

¹ Comparing human and model-based forecasts of COVID-19 in
² Germany and Poland

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⁷ **1 Abstract**

⁸ Forecasts based on epidemiological modelling have played an important role in shaping public policy throughout
⁹ the COVID-19 pandemic. This modelling combines knowledge about infectious disease dynamics with the
¹⁰ subjective opinion of the researcher who develops and refines the model and often also adjusts model outputs.
¹¹ Developing a forecast model is difficult, resource- and time-consuming. It is therefore worth asking what
¹² modelling is able to add beyond the subjective opinion of the researcher alone. To investigate this, we
¹³ analysed different real-time forecasts of cases of and deaths from COVID-19 in Germany and Poland over a
¹⁴ 1-4 week horizon submitted to the German and Polish Forecast Hub. We compared crowd forecasts elicited
¹⁵ from researchers and volunteers, against a) forecasts from two semi-mechanistic models based on common
¹⁶ epidemiological assumptions and b) the ensemble of all other models submitted to the Forecast Hub. We found
¹⁷ crowd forecasts, despite being overconfident, to outperform all other methods across all forecast horizons when
¹⁸ forecasting cases (weighted interval score relative to the Hub ensemble 2 weeks ahead: 0.89). Forecasts based
¹⁹ on computational models performed comparably better when predicting deaths (rel. WIS 1.26), suggesting
²⁰ that epidemiological modelling and human judgement can complement each other in important ways.

21 2 Author summary

22 Mathematical models of COVID-19 have played a key role in informing governments across the world. While
23 mathematical models are informed by our knowledge of infectious disease dynamics, they are ultimately
24 developed and iteratively adjusted by the researchers and shaped by their subjective opinions. To investigate
25 what modelling is able to add beyond the subjective opinion of the researcher alone, we compared human fore-
26 casts with model-based predictions of COVID-19 cases and deaths submitted to the so-called German/Polish
27 Forecast Hub (which collates a variety of models from a range of teams).

28 We found that our human forecasts consistently outperformed an aggregate of all available model-based
29 forecasts when predicting cases, but not when predicting deaths. Our findings suggest that human insight may
30 be most valuable when forecasting highly uncertain quantities, which depend on many factors that are hard
31 to model using equations, while mathematical models may be most useful in settings like predicting deaths,
32 where leading indicators with a clear connection to the target variable are available. This potentially has
33 very relevant policy implications, as agencies informing policy-makers could benefit from routinely eliciting
34 human forecasts in addition to model-based predictions to inform policies.

35 3 Introduction

36 Infectious disease modelling has a long tradition and has helped inform public health decisions both through
37 scenario modelling, as well as actual forecasts of (among others) influenza (e.g. 1,2–4), dengue fever (e.g.
38 5,6,7), ebola (e.g. 8,9), chikungunya (e.g. 10,11) and now COVID-19 (e.g. 12,13–17). Applications of
39 epidemiological models differ in the way they make statements about the future. Forecasts aim to predict the
40 future as it will occur, while scenario modelling and projections aim to represent what the future could look
41 like under certain scenario assumptions or if conditions stayed the same as they were in the past. Forecasts
42 can be judged by comparing them against observed data. Since it is much harder to fairly assess the accuracy
43 and usefulness of projections and scenario modelling in the same way, this work focuses on forecasts, which
44 represent only a subset of all epidemiological modelling.

45 Since March 2020, forecasts of COVID-19 from multiple teams have been collected, aggregated and compared

46 by Forecast Hubs such as the US Forecast Hub (13,14), the German and Polish Forecast Hub (15,16) and the
47 European Forecast Hub (17). Often, different individual forecasts are combined into a single forecast, e.g. by
48 taking the mean or median of all forecasts. These ensemble forecasts usually tend to perform better and
49 more consistently than individual forecasts (see e.g. (6); (18)).

50 Individual computational models usually rely to varying degrees on mechanistic assumptions about infectious
51 disease dynamics (such as SIR-type compartmental models that aim to represent how individuals move from
52 being susceptible to infected and then recovered or dead). Some are more statistical in nature (such as time
53 series models that detect statistical patterns without explicitly modelling disease dynamics). How exactly
54 such a mathematical or computational model is constructed and which assumptions are made depends on
55 subjective opinion and judgement of the researcher who develops and refines the model. Models are commonly
56 adjusted and improved based on whether the model output looks plausible to the researchers involved.

57 The process of model construction and refinement is laborious and time-consuming, and it is therefore worth
58 asking what modelling can add beyond the subjective judgment of the researcher alone. In this work, we
59 ask this question specifically in the context of predictive performance, and set aside other advantages of
60 epidemiological modelling (such as reproducibility or the ability to obtain a deeper fundamental understanding
61 of how diseases spread). One natural way to do this is to compare the predictive performance of forecasts
62 based on computational models (“model-based forecasts”) against forecasts made by individual humans
63 without explicit use of a computer model (“direct human forecasts”) or a combination of multiple such
64 forecasts (“crowd forecasts”).

65 Previous work has examined such direct human forecasts in various contexts, such as geopolitics (19,20),
66 meta-science (21,22), sports (23) and epidemiology (11,24,25). Several prediction platforms (26–28) and
67 prediction markets (29) have been created to collate expert and non-expert predictions. However, with the
68 notable exception of (11), these forecasts were not designed to be evaluated alongside model-based forecasts
69 and usually follow their own (often binary) prediction formats. Direct human forecasts may be able to take
70 into account insights and relationships between variables which are hard to specify using epidemiological
71 models. However, it is not entirely clear in which situations human forecasts perform well or badly. For

72 example, (11) found that humans could outperform computer models at predicting the 2014/15 and 2015/16
73 flu season in the US, a setting where the disease was well known and information about previous seasons was
74 available. However, humans tended to do slightly worse at predicting the 2014/15 outbreak of chikungunya
75 in the Americas, a disease previously largely unobserved and unknown in these regions at the time.

76 In this study, we analyse the performance of direct human forecasts relative to model-based forecasts and
77 discuss the added benefit of epidemiological modelling over human judgement alone. As a case study, we
78 use different forecasts, involving varying degrees of human intervention, which we submitted in real time to
79 the German and Polish Forecast Hub. In contrast to (11) we elicited not only point predictions, but full
80 predictive distributions (“probabilistic forecasts”, see e.g. (30)) from participants. This allows us to compare
81 not only predictive accuracy, but also how well human forecasters and model-based forecasts were able to
82 quantify forecast uncertainty.

83 4 Methods

84 We created and submitted the following forecasts to the German and Polish Forecast Hub: 1) a direct human
85 forecast (henceforth called “crowd forecast”), elicited from participants through a web application (31) and
86 2) two semi-mechanistic model-based forecasts (“renewal model” and “convolution model”) informed by
87 basic assumptions about COVID-19 epidemiology. While the two semi-mechanistic forecasts were necessarily
88 shaped by our implicit assumptions and decisions, they were designed such as to minimise the amount
89 of human intervention involved. For example, we refrained from adjusting model outputs or refining the
90 models based on past performance. Forecasts were created in real time over a period of 21 weeks from
91 October 12th 2020 until March 1st 2021 and submitted to the German and Polish Forecast hub (15,16).
92 All code and tools necessary to generate the forecasts and make a forecast submission are available in the
93 `covid.german.forecasts` R package (32). This repository also contains a record of all forecasts submitted
94 to the German and Polish Forecast Hub. Forecasts were evaluated using a variety of scoring metrics and
95 compared among each other and against an ensemble of all other models submitted to the German and Polish
96 Forecast Hub.

97 **4.1 Forecast targets and interaction with the German and Polish Forecast Hub**

98 The German and Polish Forecast Hub (now mostly merged into the (17)) elicits predictions for various
99 COVID-19 related forecast targets from different research groups every week. Forecasts had to be made
100 every Monday (with submissions allowed until Tuesday 3pm) and were permitted to use any data that was
101 available by Monday 11.59pm. We submitted forecasts for incident and cumulative weekly reported numbers
102 of cases of and deaths from COVID-19 on a national level in Germany and Poland over a one to four week
103 forecast horizon. Forecasts were submitted on Mondays, but weeks were defined as ending on a Saturday
104 (and starting on Sunday), meaning that forecast horizons were in fact 5, 12, 19 and 26 days. Submissions
105 were required in a quantile-based format with 23 quantiles of each output measure at levels 0.01, 0.025, 0.05,
106 0.10, 0.15, . . . , 0.95, 0.975, 0.99. Forecasts submitted to the Forecast Hub were combined into different
107 ensembles every week, with the median ensemble (i.e., the α -quantile of the ensemble is given by the median
108 of all submitted α -quantiles) being the default ensemble shown on all official Forecast hub visualisations
109 (<https://kitmetricslab.github.io/forecasthub/forecast>).

110 Data on daily reported test positive cases and deaths linked to COVID-19 were provided by the organisers of
111 the German and Polish Forecast hub. Until December 14th, 2020, these data were sourced from the European
112 Centre for Disease Control (33). After ECDC stopped publishing daily data, observations were sourced from
113 the Robert Koch Institute (RKI) and the Polish Ministry of Health for the remainder of the submission
114 period (34). These data are subject to reporting artefacts, (such as for example delayed case reporting in
115 Poland on the 24th November, (35)), changes in reporting over time, and variation in testing regimes (for
116 example in Germany from the 11th of November on, (36)).

117 **4.2 Crowd forecasts**

118 Our crowd forecasts were created as an ensemble of forecasts made by individual participants every week
119 through a web application (<https://cmmid-lshtm.shinyapps.io/crowd-forecast/>). Weekly forecasts had to
120 be submitted before Tuesday 12pm every week, but participants were asked to only use any information or
121 data that was already available by Monday night. The application was built using the `shiny` and `golem`
122 R packages (37,38) and is available in the `crowdforecastr` R package (31). To make a forecast in the

123 application participants could select a predictive distribution (with the default being log-normal) to represent
124 the probability that the forecasted quantity took certain values. Median and width of the uncertainty
125 could be adjusted by either interacting with a figure showing their forecast or providing numerical values
126 (see screenshot in Figure 5 in the SI). The default shown was a repetition of the last known observation
127 with constant uncertainty around it computed as the standard deviation of the last four changes in weekly
128 log observed forecasts (i.e. as $\sigma(\log(\text{value}4) - \log(\text{value}3), \log(\text{value}3) - \log(\text{value}2), \dots)$). Our interface
129 also allowed participants to view past observations based on the hub data, as well as their forecasts, on
130 a logarithmic scale and presented additional contextual COVID-19 data sourced from (39). These data
131 included, for example, notifications of both test positive COVID-19 cases and COVID-19 linked deaths and
132 the number of COVID-19 tests conducted over time.

133 Forecasts were stored in a Google Sheet and downloaded, cleaned and processed every week for submission
134 to the Forecast Hub. If a forecaster had submitted multiple predictions for a single target, only the latest
135 submission was kept. Information on the chosen distribution as well as the parameters for median and width
136 were used to obtain the required set of 23 quantiles from that distribution. Forecasts from all forecasters
137 were then aggregated using an unweighted quantile-wise mean (i.e., the α -quantile of the ensemble is given
138 by the mean of all submitted α -quantiles). On a few occasions, individual forecasts were assessed as clearly
139 erroneous by visual inspection and subsequently removed before aggregation and were excluded from the
140 submission as well as the analysis.

141 Participants were recruited mostly within the Centre of Mathematical Modeling of Infectious Diseases at the
142 London School of Hygiene & Tropical Medicine, but participants were also invited personally or via social
143 media to submit predictions. Depending on whether they had a background in either statistics, forecasting or
144 epidemiology, participants were asked to self-identify as ‘experts’ or ‘non-experts’.

145 4.3 Model-based forecasts

146 We used two Bayesian semi-mechanistic models from the EpiNow2 R package (version 1.3.3) as our model-
147 based forecasts (40). The first of these models, here called “renewal model”, used the renewal equation (41)
148 to predict reported cases and deaths (see details in the SI). It estimated the effective reproduction number

149 R_t (the average number of people each person infected at time t is expected to infect in turn) and modelled
150 future infections as a weighted sum of past infection multiplied by R_t . R_t was assumed to stay constant
151 beyond the forecast date, roughly corresponding to continuing the latest exponential trend in infections. On
152 the 9th of November we altered the date when R_t was assumed to be constant from two weeks prior to the
153 date of the forecast to the forecast date, which we found to yield a more stable R_t estimate. Reported case
154 and death notifications were obtained by convolving predicted infections over data-based delay distributions
155 (40,42–44) to model the time between infection and report date. The renewal model was used to predict cases
156 as well as deaths with forecasts being generated for each target separately. Death forecasts from the renewal
157 model were therefore not informed by past cases. One submission of the renewal model on December 28th
158 2020 was delayed and therefore not included in the official Forecast hub ensemble.

159 The second model (“convolution model”, see details in SI) was only used to forecast deaths and was added
160 later, starting December 7th 2020 (with the first forecast from December 7th suffering from a software bug
161 and therefore disregarded in all further analyses). The convolution model was submitted, but never included
162 in the official Forecast hub ensemble due to concerns that it could be too similar to the renewal model. The
163 convolution model predicted deaths as a fraction of infected people who would die with some delay, by using
164 a convolution of reported cases with a distribution that described the delay from case report to death and a
165 scaling factor (the case-fatality ratio). Both the renewal and the convolution model used daily observations
166 and assumed a negative binomial observation model with a multiplicative day-of-the-week effect (40).

167 Line list data used to inform the prior for the delay from symptom onset to test positive case report or death
168 in the model-based forecasts was sourced from (45) with data available up to the 1st of August. All model
169 fitting was done using Markov-chain Monte Carlo (MCMC) in stan (46) with each location and forecast
170 target being fitted separately.

171 4.4 Analysis

172 For the main analysis we focused mostly on two week ahead forecasts, as COVID-19 forecasts, especially
173 for cases, were in the past found to have poor predictive performance beyond this horizon (15). Forecasts
174 for cases were scored using the full period from October 2020 until March 2021. To ensure comparability

175 between models, all death forecasts were scored using only the period from December 14th on, where all
176 models including the convolution model were available. To ensure robustness of our results we conducted a
177 sensitivity analysis where all forecasts (including cases) were scored only over the later period for which all
178 forecasts were available (see Section A.11 in the SI). Results remained broadly unchanged.

179 Forecasts were analysed using the following scoring metrics: The weighted interval score (WIS) (47), the
180 absolute error, relative bias, and empirical coverage of the 50% and 90% prediction intervals. The WIS
181 is a proper scoring rule (48), meaning that in expectation the score is optimised by reporting a predictive
182 distribution that is identical to the true data-generating distribution. Forecasters are therefore incentivised
183 to report their true belief about the future. The WIS can be understood as a generalisation of the absolute
184 error to quantile-based forecasts (also meaning that smaller values are better) and can be decomposed into
185 three separate penalties: forecast spread (i.e. uncertainty of forecasts), over-prediction and under-prediction.

186 While the over- and under-prediction components of the WIS capture the amount of over-prediction and
187 under-prediction in absolute terms, we also look at a relative tendency to make biased forecasts. The bias
188 metric (9) we use captures how much probability mass of the forecast was above or below the true value
189 (mapped to values between -1 and 1) and therefore represents a general tendency to over- or under-predict in
190 relative terms. A value of -1 implies that all quantiles of the predictive distribution are below the observed
191 value and a value of 1 that all quantiles are above the observed value. Empirical coverage is the percentage
192 of observed values that fall inside a given prediction interval (e.g. how many observed values fall inside all
193 50% prediction intervals). Scoring metrics are explained in more detail in Table 1 in the SI. All scores were
194 calculated using the `scoringutils` R package (49).

195 At all stages of the evaluation our forecasts were compared to the median ensemble of all *other* models
196 submitted to the German and Polish Forecast Hub (“Hub ensemble”). This “Hub ensemble” was retrospectively
197 computed and excludes all our models. It therefore differs from the official Hub ensemble (here called
198 “hub-ensemble-realised”) which included crowd forecasts as well as renewal model forecasts. To enhance
199 interpretability of scores we mainly report WIS relative to the Hub ensemble in the main text, i.e. we divided
200 the average scores for a given model by the average score achieved by the Hub ensemble on the same set of
201 forecasts (with values >1 implying worse and values <1 implying better performance than the Hub ensemble).

202 In addition to comparing our forecasts against the hub ensemble excluding our models, we also assessed the
203 impact of our forecasts on the performance of the forecasting hub by recalculating separate versions of the
204 Hub ensemble with only some (or all) of our forecasts included. Versions that included either all of our models
205 (“hub-ensemble-with-all”) or only one of them (“hub-ensemble-with-X”) were computed retrospectively.

206 **5 Results**

207 **5.1 Crowd forecast participation**

208 A total number of 32 participants submitted forecasts, 17 of those self-identified as ‘expert’ in either forecasting
209 or epidemiology. The median number of forecasters for any given forecast target was 6, the minimum 2 and
210 the maximum 10. The mean number of submissions from an individual forecaster was 4.7 but the median
211 number was only one - most participants dropped out after their first submission. Only two participants
212 submitted a forecast every single week, both of whom are authors on this study.

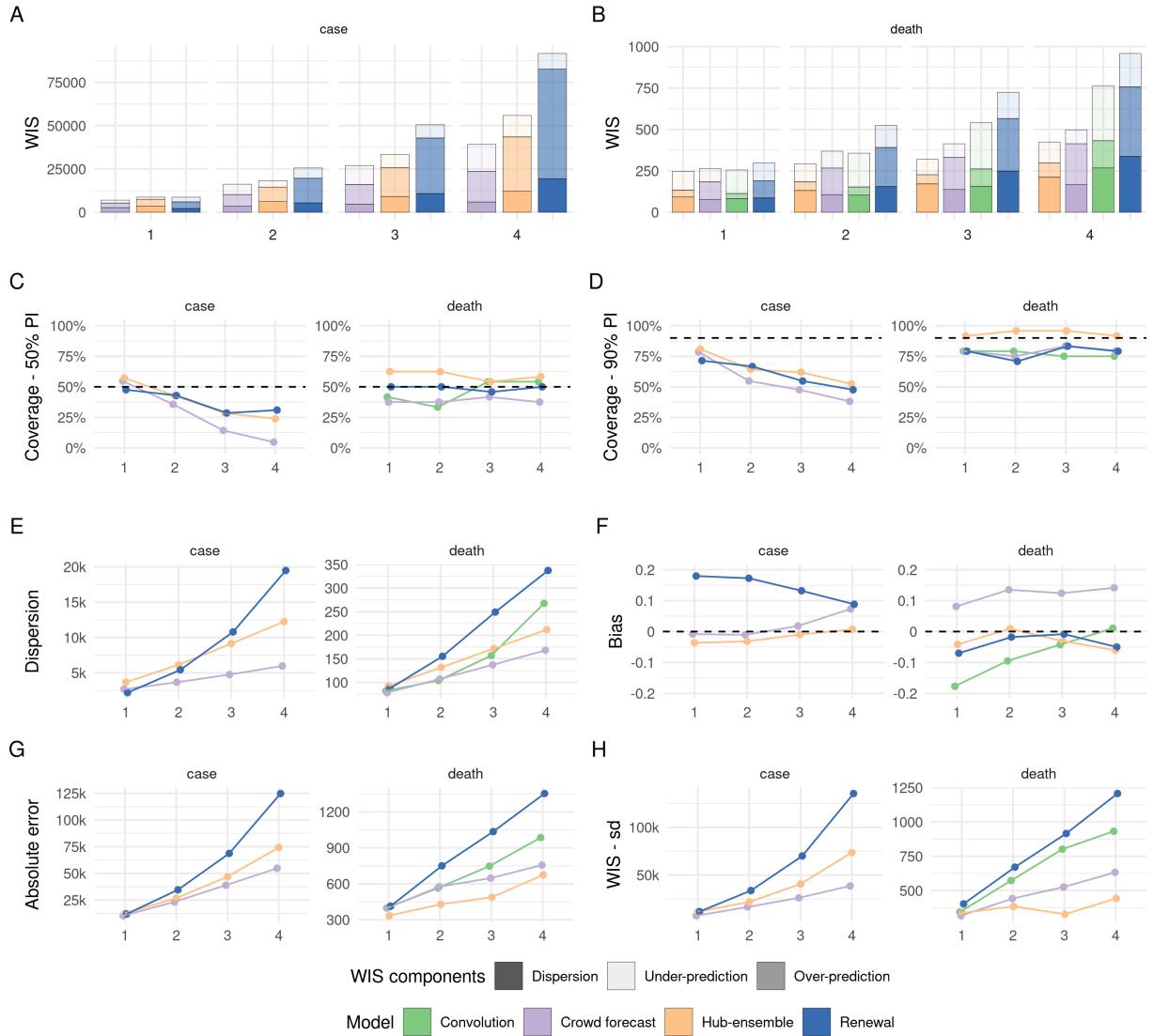


Figure 1: Visualisation of aggregate performance metrics across four weeks for forecasts one to four weeks into the future (marked as 1 - 4 on the x axis). A, B: mean weighted interval score (WIS, lower indicates better performance) across horizons. WIS is decomposed into its components dispersion, over-prediction and under-prediction. C: Empirical coverage of the 50% prediction intervals (50% coverage is perfect). D: Empirical coverage of the 90% prediction intervals. E: Dispersion (same as in panel A, B). Higher values mean greater dispersion of the forecast and imply ceteris paribus a worse score. F: Bias, i.e. general (relative) tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction) and 0 ideally. G: Absolute error of the median forecast (lower is better). H: Standard deviation of all WIS values for different horizons

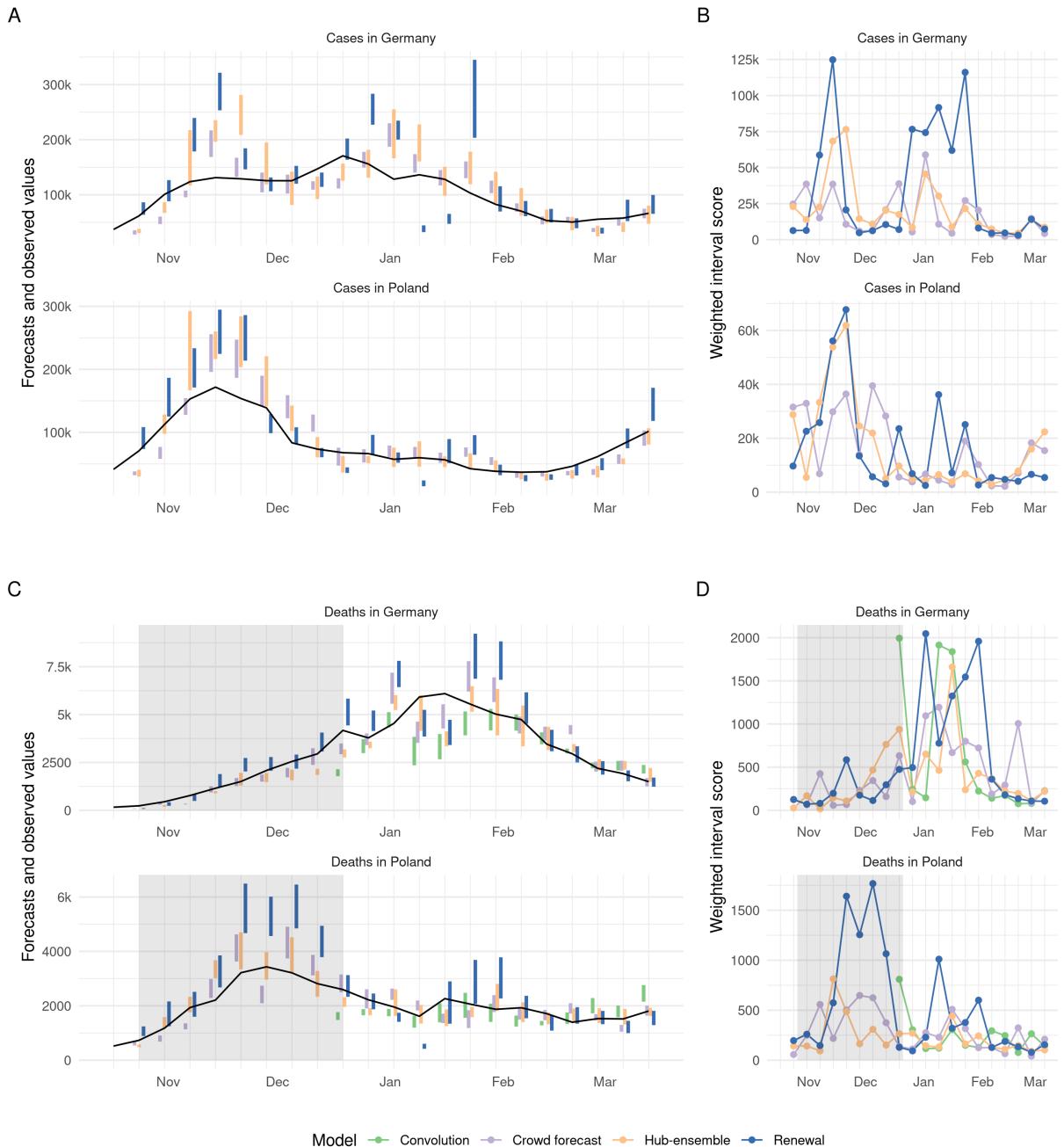


Figure 2: A, C: Visualisation of 50% prediction intervals of two week ahead forecasts against the reported values. Forecasts that were not scored (because there was no complete set of death forecasts available) are greyed out. B, D: Visualisation of corresponding WIS.

213 5.2 Case Forecasts

214 For cases, crowd forecasts had a lower mean weighted interval score (WIS, lower values indicate better
215 performance) than both the renewal model and the Hub ensemble across all forecast horizons (Figure 1A)
216 and locations (Figure 7A). For two week ahead forecasts, mean WIS relative to the Hub ensemble (= 1) was
217 0.89 for crowd forecasts and 1.40 for the renewal model (Table 2). Across all forecasting approaches, locations
218 and forecast horizons, the distribution of WIS values was very right-skewed, and average performance was
219 heavily influenced by outliers (Figure 3). Overall, low variance in forecast performance was closely linked with
220 good mean performance (Figures 1H and and 1A), suggesting that the ability to avoid large errors was an
221 important factor in determining overall performance. The impact of outlier values was especially pronounced
222 for the renewal model, which had more outliers (Figure 3, as well as the highest standard deviation of WIS
223 values (standard deviation of the WIS relative to the WIS sd of the Hub ensemble was 1.54 at the two weeks
224 ahead horizon), while the ensemble of crowd forecasts (rel. WIS sd 0.76) and the Hub ensemble (= 1) showed
225 more stable performance.

226 To varying degrees, all forecasts exhibited trend-following behaviour and were rarely able to predict a change
227 in trend before it had happened. For example, all forecasts failed to predict the change in trend from increase
228 to decrease that happened in November in Germany and severely overshot reported cases (Figure 2A). This
229 was most striking for the renewal model, which extrapolated unconstrained exponential growth based on the
230 recent past of observations. The Hub ensemble and the crowd forecast, which had both been under-predicting
231 throughout October, also failed to predict the change in trend after cases peaked, but less severely so. Human
232 forecasters, possibly aware of the semi-lockdown announced on November 2nd 2020 (50) and the change in the
233 testing regime (with stricter test criteria) on November 11th 2020 (36), were fastest to adapt to the new trend,
234 and the Hub ensemble slowest. In December, cases rose again in Germany, with all models under-predicting
235 this growth to varying extents. As in October, the renewal model captured the phase of exponential growth
236 in cases slightly better than other approaches, but again overshot when reported case numbers fell over
237 Christmas. The large variance in predictions in January in Germany (severe under-prediction followed by
238 severe over-prediction) may in part be caused by the fact that the renewal model operated on daily data and
239 therefore was susceptible to fluctuations in daily reporting around Christmas that would not have influenced

240 on weekly reporting. Similar trends in performance were evident in Poland, with the crowd forecast quickest
241 at adapting to the change in trend in November. In general, there were fewer large outlier forecasts in Poland
242 and in particular the renewal model performed more in line with other forecasts there.

243 All forecasting approaches, including the Hub ensemble, were overconfident, i.e. they showed lower than
244 nominal coverage (meaning that 50% (90%) prediction intervals generally covered less than 50% (90%) of
245 the actually observed values) (Figure 1C and 1D). Coverage for all forecasts deteriorated with increasing
246 forecast horizon, indicating that all forecasting approaches struggled to quantify uncertainty appropriately
247 for case forecasts. This was especially an issue for crowd forecasts, which had markedly shorter prediction
248 intervals (i.e., narrower and more confident predictive distributions) than other approaches (Figure 1E) and
249 only showed a small increase in uncertainty across forecast horizons. In spite of good performance in terms of
250 the absolute error (Figure 1G), the narrow forecast intervals led to forecasts which were severely overconfident
251 (covering only 36% and 55% of all observations with the 50% and 90% prediction intervals of all forecasts
252 made at a two week forecast horizon, and only 5% and 38% four weeks ahead) (Figure 1C,D and Tables 2
253 and 3). Despite worse performance in terms of absolute error (Figure 1G), the renewal model achieved better
254 calibration (comparable to the Hub ensemble), as uncertainty increased rapidly across forecast horizons.

255 The renewal model exhibited a noticeable tendency towards over-predicting reported cases across all horizons.
256 The crowd forecast tended to over-predict at longer forecast horizons, whereas the Hub ensemble showed
257 no systematic bias (Figure 1F). Regardless of a general relative tendency to over-predict, all forecasting
258 approaches incurred larger absolute penalties from over- than from under-prediction (see decomposition of
259 the WIS into absolute penalties for over-prediction, under-prediction and dispersion in Figures 1A and 1B
260 and Tables 2 and 3).

261 Generally, trends in overall performance were broadly similar across locations (Figures 6 and 7). Due to the
262 differing population sizes and numbers of notifications in Germany and Poland absolute scores were difficult
263 to compare directly. However, relative to the Hub ensemble, the crowd forecasts performed noticeably better
264 in Germany than in Poland and the renewal model better in Poland than in Germany (Figure 7A and 7G).

265 **5.3 Death Forecasts**

266 For deaths, the Hub ensemble outperformed the crowd forecasts as well as our model-based approaches across
267 all forecast horizons and locations (Figure 1B, Figure 6B). Relative WIS values for the models two weeks
268 ahead were 1.22 (convolution model), 1.26 (crowd forecast), 1 (Hub ensemble) and 1.79 (renewal model). The
269 crowd forecasts performed better than the renewal model across all forecast horizons and locations (Figure
270 1B, Figure 6B), and also better than the convolution model three and four weeks ahead. Poor performance
271 of the renewal model, especially at longer horizons, indicates that an approach that does not know about
272 past cases, but instead estimates and projects a separate R_t trace from deaths, does not use the available
273 information efficiently. The convolution model was able to outperform both the renewal model and the crowd
274 forecasts at shorter forecast horizons (where the delay between cases and deaths means that future deaths are
275 largely informed by present cases), but saw performance deteriorate at three and four weeks ahead (where
276 case predictions from the renewal model were increasingly used to inform death predictions) (Figure 1B,
277 Table 3).

278 As past cases and hospitalisations can be used as predictors, predicting a change in trend may be easier for
279 deaths than for cases. Even though all forecasts generally struggled with this, there were some instances
280 where changing trends were well captured or even anticipated. In Poland, for example, the Hub ensemble was
281 able to capture or even anticipate the peak in deaths in December quite well (whereas the renewal model and
282 crowd forecast did not). The renewal model, which mostly exhibited trend-following behaviour, correctly
283 predicted another increase in weekly deaths in mid-January (potentially based on changes in daily deaths,
284 as the renewal model did not know about past cases). In Germany in early January, all models predicted
285 a decrease in deaths two to three weeks before it actually happened. Predictions from the renewal model
286 at that time were likely strongly influenced by an unexpected drop in reported deaths in December. The
287 other forecasting approaches and in particular, the convolution model may have been affected by potentially
288 under-reported case numbers around Christmas. When the decrease that all models had predicted to happen
289 in early January failed to materialise, the renewal model and the crowd forecast noticeably over-corrected
290 and over-predicted deaths in the following weeks, while the Hub ensemble, and to a slightly lesser degree, the
291 convolution model were able to capture the downturn well when it finally happened at the end of January.

292 Death forecasts, generally, showed greater coverage of the 50% and 90% prediction intervals than case forecasts
293 and no decrease in coverage across forecast horizons, indicating that it might be easier to appropriately
294 quantify uncertainty for death forecasts. The Hub ensemble had the greatest coverage, with empirical
295 coverage of the 50% and 90% prediction intervals exceeding 50%, and 90%, respectively, across all forecast
296 horizons. Coverage for the crowd forecasts and our model-based approaches was generally lower than that
297 of the Hub ensemble and mostly slightly lower than nominal coverage (Figure 1C and 1D). As for cases,
298 the crowd forecast tended to have the narrowest prediction intervals and uncertainty increased most slowly
299 across forecast horizons, and the renewal model forecasts generally were widest. The convolution model had
300 relatively narrow prediction intervals for short forecast horizons, but had rapidly (and non-linearly) increasing
301 uncertainty for longer forecast horizons, driven by increasing uncertainty in the underlying case forecasts.

302 For deaths, the ensemble of crowd forecasts had a consistent tendency to over-predict 1F. The convolution
303 model had a strong tendency to under-predict, which steadily decreased for longer forecast horizons. The
304 renewal model (which over-predicted for cases) and the Hub ensemble slightly tended towards under-prediction.
305 For deaths, absolute over- and under-prediction penalties were more in line with a general relative tendency
306 to over- or under-predict than for cases (Figure 1A, 1B and Tables 2, 3).

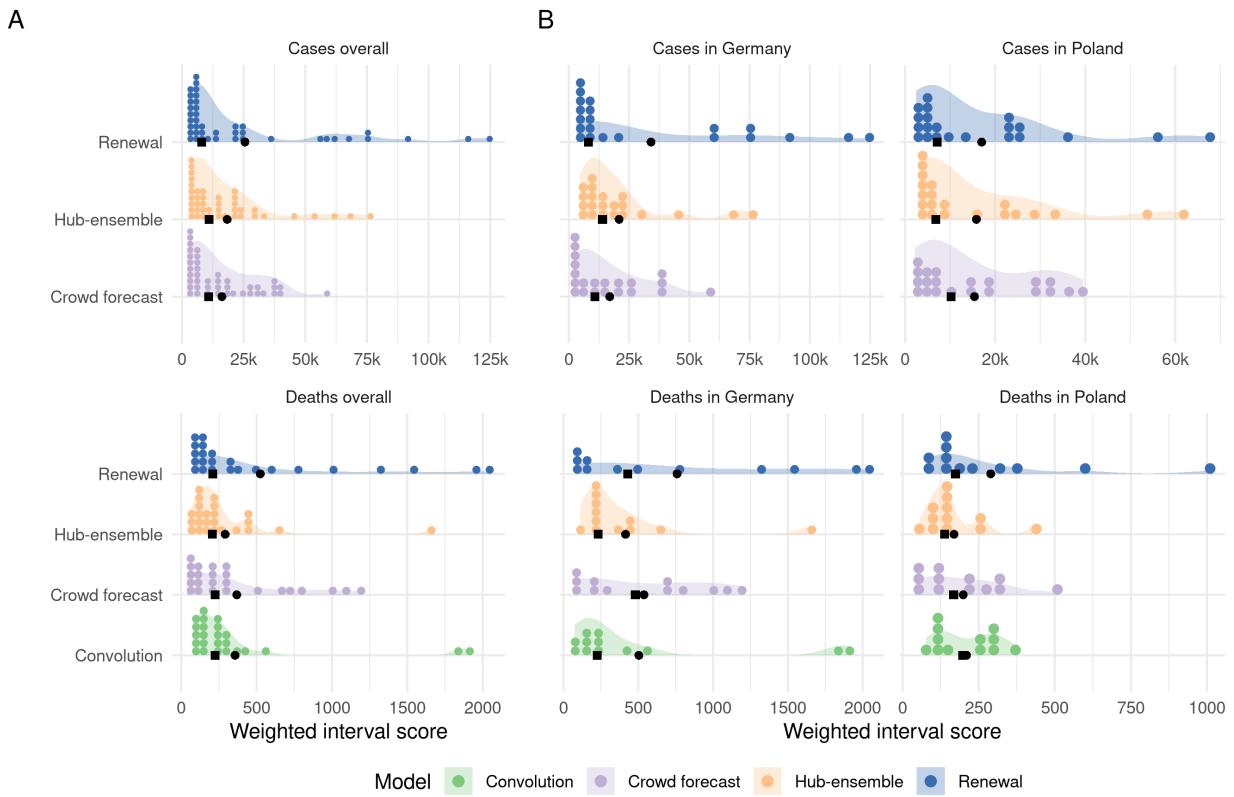


Figure 3: A: Distribution of weighted interval scores for two week ahead forecasts of the different models and forecast targets. Points denote single forecasts scores, while the shaded area shows an estimated probability density. B: Distribution of WIS separate by country.

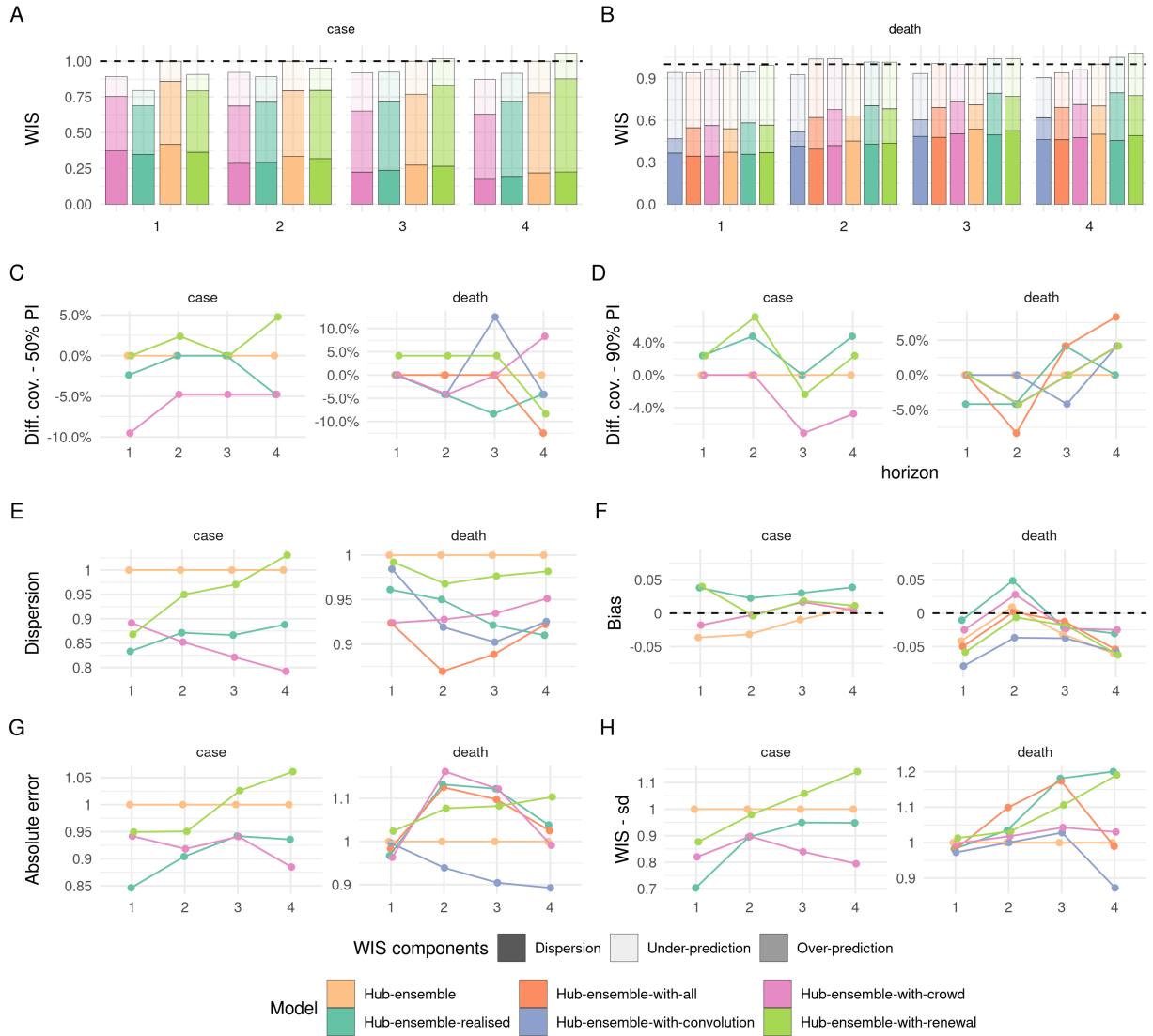


Figure 4: Visualisation of aggregate performance metrics across forecast horizons for the different versions of the Hub median ensemble. “Hub-ensemble” excludes all our models, Hub-ensemble-all includes all of our models, “Hub-ensemble-real” is the real hub-ensemble with the renewal model and the crowd forecasts included. Values (except for Bias) are computed as differences to the Hub ensemble excluding our contributions. For Coverage, this is an absolute difference, for other metrics this is a percentage difference. A: mean weighted interval score (WIS) across horizons. B: median WIS. C: Absolute error of the median forecast. D: Standard deviation of the WIS. E: Dispersion (higher values mean greater spread of the forecast). F: Bias, i.e. general tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction) and 0 ideally. G: Empirical coverage_{1%} of the 50% prediction intervals. F: Empirical coverage of the 90% prediction intervals

307 5.4 Contribution to the Forecast Hub

308 Of our three models, only the renewal model and the crowd forecast were included in the official Forecast Hub
309 median ensemble (“hub-ensemble-realised”), while the convolution model was never included as it was deemed
310 too similar to the existing renewal model. In the official Hub ensemble, there were on average 7.1 models
311 included (including our own), with a median of 7, a minimum of 4 (on 28 December 2020 over the Christmas
312 period) and a maximum of 10. Versions that included either all of our models (“hub-ensemble-with-all”) or
313 only one of them (“hub-ensemble-with-X”) were computed retrospectively. An overview of all models and
314 ensemble versions is shown in Table 10 in the SI.

315 For cases, our contributions (compared to the Hub ensemble without our contributions) consistently improved
316 performance across all forecasting horizons (rel. WIS 0.9 two weeks ahead, Table 4). Contributions from
317 the crowd forecasts alone also improved performance of the Hub ensemble across all forecast horizons, while
318 contributions from the renewal model had a negative effect for longer horizons (rel. WIS 1.02 three weeks
319 ahead, 1.06 four weeks ahead). The realised ensemble including both models performed better or equal
320 compared to all versions with only one model included for up to three weeks ahead, suggesting synergistic
321 effects. Only for predictions four weeks ahead would removing the renewal model have improved performance
322 (Table 5). The realised ensemble performed comparably to the crowd forecasts for predictions one to two
323 weeks ahead, and worse for greater forecast horizons.

324 For deaths, contributions from the renewal model and crowd forecast together improved performance only for
325 one week ahead predictions and showed an increasingly negative impact on performance for longer horizons
326 (rel. WIS of the hub-ensemble-realised 1.01 two weeks ahead, 1.05 four weeks ahead, Tables 4 and 5).
327 Individual contributions from both the renewal model and the crowd forecast were largely negative, while a
328 version of the Hub ensemble with only the convolution model included would have performed consistently
329 better across all forecast horizons (with the positive impact increasing for longer horizons). This is especially
330 interesting as the convolution model performed consistently worse than the pre-existing Hub ensemble (Figure
331 1) and especially worse for longer horizons.

332 We also considered the impact of our contributions on a version of the Hub ensemble constructed by taking

333 the quantile-wise mean, rather than the median. General trends were similar, with the notable exception of
334 the convolution model, which had a consistently positive impact on the median ensemble, but a mixed and
335 mostly slightly negative impact on the mean ensemble (Figures 4B and 19B). This may happen if a model is
336 more correct directionally relative to the pre-existing ensemble, but overshoots in absolute terms, thereby
337 moving the ensemble too far. For both the mean and the median ensemble, changes in performance from
338 adding or removing models were of a similar order of magnitude, suggesting that at least in this instance,
339 with a relatively small ensemble size, the median ensemble was not necessarily more ‘robust’ to changes than
340 the mean ensemble. However, the ensemble version with all our forecasts included (“hub-ensemble-with-all”)
341 tended to perform relatively better for the median ensemble than the mean ensemble, suggesting that adding
342 more models may be more beneficial or ‘safer’ for the median than for the mean ensemble as directional
343 errors can more easily cancel out than errors in absolute terms.

344 6 Discussion

345 Epidemiological forecasting modelling combines knowledge about infectious disease dynamics with the
346 subjective opinion of the researcher who develops and refines the model. In this study, we compared forecasts
347 of cases of and deaths from COVID-19 in Germany and Poland based purely on human judgement and elicited
348 from a crowd of researchers and volunteers against forecasts from two semi-mechanistic epidemiological
349 models. In spite of the small number of participants and a general tendency to be overconfident, crowd
350 forecasts consistently outperformed our epidemiological models as well as the Hub ensemble when forecasting
351 cases but not when forecasting deaths. This suggests that humans might be relatively good at foreseeing
352 trends that are hard to model but may struggle to form an intuition for the exact relationship between cases
353 and deaths.

354 Past studies have evaluated the performance of model-based forecasting approaches as well as human experts
355 and non-experts in various contexts. However, most of these studies either focused only on the evaluation of
356 (expert-tuned) model-based approaches (e.g. 12,13,14), or exclusively on human forecasts (19,20,24,25). In
357 contrast, we directly compared human and model-based forecasts. This is similar to the approach taken by

358 (11), but extends it in several ways. While Farrow et al. only asked for point predictions and constructed a
359 predictive distribution from these, we asked participants to provide a full predictive distribution, allowing
360 us to compare human forecasts and models without any further assumptions, as well as to analyse how
361 humans quantified their uncertainty. In addition, we compared crowd forecasts to two semi-mechanistic
362 models informed by basic epidemiological knowledge of COVID-19, allowing us to assess not only relative
363 performance but also to analyse qualitative differences between human judgement and model-based insight.
364 In terms of interpretability of the results, exact knowledge of our two models, as well as focus on a limited
365 set of targets and locations was a major advantage of our study compared to larger studies conducted by the
366 Forecast Hubs (12–15,17).

367 The strong performance of crowd forecasts in our study is in line with results from Farrow et al. who also report
368 strong performance of human predictions in past Flu challenges despite difficulties to recruit a large number
369 of participants. The advantage of crowd forecasts we observed over our semi-mechanistic models is likely in
370 part explained by the fact that we compared an ensemble of crowd forecasts with single models. However, this
371 probably explains only part of the difference, and performance relative to the Hub ensemble strongly suggests
372 that human insight is valuable when forecasting highly volatile and potentially hard-to-predict quantities such
373 as case numbers. One potential explanation is that humans can have access to data that is not available to or
374 hard to integrate into model-based forecasts. Relatively good performance of our semi-mechanistic models
375 short-term, but not longer-term, suggests that model-based forecasts are helpful to extrapolate from current
376 conditions, but require some form of human intervention or additional assumptions to inform forecasts when
377 conditions change over time. This human intervention may be particularly important when dealing with
378 artefacts in reporting and data anomalies (and especially when using daily, rather than weekly data). The
379 large variance in predictions in January in Germany for example (severe under-prediction followed by severe
380 over-prediction, see Figure 2A), may in part be caused by the fact that the renewal model operated on daily
381 data and therefore was susceptible to fluctuations in daily reporting around Christmas that would not have
382 influenced on weekly reporting.

383 Our results suggest that human intervention may be less beneficial when forecasting deaths (especially at
384 shorter horizons, when deaths are largely dependent on already observed cases), which benefits from the ability

385 to model the delays and exact epidemiological relationships between different leading and lagged indicators.

386 Relatively good performance of the convolution model, especially compared to the poor performance of the

387 renewal model on deaths (which used only deaths to estimate and predict the effective reproduction number)

388 underlines the importance of including leading indicators such as cases as a predictor for deaths.

389 Given the low number of participants in our study, it is difficult to generalise conclusions about crowd

390 predictions to other settings. Using R shiny as a platform for the web application arguably created some

391 limits to user experience and performance, influencing the number of participants and potentially creating a

392 self-selection effect. Motivating forecasters to contribute regularly proved challenging, especially given that

393 the majority of our participants were from the UK and may not have been familiar with all relevant details of

394 the situation in Germany and Poland. On the other hand, R shiny facilitated quick development and allowed

395 us to provide our crowd forecasting tooling as an open source R package, meaning that it is available for

396 others to use, for example in settings like early-stage outbreaks where model-based forecasts are not available.

397 Our work suggests that crowd forecasts and model-based forecasts have different strengths and may be able

398 to complement each other. When choosing a suitable approach for a given task it is important to take into

399 account how the output will be used. In this work we focused on forecasts (which aim to predict future data

400 points whilst accounting for all factors that might influence them), whereas policy makers might be more

401 interested in projections (which show what would happen in the absence of any events that could change

402 the trend) or scenario modelling. Forecasts may not be a suitable basis for informing policy decisions, if

403 forecasters already have factored in the expectation of a future intervention. Model-based approaches can

404 be either forecasts or projections depending on the assumptions, whereas eliciting projections that are not

405 influenced by implicit assumptions about the future from humans may be harder.

406 Further work should explore the effects of humans refining their mathematical models or changing model

407 outputs in more detail. Model-based forecasts could be used as an input to human judgement, with

408 researchers adjusting predictions generated by models. Seeing a model-based forecast could help humans

409 calibrate uncertainty better, while allowing for manual intervention to adapt spurious trend predictions.

410 Tools need to be developed to facilitate this process at a larger scale. Human insight could also be used

as an input to models. Such a ‘hybrid’ forecasting approach could for example ask humans to predict the trend of the effective reproduction number R_t or the doubling rate (i.e. how the epidemic evolves) into the future and use this to estimate the exact number of cases, hospitalisations or deaths this would imply. In light of severe overconfidence, yet good performance in terms of the absolute error, post-processing of human forecasts to adjust and widen prediction intervals may be another promising approach. Crowd forecasting in general could benefit greatly from the availability of tools suitable to appeal to a greater audience. Given the good performance we and previous authors observed in spite of the limited resources available and the small number of participants, this seems worthwhile to further develop and explore.

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⁴⁴⁶ **A Supplementary information**

⁴⁴⁷ **A.1 Scoring metrics used**

Table 1: Overview of the scoring metrics used.

Metric	Explanation
WIS (Weighted interval score)	<p>The weighted interval score (smaller values are better) is a proper scoring rule for quantile forecasts. It converges to the continuos ranked probability score (which itself is a generalisation of the absolute error to probabilistic forecasts) for an increasing number of intervals. The score can be decomposed into a dispersion (uncertainty) component and penalties for over- and underprediction. For a single interval, the score is computed as</p> $IS_\alpha(F, y) = (u - l) + \frac{2}{\alpha} \cdot (l - y) \cdot 1(y \leq l) + \frac{2}{\alpha} \cdot (y - u) \cdot 1(y \geq u),$ <p>where $1()$ is the indicator function, y is the true value, and l and u are the $\frac{\alpha}{2}$ and $1 - \frac{\alpha}{2}$ quantiles of the predictive distribution F, i.e. the lower and upper bound of a single prediction interval. For a set of K prediction intervals and the median m, the score is computed as a weighted sum,</p> $WIS = \frac{1}{K + 0.5} \cdot \left(w_0 \cdot y - m + \sum_{k=1}^K w_k \cdot IS_\alpha(F, y) \right),$ <p>where w_k is a weight for every interval. Usually, $w_k = \frac{\alpha_k}{2}$ and $w_0 = 0.5$. Its proximity to the absolute error means that when averaging across multiple targets (e.g. different weeks), it will be dominated by targets with higher absolute values.</p>

Table 1: Overview of the scoring metrics used. (*continued*)

Metric	Explanation
Interval coverage	<p>Interval coverage is a measure of marginal calibration and indicates the proportion of observed values that fall in a given prediction interval range. Nominal coverage represents the percentage of observed values that should ideally be covered (e.g. we would like a 50 percent prediction interval to cover on average 50 percent of the observations), while empirical coverage is the actual percentage of observations covered by a certain prediction interval.</p>
Bias	<p>(Relative) bias is a measure of the general tendency of a forecaster to over- or underpredict. Values are between -1 and 1 and 0 ideally. For continuous forecasts, bias is given as</p> $B(F, y) = 1 - 2 \cdot (F(y)),$ <p>where F is the CDF of the predictive distribution and y is the observed value. For quantile forecasts, $F(y)$ is replaced by a quantile rank. The appropriate quantile rank is determined by whether the median forecast is below or above the true value. We then take the innermost quantile rank for which the quantile is still larger (under-prediction) or smaller (over-prediction) than the observed value. In contrast to the over- and underprediction penalties of the interval score it is bound between 0 and 1 and represents a general tendency of forecasts to be biased rather than the absolute amount of over- and underprediction. It is therefore a more robust measurement.</p>

448 A.2 The crowdforecasting app

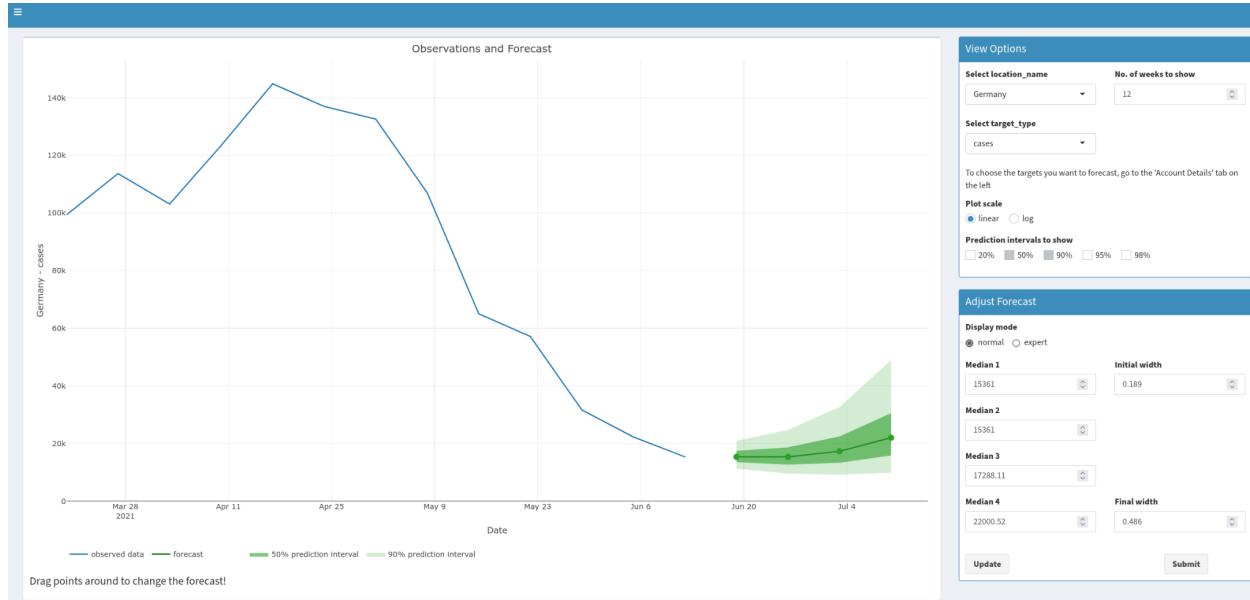


Figure 5: Screenshot of the crowdforecasting app used to elicit predictions (made in June 2021).

449 **A.3 Further details on the semi-mechanistic forecasting models**

450 **A.3.1 Renewal equation model**

451 The model was initialised prior to the first observed data point by assuming constant exponential growth for
 452 the mean of assumed delays from infection to case report.

$$I_t = I_0 \exp(rt) \quad (1)$$

$$I_0 \sim \mathcal{LN}(\log I_{obs}, 0.2) \quad (2)$$

$$r \sim \mathcal{LN}(r_{obs}, 0.2) \quad (3)$$

453 Where I_{obs} and r_{obs} are estimated from the first week of observed data. For the time window of the observed
 454 data infections were then modelled by weighting previous infections by the generation time and scaling by the
 455 instantaneous reproduction number. These infections were then convolved to cases by date (O_t) and cases
 456 by date of report (D_t) using log-normal delay distributions. This model can be defined mathematically as
 457 follows,

$$\log R_t = \log R_{t-1} + \text{GP}_t \quad (4)$$

$$I_t = R_t \sum_{\tau=1}^{15} w(\tau | \mu_w, \sigma_w) I_{t-\tau} \quad (5)$$

$$O_t = \sum_{\tau=0}^{15} \xi_O(\tau | \mu_{\xi_O}, \sigma_{\xi_O}) I_{t-\tau} \quad (6)$$

$$D_t = \alpha \sum_{\tau=0}^{15} \xi_D(\tau | \mu_{\xi_D}, \sigma_{\xi_D}) O_{t-\tau} \quad (7)$$

$$C_t \sim \text{NB}(\omega_{(t \mod 7)} D_t, \phi) \quad (8)$$

Where,

$$w \sim \mathcal{G}(\mu_w, \sigma_w) \quad (9)$$

$$\xi_O \sim \mathcal{LN}(\mu_{\xi_O}, \sigma_{\xi_O}) \quad (10)$$

$$\xi_D \sim \mathcal{LN}(\mu_{\xi_D}, \sigma_{\xi_D}) \quad (11)$$

⁴⁵⁸ This model used the following priors for cases,

$$R_0 \sim \mathcal{LN}(0.079, 0.18) \quad (12)$$

$$\mu_w \sim \mathcal{N}(3.6, 0.7) \quad (13)$$

$$\sigma_w \sim \mathcal{N}(3.1, 0.8) \quad (14)$$

$$\mu_{\xi_O} \sim \mathcal{N}(1.62, 0.064) \quad (15)$$

$$\sigma_{\xi_O} \sim \mathcal{N}(0.418, 0.069) \quad (16)$$

$$\mu_{\xi_D} \sim \mathcal{N}(0.614, 0.066) \quad (17)$$

$$\sigma_{\xi_D} \sim \mathcal{N}(1.51, 0.048) \quad (18)$$

$$\alpha \sim \mathcal{N}(0.25, 0.05) \quad (19)$$

$$\frac{\omega}{7} \sim \text{Dirichlet}(1, 1, 1, 1, 1, 1, 1) \quad (20)$$

$$\phi \sim \frac{1}{\sqrt{\mathcal{N}(0, 1)}} \quad (21)$$

⁴⁵⁹ and updated the reporting process as follows when forecasting deaths,

$$\mu_{\xi_D} \sim \mathcal{N}(2.29, 0.076) \quad (22)$$

$$\sigma_{\xi_D} \sim \mathcal{N}(0.76, 0.055) \quad (23)$$

$$\alpha \sim \mathcal{N}(0.005, 0.0025) \quad (24)$$

460 α , μ , σ , and ϕ were truncated to be greater than 0 and with ξ , and w normalised to sum to 1.

461 The prior for the generation time was sourced from (51) but refit using a log-normal incubation period with
462 a mean of 5.2 days (SD 1.1) and SD of 1.52 days (SD 1.1) with this incubation period also being used as
463 a prior (52) for ξ_O . This resulted in a gamma-distributed generation time with mean 3.6 days (standard
464 deviation (SD) 0.7), and SD of 3.1 days (SD 0.8) for all estimates. We estimated the delay between symptom
465 onset and case report or death required to convolve latent infections to observations by fitting an integer
466 adjusted log-normal distribution to 10 subsampled bootstraps of a public linelist for cases in Germany from
467 April 2020 to June 2020 with each bootstrap using 1% or 1769 samples of the available data (45,53) and
468 combining the posteriors for the mean and standard deviation of the log-normal distribution (40,42,46,54).

469 GP_t is an approximate Hilbert space Gaussian process as defined in (55) using a Matern 3/2 kernel using a
470 boundary factor of 1.5 and 17 basis functions (20% of the number of days used in fitting). The length scale
471 of the Gaussian process was given a log-normal prior with a mean of 21 days, and a standard deviation of 7
472 days truncated to be greater than 3 days and less than 60 days. The magnitude of the Gaussian process was
473 assumed to be normally distributed centred at 0 with a standard deviation of 0.1.

474 From the forecast time horizon (T) and onwards the last value of the Gaussian process was used (hence R_t
475 was assumed to be fixed) and latent infections were adjusted to account for the proportion of the population
476 that was susceptible to infection as follows,

$$I_t = (N - I_{t-1}^c) \left(1 - \exp \left(\frac{-I'_t}{N - I_T^c} \right) \right), \quad (25)$$

477 where $I_t^c = \sum_{s < t} I_s$ are cumulative infections by $t - 1$ and I'_t are the unadjusted infections defined above.

478 This adjustment is based on that implemented in the `epidemia` R package (56,57).

479 **A.3.1.1 Convolution model** The convolution model shares the same observation model as the renewal
480 model but rather than assuming that an observation is predicted by itself using the renewal equation instead
481 assumes that it is predicted entirely by another observation after some parametric delay. It can be defined
482 mathematically as follows,

$$D_t \sim \text{NB} \left(\omega_{(t \mod 7)} \alpha \sum_{\tau=0}^{30} \xi(\tau | \mu, \sigma) C_{t-\tau}, \phi \right) \quad (26)$$

483 with the following priors,

$$\frac{\omega}{7} \sim \text{Dirichlet}(1, 1, 1, 1, 1, 1, 1) \quad (27)$$

$$\alpha \sim \mathcal{N}(0.01, 0.02) \quad (28)$$

$$\xi \sim \mathcal{LN}(\mu, \sigma) \quad (29)$$

$$\mu \sim \mathcal{N}(2.5, 0.5) \quad (30)$$

$$\sigma \sim \mathcal{N}(0.47, 0.2) \quad (31)$$

$$\phi \sim \frac{1}{\sqrt{\mathcal{N}(0, 1)}} \quad (32)$$

484 with α , μ , σ , and ϕ truncated to be greater than 0 and with ξ normalised such that $\sum_{\tau=0}^{30} \xi(\tau | \mu, \sigma) = 1$.

485 **A.3.2 Model fitting**

486 Both models were implemented using the `EpiNow2` R package (version 1.3.3) (40). Each forecast target was
487 fitted independently for each model using Markov-chain Monte Carlo (MCMC) in `stan` (46). A minimum of 4
488 chains were used with a warmup of 250 samples for the renewal equation-based model and 1000 samples for
489 the convolution model. 2000 samples total post warmup were used for the renewal equation model and 4000

⁴⁹⁰ samples for the convolution model. Different settings were chosen for each model to optimise compute time
⁴⁹¹ contingent on convergence. Convergence was assessed using the R hat diagnostic (46). For the convolution
⁴⁹² model forecast the case forecast from the renewal equation model was used in place of observed cases beyond
⁴⁹³ the forecast horizon using 1000 posterior samples. 12 weeks of data was used for both models though only 3
⁴⁹⁴ weeks of data were included in the likelihood for the convolution model.

495 **A.4 Tables with results of the forecast evaluation**

Table 2: Scores for one and two week ahead forecasts (cut to three significant digits and rounded). Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
1 wk ahead	Crowd forecast	7010 (0.8)	7480 (0.64)	2680 (0.73)	1700 (1.38)	2630 (0.68)	-0.01	10400 (0.82)	0.55	0.79
	Hub-ensemble	8770 (1)	11700 (1)	3670 (1)	1230 (1)	3870 (1)	-0.04	12700 (1)	0.57	0.81
	Renewal	8740 (1)	11800 (1.01)	2190 (0.6)	2720 (2.21)	3830 (0.99)	0.18	12000 (0.94)	0.48	0.71
2 wk ahead	Crowd forecast	16200 (0.89)	16600 (0.76)	3660 (0.6)	5930 (1.56)	6600 (0.78)	-0.01	23300 (0.87)	0.36	0.55
	Hub-ensemble	18300 (1)	21900 (1)	6140 (1)	3800 (1)	8410 (1)	-0.03	26800 (1)	0.43	0.64
	Renewal	25600 (1.4)	33800 (1.54)	5420 (0.88)	5920 (1.56)	14200 (1.69)	0.17	34600 (1.29)	0.43	0.67
Deaths										
1 wk ahead	Convolution	255 (1.03)	343 (1.01)	82 (0.89)	142 (1.23)	31.1 (0.75)	-0.18	399 (1.19)	0.42	0.79
	Crowd forecast	265 (1.07)	317 (0.94)	78.2 (0.85)	82 (0.71)	105 (2.52)	0.08	402 (1.2)	0.38	0.79
	Hub-ensemble	248 (1)	338 (1)	92.2 (1)	115 (1)	41.6 (1)	-0.04	334 (1)	0.62	0.92
2 wk ahead	Renewal	298 (1.2)	403 (1.19)	87 (0.94)	107 (0.93)	105 (2.52)	-0.07	413 (1.24)	0.50	0.79
	Convolution	357 (1.22)	573 (1.49)	104 (0.79)	204 (1.89)	48.8 (0.94)	-0.10	565 (1.32)	0.33	0.79
	Crowd forecast	368 (1.26)	442 (1.15)	107 (0.81)	102 (0.94)	160 (3.08)	0.14	576 (1.34)	0.38	0.75
Renewal	Hub-ensemble	292 (1)	385 (1)	132 (1)	108 (1)	51.9 (1)	0.01	429 (1)	0.62	0.96
	Renewal	524 (1.79)	671 (1.74)	155 (1.17)	133 (1.23)	236 (4.55)	-0.02	750 (1.75)	0.50	0.71

Table 3: Scores for three and four week ahead forecasts (cut to three significant digits and rounded). Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
3 wk ahead	Crowd forecast	27000 (0.81)	26200 (0.64)	4750 (0.52)	11000 (1.43)	11200 (0.67)	0.02	39000 (0.83)	0.14	0.48
	Hub-ensemble	33400 (1)	40700 (1)	9130 (1)	7690 (1)	16600 (1)	-0.01	46900 (1)	0.29	0.62
	Renewal	50600 (1.51)	70000 (1.72)	10800 (1.18)	7710 (1)	32100 (1.93)	0.13	68700 (1.46)	0.29	0.55
4 wk ahead	Crowd forecast	39200 (0.7)	38600 (0.52)	5970 (0.49)	15600 (1.26)	17600 (0.56)	0.07	54800 (0.74)	0.05	0.38
	Hub-ensemble	55900 (1)	73700 (1)	12200 (1)	12400 (1)	31300 (1)	0.01	74400 (1)	0.24	0.52
	Renewal	91700 (1.64)	135000 (1.83)	19500 (1.6)	8990 (0.72)	63200 (2.02)	0.09	125000 (1.68)	0.31	0.48
Deaths										
3 wk ahead	Convolution	541 (1.7)	802 (2.45)	157 (0.91)	279 (3.01)	105 (1.91)	-0.04	747 (1.53)	0.54	0.75
	Crowd forecast	414 (1.3)	526 (1.6)	137 (0.8)	82 (0.88)	194 (3.52)	0.12	648 (1.33)	0.42	0.83
	Hub-ensemble	319 (1)	328 (1)	172 (1)	92.7 (1)	55.1 (1)	-0.03	488 (1)	0.54	0.96
4 wk ahead	Renewal	724 (2.27)	916 (2.79)	249 (1.45)	158 (1.7)	317 (5.75)	-0.01	1040 (2.13)	0.46	0.83
	Convolution	763 (1.8)	932 (2.1)	268 (1.26)	331 (2.63)	164 (1.91)	0.01	985 (1.46)	0.54	0.75
	Crowd forecast	498 (1.17)	633 (1.43)	168 (0.79)	83.6 (0.66)	246 (2.87)	0.14	756 (1.12)	0.38	0.79
	Hub-ensemble	424 (1)	443 (1)	212 (1)	126 (1)	85.7 (1)	-0.06	675 (1)	0.58	0.92
	Renewal	959 (2.26)	1210 (2.73)	337 (1.59)	200 (1.59)	421 (4.91)	-0.05	1350 (2)	0.50	0.79

496 **A.5 Aggregate performance by location**

497 **A.5.1 Performance across locations in absolute terms**

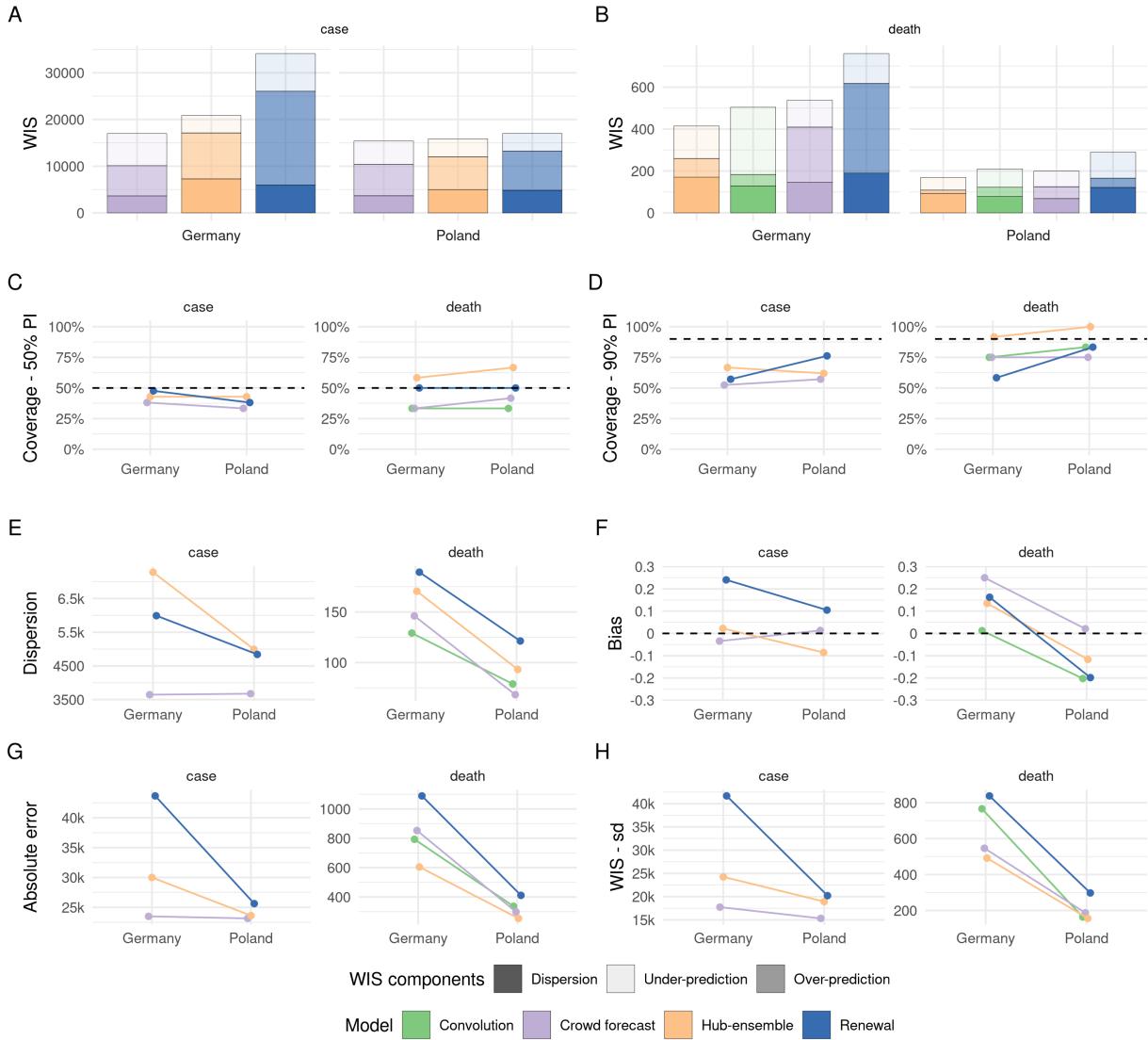


Figure 6: Visualisation of aggregate performance metrics across locations. A: mean weighted interval score (WIS) across horizons. B: median WIS. C: Absolute error of the median forecast. D: Standard deviation of the WIS. E: Dispersion (higher values mean further spread out forecast). F: Bias, i.e. general tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction) and 0 ideally. G: Empirical coverage of the 50% prediction intervals. F: Empirical coverage of the 90% prediction intervals.

498 **A.6 Performance across locations in relative terms**

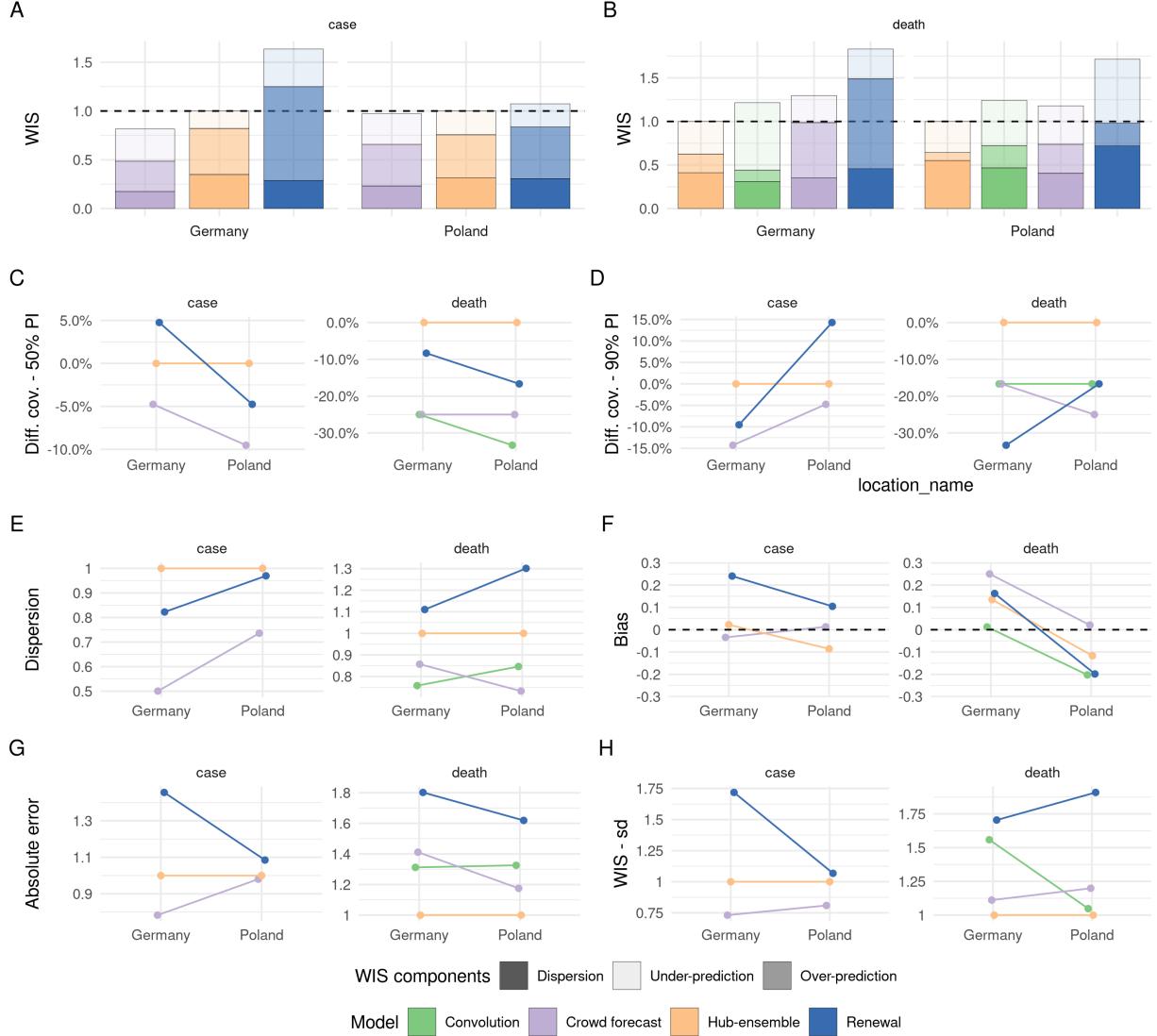


Figure 7: Visualisation of aggregate performance metrics across locations relative to the Hub ensemble (excluding our contributions). A: mean weighted interval score (WIS) across horizons. B: median WIS. C: Absolute error of the median forecast. D: Standard deviation of the WIS. E: Dispersion (higher values mean further spread out forecast). F: Bias, i.e. general tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction) and 0 ideally. G: Empirical coverage of the 50% prediction intervals. F: Empirical coverage of the 90% prediction intervals.

⁴⁹⁹ A.7 Visualisation of daily reported cases and deaths

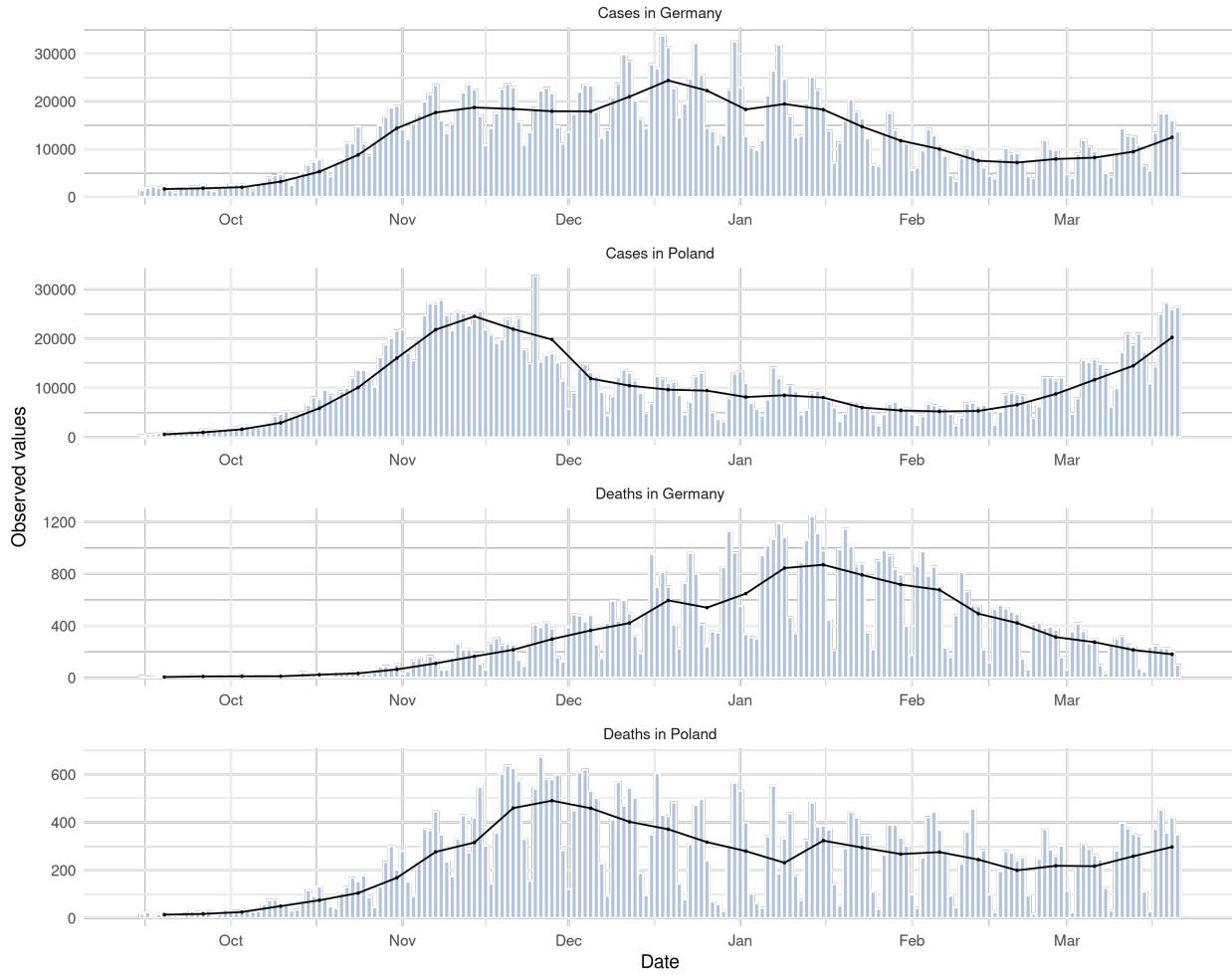


Figure 8: Visualisation of daily report data. The black line represents weekly data divided by seven. Data were last accessed through the German and Polish Forecast Hub on August 21 2021.

500 A.8 Visualisation of scores and forecasts 1, 3, 4 weeks ahead

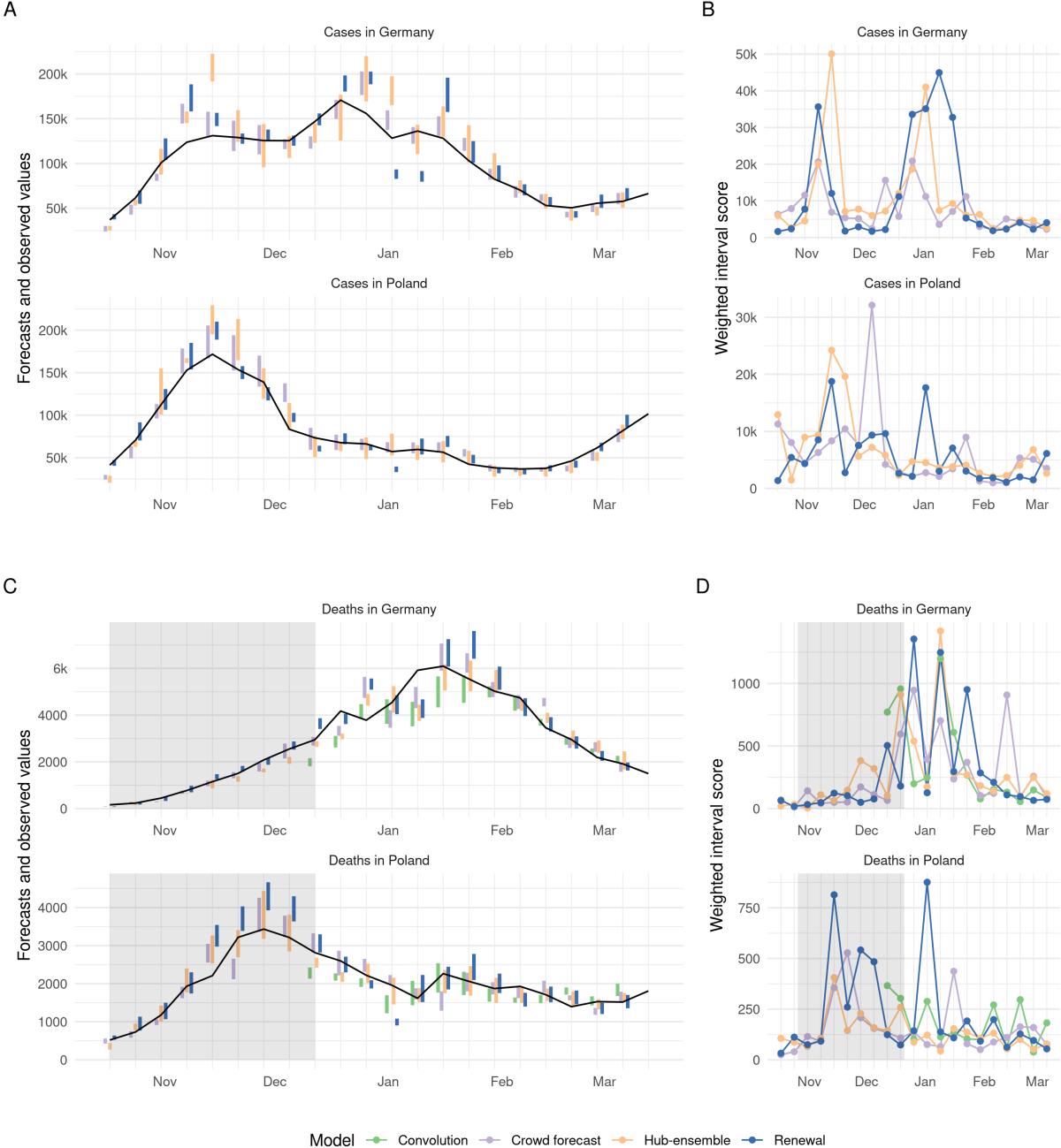


Figure 9: A, C: Visualisation of 50% prediction intervals of one week ahead forecasts against the reported values. Forecasts that were not scored (because there was no complete set of death forecasts available) are greyed out. B, D: Visualisation of corresponding WIS.

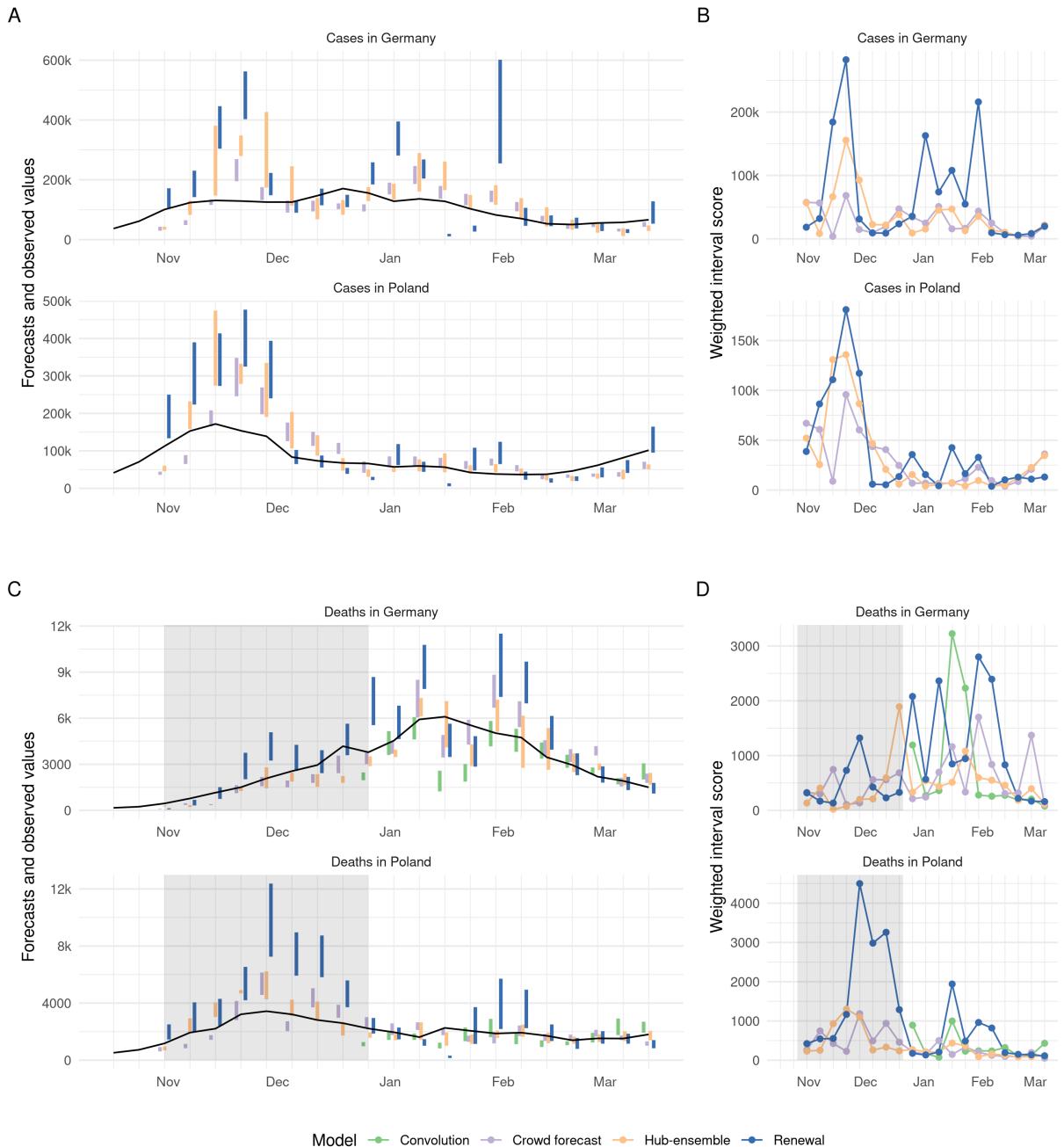


Figure 10: A, C: Visualisation of 50% prediction intervals of three week ahead forecasts against the reported values. Forecasts that were not scored (because there was no complete set of death forecasts available) are greyed out. B, D: Visualisation of corresponding WIS.

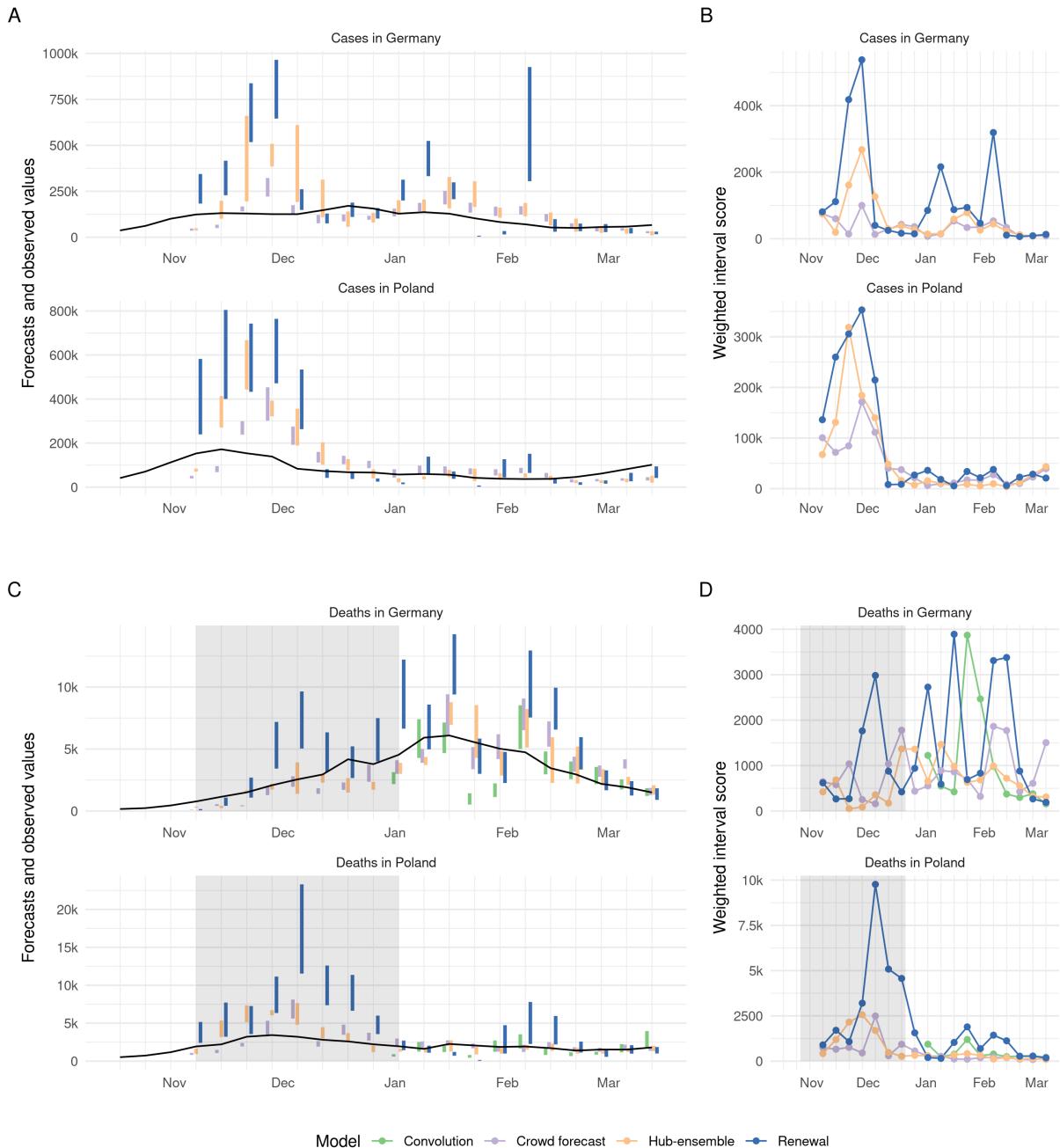


Figure 11: A, C: Visualisation of 50% prediction intervals of four week ahead forecasts against the reported values. Forecasts that were not scored (because there was no complete set of death forecasts available) are greyed out. B, D: Visualisation of corresponding WIS.

501 **A.9 Distribution of scores**

502 **A.9.1 Absolute scores**

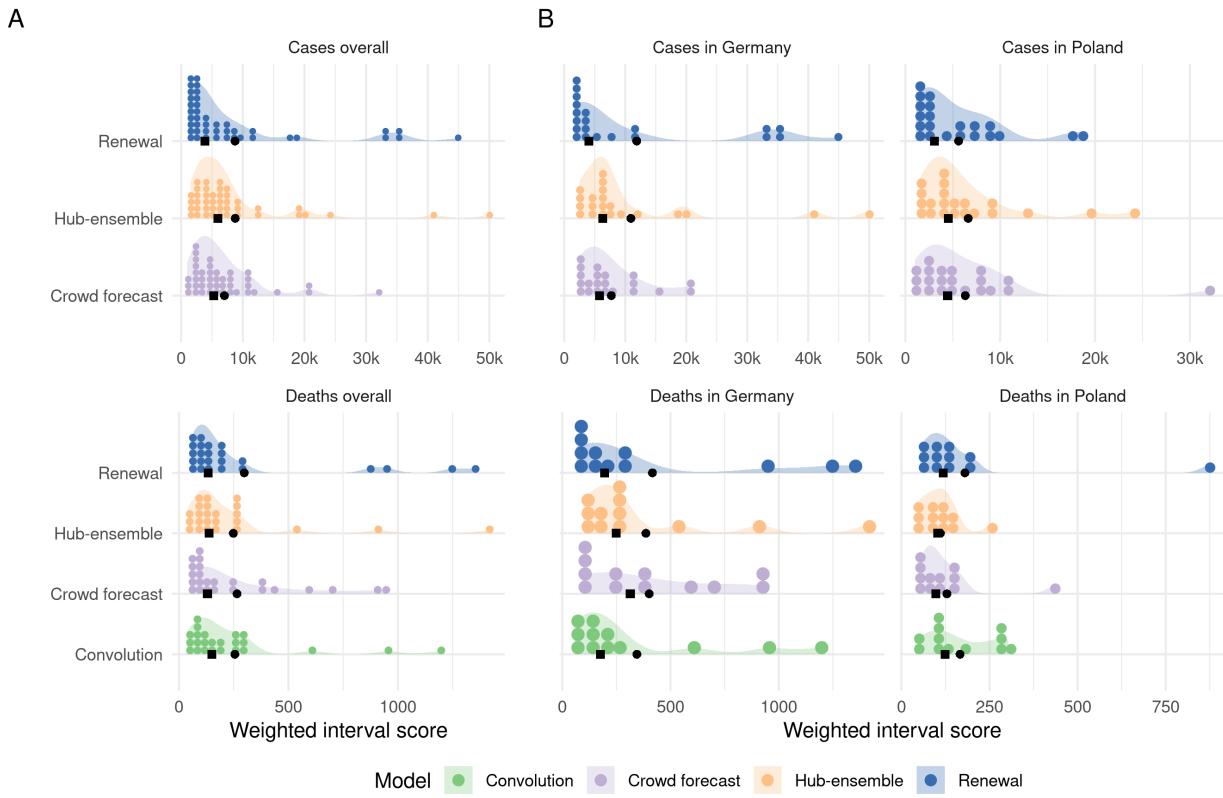


Figure 12: A: Distribution of weighted interval scores for one week ahead forecasts of the different models and forecast targets. B: Distribution of WIS separate by country.

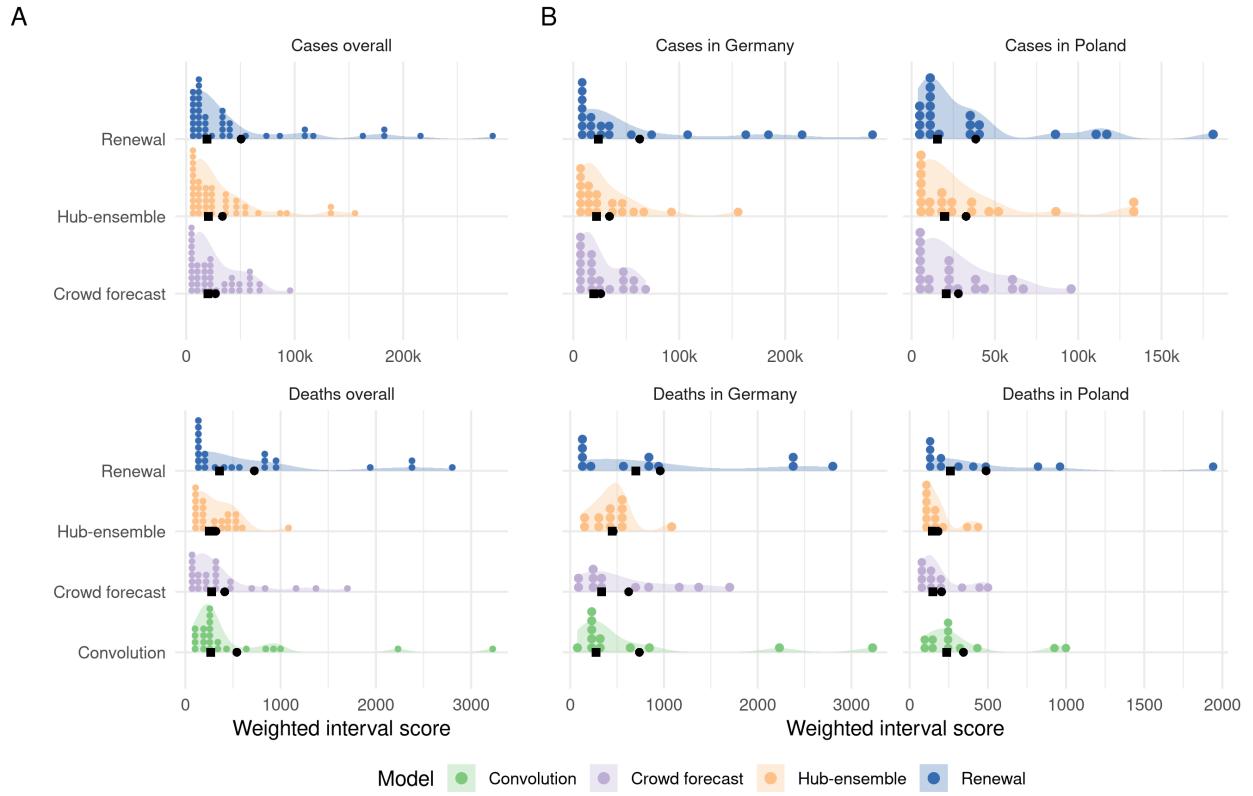


Figure 13: A: Distribution of weighted interval scores for three week ahead forecasts of the different models and forecast targets. B: Distribution of WIS separate by country.

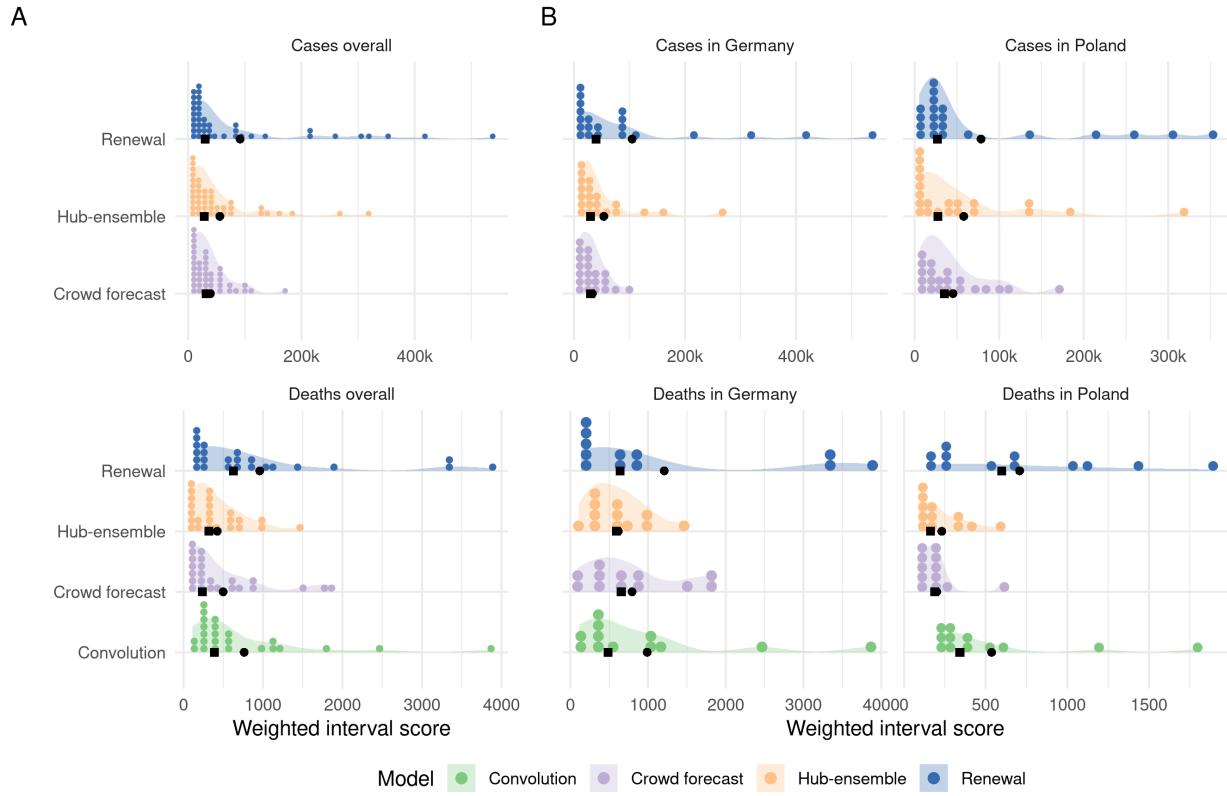


Figure 14: A: Distribution of weighted interval scores for four week ahead forecasts of the different models and forecast targets. B: Distribution of WIS separate by country.

503 A.9.2 Ranks achieved by forecasts

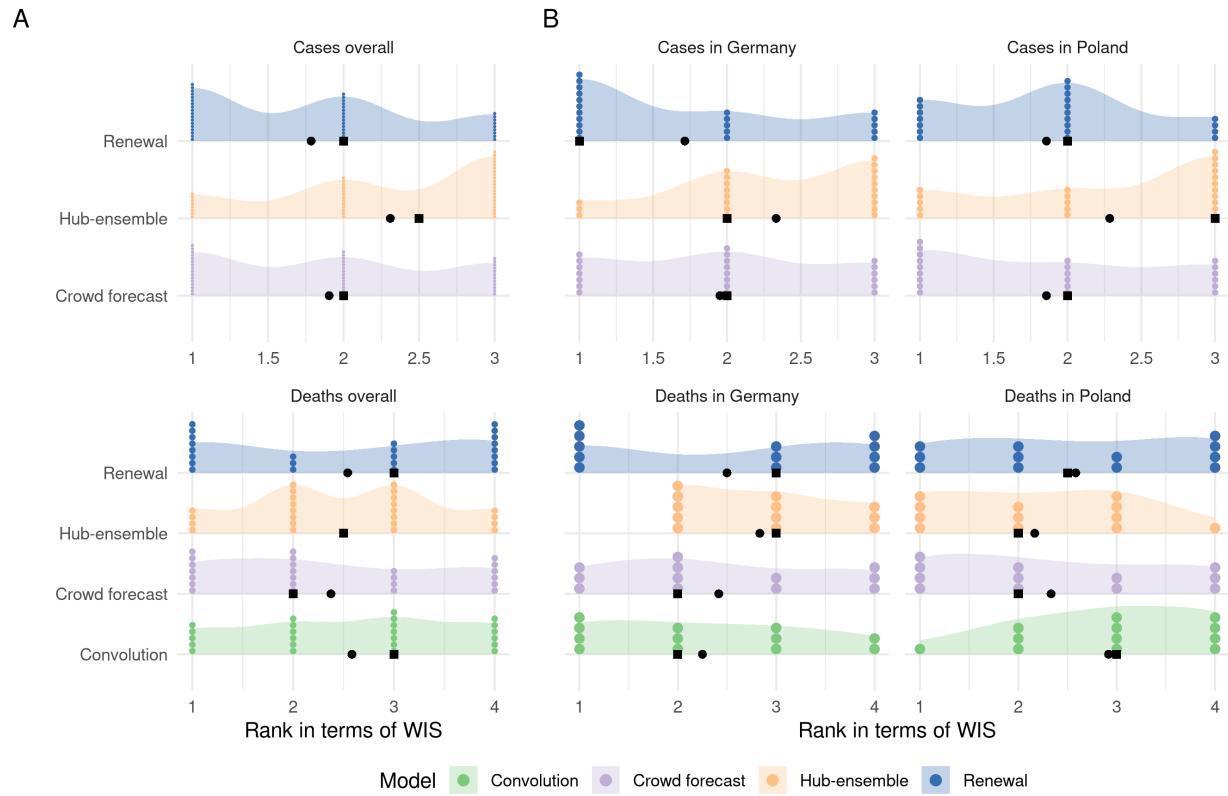


Figure 15: A: Distribution of the ranks (determined by the weighted interval score) for one week ahead forecasts of the different models and forecast targets. B: Distribution of ranks separate by country.

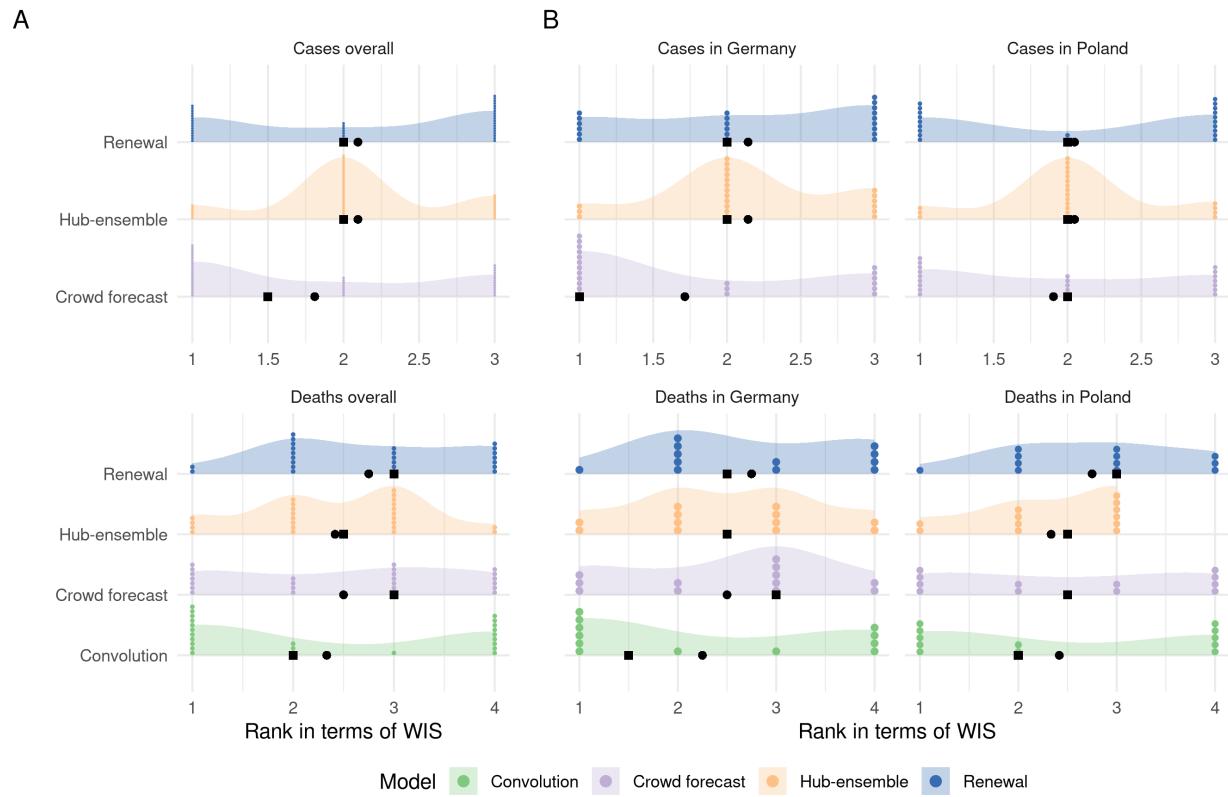


Figure 16: A: Distribution of the ranks (determined by the weighted interval score) for two week ahead forecasts of the different models and forecast targets. B: Distribution of ranks separate by country.

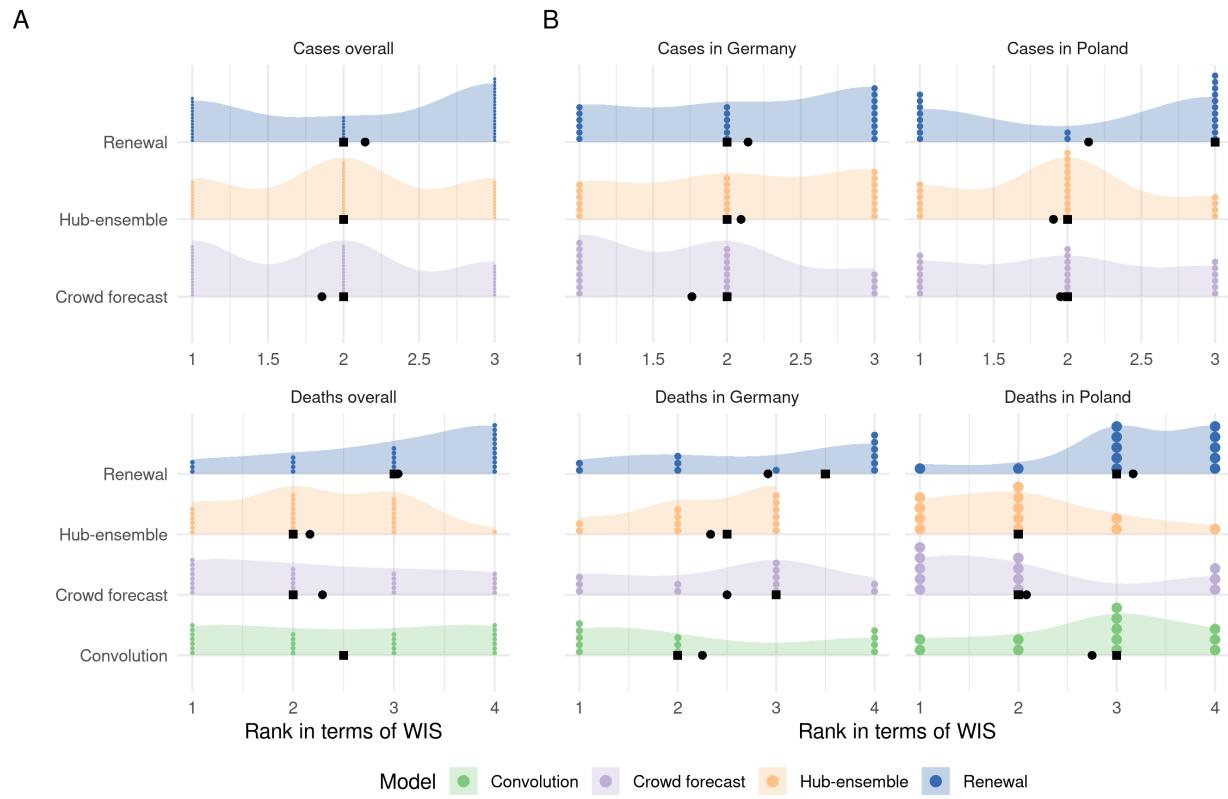


Figure 17: A: Distribution of the ranks (determined by the weighted interval score) for three week ahead forecasts of the different models and forecast targets. B: Distribution of ranks separate by country.

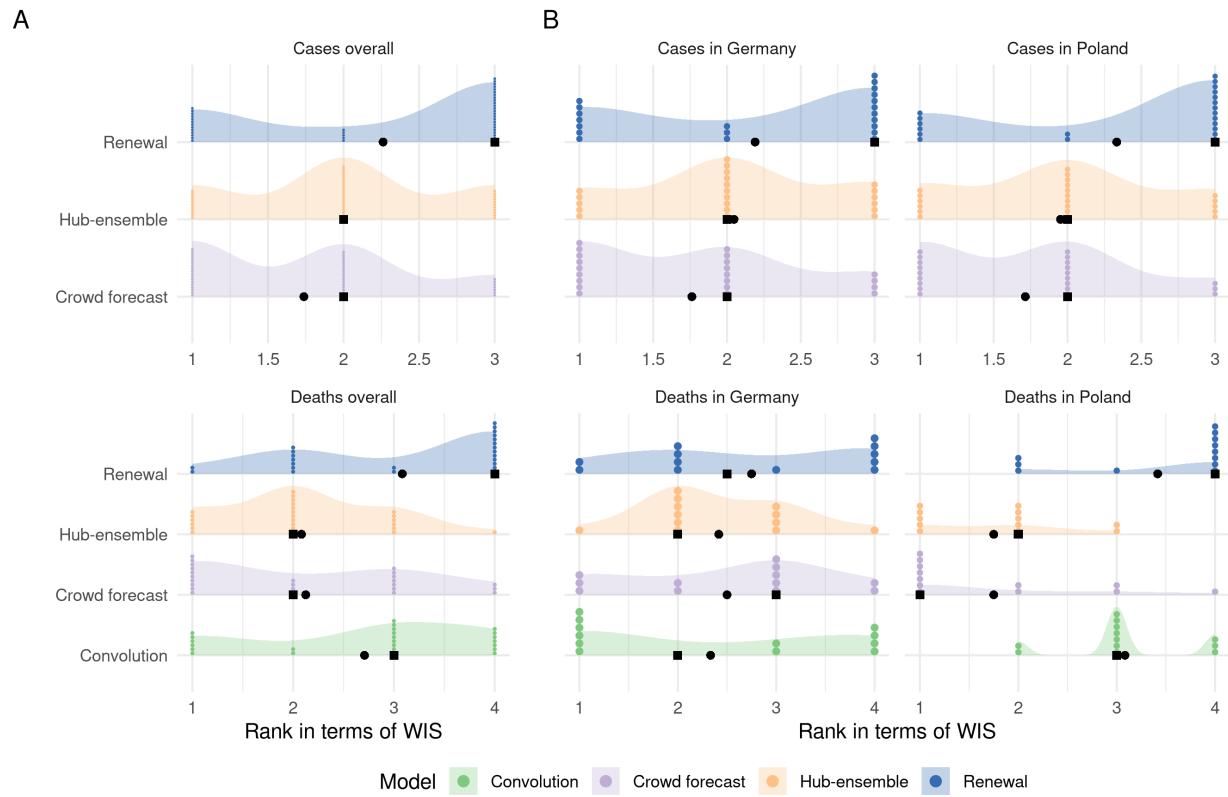


Figure 18: A: Distribution of the ranks (determined by the weighted interval score) for four week ahead forecasts of the different models and forecast targets. B: Distribution of ranks separate by country.

504 **A.10 Comparison of ensembles**

505 **A.10.1 Performance visualisation mean ensemble**

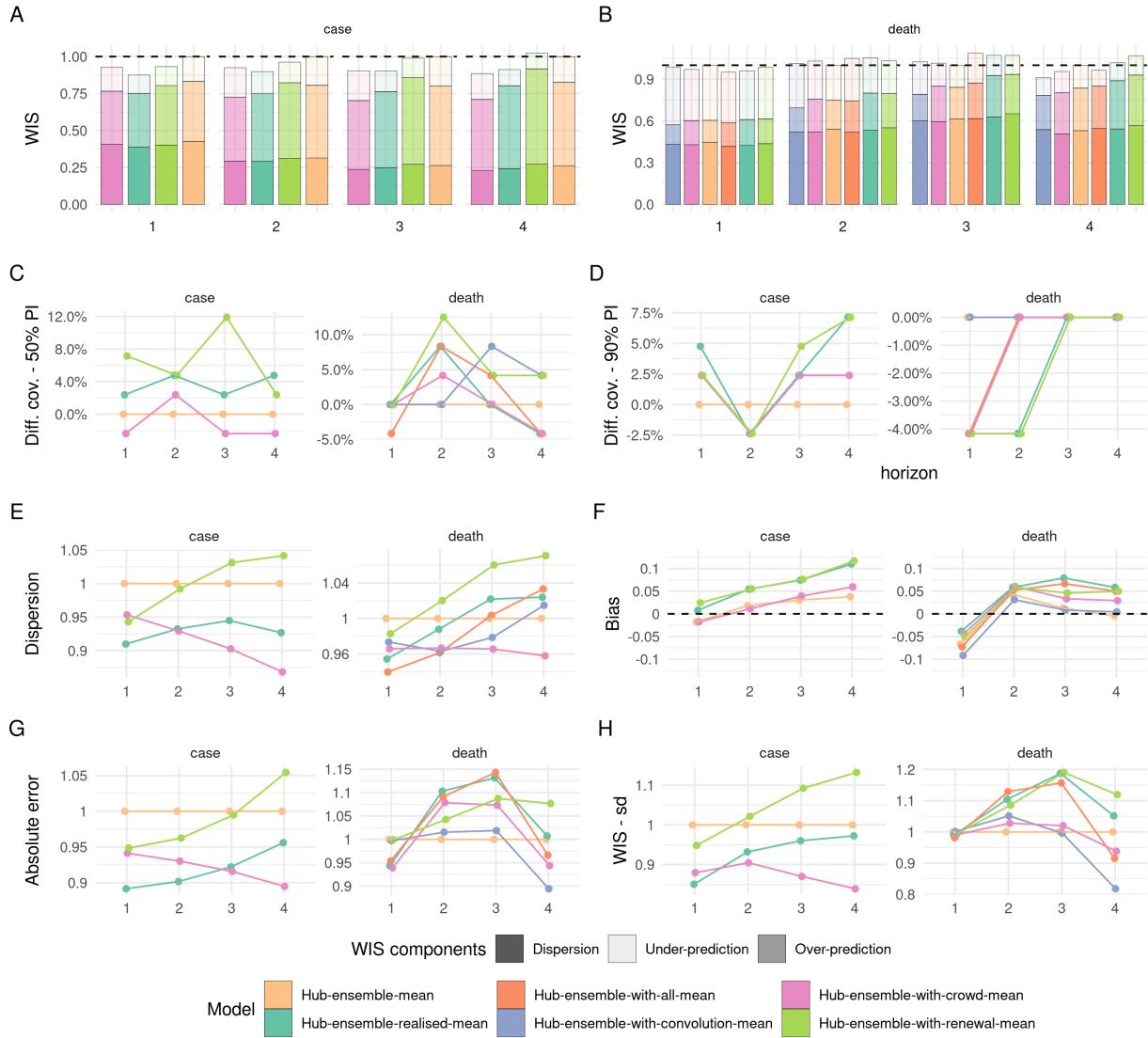


Figure 19: Visualisation of aggregate performance metrics across forecast horizons for the different versions of the Hub mean ensemble. “Hub-ensemble” excludes all our models, Hub-ensemble-all includes all of our models, “Hub-ensemble-real” is the real hub-ensemble with the renewal model and the crowd forecasts included. Values (except for Bias) are computed as differences to the Hub ensemble excluding our contributions. For Coverage, this is an absolute difference, for other metrics this is a percentage difference. A: mean weighted interval score (WIS) across horizons. B: median WIS. C: Absolute error of the median forecast. D: Standard deviation of the WIS. E: Dispersion (higher values mean greater spread of the forecast). F: Bias, i.e. general tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction)

506 **A.10.2 Tables median ensemble**

Table 4: Scores for one and two week ahead forecasts (cut to three significant digits and rounded) for the different versions of the median ensemble. Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.	
Cases										
Hub-ensemble	8770 (1)	11700 (1)	3670 (1)	1230 (1)	3870 (1)	-0.04	12700 (1)	0.57	0.81	
Hub-ensemble-realised	6970 (0.79)	8260 (0.71)	3060 (0.83)	943 (0.77)	2970 (0.77)	0.04	10800 (0.85)	0.55	0.83	
1 wk ahead	Hub-ensemble-with-crowd	7820 (0.89)	9630 (0.82)	3270 (0.89)	1210 (0.98)	3330 (0.86)	-0.02	12000 (0.94)	0.48	0.81
	Hub-ensemble-with-renewal	7960 (0.91)	10300 (0.88)	3190 (0.87)	1020 (0.83)	3760 (0.97)	0.04	12100 (0.95)	0.57	0.83
	Hub-ensemble	18300 (1)	21900 (1)	6140 (1)	3800 (1)	8410 (1)	-0.03	26800 (1)	0.43	0.64
	Hub-ensemble-realised	16400 (0.9)	19600 (0.89)	5350 (0.87)	3290 (0.87)	7730 (0.92)	0.02	24200 (0.9)	0.43	0.69
2 wk ahead	Hub-ensemble-with-crowd	16900 (0.92)	19600 (0.89)	5230 (0.85)	4310 (1.13)	7370 (0.88)	0.00	24600 (0.92)	0.38	0.64
	Hub-ensemble-with-renewal	17500 (0.96)	21400 (0.98)	5830 (0.95)	2880 (0.76)	8770 (1.04)	0.00	25500 (0.95)	0.45	0.71
Deaths										
Hub-ensemble	248 (1)	338 (1)	92.2 (1)	115 (1)	41.6 (1)	-0.04	334 (1)	0.62	0.92	
Hub-ensemble-realised	235 (0.95)	332 (0.98)	88.6 (0.96)	90.4 (0.79)	55.5 (1.33)	-0.01	323 (0.97)	0.62	0.88	
1 wk ahead	Hub-ensemble-with-all	234 (0.94)	331 (0.98)	85.2 (0.92)	98.1 (0.85)	50.2 (1.21)	-0.05	329 (0.99)	0.62	0.92
	Hub-ensemble-with-convolution	234 (0.94)	329 (0.97)	90.7 (0.98)	118 (1.03)	25.3 (0.61)	-0.08	333 (1)	0.62	0.92
	Hub-ensemble-with-crowd	239 (0.96)	337 (1)	85.2 (0.92)	99.6 (0.87)	54.2 (1.3)	-0.03	322 (0.96)	0.62	0.92
	Hub-ensemble-with-renewal	246 (0.99)	342 (1.01)	91.5 (0.99)	106 (0.92)	48.6 (1.17)	-0.06	342 (1.02)	0.67	0.92
	Hub-ensemble	292 (1)	385 (1)	132 (1)	108 (1)	51.9 (1)	0.01	429 (1)	0.62	0.96
	Hub-ensemble-realised	296 (1.01)	398 (1.03)	125 (0.95)	91 (0.84)	80.2 (1.55)	0.05	486 (1.13)	0.58	0.92
2 wk ahead	Hub-ensemble-with-all	303 (1.04)	423 (1.1)	115 (0.87)	122 (1.13)	66.1 (1.27)	0.00	483 (1.13)	0.62	0.88
	Hub-ensemble-with-convolution	270 (0.92)	385 (1)	121 (0.92)	119 (1.1)	29.9 (0.58)	-0.04	403 (0.94)	0.58	0.96
	Hub-ensemble-with-crowd	303 (1.04)	392 (1.02)	122 (0.92)	106 (0.98)	74.6 (1.44)	0.03	499 (1.16)	0.58	0.92
	Hub-ensemble-with-renewal	296 (1.01)	397 (1.03)	128 (0.97)	97.1 (0.9)	71.2 (1.37)	-0.01	462 (1.08)	0.67	0.92

507 **A.10.3 Tables mean ensemble**

Table 5: Scores for three and four week ahead forecasts (cut to three significant digits and rounded) for the different versions of the median ensemble. Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
3 wk ahead	Hub-ensemble	33400 (1)	40700 (1)	9130 (1)	7690 (1)	16600 (1)	-0.01	46900 (1)	0.29	0.62
	Hub-ensemble-realised	30800 (0.92)	38600 (0.95)	7910 (0.87)	6890 (0.9)	16000 (0.96)	0.03	44200 (0.94)	0.29	0.62
	Hub-ensemble-with-crowd	30800 (0.92)	34100 (0.84)	7500 (0.82)	8960 (1.17)	14300 (0.86)	0.02	44100 (0.94)	0.24	0.55
	Hub-ensemble-with-renewal	34000 (1.02)	43100 (1.06)	8860 (0.97)	6300 (0.82)	18900 (1.14)	0.02	48100 (1.03)	0.29	0.60
4 wk ahead	Hub-ensemble	55900 (1)	73700 (1)	12200 (1)	12400 (1)	31300 (1)	0.01	74400 (1)	0.24	0.52
	Hub-ensemble-realised	51200 (0.92)	69900 (0.95)	10900 (0.89)	11100 (0.9)	29300 (0.94)	0.04	69600 (0.94)	0.19	0.57
	Hub-ensemble-with-crowd	48800 (0.87)	58600 (0.8)	9700 (0.8)	13700 (1.1)	25400 (0.81)	0.00	65800 (0.88)	0.19	0.48
	Hub-ensemble-with-renewal	59100 (1.06)	84100 (1.14)	12600 (1.03)	10100 (0.81)	36400 (1.16)	0.01	78900 (1.06)	0.29	0.55
Deaths										
3 wk ahead	Hub-ensemble	319 (1)	328 (1)	172 (1)	92.7 (1)	55.1 (1)	-0.03	488 (1)	0.54	0.96
	Hub-ensemble-realised	332 (1.04)	388 (1.18)	158 (0.92)	78.7 (0.85)	95 (1.72)	-0.02	547 (1.12)	0.46	1.00
	Hub-ensemble-with-all	321 (1.01)	385 (1.17)	153 (0.89)	100 (1.08)	68.1 (1.24)	-0.01	535 (1.1)	0.54	1.00
	Hub-ensemble-with-convolution	298 (0.93)	337 (1.03)	155 (0.9)	106 (1.14)	37.5 (0.68)	-0.04	441 (0.9)	0.67	0.92
	Hub-ensemble-with-crowd	319 (1)	342 (1.04)	160 (0.93)	85.1 (0.92)	73.6 (1.34)	-0.02	547 (1.12)	0.54	0.96
	Hub-ensemble-with-renewal	332 (1.04)	363 (1.11)	168 (0.98)	86.1 (0.93)	78.2 (1.42)	-0.02	528 (1.08)	0.58	0.96
4 wk ahead	Hub-ensemble	424 (1)	443 (1)	212 (1)	126 (1)	85.7 (1)	-0.06	675 (1)	0.58	0.92
	Hub-ensemble-realised	445 (1.05)	532 (1.2)	193 (0.91)	107 (0.85)	144 (1.68)	-0.03	700 (1.04)	0.54	0.92
	Hub-ensemble-with-all	399 (0.94)	438 (0.99)	195 (0.92)	105 (0.83)	97.9 (1.14)	-0.05	692 (1.03)	0.46	1.00
	Hub-ensemble-with-convolution	384 (0.91)	387 (0.87)	196 (0.92)	122 (0.97)	65.9 (0.77)	-0.06	602 (0.89)	0.54	0.96
	Hub-ensemble-with-crowd	407 (0.96)	456 (1.03)	202 (0.95)	105 (0.83)	101 (1.18)	-0.03	669 (0.99)	0.67	0.96
	Hub-ensemble-with-renewal	457 (1.08)	527 (1.19)	208 (0.98)	129 (1.02)	121 (1.41)	-0.06	744 (1.1)	0.50	0.96

Table 6: Scores for one and two week ahead forecasts (cut to three significant digits and rounded) for the different versions of the mean ensemble. Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub mean ensemble (i.e. the mean ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
1 wk ahead	Hub-ensemble-mean	8680 (1)	10300 (1)	3700 (1)	1460 (1)	3520 (1)	-0.02	13400 (1)	0.50	0.86
	Hub-ensemble-realised-mean	7600 (0.88)	8770 (0.85)	3360 (0.91)	1090 (0.75)	3140 (0.89)	0.01	11900 (0.89)	0.52	0.90
	Hub-ensemble-with-crowd-mean	8050 (0.93)	9070 (0.88)	3520 (0.95)	1410 (0.97)	3120 (0.89)	-0.02	12600 (0.94)	0.48	0.88
	Hub-ensemble-with-renewal-mean	8090 (0.93)	9780 (0.95)	3490 (0.94)	1110 (0.76)	3490 (0.99)	0.02	12700 (0.95)	0.57	0.88
2 wk ahead	Hub-ensemble-mean	19000 (1)	22100 (1)	5960 (1)	3690 (1)	9340 (1)	0.02	28800 (1)	0.33	0.79
	Hub-ensemble-realised-mean	17100 (0.9)	20600 (0.93)	5550 (0.93)	2850 (0.77)	8660 (0.93)	0.05	26000 (0.9)	0.38	0.76
	Hub-ensemble-with-crowd-mean	17600 (0.93)	20000 (0.9)	5540 (0.93)	3790 (1.03)	8230 (0.88)	0.01	26800 (0.93)	0.36	0.76
	Hub-ensemble-with-renewal-mean	18300 (0.96)	22600 (1.02)	5910 (0.99)	2640 (0.72)	9720 (1.04)	0.06	27700 (0.96)	0.38	0.76
Deaths										
1 wk ahead	Hub-ensemble-mean	229 (1)	292 (1)	101 (1)	90.4 (1)	36.7 (1)	-0.07	315 (1)	0.71	0.92
	Hub-ensemble-realised-mean	219 (0.96)	289 (0.99)	96.8 (0.96)	79.8 (0.88)	42.6 (1.16)	-0.04	297 (0.94)	0.71	0.88
	Hub-ensemble-with-all-mean	217 (0.95)	287 (0.98)	95.3 (0.94)	83.1 (0.92)	38.7 (1.05)	-0.07	300 (0.95)	0.67	0.88
	Hub-ensemble-with-convolution-mean	225 (0.98)	292 (1)	98.7 (0.98)	94.2 (1.04)	32 (0.87)	-0.09	314 (1)	0.71	0.92
	Hub-ensemble-with-crowd-mean	222 (0.97)	289 (0.99)	98 (0.97)	84.1 (0.93)	39.6 (1.08)	-0.04	295 (0.94)	0.71	0.88
	Hub-ensemble-with-renewal-mean	225 (0.98)	290 (0.99)	99.7 (0.99)	84.7 (0.94)	40.5 (1.1)	-0.05	314 (1)	0.71	0.88
2 wk ahead	Hub-ensemble-mean	256 (1)	306 (1)	138 (1)	64.5 (1)	53.2 (1)	0.04	374 (1)	0.67	0.96
	Hub-ensemble-realised-mean	270 (1.05)	338 (1.1)	136 (0.99)	65.2 (1.01)	68.1 (1.28)	0.06	413 (1.1)	0.75	0.92
	Hub-ensemble-with-all-mean	268 (1.05)	346 (1.13)	133 (0.96)	78.7 (1.22)	57.1 (1.07)	0.05	408 (1.09)	0.75	0.96
	Hub-ensemble-with-convolution-mean	259 (1.01)	322 (1.05)	133 (0.96)	81.7 (1.27)	44.4 (0.83)	0.03	380 (1.02)	0.67	0.96
	Hub-ensemble-with-crowd-mean	264 (1.03)	315 (1.03)	133 (0.96)	70.1 (1.09)	60 (1.13)	0.06	404 (1.08)	0.71	0.96
	Hub-ensemble-with-renewal-mean	264 (1.03)	332 (1.08)	141 (1.02)	60.1 (0.93)	63.1 (1.19)	0.06	390 (1.04)	0.79	0.92

Table 7: Scores for three and four week ahead forecasts (cut to three significant digits and rounded) for the different versions of the mean ensemble. Note that scores for cases (which include the whole period from October 12th 2020 until March 1st 2021) and deaths (which include only forecasts from the 21st of December 2020 on) are computed on different subsets. Numbers in brackets show the metrics relative to the Hub mean ensemble (i.e. the mean ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
3 wk ahead	Hub-ensemble-mean	35600 (1)	42100 (1)	9340 (1)	7050 (1)	19200 (1)	0.03	51200 (1)	0.26	0.62
	Hub-ensemble-realised-mean	32100 (0.9)	40500 (0.96)	8830 (0.95)	4920 (0.7)	18300 (0.95)	0.07	47200 (0.92)	0.29	0.64
	Hub-ensemble-with-crowd-mean	32200 (0.9)	36700 (0.87)	8430 (0.9)	7190 (1.02)	16500 (0.86)	0.04	46900 (0.92)	0.24	0.64
	Hub-ensemble-with-renewal-mean	35200 (0.99)	46000 (1.09)	9630 (1.03)	4600 (0.65)	20900 (1.09)	0.08	51000 (1)	0.38	0.67
4 wk ahead	Hub-ensemble-mean	60300 (1)	79300 (1)	15700 (1)	10400 (1)	34100 (1)	0.04	78600 (1)	0.29	0.57
	Hub-ensemble-realised-mean	55000 (0.91)	77100 (0.97)	14600 (0.93)	6620 (0.64)	33800 (0.99)	0.11	75200 (0.96)	0.33	0.64
	Hub-ensemble-with-crowd-mean	53400 (0.89)	66600 (0.84)	13700 (0.87)	10600 (1.02)	29200 (0.86)	0.06	70400 (0.9)	0.26	0.60
	Hub-ensemble-with-renewal-mean	61700 (1.02)	89800 (1.13)	16400 (1.04)	6400 (0.62)	38900 (1.14)	0.12	82900 (1.05)	0.31	0.64
Deaths										
3 wk ahead	Hub-ensemble-mean	289 (1)	293 (1)	178 (1)	45.9 (1)	65.7 (1)	0.01	443 (1)	0.58	1.00
	Hub-ensemble-realised-mean	310 (1.07)	348 (1.19)	182 (1.02)	42 (0.92)	86.5 (1.32)	0.08	502 (1.13)	0.58	1.00
	Hub-ensemble-with-all-mean	315 (1.09)	339 (1.16)	178 (1)	62.2 (1.36)	74 (1.13)	0.07	507 (1.14)	0.62	1.00
	Hub-ensemble-with-convolution-mean	297 (1.03)	292 (1)	174 (0.98)	67.7 (1.47)	55 (0.84)	0.01	452 (1.02)	0.67	1.00
	Hub-ensemble-with-crowd-mean	294 (1.02)	299 (1.02)	172 (0.97)	48 (1.05)	74.2 (1.13)	0.03	476 (1.07)	0.58	1.00
	Hub-ensemble-with-renewal-mean	310 (1.07)	349 (1.19)	189 (1.06)	39.4 (0.86)	81.9 (1.25)	0.05	482 (1.09)	0.62	1.00
4 wk ahead	Hub-ensemble-mean	437 (1)	568 (1)	232 (1)	72 (1)	134 (1)	0.00	702 (1)	0.62	1.00
	Hub-ensemble-realised-mean	445 (1.02)	598 (1.05)	237 (1.02)	56.4 (0.78)	152 (1.13)	0.06	707 (1.01)	0.58	1.00
	Hub-ensemble-with-all-mean	421 (0.96)	520 (0.92)	239 (1.03)	49.9 (0.69)	132 (0.99)	0.05	678 (0.97)	0.58	1.00
	Hub-ensemble-with-convolution-mean	398 (0.91)	465 (0.82)	235 (1.01)	55.6 (0.77)	107 (0.8)	0.00	628 (0.89)	0.67	1.00
	Hub-ensemble-with-crowd-mean	418 (0.96)	533 (0.94)	222 (0.96)	66.8 (0.93)	129 (0.96)	0.03	662 (0.94)	0.58	1.00
	Hub-ensemble-with-renewal-mean	467 (1.07)	636 (1.12)	248 (1.07)	61 (0.85)	158 (1.18)	0.05	755 (1.08)	0.67	1.00

508 **A.11 Sensitivity analysis**

509 In the original analysis, cases and deaths were scored on different periods, as the convolution model was only
510 added later. This sensitivity shows performance of all models restricted to the period from October 14 2020
511 until March 1st 2021 where all models were available.

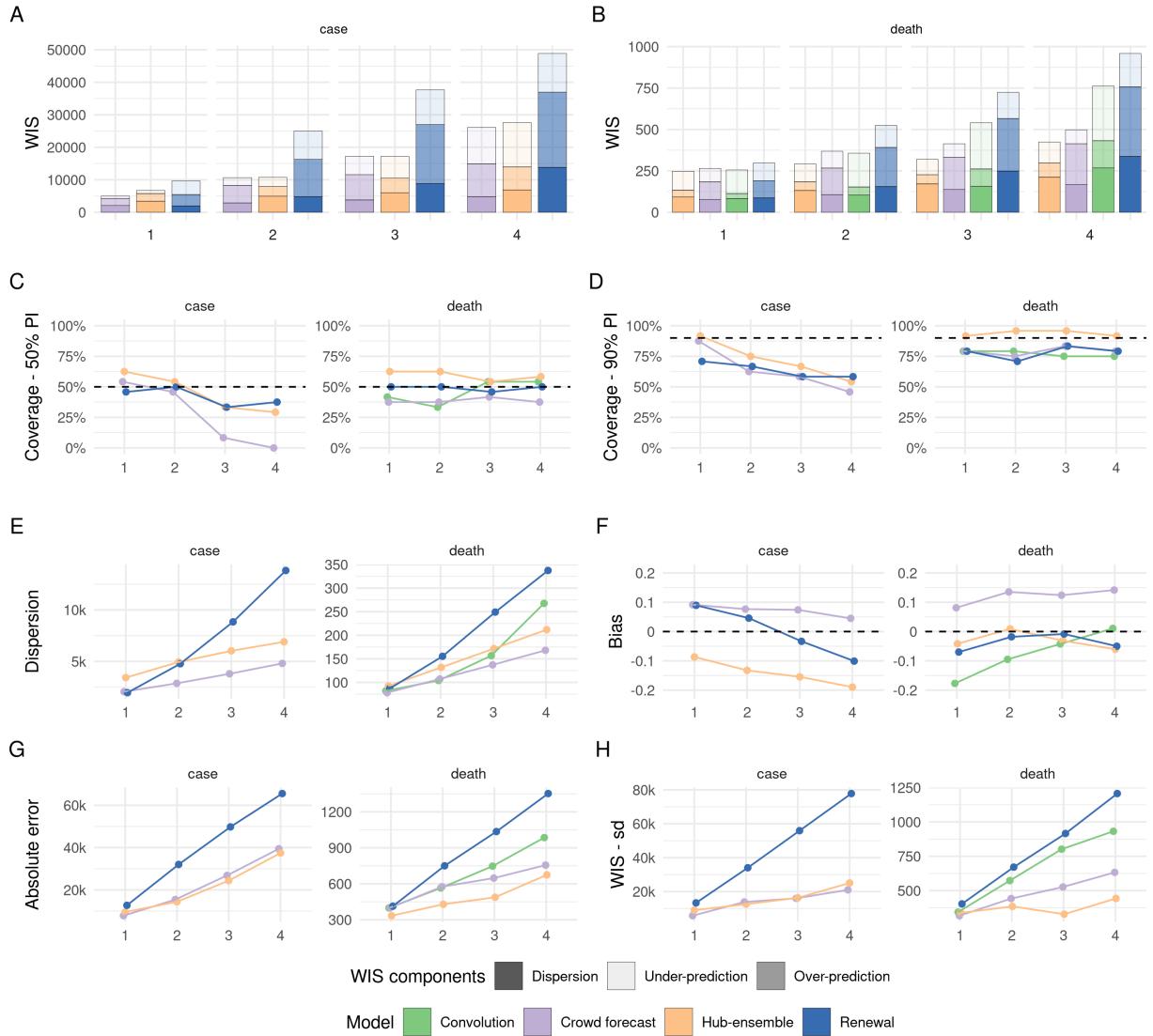


Figure 20: Visualisation of aggregate performance metrics across forecast horizons only for the period from October 14th 2020 on where all models were available. A, B: mean weighted interval score (WIS, lower indicates better performance) across horizons. WIS is decomposed into its components dispersion, over-prediction and under-prediction. C: Empirical coverage of the 50% prediction intervals (50% coverage is perfect). D: Empirical coverage of the 90% prediction intervals. E: Dispersion (same as in panel A, B). Higher values mean greater dispersion of the forecast and imply ceteris paribus a worse score. F: Bias, i.e. general (relative) tendency to over- or underpredict. Values are between -1 (complete under-prediction) and 1 (complete over-prediction) and 0 ideally. G: Absolute error of the median forecast (lower is better). H: Standard deviation of all WIS values for different horizons

Table 8: Scores for one and two week ahead forecasts (cut to three significant digits and rounded) calculated on forecasts made between December 14th 2020 and March 1st 2021. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
1 wk ahead	Crowd forecast	4980 (0.74)	5730 (0.64)	2070 (0.6)	728 (0.74)	2190 (0.94)	0.09	7810 (0.82)	0.54	0.88
	Hub-ensemble	6730 (1)	8960 (1)	3430 (1)	978 (1)	2330 (1)	-0.09	9550 (1)	0.62	0.92
	Renewal	9640 (1.43)	13300 (1.48)	1970 (0.57)	4170 (4.26)	3500 (1.5)	0.09	12700 (1.33)	0.46	0.71
2 wk ahead	Crowd forecast	10700 (0.99)	13800 (1.1)	2880 (0.58)	2350 (0.85)	5430 (1.79)	0.08	15400 (1.07)	0.46	0.62
	Hub-ensemble	10800 (1)	12500 (1)	4940 (1)	2780 (1)	3030 (1)	-0.13	14400 (1)	0.54	0.75
	Renewal	25000 (2.31)	34000 (2.72)	4780 (0.97)	8710 (3.13)	11500 (3.8)	0.05	32000 (2.22)	0.50	0.67
Deaths										
1 wk ahead	Convolution	255 (1.03)	343 (1.01)	82 (0.89)	142 (1.23)	31.1 (0.75)	-0.18	399 (1.19)	0.42	0.79
	Crowd forecast	265 (1.07)	317 (0.94)	78.2 (0.85)	82 (0.71)	105 (2.52)	0.08	402 (1.2)	0.38	0.79
	Hub-ensemble	248 (1)	338 (1)	92.2 (1)	115 (1)	41.6 (1)	-0.04	334 (1)	0.62	0.92
2 wk ahead	Renewal	298 (1.2)	403 (1.19)	87 (0.94)	107 (0.93)	105 (2.52)	-0.07	413 (1.24)	0.50	0.79
	Convolution	357 (1.22)	573 (1.49)	104 (0.79)	204 (1.89)	48.8 (0.94)	-0.10	565 (1.32)	0.33	0.79
	Crowd forecast	368 (1.26)	442 (1.15)	107 (0.81)	102 (0.94)	160 (3.08)	0.14	576 (1.34)	0.38	0.75
	Hub-ensemble	292 (1)	385 (1)	132 (1)	108 (1)	51.9 (1)	0.01	429 (1)	0.62	0.96
	Renewal	524 (1.79)	671 (1.74)	155 (1.17)	133 (1.23)	236 (4.55)	-0.02	750 (1.75)	0.50	0.71

Table 9: Scores for three and four week ahead forecasts (cut to three significant digits and rounded) calculated on forecasts made between December 14th 2020 and March 1st 2021. Numbers in brackets show the metrics relative to the Hub ensemble (i.e. the median ensemble of all other models submitted to the German and Polish Forecast Hub, excluding our contributions). WIS is the mean weighted interval score (lower values are better), WIS - sd is the standard deviation of all scores achieved by a model. Dispersion, over-prediction and under-prediction together sum up to the weighted interval score. Bias (between -1 and 1, 0 is ideal) represents the general average tendency of a model to over- or underpredict. 50% and 90%-coverage are the percentage of observed values that fell within the 50% and 90% prediction intervals of a model.

	Model	WIS	WIS - sd	dispersion	Underpred.	Overpred.	Bias	Abs. error	50%-Cov.	90%-Cov.
Cases										
3 wk ahead	Crowd forecast	17200 (1)	16000 (0.98)	3800 (0.63)	5660 (0.85)	7770 (1.74)	0.07	26800 (1.1)	0.08	0.58
	Hub-ensemble	17200 (1)	16300 (1)	6030 (1)	6670 (1)	4470 (1)	-0.16	24400 (1)	0.33	0.67
	Renewal	37700 (2.19)	55900 (3.43)	8840 (1.47)	10700 (1.6)	18100 (4.05)	-0.03	49800 (2.04)	0.33	0.58
4 wk ahead	Crowd forecast	26100 (0.95)	21000 (0.84)	4810 (0.7)	11300 (0.83)	10100 (1.43)	0.04	39400 (1.05)	0.00	0.46
	Hub-ensemble	27600 (1)	25000 (1)	6900 (1)	13600 (1)	7060 (1)	-0.19	37400 (1)	0.29	0.54
	Renewal	48900 (1.77)	77800 (3.11)	13800 (2)	11900 (0.88)	23200 (3.29)	-0.10	65500 (1.75)	0.38	0.58
Deaths										
3 wk ahead	Convolution	541 (1.7)	802 (2.45)	157 (0.91)	279 (3.01)	105 (1.91)	-0.04	747 (1.53)	0.54	0.75
	Crowd forecast	414 (1.3)	526 (1.6)	137 (0.8)	82 (0.88)	194 (3.52)	0.12	648 (1.33)	0.42	0.83
	Hub-ensemble	319 (1)	328 (1)	172 (1)	92.7 (1)	55.1 (1)	-0.03	488 (1)	0.54	0.96
4 wk ahead	Renewal	724 (2.27)	916 (2.79)	249 (1.45)	158 (1.7)	317 (5.75)	-0.01	1040 (2.13)	0.46	0.83
	Convolution	763 (1.8)	932 (2.1)	268 (1.26)	331 (2.63)	164 (1.91)	0.01	985 (1.46)	0.54	0.75
	Crowd forecast	498 (1.17)	633 (1.43)	168 (0.79)	83.6 (0.66)	246 (2.87)	0.14	756 (1.12)	0.38	0.79
	Hub-ensemble	424 (1)	443 (1)	212 (1)	126 (1)	85.7 (1)	-0.06	675 (1)	0.58	0.92
	Renewal	959 (2.26)	1210 (2.73)	337 (1.59)	200 (1.59)	421 (4.91)	-0.05	1350 (2)	0.50	0.79

⁵¹² **A.12 Overview of models and forecasters**

Table 10: Overview of the models and ensembles used.

Name	Explanation
Hub-ensemble-realised	Official Forecast Hub median ensemble. Created by the Forecast Hub officially under the name 'KITCOVIDhub-median_ensemble' and used as the default ensemble. Included are our crowd forecasts as well as the renewal model (with one missed submission on December 28 2020, but not the convolution model which was deemed to similar to the renewal model).
Hub-ensemble-realised-mean	Official Forecast Hub mean ensemble. Created by the Forecast Hub officially under the name 'KITCOVIDhub-mean_ensemble'.
Hub-ensemble	Version of the official Hub median ensemble which excludes all our contributions.
Hub-ensemble-mean	Version of the official Hub mean ensemble which excludes all our contributions.
Hub-ensemble-with-renewal, Hub-ensemble-with-renewal- mean	Versions of the official Hub ensembles which of our contributions includes only the Renewal model.
Hub-ensemble-with-crowd, Hub-ensemble-with-crowd- mean	Versions of the official Hub ensembles which of our contributions includes only the Crowd forecast.

Table 10: Overview of the models and ensembles used. (*continued*)

Name	Explanation
Hub-ensemble-with-convolution,	Versions of the official Hub ensembles which of our contributions includes only the Convolution model (which originally was never included in any official Hub ensemble).
Hub-ensemble-with-convolution-mean	
Hub-ensemble-with-all,	Versions of the official Hub ensembles which includes all our contributions. For cases, this is identical to the official Hub ensembles, but for deaths the convolution model was added.
Hub-ensemble-with-all-mean	
Crowd forecast	Submitted to the Forecast Hub as 'epiforecasts-EpiExpert'
Renewal model	Submitted to the Forecast Hub as 'epiforecasts-EpiNow2'
Convolution model	Submitted to the Forecast Hub as 'epiforecasts-EpiNow2_secondary'

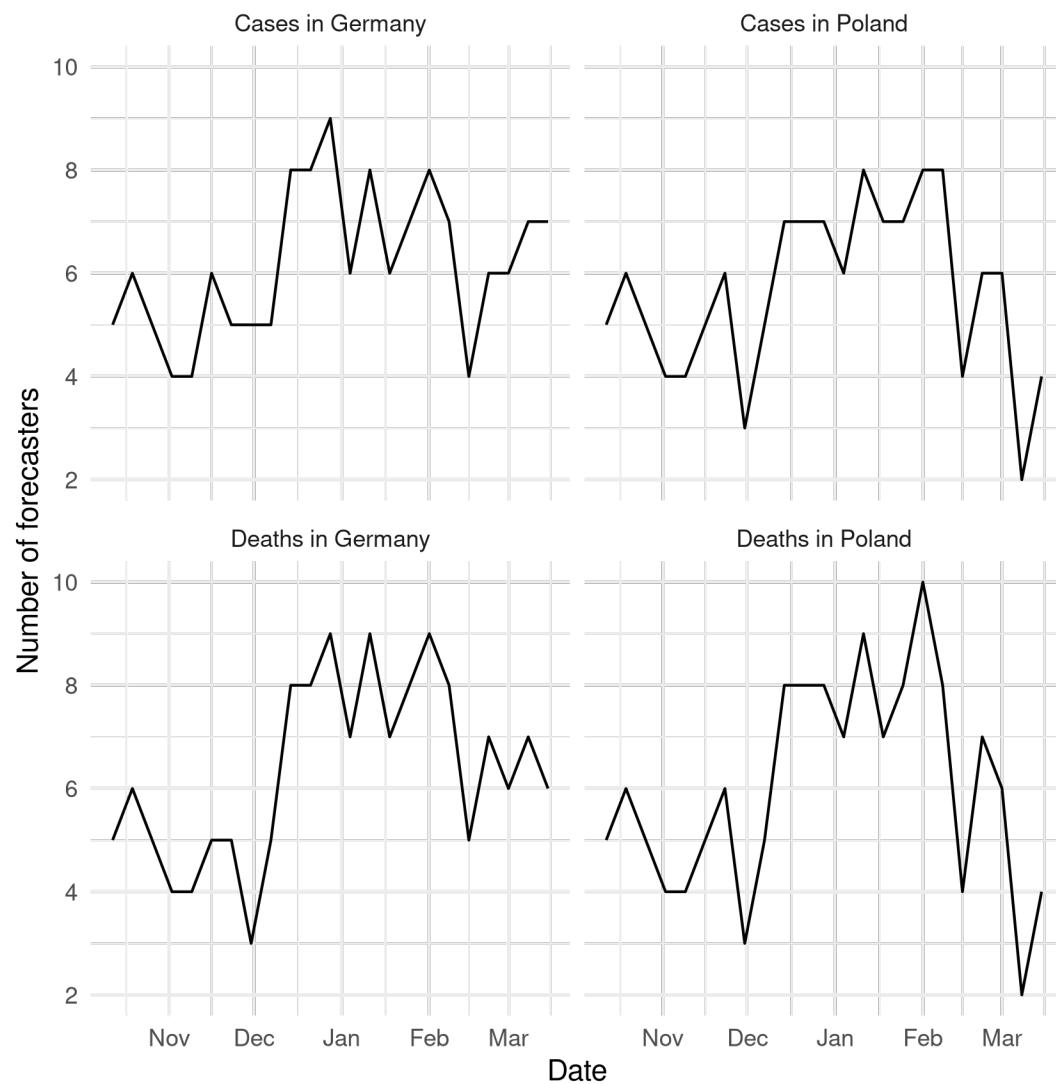


Figure 21: Number of participants who submitted a forecast over time.

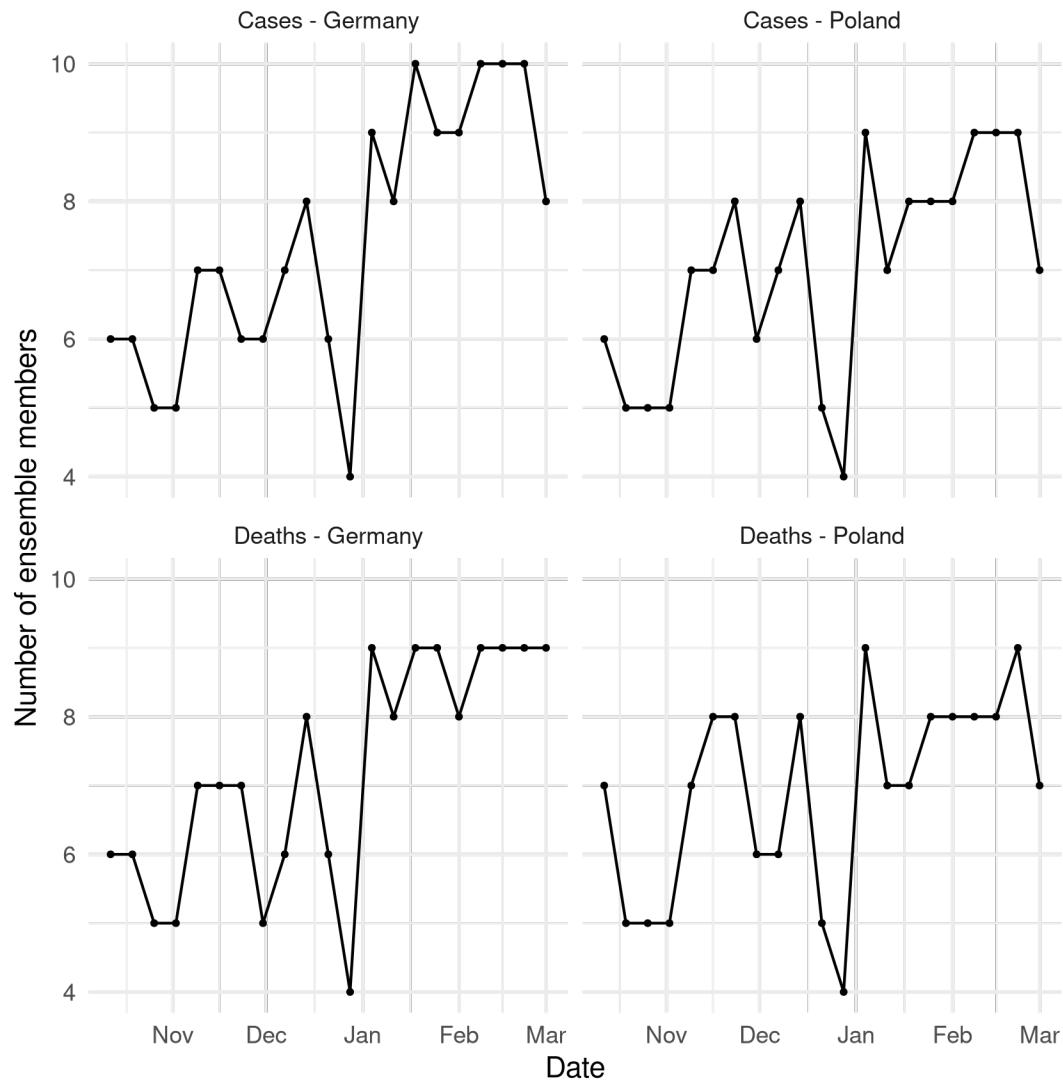


Figure 22: Number of member models (including our crowd forecasts and the renewal model) in the official Hub ensemble. Note that the renewal model was not included in the ensemble on December 28th 2020.

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