the first, aligning well with the findings from the decomposition literature.

Focusing on the specific task, of predicting the effect of COVID-19 on tourism, we note that there have been numerous papers that advocate the use of judgement. Zhang et al. (2021) use the Delphi method to identify the expected decrease due to COVID-19 and the period when tourist arrivals will return to the baseline period, for three scenarios: pessimistic, normal, optimistic. By interpolating between these two points they construct weights with which they adjust econometric forecasts to reflect the impact of the pandemic. Qiu et al. (2021) construct three judgemental scenarios following a structured approach with no external experts. They use scenario projections from the United Nations World Tourism Organisation to obtain the projected recoveries and linearly interpolate from observations at the onset of the pandemic. The linear interpolation is further enhanced by superimposing seasonality extracted through decomposition from the pre-pandemic data. Liu et al. (2021) use the Delphi method to obtain a judgemental index with two major components, the accessibility risk and the self-protecting measures, decomposing the predictive problem. These are then combined into a single index that is judgementally translated into adjustments for statistical forecasts. Finally, Kourentzes et al. (2021) rely on a panel of forecasters to obtain recovery projections, which are used to adjust model forecasts. As they ask for forecasts for multiple periods and combinations of origin-destination countries, they simplify the task into forecasting a binary restricted-unrestricted travelling outcome. They also ask forecasters to provide a percentage of recovery for the unrestricted travelling case. Recognising the difficulty of the forecasting task, they combine all judgemental forecasts to obtain the adjustment weights for the model predictions. Combinations of forecasts have been shown to be an effective way to reduce individual biases, and improve the accuracy of the final prediction (Lawrence et al. 2006; Ord, Fildes & Kourentzes 2017), relying on a ‘wisdom of the crowd’ approach (Surowiecki 2004; Petropoulos et al. 2018). Finally, we note that none of these studies provide probabilistic forecasts, but rather alternative point forecasts, matching three scenarios.

3 Methodology

As demonstrated in Figure 1 the effect of the COVID-19 pandemic is such that historical data cannot be used to project forward without explicitly accounting for the depth and the length

of the structural break caused by COVID-19, and the subsequent unknown and unprecedented path to recovery. Both the depth and length of the effect of the pandemic are extremely challenging or even impossible to estimate and predict statistically, and therefore we revert to a novel approach of judgemental forecasting. In this section we describe the methodology used to generate the post-COVID-19 scenario-based probabilistic forecasts and also the methodology implemented to generate counterfactual COVID-19-free forecasts which set the expected future paths had the pandemic never occurred.

3.1 Scenario-based probabilistic forecasts post-COVID-19

In order to generate scenario-based probabilistic forecasts, we survey tourism experts asking them to provide judgement on the future of tourism based on two types of questions. The first focuses on the level of tourism flows post-COVID-19 while the second focuses on the timing of the recovery to pre-COVID-19 levels.

Question Type I: *What will the level of tourism be at some point in time in the future, e.g., 2021 Q4, compared to last observed flows prior to the COVID-19 pandemic, 2019 Q4.*

Each respondent is asked to provide a high probability ‘Most likely’ scenario, as well as low probability ‘Pessimistic’ and ‘Optimistic’ scenarios. The respondents are asked to choose from the categories shown in the left column of Table 1. We convert the discrete categories for each question into the scaling factors shown in the right column of the same table, using the midpoint of each range. For example, a response of “Lower 90–100%” means that the respondent expects that international arrivals in 2021 Q4 will be between 90% and 100% lower than they were in 2019 Q4. We convert this to the midpoint of “95% lower”, or equivalently at 5% of what they were in 2019 Q4 giving a scaling factor of 0.05.

[Please insert Table 1 here]

Reflecting these design choices to the literature, for each scenario we ask the participants to provide a choice without prior forecasts (e.g., some point forecast from a model), to avoid any anchoring bias. Participants have to respond for the three scenarios, forcing them to contrast the alternatives, therefore mitigating any implicit assumptions on the likelihood of a single prediction that can occur by mixing probabilities with scenarios. We do not ask participants to provide a specific value, but rather to select amongst options, once for each scenario. This is done to mitigate other biases, such as overoptimism and overconfidence that may push predictions to extreme values, but also to manage the cognitive load. Finally, we pool the

responses from multiple participants, to offset individual biases, but also building on the benefits of combining different judgemental forecasts.

The top three rows of Figure 2 show bar plots and estimated probability densities of the responses for what the level of tourism flows be in 2021 Q4 compared to the last observed quarter of 2019 Q4. The example is based on Question 4 of the survey that follows and is used here for the purpose of demonstration (full details and analysis is presented in Section 5). The bar plots have been scaled to form probability densities, with the bar height adjusted according to the width of the corresponding interval and scaled to have area equal to 1.

[Please insert Figure 2 here]

This gives us a discrete probability distribution which is converted into a continuous distribution by summing zero-truncated Gaussian kernels (Jones 1993) placed at each point mass. We use a zero-truncated Gaussian kernel to ensure the distribution lies on the positive scale, to retain the probabilistic interpretation. The kernel density estimates (with bandwidth 0.1) are shown as the lines in the first three panels of Figure 2. They effectively combine neighbouring options to give a smooth density across all possible scaling factors.

We next combine the three scenarios to form a weighted mixture distribution, shown in the fourth row of Figure 2. The weights used to combine the three scenarios are 0.1, 0.8, and 0.1; that is, we give the 'Most likely' scenario an 80% probability of occurring and just 10% each for the other two highly unlikely scenarios. Combining the three scenarios using a mixture distribution accounts for both the uncertainty across the respondents and across each scenario, further offsetting individual biases.¹ Furthermore, the resulting mixtures help to simplify the communication of results and information to policy makers.

Our approach also allows a policy maker to weigh the scenarios asymmetrically as the circumstances change going forward. For example, as vaccinations progress, we can place more weight on the 'Optimistic' scenario by setting the weights to 0.1, 0.1, 0.8 for 'Pessimistic', 'Most likely' and 'Optimistic' scenarios respectively. The resulting mixture is shown in the fifth row of Figure 2.

In the last step of our method, we multiply the last pre-COVID-19 observation, 2019 Q4, with the estimated scaling factor density to obtain probabilistic scenario-based forecasts.

¹All estimations are performed in R version 4.0.4. (R Core Team 2020). Truncated Gaussian Kernels are estimated using the `truncdist` package (Novomestky & Nadarajah 2016), and the mixture distributions are estimated using the `distributional` package (O'Hara-Wild & Hayes 2020).

Question Type II: *What year do you think the level of tourism flows will return to pre-COVID-19 levels?*

Again the respondents are asked to provide a high probability ‘Most likely’ scenario, as well as low probability ‘Pessimistic’ and ‘Optimistic’ scenarios. The choice is set across the year range: 2021-2028. For this question type the discrete probability distribution based on years selected by the respondents is directly converted into a continuous distribution for the year of recovery by summing Gaussian kernels placed at each point mass with the bandwidth set to 0.6. Figure 3 shows an example based on Question 5 (full details and analysis is presented in Section 5). The top three panels show the the raw responses and kernel density estimates. The two bottom rows show the estimated mixture distributions.

[Please insert Figure 3 here]

3.2 COVID-free counterfactual forecasts

Analysing historical data gives us a good understanding of the trends and patterns within a tourism sector. Projecting them into the future reveals the expected future paths of tourism had the COVID-19 pandemic never occurred. Therefore it can be seen as what the tourism sector should possibly aspire to return to after the pandemic is over and the tourism industry has recovered. We label these as counterfactual ‘COVID-free’ forecasts. Using counterfactual forecasts, policy makers can assess the difference between the judgemental scenarios that account for COVID-19 and the projections generated as if the pandemic had never occurred.

A commonly observed feature of tourism time series is that they form natural aggregation structures with attributes such as, geographical location and purpose of travel, that are of interest to policy makers and tourism operators. Cross-products of such attributes form what are referred to as grouped-time series (see Hyndman & Athanasopoulos 2021, Chapter 11). Over the last decade the concept of forecast reconciliation has been developed with the aim of generating coherent forecasts for such structures, i.e., forecasts that adhere to the aggregation constraints and therefore aggregate in a consistent manner as the data. The concept was first introduced and implemented by Hyndman et al. (2011) and Athanasopoulos, Ahmed & Hyndman (2009) with tourism aggregation structures the centrepiece of the literature as it has developed.

In this paper we implement the MinT (Minimum Trace) optimal forecast reconciliation approach of Wickramasuriya, Athanasopoulos & Hyndman (2019). Besides achieving coherency, Panagiotelis et al. (2021) and Kourentzes & Athanasopoulos (2019), and references therein,

prove theoretical advantages and present ample empirical evidence that forecast reconciliation improves forecast accuracy over: (i) forecasting without taking into account aggregation constraints, which leads to generating incoherent forecasts, and (ii) applying traditional approaches for forecasting aggregation structures such as bottom-up or top-down. Kourentzes et al. (2021) provide further evidence of the benefits of forecast reconciliation for tourism forecasting.

Forecast reconciliation is implemented by linearly combining a set of incoherent forecasts referred to as *base* forecasts and denoted here by \hat{y}_{T+h} , using

$$\tilde{y}_{T+h} = \mathbf{S}\mathbf{G}\hat{y}_{T+h}, \quad (1)$$

where \mathbf{G} is a matrix that maps the base forecasts into the bottom-level of the aggregation structure, and \mathbf{S} is a summing matrix that sums these up using the aggregation constraints, to produce a set of *coherent* forecasts denoted by \tilde{y}_{T+h} . For the optimal MinT approach

$$\mathbf{G} = (\mathbf{S}'\mathbf{W}^{-1}\mathbf{S})^{-1}\mathbf{S}'\mathbf{W}^{-1} \quad (2)$$

where $\mathbf{W} = \text{Var}[(\mathbf{y}_{T+h} - \hat{y}_{T+h})]$ is the variance-covariance matrix of the base forecast errors and is estimated using a weighted least squares approximation, $\hat{\mathbf{W}} = \frac{1}{T} \sum_{t=1}^T \mathbf{e}_t \mathbf{e}_t'$ where \mathbf{e}_t is a vector of residuals of the models that generated the base forecasts.

Furthermore, we use combinations of statistical forecasts to further enhance accuracy. Since the seminal work of Bates & Granger (1969) there has been a flurry of papers in implementing forecast combinations for improving accuracy over individual forecasts. These have been prominent within the tourism literature, see Li et al. (2019) and references therein, but also in general forecast practices highlighted by the dominance of methods based on forecast combinations, see Smith & Wallis (2009), Chan & Pauwels (2018), Kourentzes, Barrow & Petropoulos (2019) and references therein.

With the above features in mind we generate base forecasts for each times series within each aggregation structure from ARIMA and ETS (exponential smoothing) models, automatically selected in the *fable* package (O'Hara-Wild, Hyndman & Wang 2020) using the AICc, and also a combination (the average) of the two. We then reconcile forecasts across each structure to generate coherent forecasts, i.e., point and probabilistic forecasts, using the WLS estimator in the Wickramasuriya, Athanasopoulos & Hyndman (2019) optimal MinT (minimum trace)

forecast reconciliation approach. Further, details of the processes used here are available in Hyndman & Athanasopoulos (2021), Chapter 11.

4 Experimental design: sectors, historical data, counterfactual forecasts and evaluation

We focus on the two largest sectors of Australian tourism namely international arrivals and domestic flows (the third one being outbound travel). Table 2 shows the details of grouped aggregation structures for the time series of each sector. For international arrivals we consider six international “Regions” crossed with five purposes of travel, while for domestic flows there are eight Australian states and territories crossed with four purposes of travel. These lead to a total of 42 and 45 series respectively that follow grouped aggregation structures with 30 and 32 series at the bottom-levels as a result of the two-way interactions between *Region* and *Purpose* for international arrivals, and *State* and *Purpose* for domestic visitor nights.

[Please insert Table 2 here]

4.1 International arrivals

International arrivals data span the period 2005 Q1 – 2019 Q4 and include all arrivals to Australia. The source of this data is the Australian Bureau of Statistics (ABS) Catalogue 3401.0 covering overseas arrivals and departures data. The left column in Table 3 shows the nineteen source countries considered. To facilitate the judgemental predictions, these are aggregated into six international ‘Regions’ of interest to the Australian tourism industry shown in the right column. Also of interest is the ‘Purpose’ of travel, as traveller behaviour and the impact of COVID-19 will vary across different purposes of travel. The purposes of travel for international arrivals to Australia are categorised as ‘Holiday’, ‘VFR’ (visiting friends and relatives), ‘Education’, ‘Business’ and ‘Other’.

[Please insert Table 3 here]

The quarterly time series for the overall aggregate, and the aggregates for regions and purposes of travel are shown in Figure 4, together with counterfactual forecasts, generated by the process described in Section 3.2. Some interesting and important observations emerge. International arrivals to Australia show a strong and consistent positive trend over the last few years. This is captured and projected in the counterfactual forecasts. An anomaly appears

in the 'Business' and 'Other' series; there seems to be a direct substitution or redefinition between 'Business' and 'Other' travel in 2017 Q2, with an abrupt upward shift in the former matched by a downturn shift of equal size in the latter, possibly related to changes in visa entry rules to Australia in 2017.

[Please insert Figure 4 here]

All arrivals also display a strong seasonal component which is reflected in the counterfactual forecasts. In almost all cases, this component appears to be multiplicative in nature, so that seasonal deviations increase proportionally to the increasing level of the series. Figure 5 is a seasonal plot (Hyndman & Athanasopoulos 2021) providing a more detailed view of the seasonal patterns. 'Holiday' and 'VFR' seem to be the main drivers of the seasonality in the aggregate series as well as for 'The Americas', Europe and the 'Other World' series. For these series, peaks are observed in Q1 and Q4, which include the summer period in Australia. In contrast, the 'Education' series shows peaks in Q1 and Q3 corresponding to the beginning and the mid-point of the academic year in Australia. This seems to be the main source driving arrivals from Mainland China. One region showing asynchronous seasonality with the rest of the world is New Zealand with troughs in Q1 and peaks in Q3. Note the importance of considering these at the disaggregate level and implementing forecast reconciliation, as these country based and purpose specific features are lost at the aggregate level.

[Please insert Figure 5 here]

4.2 Domestic visitor nights

We consider 'visitor nights' across Australia as a measure of domestic tourism flows. The data are provided by the National Visitor Survey based on an annual sample of 120,000 Australian residents aged 15 years and older. The way the data is collected has developed over the years, switching at the beginning of 2014 from telephone interviews to a 50:50 mobile/landline split. The sample spans the period 1998 Q1–2019 Q4. We disaggregate these into the eight Australian states and territories, and four purposes of travel.

Figure 6 shows time plots and counterfactual forecasts for the aggregate, across each of the states and territories and for each purpose of travel. The states show positive consistent trends since 2012, and these are reflected in the counterfactual forecasts. There appear to be some structural breaks in the series for the Northern Territory and Western Australia, perhaps due to changing definitions or data recording practices. All series by purpose of travel also

show significant positive trends over the last few years. The seasonal plots in Figure 7 highlight the differences in the northern states, such as Queensland and the Northern Territory and southern states, such as New South Wales, Victoria, South Australia and Tasmania. The peak visits for the former occur in winter (corresponding to Q3) due to the tropical climate and rainy summer months while for the latter the peak is in summer (corresponding to Q1).

[Please insert Figure 6 here]

[Please insert Figure 7 here]

4.3 Out-of-sample forecast evaluation

Withholding the last two years of data, 2018 Q1-2019 Q4, across all the series as a test-set, we generate 1- to 8-steps-ahead forecasts and evaluate their accuracy against the actual observations of the test-set. Table 4 shows the MAPE (mean absolute percentage error) and MASE (mean absolute squared error) calculated over the test-sets across all the series for each of the international and domestic grouped structures. The results show that for both structures the combined and reconciled forecasts are the most accurate. I.e., the process of first combining ARIMA and ETS forecasts, to generate incoherent base forecasts, and then using MinT to optimally reconcile these, results to the most accurate pre-COVID-19 forecasts.

[Please insert Table 4 here]

A note on the evaluation.

The purpose of Table 4 is to allow for the comparison of forecast accuracy between methods within each structure and not to compare across the two structures. However, there is an obvious drop in forecast accuracy between international arrivals and domestic visitor nights, although it is worth reiterating that the rankings between methods within each structure remain consistent. Such anomalies are always worth investigating. Figures 20 and 21 in Appendix A present point and interval forecasts as well as the actual values for the test-period 2018 Q1-2019 Q4, for international arrivals and domestic flows respectively.

Visual inspection indicates that the forecasts perform remarkably well in capturing the movements in the international arrivals test-set data. In contrast, for many of the domestic series, there seems to be a very strong and sudden increase in the trend during the test-set period with not enough history provided for the models to capture this. The sudden increase can be seen in the aggregate series and also throughout the various components. This highlights the

relatively lower accuracy of the domestic forecasts over the test-set compared to the international arrivals. We note that with another two years of history, this trend correction has been captured by the models and is included in the counterfactual forecasts as shown in Figure 6.

5 Results

5.1 Survey design and participants

In order to generate scenario-based probabilistic forecasts, we surveyed tourism experts asking them to provide judgement on the future of both international arrivals to Australia and domestic visitor nights. The survey took place in September 2020 and there were 443 participants with valid responses.

We sought a wide participation, as this is beneficial for judgemental forecasts, both in terms of sample to counterbalance biases and for incorporating viewpoints from multiple sectors and stakeholders. The latter is important to include a wide variety of perspectives, so as to avoid relying on a small sample of experts who may have a similarly biased viewpoint. The survey comprised of only eleven questions ensuring that it was engaging and manageable for participants. In the following sections we summarise and analyse the key results. The complete survey design and questionnaire is presented in Appendix B. The descriptive analysis in this section shows the diversity of the respondents in terms of: sector, size of organisation and the direct effect of the COVID-19 pandemic has had on their organisation.

Question 1: Which sector best describes your organisation?

The sector distribution from which the participants came is shown in Figure 8. The left panel shows that the largest proportion of participants came from ‘Industry’, followed by ‘Government’. The breakdown within each sector is shown in the right panel.

[Please insert Figure 8 here]

Question 2: How many people are currently employed by your organisation?

Figure 9 shows the size distribution of employer organisations for the respondents. Small industry businesses are well represented in the sample as well as larger government organisations.

[Please insert Figure 9 here]

Question 3: How does this employment figure compare with the start of 2020?

Figure 10 shows the change in the numbers employed in the organisations compared to the beginning of 2020, hence just pre-COVID-19. The top panel shows the distributions collectively. The most common response seems to be a 0–10% decrease followed by a 0–10% increase. Hence, overall it is most common to observe a change of up to 10% in absolute value. However, there is a long left tail to this distribution with mostly small businesses (fewer than 20 employees) taking the biggest hit. The bottom panels break this down by sector and shows that most of the decreases come from organisations labelled as ‘Industry’ or ‘Consultant’, with the ‘Government’ sector not being significantly affected outside the 10% change range.

[Please insert Figure 10 here]

5.2 Scenario-based probabilistic forecasts for international arrivals

In this section we present the results and detailed analysis for Questions 4-7 related to international arrivals to Australia.

Question 4: What will the level of international arrivals to Australia be in 2021 Q4 compared to 2019 Q4?

Implementing the methodology of Section 3, results to the scenario-based forecast distributions together with the path and the distributions of the COVID-free counterfactual forecasts, plotted in Figure 11. This plot provides a good understanding of the locations of the distributions relative to the counterfactual forecasts and the last observed value, as well as an excellent visual on the differences between the distributions. Note that we drop the ‘Mixture (10,10,80)’ from all figures to avoid congesting the plots. The counterfactual forecast distribution has been truncated in order to assist with visualisation. The figure also highlights the substantial difference in the uncertainty between the scenario-based forecasts under COVID-19 and the counterfactual COVID-free forecasts for 2021 Q4.

[Please insert Figure 11 here]

Some specific statistics of interest are presented in Table 5. By comparison, the value of 2019 Q4, the last pre-COVID-19 quarter, is 2.67 million arrivals. Under the ‘Mixture (10,80,10)’ distribution, the median forecast value for 2021 Q4 shows 1.30 million arrivals. This is a predicted decrease of 51% compared to 2019 Q4, instead of a 4% increase shown by the counterfactual COVID-free forecast value. The 80% prediction interval for the same ‘Mixture (10,80,10)’ distribution scenario returns a range for the decrease in international arrivals between 7% and 85%. The width of the prediction interval further highlights the tremendous

uncertainty of the future of international arrivals after the COVID-19 pandemic has hit, compared to the tightness of the counterfactual COVID-free 80% prediction interval which shows an increase between 2% and 7%.

[Please insert Table 5 here]

Question 5: In what year do you think international visitor numbers will return to 2019 levels?

Figure 12 shows the raw responses, kernel density estimates (bandwidth 0.6), and the estimated mixture distributions for when respondents anticipate international arrivals to recover to 2019 Q4 levels. The bottom panel plots the estimated forecast distributions superimposed on each other across the time axis for international arrivals. The plot shows the contrasts between the distributions for the different scenarios as the peak of the estimated densities moves further into the future as the scenario moves from 'Optimistic' to 'Most likely' to 'Pessimistic'. Table 6 shows some specific statistics of interest. The median recovery quarter varies from 2022 Q4 in the 'Optimistic' scenario to 2025 Q1 in the 'Pessimistic' scenario. The median recovery quarter for the 'Mixture (10,80,10)' distribution is 2023 Q4 with the 80% prediction interval showing as lower bound 2022 Q2 and upper bound 2025 Q2.

[Please insert Figure 12 here]

[Please insert Table 6 here]

Questions 6 & 7: In what year do you think international visitor numbers for the following markets will return to 2019 levels? Please provide estimates only for the most likely scenario.

In order to keep the respondents engaged and the survey manageable, respondents were required to provide estimates only for the 'Most likely' scenario for the markets segmented by the five international 'Regions' as shown in Table 3 and for the 'Purposes' of travel. The bar plots of the raw responses and fitted kernel density estimates (bandwidth = 0.5) are presented in Figure 13. Table 7 shows some specific statistics of interest. The results show that the respondents have selected New Zealand as the international arrivals source that will recover the quickest with median predicted quarter of full recovery 2022 Q2. Mainland China is selected to be the slowest to recover, with median predicted quarter of full recovery 2024 Q1. In terms of purpose of travel the results show that 'Holiday' travel will be the slowest to recover with median predicted quarter of full recovery 2023 Q4, with 'VFR' the quickest to recover with median predicted quarter of full recovery 2022 Q4. Of course, there is high uncertainty surrounding these point predictions as indicated by the width and the asymmetry of the prediction intervals with most distributions showing a very long right tail.

[Please insert Figure 13 here]

[Please insert Table 7 here]

5.3 Scenario-based probabilistic forecasts for domestic visitor nights

In this section we present the results for Australian domestic visitor nights. In contrast to international arrivals respondents were asked to provide scenarios for both 2020 Q4 as well as 2021 Q4.

Question 8: What will the level of domestic visitor nights be in 2020 Q4 and 2021 Q4 compared to 2019 Q4?

The left column of Figure 14 shows bar plots and estimated densities for the survey responses for 2020 Q4 while the results for 2021 Q4 are shown in the right column. The rows summarise the results for the ‘Pessimistic’, ‘Most likely’ and ‘Optimistic’ scenarios as well as the ‘Mixture (10,80,10)’ distribution. The peak of the ‘Mixture (10,80,10)’ distribution shows approximately 50% of the domestic visitor nights will be maintained for 2020 Q4 compared to 2019 Q4, while moving closer to full recovery for 2021 Q4.

[Please insert Figure 14 here]

The scenario-based forecast distributions as well as the paths and prediction intervals for the counterfactual COVID-free forecasts are shown in Figure 15. All scenarios show a substantial decrease compared to the counterfactual forecasts for both 2020 Q4 and 2021 Q4, with the exception of the ‘Optimistic’ scenario for 2021 Q4. The shapes of the forecast distributions reflect the tremendous uncertainty surrounding domestic tourism due to the COVID-19 pandemic when compared to the COVID-free counterfactual forecast distributions.

[Please insert Figure 15 here]

Figure 16 provides insights on the projections of the scenario based forecasts between the two years. The plot shows that the trends (both means and medians) projected between 2020 Q4 and 2021 Q4 are fairly consistent across the three scenarios and the mixture. It also shows the higher growth between the two years across all scenarios compared to the growth shown for the counterfactual COVID-free forecasts, anticipating a faster rate of recovery.

[Please insert Figure 16 here]

Table 8 provides some specific statistics of interest. The median forecasts for the ‘Mixture’ distribution are 57.2 and 90.0 million visitor nights for 2020 Q4 and 2021 Q4 respectively.

These show a decrease of 44% and 12% compared to projected increases of % and % for the counterfactual COVID-free forecasts. Hence, the expectation for domestic tourism seems to be that after the deep hit of 2020, there will be a rapid recovery for 2021 although one should always keep in mind the considerable width of the prediction intervals. Specifically, the 80% interval for the 'Mixture' distribution shows decreases ranging between 84% and 14% for 2020 Q4. For 2021 Q4, the lower bound shows a decrease of 62% while the upper bound an increase by 25%.

[Please insert Table 8 here]

Question 9: In what year do you think domestic visitor nights will return to 2019 levels?

Figure 17 shows the bar plots, kernel density estimates and superimposed forecast distributions for when respondents anticipate domestic visitor nights to recover to 2019 Q4 pre-COVID-19 levels. The plot shows the contrasts between the distributions for the different scenarios as the peak of the estimated densities moves further into the future as the scenario moves from 'Optimistic' to 'Most Likely' to 'Pessimistic'.

[Please insert Figure 17 here]

Table 9 shows some specific statistics of interest. The median recovery quarter varies from 2021 Q4 for the 'Optimistic' scenario to 2023 Q2 for the 'Pessimistic' scenario. The median recovery quarter for the 'Mixture (10,80,10)' distribution is 2022 Q3 with the 80% prediction interval showing as lower bound 2021 Q2 and upper bound 2023 Q4.

[Please insert Table 9 here]

Questions 10 & 11: In what year do you think domestic visitor nights will return to 2019 levels for the following markets?

Similar to Questions 6 and 7, respondents were required to provide estimates only for the 'Most likely' scenario for the markets segmented by 'States' and 'Purpose' of travel. The bar plots of the raw responses and fitted kernel density estimates are presented in Figure 18.

[Please insert Figure 18 here]

Table 10 shows some specific statistics of interest. The results do not show much variation across the states with the median expected quarter of full recovery to 2019 Q4 levels, being 2022 Q2. The only slight variations seems to be an anticipated earlier recovery by one quarter for Queensland, and a later recovery also by one quarter for Victoria. We should note that

at the time of the survey being conducted Victoria was going through a second wave with severe lockdown measures and a night curfew in place.

[Please insert Table 10 here]

In terms of purpose of travel, the results show that VFR is anticipated to be the quickest to recover with median predicted quarter of full recovery 2021 Q4 followed by Holiday with median predicted quarter of recovery 2022 Q2. The slowest to recover is anticipated to be Business travel with median predicted quarter of full recovery 2022 Q3. Of course, the high uncertainty surrounding these point predictions is highlighted by the width and the asymmetry of the prediction intervals with most distributions showing a considerably long right tail.

5.4 A post-survey real time evaluation

Upon completing the write up of the paper and with many developments related to COVID-19 pandemic, such as several vaccines being available around the world, we had the opportunity to evaluate the quality of our probabilistic scenario-based forecasts. We do this for Australian domestic tourism as the Australian international border remains closed to arrivals at the time of evaluation. Figure 19 shows the updated data for Australian domestic visitor nights, now including observations up to 2020 Q3. After reaching a low point of approximately 40 million in 2020 Q2, Australian domestic visitor nights increased to over 60 million in 2020 Q3. The second wave of the pandemic hit Australia during the months of July-August 2020 with the majority of cases concentrated in the state of Victoria. With the tight controls, in terms of regional and very strict and effective lockdowns by Australian state governments where they are deemed to be necessary, it seems that Australian domestic tourism may be well on the road to recovery to pre-pandemic levels. The scenario-based probabilistic forecasts seem to cover well such a possibility. We can speculate at this stage that the optimistic scenario may be the one to most likely prevail.

[Please insert Figure 19 here]

6 Discussion and conclusions

The onset of the COVID-19 pandemic has been arguably the greatest challenge faced by the global community over the last few decades. The necessary efforts of nations to slow down the transmission of the virus has severely affected global tourism. Understanding how the

sector may recover is key for policy makers, tourism planners and destination marketers, whether they are in government or in business. The depth and severity of the disruption has meant that forecasting practice “as usual” is no longer possible.

In this paper we have provided an innovative methodology to generate probabilistic forecasts for the path to recovery that can support policy and planning. Conducting a large scale survey we asked tourism experts to provide their judgement for three alternative scenarios: ‘Pessimistic’, ‘Most likely’ and ‘Optimistic’. Using their responses we built judgemental scenario-based probabilistic forecasts for numerous segments of the Australian tourism industry that are of interest to policy makers. The experts anticipated different markets to be affected at different levels and to recover at different rates.

Our proposed approach can serve as a blueprint for generating similar forecasts for different countries and regions. We argue that the collection of data from participants is relatively easy, as we do not require the composition of an expert panel, which can be time-consuming and potentially expensive, but rather rely on the wide participation from various stakeholders and sectors. Our online survey was engaging and allowed us for a wide reach, as evident by the number of participants. This easiness of collecting views from a large number of participants mitigates judgemental biases, that may remain in smaller panels of experts, for instance by relying on the same sources of information.

Although human judgement is very useful for generating forecasts in situations where past historical observations are of little relevance, as is the case for the COVID-19 pandemic, we recognise that there are still weaknesses in the approach. We remedy these by, first, generating multiple probabilistic scenarios, and second, offering a way for decisions makers to weigh and mix these scenarios. On the one hand, the multiple probabilistic scenarios enable us to assess not only the different potential futures but also the uncertainty in each of these, as reflected in the shape of the distributions. On the other hand, the mixture result is robust in both reducing any estimation issues coming from the statistical treatment of the forecasts, but also in further mitigating any biases or misunderstandings by the participants. We argue that the last point is crucial. There is evidence in the literature that humans can obfuscate the generation of scenarios with the extremes of probabilistic forecasts, as discussed in Section 2. By asking explicitly to provide both scenarios and recovery probabilities we structure the cognitive task so as the participants can disentangle these two concepts. As there is no conclusive research on how to resolve this in the literature, we rely on the mixtures to counteract remaining biases and potential confusions from the participants. Nonetheless, further

research is needed in this area. Our work is complementary to the increasing body of work on using scenarios to forecast the road to recovery from the COVID-19 pandemic. We provide a convenient way for generating scenarios, and methods to enrich these with a probabilistic view, as well as how to get a single mixture representation. The latter can be useful to enhance the scenario generation in existing research.

Some general conclusions can be drawn for the Australian tourism sector. Compared to the domestic market the loss in the international arrivals market is expected to be substantially higher and the recovery period substantially longer, stretching to possibly beyond 2023. This may encourage policy makers to concentrate on turning internationally focused operations to domestic ones. In the short-term this will assist local operators to survive and recover from the current recessionary phase. Arrivals from New Zealand, Australia's fourth largest market at the country level in terms of volume, are expected to recover the quickest compared to all other international destinations. For both international and domestic markets, VFR is expected to recover the quickest with people eager to physically reconnect with family and friends. Holiday travel is expected to take longer. The uncertainty surrounding attractive destinations, the use of aviation travel, and the associated expense, may encourage people to spend money elsewhere. Somewhere in between are education and business travel, with the rapid development of an online environment for both these segments delaying and possibly permanently hindering a full recovery to pre-COVID levels.

Of course one must be mindful of the high degree of uncertainty currently surrounding the outlook of tourism. In our study this is reflected by the width of the scenario-based probabilistic forecasts compared to the counterfactual COVID-free forecasts. Dealing with the pandemic is highly dynamic and extremely volatile. How the Australian government allows for international tourism, and the prevalence of the pandemic in different parts of the world, can result in rapidly modified dynamics. For example, the explosive nature of the second wave in Victoria, Australia, which started in July 2020, led to a second unexpected round of strict state-wide restrictions and interstate border closures.

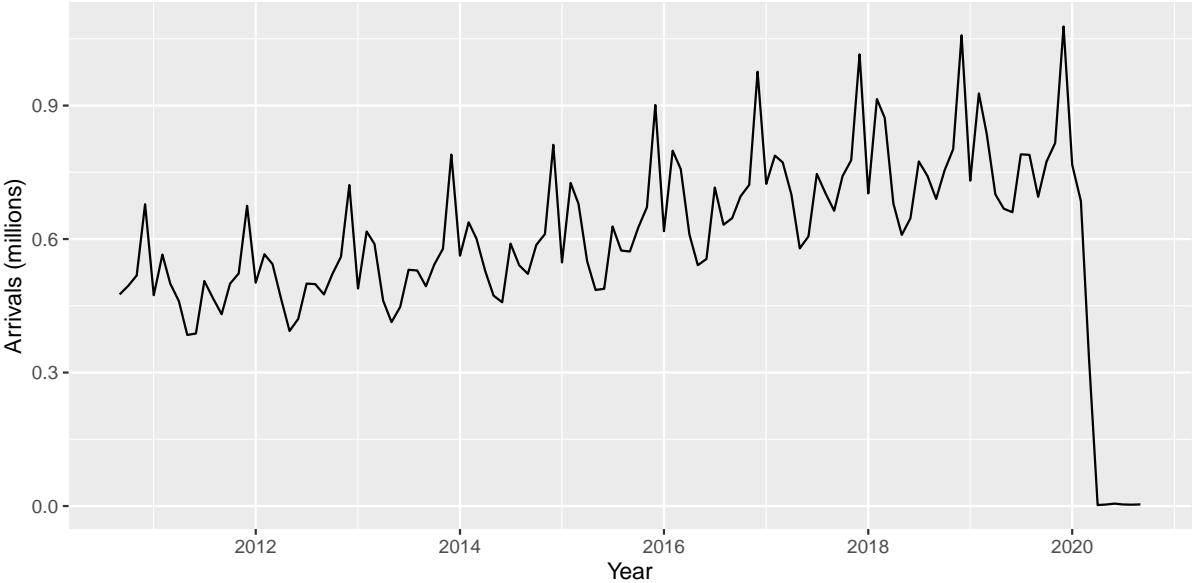


Figure 1: Short-term international arrivals to Australia up to September 2020.

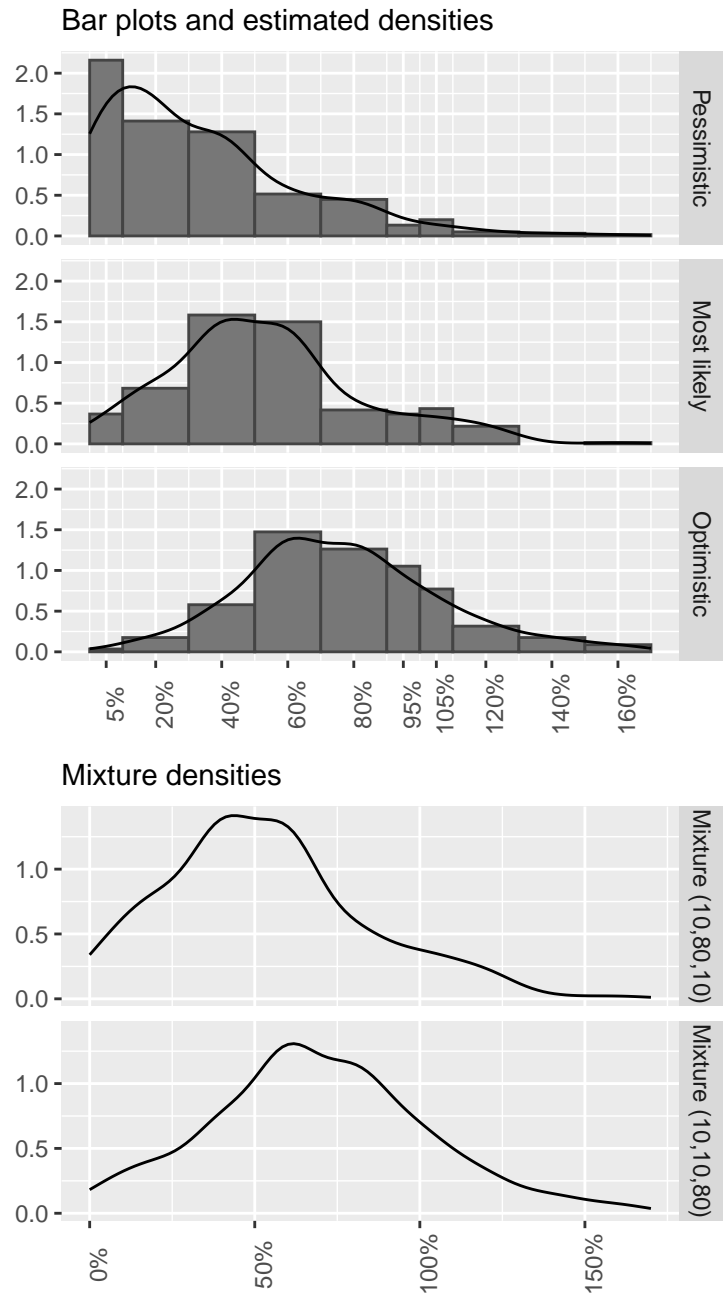


Figure 2: Scenario-based forecast distributions for international arrivals for 2021 Q4 compared to 2019 Q4, assuming international borders reopen in mid-2021. The horizontal scale represents the scaling factor applied to 2019 Q4 arrivals in order to estimate forecast distributions for 2021 Q4. The example is based on Question 4 of the survey.

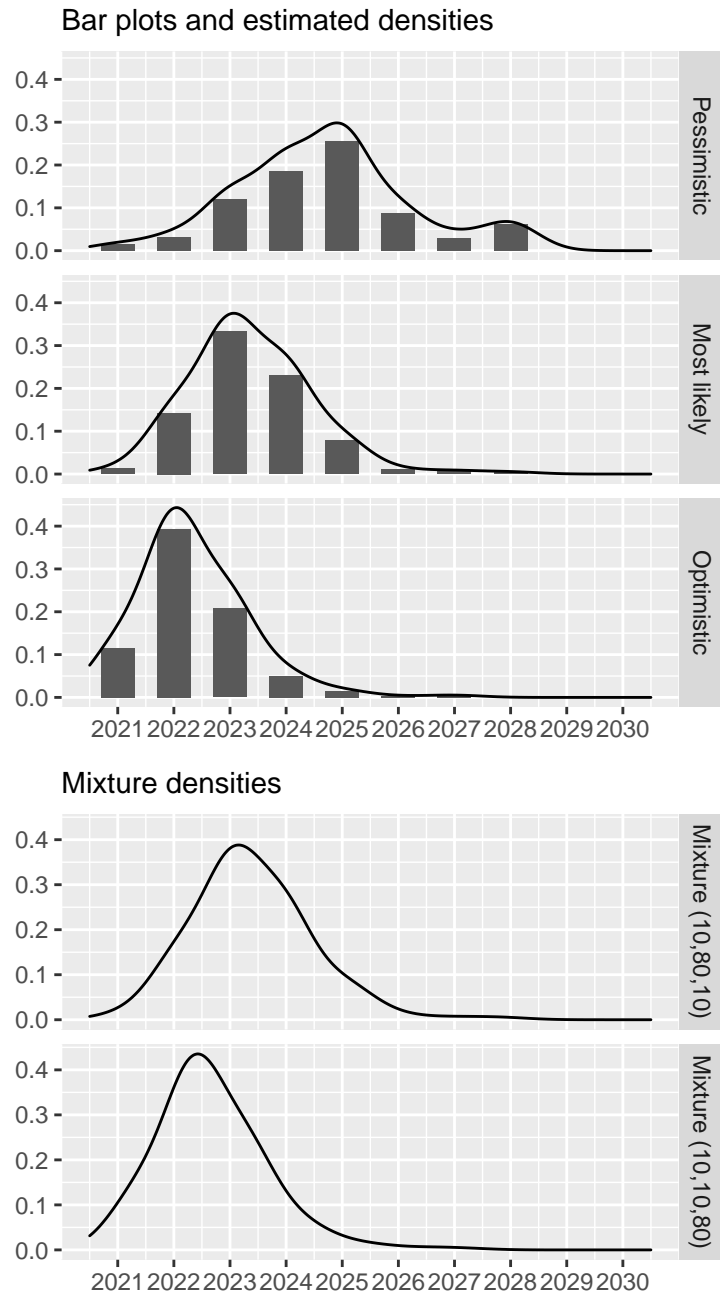


Figure 3: Scenario-based forecast distributions for the year international arrivals will recover to 2019 levels. The example is based on Question 5 of the survey.

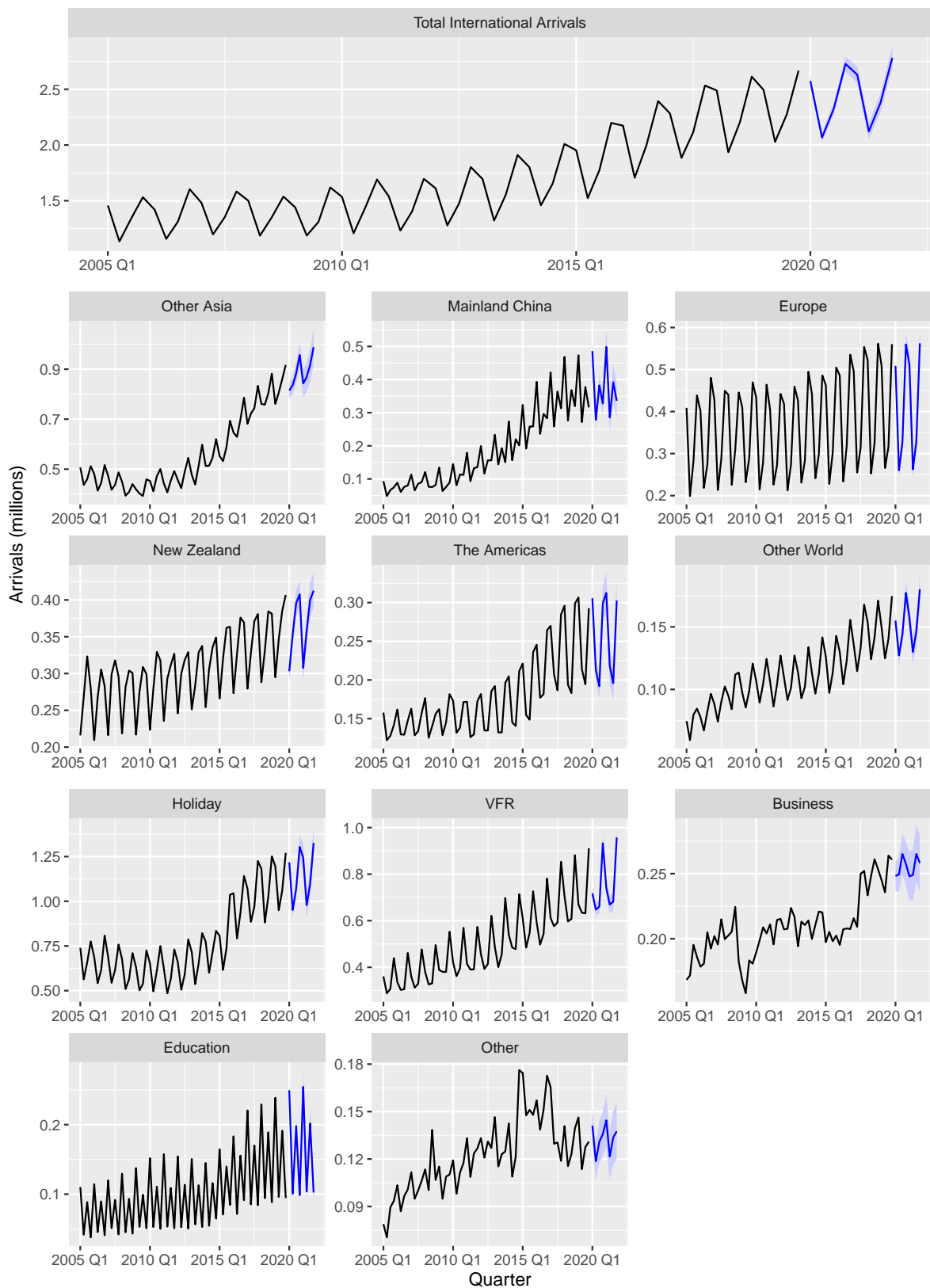


Figure 4: Time series and counterfactual COVID-free forecasts for 2020–2021 for total international arrivals to Australia, and the same data disaggregated by state and by purpose of travel. The shaded regions correspond to 95% prediction intervals.

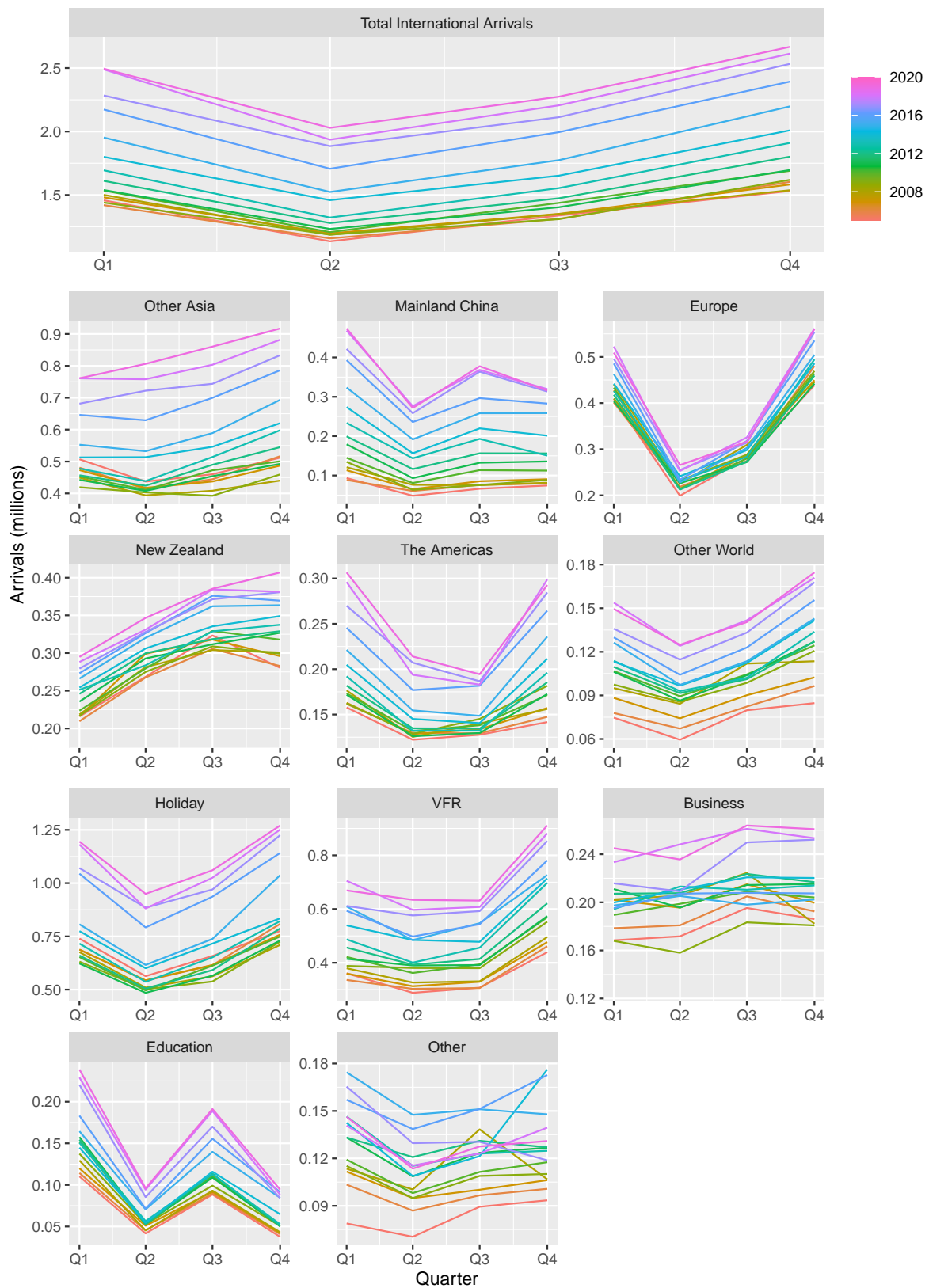


Figure 5: Seasonal plots of total international arrivals to Australia, and the same data disaggregated by region and by purpose of travel.

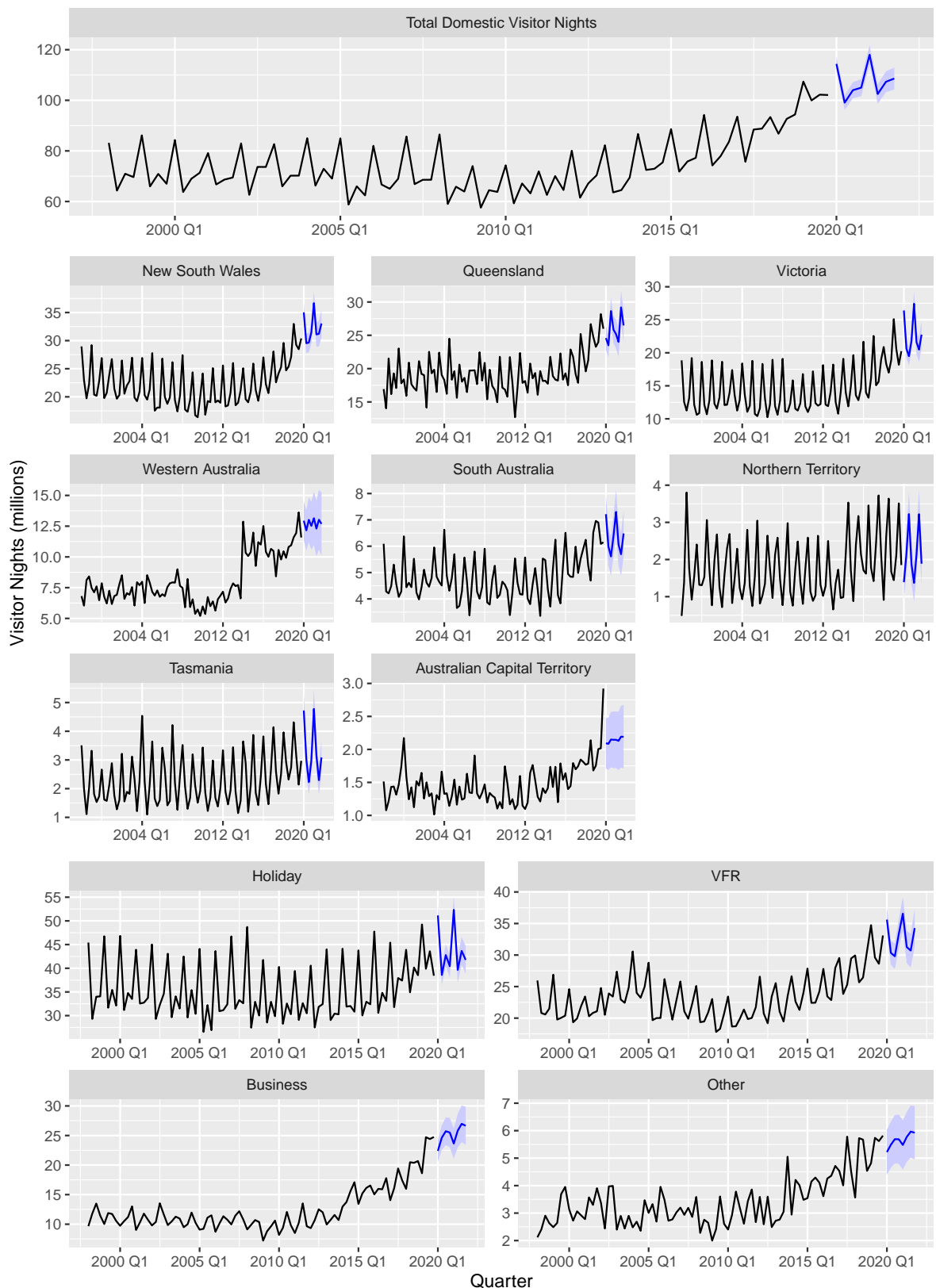


Figure 6: Time series and counterfactual COVID-free forecasts for 2020–2021 for total Australian domestic visitor nights, and the same data disaggregated by state and by purpose of travel. The shaded regions correspond to 95% prediction intervals.



Figure 7: Seasonal plots of total Australian domestic visitor nights, and the same data disaggregated by state and by purpose of travel.

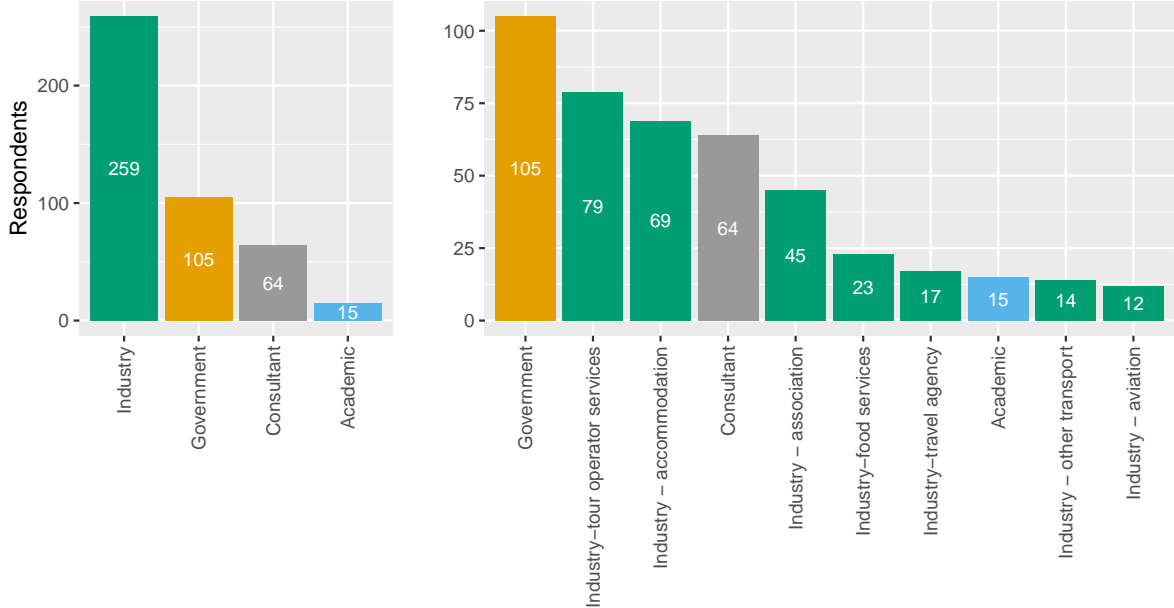


Figure 8: Which sector best describes your organisation?

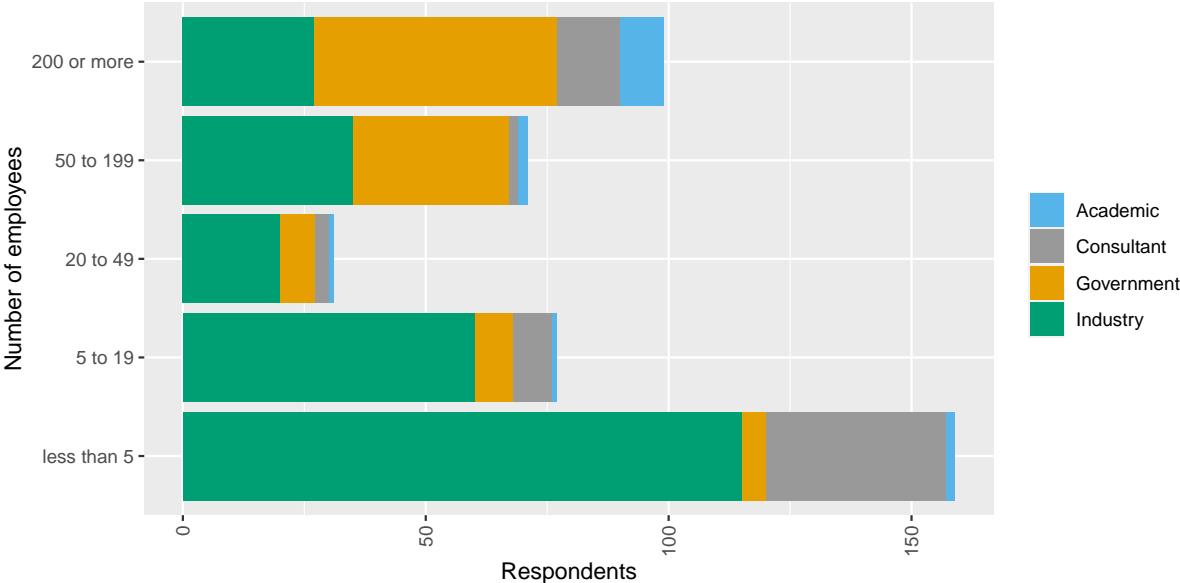


Figure 9: How many people are currently employed by your organisation?

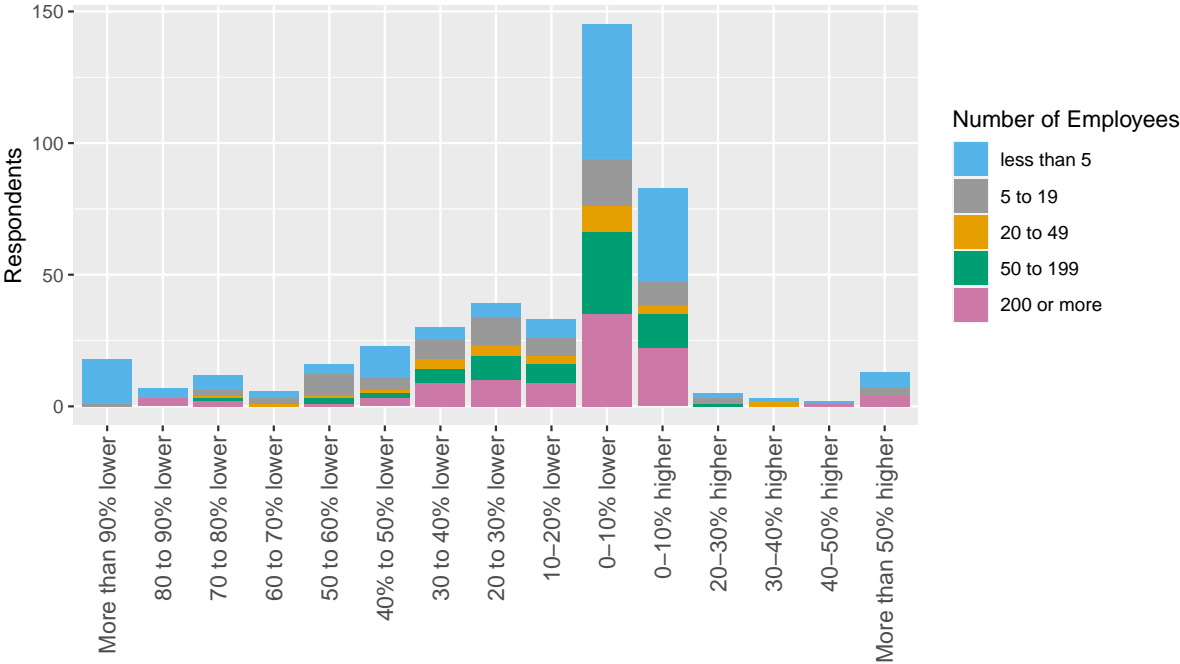


Figure 10: How does the number of people employed in your organisation compare with the start of 2020?

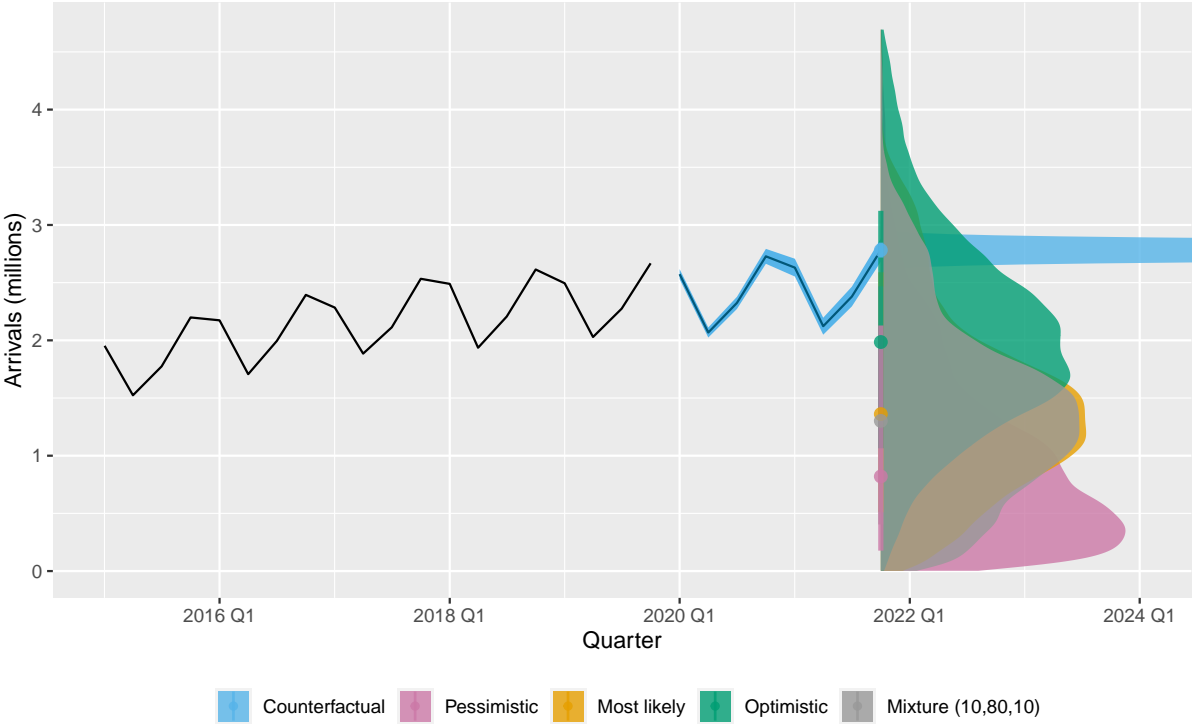


Figure 11: Scenario-based and counterfactual COVID-free forecast distributions for international arrivals to Australia for 2021 Q4. Note that the counterfactual forecast distribution has been truncated in order to assist with visualisation.

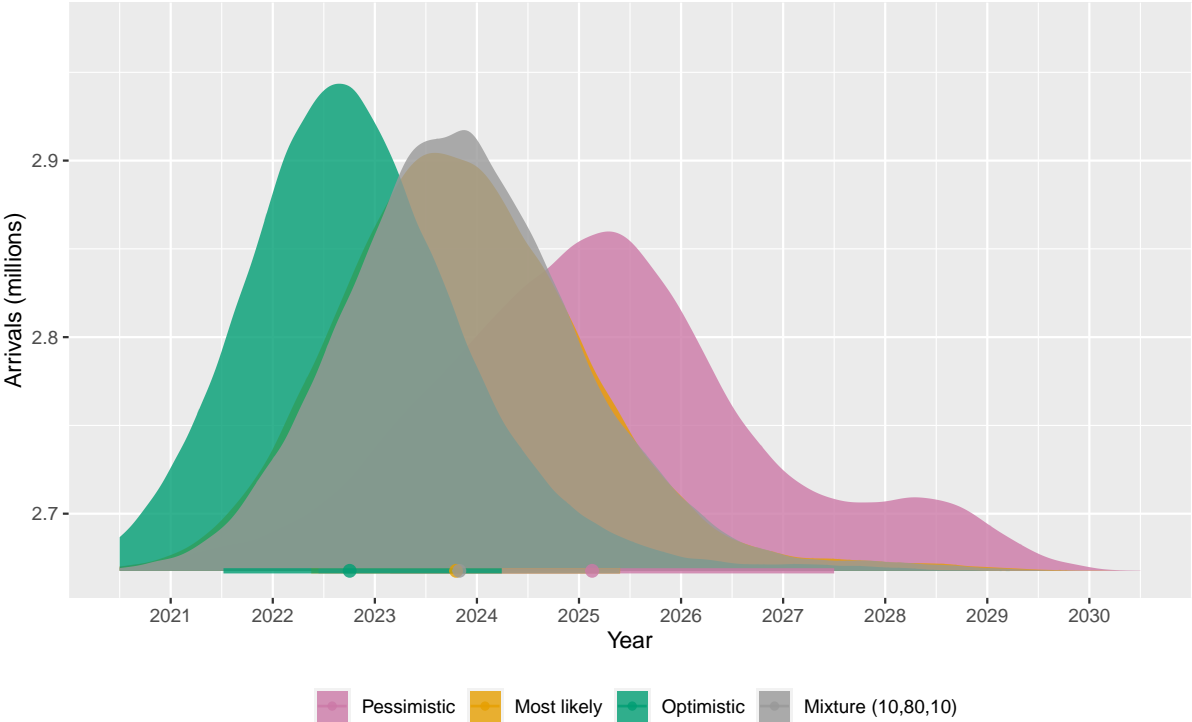


Figure 12: Forecast distributions of when international arrivals will recover to 2019 levels estimated from survey responses to Question 5.

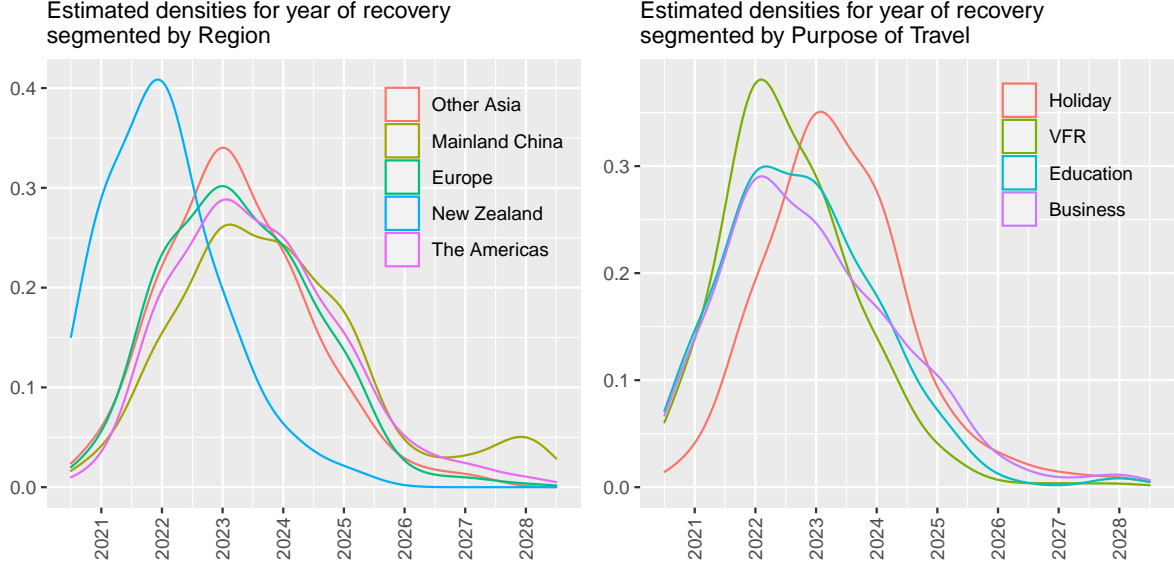


Figure 13: *Estimated densities for the most likely year international visitor numbers will return to 2019 levels for Regions and for Purpose of Travel.*

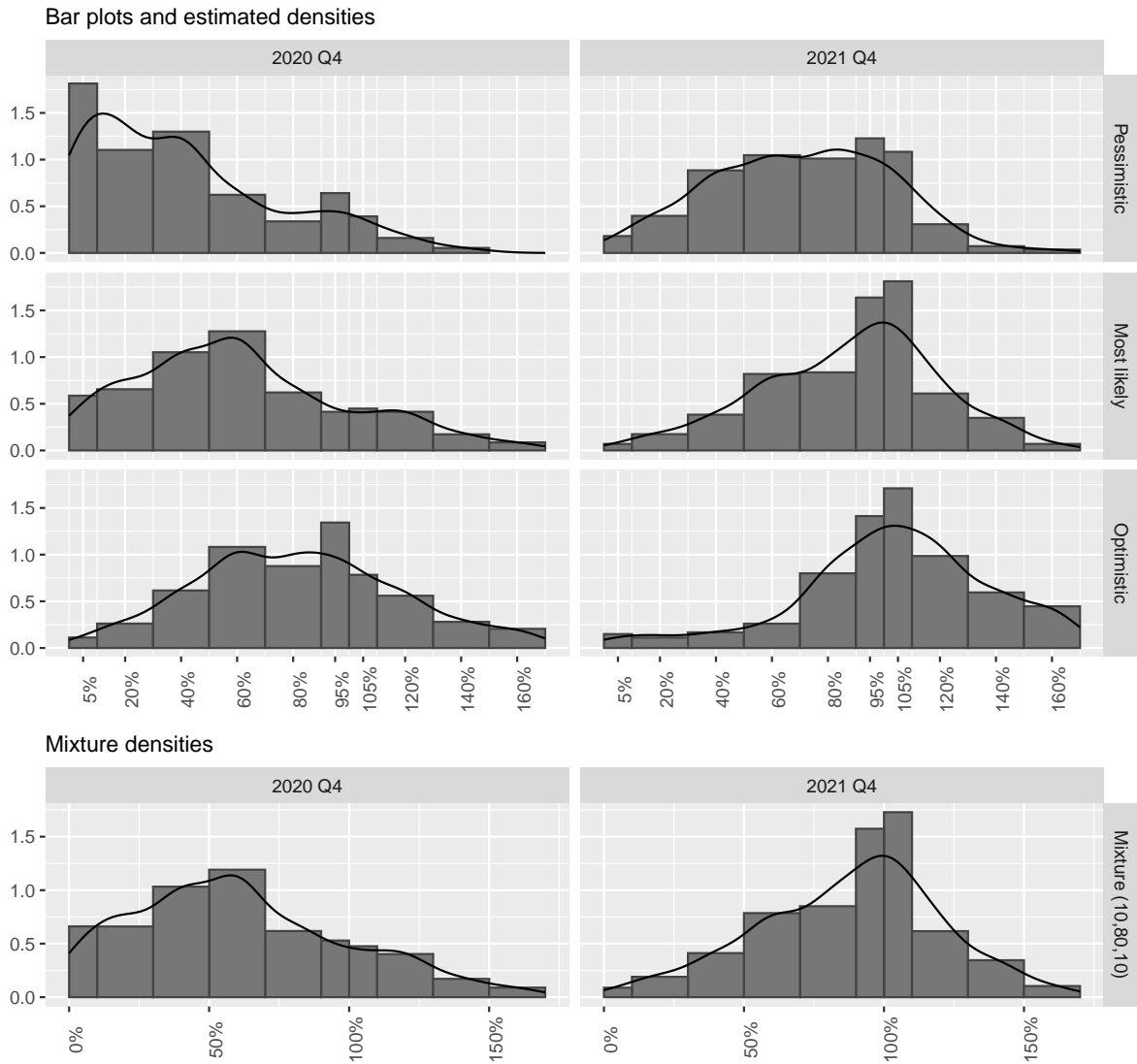


Figure 14: Scenarios for domestic visitor nights for 2020 Q4 and 2021 Q4 compared to 2019 Q4. The *x*-scale for the fitted densities represents the scaling factor applied to domestic flow counts of 2019 Q4 in order to estimate forecast distributions for 2020 Q4 and 2021 Q4.

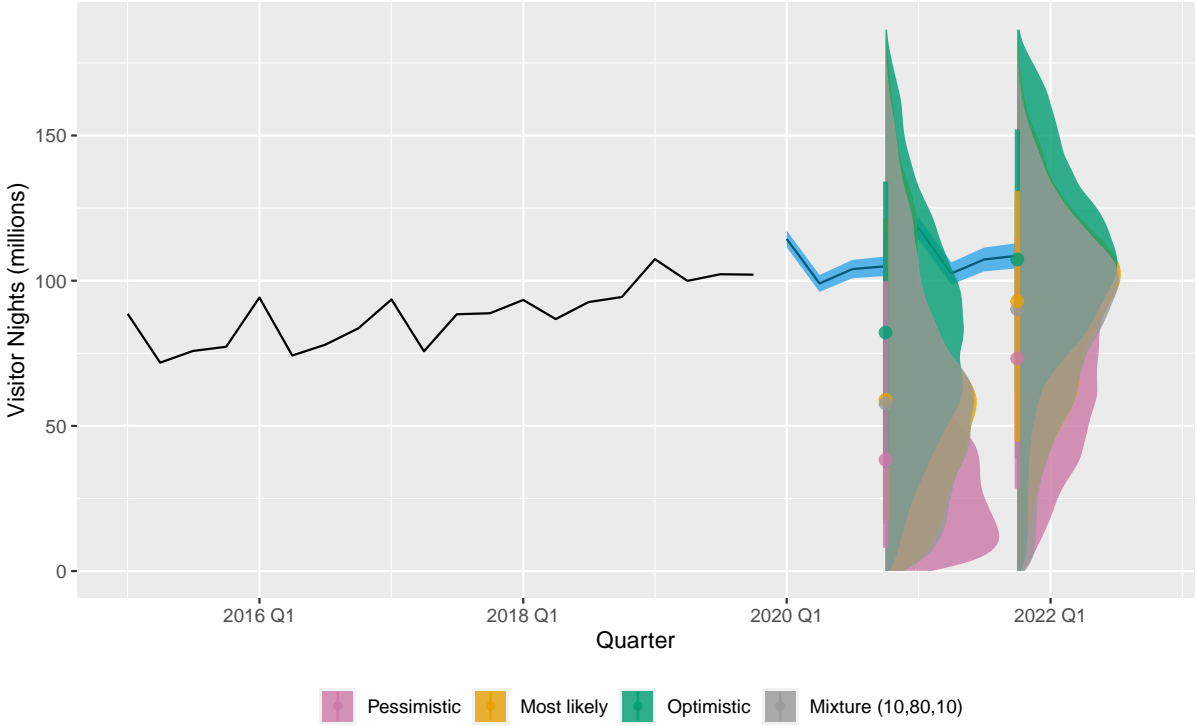


Figure 15: Scenario-based and COVID-free counterfactual forecast distributions for Australia domestic visitor nights for 2020 Q4 and 2021 Q4

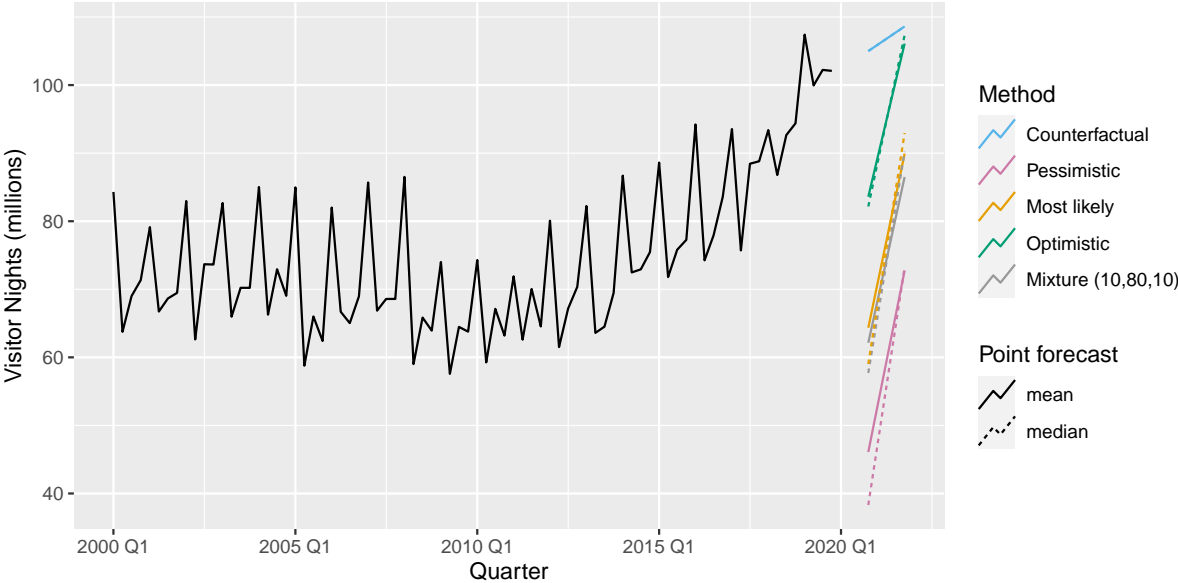


Figure 16: Paths of projections for domestic visitor nights showing consistency in respondents

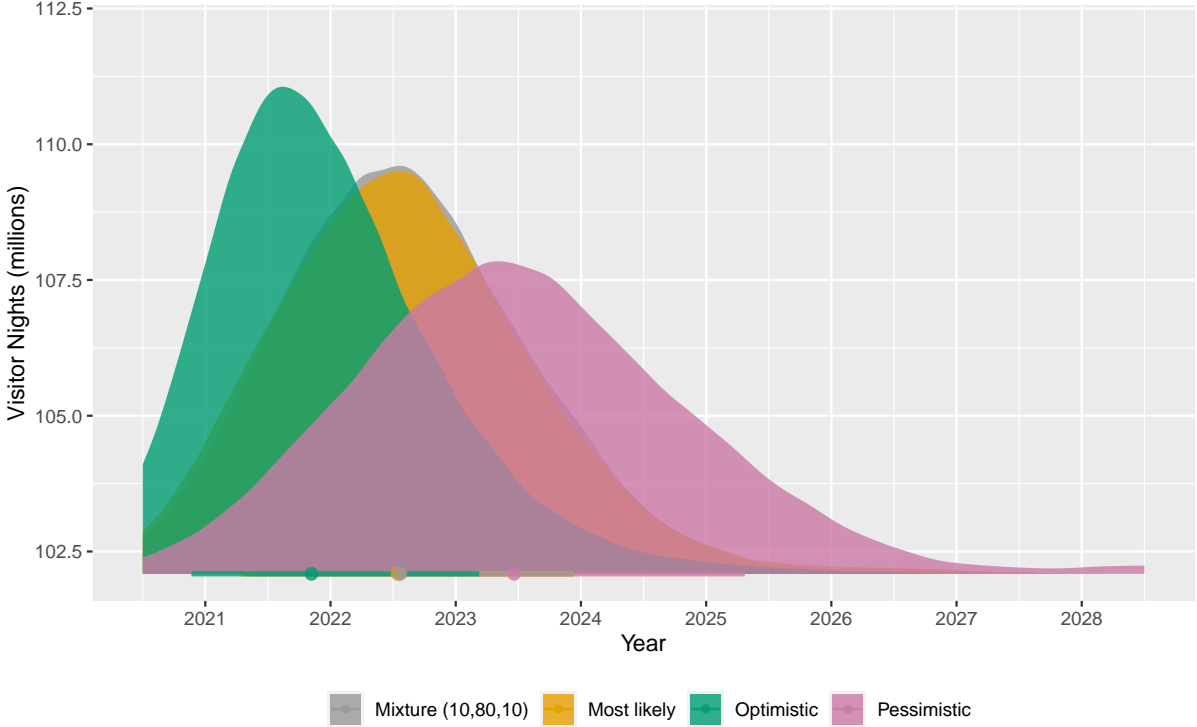


Figure 17: Scenarios for the year domestic visitor nights will recover to 2019 levels.

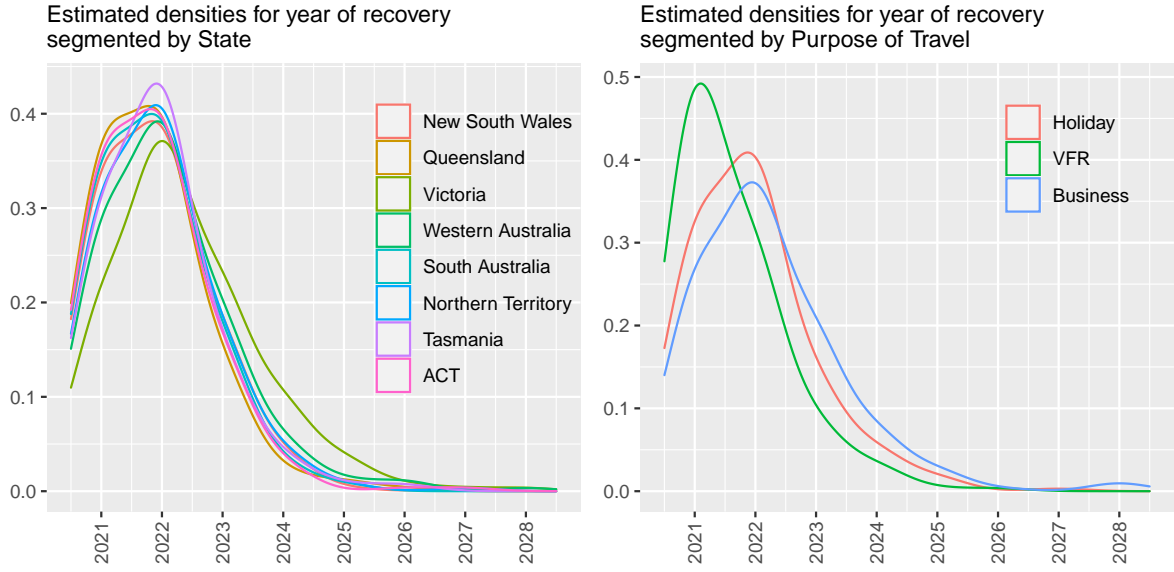


Figure 18: Estimated densities for the most likely year that domestic visitor nights will return to 2019 levels for states and purpose of travel.

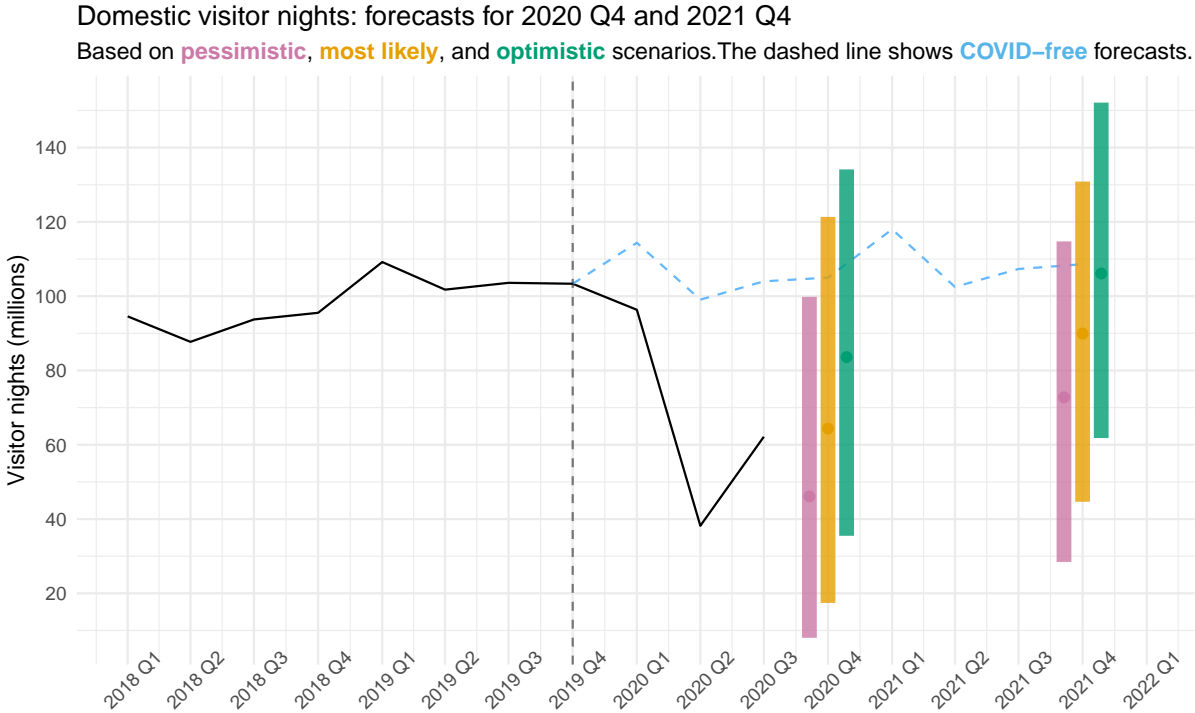


Figure 19: A post-survey real time evaluation for Australian domestic visitor nights. The plot shows scenario-based judgemental forecasts from experts taking into account the COVID-19 pandemic as well as COVID-free statistical forecasts, plotted against data observed post the survey being completed.

Table 1: *Scaling factors to convert survey scenario categorical responses to a continuous distribution.*

Category	Factor
Lower 90-100%	0.05
Lower 70-90%	0.20
Lower 50-70%	0.40
Lower 30-50%	0.60
Lower 10-30%	0.80
Lower 0-10%	0.95
Higher 0-10%	1.05
Higher 10-30%	1.20
Higher 30-50%	1.40
Higher than 50%	1.60

Table 2: *Grouped structures for international arrivals and domestic visitor nights.*

Grouping	No. of Series	Grouping	No. of Series
<i>International Arrivals</i>		<i>Domestic visitor nights</i>	
Total aggregate	1	Total aggregate	1
Region	6	States	8
Purpose	5	Purpose	4
Region \times Purpose	30	States \times Purpose	32

Table 3: *Source countries and regions for Australian international arrivals.*

Country	Region	
China	China	
Hong Kong	Other Asia	
Thailand		
Malaysia		
Indonesia		
Singapore		
Japan		
South Korea		
India		
Other Asia		
United Kingdom		Europe
Germany		
France		
Other Europe		
New Zealand	New Zealand	
United States	The Americas	
Canada		
Middle East	Other World	
Other World		

Table 4: *1 to 8-steps ahead out-of-sample forecast accuracy evaluation over the test-set period 2018 Q1-2019 Q4 for Australian international arrivals and domestic visitor nights.*

Model	International arrivals		Domestic visitor nights	
	MAPE	MASE	MAPE	MASE
ARIMA	10.43	1.34	21.98	1.74
ETS	8.16	1.16	21.38	1.69
Combined	8.35	1.10	21.38	1.68
Combined and Reconciled	7.95	1.05	20.80	1.65

Table 5: *Scenario-based and counterfactual COVID-free forecasts for international arrivals to Australia in (millions) for 2021 Q4. The observed value for 2019 Q4 is 2.67.*

Scenario	Mean	Median	80%	95%
Counterfactual	2.78	2.78	[2.72, 2.85]	[2.68, 2.88]
Pessimistic	1.00	0.82	[0.18, 2.13]	[0.05, 2.97]
Most likely	1.45	1.36	[0.51, 2.59]	[0.19, 3.24]
Optimistic	2.05	1.99	[1.06, 3.12]	[0.56, 3.91]
Mixture (10,80,10)	1.37	1.30	[0.40, 2.47]	[0.13, 3.07]
Mixture (10,10,80)	1.70	1.69	[0.44, 2.84]	[0.12, 3.52]

Table 6: Recovery scenarios for international arrivals

Scenario	Mean	Median	80%	95%
Pessimistic	2025 Q1	2025 Q1	[2023 Q1, 2027 Q3]	[2022 Q1, 2028 Q4]
Most likely	2023 Q4	2023 Q4	[2022 Q2, 2025 Q2]	[2021 Q3, 2026 Q3]
Optimistic	2022 Q4	2022 Q4	[2021 Q3, 2024 Q1]	[2020 Q4, 2025 Q2]
Mixture (10,80,10)	2023 Q4	2023 Q4	[2022 Q2, 2025 Q2]	[2021 Q4, 2026 Q2]
	2023 Q1	2023 Q1	[2021 Q4, 2024 Q3]	[2021 Q1, 2025 Q3]

Table 7: Recovery scenarios for international markets

	Mean	Median	80%	95%
International Regions				
Other Asia	2023 Q3	2023 Q3	[2022 Q1, 2025 Q2]	[2021 Q2, 2026 Q3]
Mainland China	2024 Q2	2024 Q1	[2022 Q2, 2026 Q3]	[2021 Q3, 2028 Q3]
Europe	2023 Q4	2023 Q3	[2022 Q1, 2025 Q3]	[2021 Q2, 2026 Q3]
New Zealand	2022 Q3	2022 Q2	[2021 Q1, 2024 Q1]	[2020 Q3, 2025 Q1]
The Americas	2024 Q1	2023 Q4	[2022 Q2, 2025 Q4]	[2021 Q3, 2027 Q2]
Purpose of Travel				
Holiday	2023 Q4	2023 Q4	[2022 Q2, 2025 Q3]	[2021 Q3, 2027 Q1]
VFR	2023 Q1	2022 Q4	[2021 Q3, 2024 Q3]	[2020 Q4, 2025 Q3]
Business	2023 Q2	2023 Q2	[2021 Q3, 2025 Q3]	[2020 Q4, 2026 Q4]
Education	2023 Q2	2023 Q1	[2021 Q3, 2025 Q1]	[2020 Q4, 2026 Q1]

Table 8: *Scenario-based and counterfactual COVID-free forecasts for Australian domestic visitor nights in (millions) for 2020 Q4 and 2021 Q4. The observed value for 2019 Q4 is 102.09.*

Quarter	Scenario	Mean	Median	80%	95%
2020 Q4	Counterfactual	104.99	104.99	[102.80, 107.19]	[101.64, 108.35]
2020 Q4	Pessimistic	46.09	38.30	[8.02, 99.83]	[2.28, 124.86]
2020 Q4	Most likely	64.35	59.02	[17.42, 121.35]	[5.44, 149.32]
2020 Q4	Optimistic	83.60	82.16	[35.49, 134.14]	[15.29, 161.59]
2020 Q4	Mixture (10,80,10)	62.14	57.71	[16.28, 116.53]	[5.33, 145.28]
2021 Q4	Counterfactual	108.61	108.61	[105.78, 111.44]	[104.28, 112.94]
2021 Q4	Pessimistic	72.75	73.23	[28.45, 114.74]	[11.61, 135.06]
2021 Q4	Most likely	89.93	92.96	[44.65, 130.87]	[20.53, 151.48]
2021 Q4	Optimistic	106.10	107.34	[61.81, 152.12]	[20.87, 169.68]
2021 Q4	Mixture (10,80,10)	86.50	90.22	[38.75, 127.91]	[11.93, 147.75]

Table 9: Recovery scenarios for domestic visitor nights

Scenario	Mean	Median	80%	95%
Pessimistic	2023 Q3	2023 Q2	[2021 Q4, 2025 Q2]	[2021 Q1, 2026 Q3]
Most likely	2022 Q3	2022 Q3	[2021 Q2, 2023 Q4]	[2020 Q3, 2024 Q4]
Optimistic	2021 Q4	2021 Q4	[2020 Q4, 2023 Q1]	[2020 Q2, 2024 Q1]
Mixture (10,80,10)	2022 Q3	2022 Q3	[2021 Q2, 2023 Q4]	[2020 Q4, 2024 Q4]

Table 10: *Recovery scenarios for domestic visitor nights.*

	Mean	Median	80%	95%
States				
New South Wales	2022 Q2	2022 Q2	[2021 Q1, 2023 Q4]	[2020 Q3, 2024 Q4]
Queensland	2022 Q2	2022 Q1	[2021 Q1, 2023 Q3]	[2020 Q3, 2024 Q4]
Victoria	2022 Q4	2022 Q3	[2021 Q2, 2024 Q3]	[2020 Q4, 2025 Q4]
Western Australia	2022 Q3	2022 Q2	[2021 Q1, 2024 Q1]	[2020 Q3, 2025 Q3]
South Australia	2022 Q2	2022 Q2	[2021 Q1, 2023 Q3]	[2020 Q3, 2024 Q3]
Northern Territory	2022 Q2	2022 Q2	[2021 Q1, 2023 Q4]	[2020 Q3, 2024 Q4]
Tasmania	2022 Q2	2022 Q2	[2021 Q1, 2023 Q4]	[2020 Q3, 2024 Q4]
Australian Capital Territory	2022 Q2	2022 Q2	[2021 Q1, 2023 Q3]	[2020 Q3, 2024 Q3]
Purpose of Travel				
Holiday	2022 Q2	2022 Q2	[2021 Q1, 2023 Q4]	[2020 Q3, 2025 Q1]
VFR	2022 Q1	2021 Q4	[2020 Q4, 2023 Q2]	[2020 Q2, 2024 Q3]
Business	2022 Q3	2022 Q3	[2021 Q1, 2024 Q2]	[2020 Q3, 2025 Q4]

A Supplementary plots for forecast evaluation

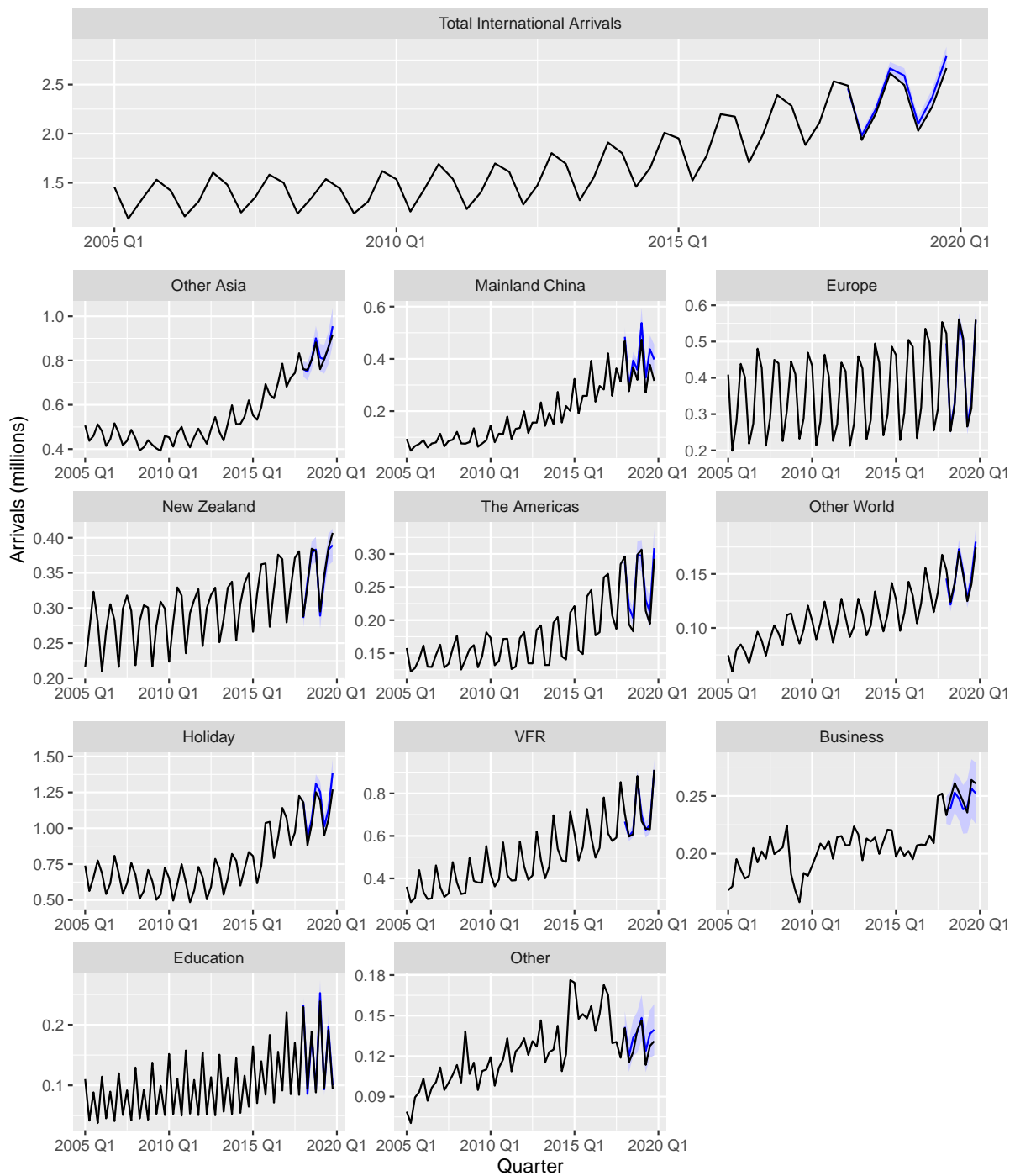


Figure 20: Forecast accuracy evaluation over the 2018 Q1–2019 Q4 test-set for international arrivals to Australia

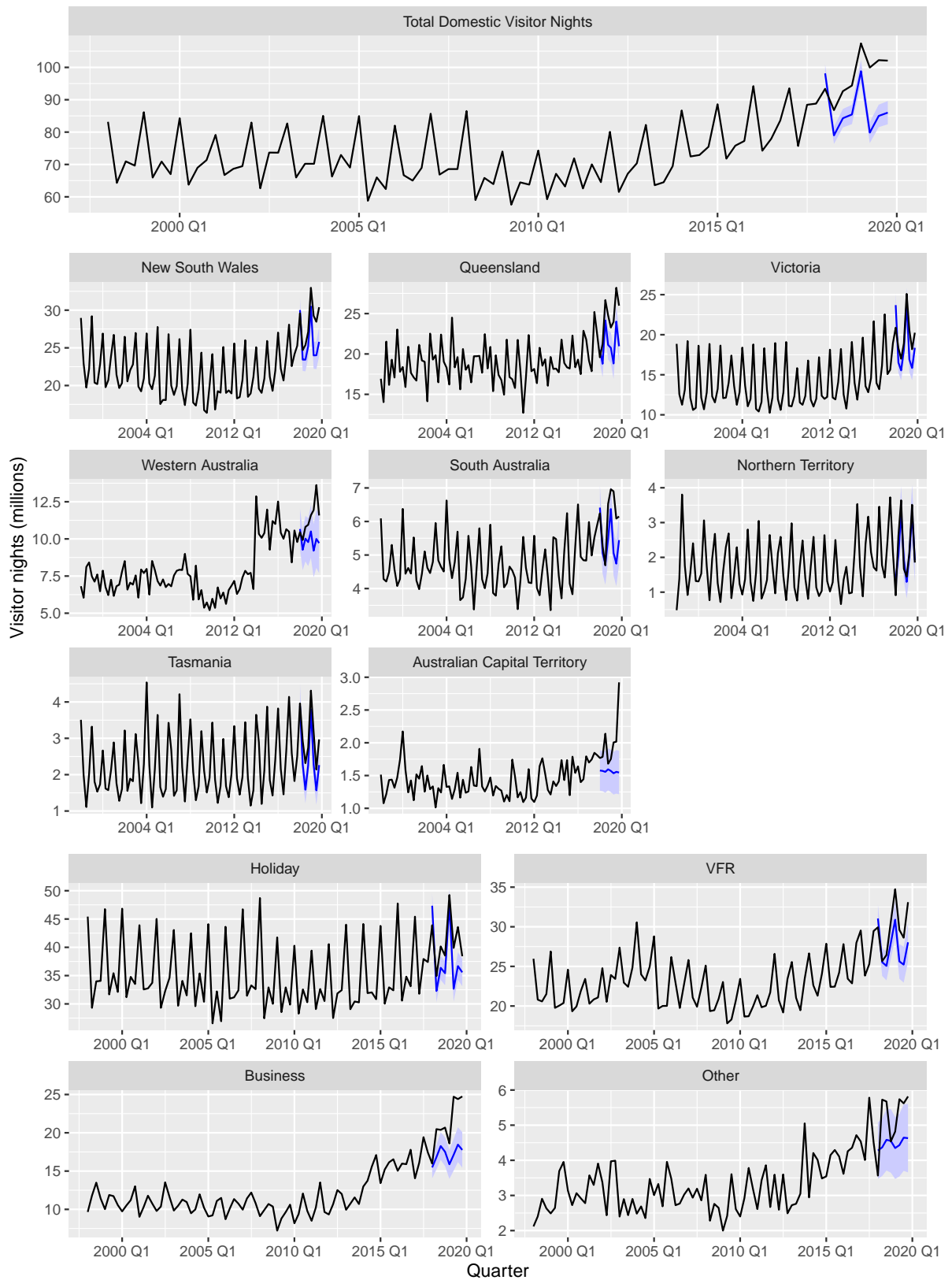


Figure 21: Time series and counterfactual forecasts for the period 2020 Q1–2019 Q4 for Australian domestic visitor nights

B Survey questionnaire design

In this appendix we provide the details of the questionnaire. Our aim was to make this as simple as possible for respondents in order to keep them engaged, but at the same time collect valuable information that will enable us to generate probabilistic scenario-based forecasts for the future of Australian tourism having endured the effect of COVID-19.

Background information

The COVID-19 Pandemic has resulted in massive disruptions to tourism worldwide and at this stage the timeframe for recovery is both long and uncertain. In this environment, where so much can change so quickly, producing conventional tourism forecasts is not appropriate.

There is however a need to consider the range of plausible recovery scenarios that draw on the collective views of tourism experts and practitioners. It is inevitable that tourism will eventually find its feet, and having a better understanding of how it might recover will assist with planning, policy formulation and industry advocacy.

By completing this short survey you are contributing to this information gathering process. We also understand that the uncertainty of the situation will limit the amount of information you may be able to provide and have designed the survey to reflect this.

About you and your sector

Question 1: Which sector best describes your organisation?

- Academic
- Consultant
- Government
- Industry - accommodation
- Industry - association
- Industry - aviation
- Industry - other transport
- Industry-food services
- Industry-tour operator services
- Industry-travel agency
- Other (please specify)

Question 2: How many people are currently employed by your organisation?

- less than 5
- 5 to 19
- 20 to 49
- 50 to 199
- 200 or more

Question 3: How does this employment figure compare with the start of 2020?

- Lower 90-100%
- Lower 70-90%
- Lower 50-70%
- Lower 30-50%
- Lower 10-30%
- Lower 0-10%
- Higher 0-10%
- Higher 10-30%
- Higher 30-50%
- Higher than 50%

International arrivals to Australia

The purpose of the following questions is to get your views on the recovery trajectory for international tourism in terms of visitor numbers. With so much uncertainty we'd like you to consider future scenarios that take into account factors such as changing economic conditions, concerns around travel and safety, aviation access, the price of travel and potential discovery of a vaccine.

We appreciate that some of you may have more detailed knowledge than others. Please provide estimates for specific markets and specific travel categories should you wish.

Question 4: International arrivals to Australia have grown an average of 6% p.a. over the last 5 years. In the December quarter 2019, there were 2.7 million international visitors to Australia. Assuming that international borders reopen in the middle of 2021, what do you think international visitors will be for the December quarter of 2021 compared to the December quarter 2019 under a most likely scenario – your best estimate based on your knowledge and insight; a pessimistic scenario – reflecting a worse case highly unlikely, but still plausible outcome; an optimistic scenario – reflecting a best case highly unlikely, but still plausible outcome.

Most likely	Pessimistic	Optimistic
Lower 90-100%	Lower 90-100%	Lower 90-100%
Lower 70-90%	Lower 70-90%	Lower 70-90%
Lower 50-70%	Lower 50-70%	Lower 50-70%
Lower 30-50%	Lower 30-50%	Lower 30-50%
Lower 10-30%	Lower 10-30%	Lower 10-30%
Lower 0-10%	Lower 0-10%	Lower 0-10%
Higher 0-10%	Higher 0-10%	Higher 0-10%
Higher 10-30%	Higher 10-30%	Higher 10-30%
Higher 30-50%	Higher 30-50%	Higher 30-50%
Higher than 50%	Higher than 50%	Higher than 50%

Note: the rows were embedded in a dropdown menu.

Question 5: *In what year do you think international visitor numbers will return to 2019 levels?*

Please provide estimates for the most likely, pessimistic and optimistic scenario.

	2021	2022	2023	2024	2025	2026	2027	2028
Most likely								
Pessimistic								
Optimistic								

Question 6: *In what year do you think international visitor numbers for the following segments will return to 2019 levels? Please provide estimates only for the most likely scenario (This is an optional question- please provide information only where you have a view)*

	2021	2022	2023	2024	2025	2026	2027	2028
Holiday								
VFR								
Business								
Education								

Question 7: *In what year do you think international visitor numbers for the following markets will recover to 2019 levels? Please provide estimates only for the most likely scenario. (This is an optional question- please provide information only where you have a view)*

	2021	2022	2023	2024	2025	2026	2027	2028
New Zealand								
Mainland China								
Other Asia								
Europe								
The Americas								

Australian domestic tourism

The purpose of the questions that follow is to get your views on the recovery trajectory for domestic tourism. Factors we’d like you to consider in these future scenarios are the timing of

interstate border openings, transport access to the regions, domestic economic conditions, the price of travel, safety concerns and potential discovery of a vaccine. We appreciate that some of you may have more detailed knowledge than others. Please provide estimates for specific markets and specific travel categories should you wish.

Question 8: Domestic visitor nights have grown an average of 7% p.a. over the last 5 years. In the December quarter 2019, there were 103.4 million domestic visitor nights around Australia. Compared to these levels what do you think the number of domestic visitor nights will be for the December quarter 2020 and the December quarter 2021 compared to the December quarter 2019 under: a most likely scenario – your best estimate based on your knowledge and insight; a pessimistic scenario – reflecting a worse case highly unlikely, but still plausible outcome; an optimistic scenario – reflecting a best case highly unlikely, but still plausible outcome.

Same dropdown menu as in Question 4 was used but for both December quarter 2020 and December quarter 2021.

Question 9: In what year do you think domestic visitor nights will return to 2019 levels? Please provide a most likely, a pessimistic and an optimistic scenario.

Same options menu as in Question 5 were used.

Question 10: In what year do you think domestic visitor nights will return to 2019 levels for the following markets? Please provide estimates only for the most likely scenario. (This is an optional question-please provide market information only where you have a view)

	2021	2022	2023	2024	2025	2026	2027	2028
New South Wales								
Victoria								
Queensland								
South Australia								
Western Australia								
Tasmania								
Northern Territory								
ACT								

Question 11: In what year do you think domestic visitor nights for the following markets will return to 2019 levels? Please provide estimates only for the most likely scenario. (This is an optional question-please provide market information only where you have a view).

	2021	2022	2023	2024	2025	2026	2027	2028
Holiday								
VFR								
Business								

References

- Airports Council International (ACI) Europe (2020). *Impact of COVID-19 on European airport passenger traffic*. Tech. rep. Airports Council International. <https://www.aci-europe.org/airport-traffic-covid-19>.
- Armstrong, JS (2006). How to make better forecasts and decisions: Avoid face-to-face meetings. *Foresight: The International Journal of Applied Forecasting* (5), 3–15.
- Armstrong, JS (2008). Methods to elicit forecasts from groups: Delphi and prediction markets compared. *Available at SSRN 1153124*.
- Arvan, M, B Fahimnia, M Reisi & E Siemsen (2019). Integrating human judgement into quantitative forecasting methods: A review. *Omega* **86**, 237–252.
- Athanasopoulos, G, RA Ahmed & RJ Hyndman (2009). Hierarchical forecasts for Australian domestic tourism. *International Journal of Forecasting* **25**, 146–166.
- Bates, JM & CWJ Granger (1969). The Combination of Forecasts. *Operations Research* **20**(4), 451–468.
- Bausch, T, WC Gartner & F Ortanderl (2020). How to avoid a COVID-19 research paper tsunami? A tourism system approach. *Journal of Travel Research*. in press.
- Chan, F & LL Pauwels (2018). Some theoretical results on forecast combinations. *International Journal of Forecasting* **34**(1), 64–74. <http://dx.doi.org/10.1016/j.ijforecast.2017.08.005>.
- Cook, MP (2006). Visual representations in science education: The influence of prior knowledge and cognitive load theory on instructional design principles. *Science Education* **90**(6), 1073–1091. eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/sce.20164>.
- Davis, FD, GL Lohse & JE Kottmann (1994). Harmful effects of seemingly helpful information on forecasts of stock earnings. *Journal of economic psychology* **15**(2), 253–267.
- Edmundson, R (1990). Decomposition; a strategy for judgemental forecasting. *Journal of Forecasting* **9**(4), 305–314.
- Fildes, R, P Goodwin, M Lawrence & K Nikolopoulos (2009). Effective forecasting and judgemental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning. *International journal of forecasting* **25**(1), 3–23.
- Fildes, R, P Goodwin & D Önköl (2019). Use and misuse of information in supply chain forecasting of promotion effects. *International Journal of Forecasting* **35**(1), 144–156.
- Forsyth, P, C Guiomard & HM Niemeier (2020). Covid-19, the collapse in passenger demand and airport charges. *Journal of Air Transport Management* **89**, 101932.

- Goodwin, P, S Gönül, D Önkal, A Kocabıyıkoglu & CI Göğüş (2019). Contrast effects in judgmental forecasting when assessing the implications of worst and best case scenarios. *Journal of Behavioral Decision Making* **32**(5), 536–549.
- Goodwin, P & G Wright (1993). Improving judgmental time series forecasting: A review of the guidance provided by research. *International Journal of Forecasting* **9**(2), 147–161.
- Graefe, A & JS Armstrong (2011). Comparing face-to-face meetings, nominal groups, Delphi and prediction markets on an estimation task. *International journal of forecasting* **27**(1), 183–195.
- Gursoy, D & CG Chi (2020). Effects of COVID-19 pandemic on hospitality industry: review of the current situations and a research agenda. *Journal of Hospitality Marketing and Management* **29**(5), 527–529.
- Hyndman, RJ & G Athanasopoulos (2021). *Forecasting: Principles and Practice*. 3rd edn. Melbourne, Australia: OTexts. <https://OTexts.com/fpp3/>.
- Hyndman, RJ, RA Ahmed, G Athanasopoulos & HL Shang (2011). Optimal combination forecasts for hierarchical time series. *Computational Statistics and Data Analysis* **55**(9), 2579–2589. <http://dx.doi.org/10.1016/j.csda.2011.03.006>.
- Jones, MC (1993). Simple boundary correction for kernel density estimation. *Statistics and Computing* **3**(3), 135–146.
- Jørgensen, M & DIK Sjoeberg (2003). An effort prediction interval approach based on the empirical distribution of previous estimation accuracy. *Information and Software Technology* **45**(3), 123–136.
- Kahneman, D & D Lovallo (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management science* **39**(1), 17–31.
- Kauko, K & P Palmroos (2014). The Delphi method in forecasting financial markets—An experimental study. *International Journal of Forecasting* **30**(2), 313–327.
- Kourentzes, N & G Athanasopoulos (2019). Cross-temporal coherent forecasts for Australian tourism. *Annals of Tourism Research* **75**, 393–409. <https://doi.org/10.1016/j.annals.2019.02.001>.
- Kourentzes, N, D Barrow & F Petropoulos (2019). Another look at forecast selection and combination: Evidence from forecast pooling. *International Journal of Production Economics* **209**, 226–235. <https://doi.org/10.1016/j.ijpe.2018.05.019>.
- Kourentzes, N, A Saayman, P Jean-Pierre, D Provenzano, M Sahli, N Seetaram & S Volo (2021). Visitor arrivals forecasts amid COVID-19: A perspective from the Africa team. *Annals of Tourism Research*, 103197.

- Lawrence, M, P Goodwin, M O'Connor & D Önkal (2006). Judgmental forecasting: A review of progress over the last 25 years. *International Journal of forecasting* **22**(3), 493–518.
- Li, G, DC Wu, M Zhou & A Liu (2019). The combination of interval forecasts in tourism. *Annals of Tourism Research* **75**(August 2018), 363–378. <https://doi.org/10.1016/j.annals.2019.01.010>.
- Lin, VS, P Goodwin & H Song (2014). Accuracy and bias of experts' adjusted forecasts. *Annals of Tourism Research* **48**, 156–174.
- Lin, VS & H Song (2015). A review of Delphi forecasting research in tourism. *Current Issues in Tourism* **18**(12), 1099–1131.
- Liu, A, L Vici, V Ramos, S Giannoni & A Blake (2021). Visitor arrivals forecasts amid COVID-19: A perspective from the EUROPE team. *Annals of Tourism Research*, 103182.
- MacGregor, DG (2001). "Decomposition for judgmental forecasting and estimation". In: *Principles of forecasting*. Springer, pp.107–123.
- Maneenop, S & S Kotcharin (2020). The impacts of COVID-19 on the global airline industry: An event study approach. *Journal of Air Transport Management* **89**, 101920.
- Miles, J et al. (2008). A Primer on Prediction Markets. *Foresight: The International Journal of Applied Forecasting* (9), 33–35.
- Miller, KM, R Hofstetter, H Krohmer & ZJ Zhang (2011). How should consumers' willingness to pay be measured? An empirical comparison of state-of-the-art approaches. *Journal of Marketing Research* **48**(1), 172–184.
- Novomestky, F & S Nadarajah (2016). *truncdist: Truncated Random Variables*. R package version 1.0-2. <https://CRAN.R-project.org/package=truncdist>.
- O'Hara-Wild, M & A Hayes (2020). *distributional: Vectorised Probability Distributions*. R package version 0.2.1. <https://CRAN.R-project.org/package=distributional>.
- O'Hara-Wild, M, R Hyndman & E Wang (2020). *fable: Forecasting Models for Tidy Time Series*. R package version 0.2.1. <https://CRAN.R-project.org/package=fable>.
- O'Leary, DE (2017). Crowd performance in prediction of the World Cup 2014. *European Journal of Operational Research* **260**(2), 715–724.
- Ord, JK, R Fildes & N Kourentzes (2017). *Principles of Business Forecasting*. 2nd. Wessex Press Publishing Co.
- Panagiotelis, A, G Athanasopoulos, P Gamakumara & RJ Hyndman (2021). Forecast reconciliation: A geometric view with new insights on bias correction. *International Journal of Forecasting* **37**(1), 343–359. <https://doi.org/10.1016/j.ijforecast.2020.06.004>.

- Perera, HN, J Hurley, B Fahimnia & M Reisi (2019). The human factor in supply chain forecasting: A systematic review. *European Journal of Operational Research* **274**(2), 574–600.
- Petropoulos, F, R Fildes & P Goodwin (2016). Do 'big losses' in judgmental adjustments to statistical forecasts affect experts' behaviour? *European Journal of Operational Research* **249**(3), 842–852.
- Petropoulos, F, N Kourentzes, K Nikolopoulos & E Siemsen (2018). Judgmental selection of forecasting models. *Journal of Operations Management* **60**, 34–46.
- Qiu, RT, DC Wu, V Dropsy, S Petit, S Pratt & Y Ohe (2021). Visitor arrivals forecasts amid COVID-19: A perspective from the Asia and Pacific team. *Annals of Tourism Research* **88**, 103155.
- R Core Team (2020). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. <https://www.R-project.org/>.
- Richter, W (2020). *Going to Be Tough for Airlines, Full Recovery Moved to 2024: IATA*. Tech. rep. Wolf Street. <https://wolfstreet.com/2020/07/29/what-the-iata-said-about-the-global-recovery-in-air-passenger-traffic-2019-level-regained-only-by-2024/>.
- Ronis, DL & JF Yates (1987). Components of probability judgment accuracy: Individual consistency and effects of subject matter and assessment method. *Organizational Behavior and Human Decision Processes* **40**(2), 193–218.
- Rowe, G et al. (2007). A guide to Delphi. *Foresight* **8**, 11–16.
- Schoemaker, PJ (2004). "Forecasting and scenario planning: The challenges of uncertainty and complexity". In: *Blackwell handbook of judgment and decision making*. Wiley Online Library, pp.274–296.
- Schoemaker, PJ & PE Tetlock (2016). Superforecasting: How to upgrade your company's judgment. *Harvard Business Review* **94**(5), 73–78.
- Smith, J & KF Wallis (2009). A simple explanation of the forecast combination puzzle. *Oxford Bulletin of Economics and Statistics* **71**(3), 331–355.
- Song, H, BZ Gao & VS Lin (2013). Combining statistical and judgmental forecasts via a web-based tourism demand forecasting system. *International Journal of Forecasting* **29**(2), 295–310.
- Song, H, RT Qiu & J Park (2019). A review of research on tourism demand forecasting: Launching the *Annals of Tourism Research* Curated Collection on tourism demand forecasting. *Annals of Tourism Research* **75**, 338–362.

- Surowiecki, J (2004). *The wisdom of the crowds: why the many are smarter than the few*. *Abacus*.
- Tetlock, PE (2017). *Expert Political Judgment: How Good Is It? How Can We Know? -New Edition*. Princeton University Press.
- Tourism Research Australia (2019). International tourism forecasts. *Canberra*. <https://www.tra.gov.au/International/international-tourism-forecasts>.
- Tziralis, G & I Tatsiopoulou (2007). Prediction markets: An extended literature review. *The journal of prediction markets* **1**(1), 75–91.
- UNWTO (2020). UNWTO World Tourism Barometer and Statistical Annex, January 2020. *UNWTO World Tourism Barometer* **18**(1), 1–6.
- Webby, R, M O'Connor & B Edmundson (2005). Forecasting support systems for the incorporation of event information: An empirical investigation. *International Journal of Forecasting* **21**(3), 411–423.
- Wickramasuriya, SL, G Athanasopoulos & RJ Hyndman (2019). Optimal Forecast Reconciliation for Hierarchical and Grouped Time Series Through Trace Minimization. *Journal of the American Statistical Association* **114**(526), 804–819.
- Yang, S, J Fang & S Mantesso (2020). *International border closures push Australian businesses to the brink of collapse*. <https://www.abc.net.au/news/2020-12-05/covid-19-continues-to-hurt-australian-businesses-border-closures/12948776>.
- Zhang, H, H Song, L Wen & C Liu (2021). Forecasting tourism recovery amid COVID-19. *Annals of Tourism Research* **87**, 103149.