

## PROBABILITY AGGREGATION IN TIME-SERIES: DYNAMIC HIERARCHICAL MODELING OF SPARSE EXPERT BELIEFS

BY VILLE A. SATOPÄÄ, SHANE T. JENSEN, BARBARA A. MELLERS, PHILIP E. TETLOCK, AND LYLE H. UNGAR

*Department of Statistics, The Wharton School of the University of Pennsylvania*

*E-mail: [satopaa@wharton.upenn.edu](mailto:satopaa@wharton.upenn.edu); [stjensen@wharton.upenn.edu](mailto:stjensen@wharton.upenn.edu)*

*Department of Psychology, University of Pennsylvania*

*E-mail: [mellers@wharton.upenn.edu](mailto:mellers@wharton.upenn.edu); [tetlock@wharton.upenn.edu](mailto:tetlock@wharton.upenn.edu)*

*Department of Computer and Information Science, University of Pennsylvania*

*E-mail: [ungar@cis.upenn.edu](mailto:ungar@cis.upenn.edu)*

Most subjective probability aggregation procedures use a single probability judgement from each expert, even though it is common for experts studying real problems to update their probability estimates over time. This paper advances into unexplored areas of probability aggregation by considering a dynamic context in which experts can update their beliefs at random intervals. The updates occur very infrequently, resulting in a highly sparse dataset that cannot be modeled by standard time-series procedures. In response to the lack of appropriate methodology, this paper presents a hierarchical model that takes into account the expert's level of self-reported expertise and produces aggregate probabilities that are sharp and well-calibrated both in- and out-of-sample. The model is demonstrated on a real-world dataset that includes over 2,300 experts making multiple probability forecasts over a period of two years on different subsets of 166 international political events.

**1. Introduction.** Individual experts can differ radically from one another in their abilities to assess probabilities of future events. Their probability assessments are often evaluated and compared on *calibration*, which measures how closely the frequency of event occurrence agrees with the assigned probabilities. For instance, the proportion of occurrences is 60% for all those events to which a well-calibrated expert assigned a probability of 0.60. Even though several experiments have been conducted to show that experts are generally poorly calibrated (see, e.g., [Cooke \(1991\)](#); [Shlyakhter et al. \(1994\)](#)), relative differences can occur among different types of experts. In particular, [Wright et al. \(1994\)](#) argue that higher self-reported expertise can be associated with better calibration.

Calibration by itself, however, is not sufficient for useful probability estimation. Consider a relatively stationary process, such as rain on different days in a given geographic region, where the observed frequency of occurrence in the last 10 years

---

*Keywords and phrases:* Probability Aggregation, Dynamic Linear Model, Hierarchical Modeling, Expert Forecast, Subjective Probability, Bias Estimation, Calibration, Time Series

is 45%. In this setting an expert could always assign a constant probability of 0.45 and be well-calibrated. His assessment, however, can be made without any subject-matter expertise. For this reason the long-term frequency is often considered as the baseline probability – a naive assessment that provides the decision-maker very little extra information. Experts should aim to make probability assessments that are as far from the baseline as possible. The extent to which their probabilities differ from the baseline is measured by *sharpness* (Gneiting et al. (2008); Winkler and Jose (2008)). If the experts are both sharp and well-calibrated, they can forecast the behavior of the process with high certainty and accuracy. Therefore useful probability estimation should aim to maximize sharpness subject to calibration (see, e.g., Raftery et al. (2005); Murphy and Winkler (1987)).

There is strong empirical evidence that bringing together the strengths of different experts by combining their probability forecasts into a single consensus, known as the *crowd belief*, improves predictive performance. Prompted by the many applications of probability forecasts, including medical diagnosis (Wilson et al. (1998); Pepe (2003)), political and socio-economic foresight (Tetlock (2005)), and meteorology (Sanders (1963); Vislocky and Fritsch (1995); Baars and Mass (2005)), researchers have proposed many approaches to combining probability forecasts (see, e.g., Ranjan and Gneiting (2010); Satopää et al. (2014); Batchelder, Strashny and Romney (2010) for some recent studies, and Genest and Zidek (1986); Wallsten, Budescu and Erev (1997); Clemen and Winkler (2007); Primo et al. (2009) for a comprehensive overview). The general focus, however, has been on developing one-time aggregation procedures that consult the experts' advice only once before the event resolves.

Consequently, many areas of probability aggregation still remain rather unexplored. For instance, consider investors aiming to assess whether a stock index will finish trading above a threshold on a given date. To maximize their overall predictive accuracy, they may consult a group of experts repeatedly over a period of time and adjust their estimate of the aggregate probability accordingly. Given that the experts are allowed to update their probability assessments, the aggregation should be performed by taking into account the temporal correlation in their advice.

This paper adds another layer of complexity by assuming a heterogeneous set of experts, most of whom only make one or two probability assessments over the hundred or so days before the event resolves. This means that the decision-maker faces a different group of experts every day, with only a few experts returning later on for a second round of advice. The problem at hand is therefore strikingly different from many time-series estimation problems, where one has an observation at every time point – or almost every time point. As a result, standard time-series procedures like ARIMA (see, e.g., Mills (1991)) are not directly applicable. This paper introduces a time-series model that incorporates self-reported expertise and

TABLE 1  
*Five-number summaries of our real-world data.*

Statistic	Min.	$Q_1$	Median	Mean	$Q_3$	Max.
# of Days a Question is Active	4	35.6	72.0	106.3	145.20	418
# of Experts per Question	212	543.2	693.5	783.7	983.2	1690
# Forecasts given by each Expert on a Question	1	1.0	1.0	1.8	2.0	131
# Questions participated by an Expert	1	14.0	36.0	55.0	90.0	166

TABLE 2  
*Frequencies of the self-reported expertise (1 = Not At All Expert and 5 = Extremely Expert) levels across all the 166 questions in our real-world data.*

Expertise Level	1	2	3	4	5
Frequency (%)	25.3	30.7	33.6	8.2	2.1

captures a sharp and well-calibrated estimate of the crowd belief. The model is highly interpretable and can be used for:

- borrowing strength across the hierarchy to analyze under- and overconfidence in different groups of experts,
- accurate probability forecasts, and
- many question-specific quantities that have easy interpretations, such as expert disagreement and problem difficulty, and can be used to gain novel insight in the social sciences.

This paper begins by describing our geopolitical database. The paper then introduces a dynamic hierarchical model for capturing the crowd belief. The model is estimated in a two-step procedure: first, a sampling step produces constrained parameter estimates via Gibbs sampling (see, e.g., [Geman and Geman \(1984\)](#)); second, a calibration step transforms these estimates to their unconstrained equivalents via a one-dimension optimization procedure. The model introduction is followed by the first evaluation section that uses synthetic data to study how accurately the two-step procedure can estimate the crowd belief. The second evaluation section applies the model to our real-world geopolitical forecasting database. The paper concludes with a discussion on future research directions and model limitations.

**2. Geopolitical Forecasting Data.** The data collection began with a recruitment of 2,365 experts ranging from graduate students to political science faculty and practitioners. The recruiting was made from professional societies, research centers, alumni associations, science bloggers, and word of mouth. Requirements included at least a Bachelor’s degree and completion of psychological and political tests that took roughly two hours. These measures assessed cognitive styles, cognitive abilities, personality traits, political attitudes, and real-world knowledge. The

experts were asked to give probability forecasts (to the second decimal point) and to self-assess their level of expertise (on a 1-to-5 scale with 1 = Not At All Expert and 5 = Extremely Expert) on a number of 166 geopolitical binary events taking place between September 29, 2011 and May 8, 2013. Each question was active for a period during which the participating experts could update their forecasts as frequently as they liked without penalty. The experts knew that their probability estimates would be assessed for accuracy using Brier scores<sup>1</sup>. This incentivized them to report their true beliefs instead of attempting to game the system (Winkler and Murphy (1968)). In addition to receiving \$150 for meeting minimum participation requirements that did not depend on prediction accuracy, the experts received status rewards for their performance via leader-boards displaying Brier scores for the top 20 experts. Given that a typical expert participated only in a small subset of the 166 questions, the experts are considered indistinguishable conditional on the level of self-reported expertise.

The average number of forecasts made by a single expert in one day was around 0.017, and the average group-level response rate was around 13.5 forecasts per day. Given that the group of experts is large and diverse, the resulting dataset is very sparse. Tables 1 and 2 provide relevant summary statistics on the data. Notice that the distribution of the self-reported expertise is skewed to the right and that some questions remained active longer than others. For more details on the dataset and its collection see Ungar et al. (2012).

To illustrate the nature of the data with some concrete examples, Figures 1(a) and 1(b) show scatterplots of the probability forecasts given for (a) *Will the expansion of the European bailout fund be ratified by all 17 Eurozone nations before 1 November 2011?*, and (b) *Will the Nikkei 225 index finish trading at or above 9,500 on 30 September 2011?*. The points have been shaded according to the level of self-reported expertise and jittered slightly to make overlaps visible. The solid line gives the posterior mean of the calibrated crowd belief as estimated by our model. The surrounding dashed lines connect the point-wise 95% posterior intervals. Given that the European bailout fund was ratified before November 1, 2011 and that the Nikkei 225 index finished trading at around 8,700 on September 30, 2011, the general trend of the probability forecasts tends to converge towards the correct answers. The individual experts, however, sometimes disagree strongly, with the disagreement persisting even near the closing dates of the questions.

**3. Model.** Let  $p_{i,t,k} \in (0, 1)$  be the probability forecast given by the  $i$ th expert at time  $t$  for the  $k$ th question, where  $i = 1, \dots, I_k$ ,  $t = 1, \dots, T_k$ , and

---

<sup>1</sup>The Brier score is the squared distance between the probability forecast and the event indicator that equals 1.0 or 0.0 depending on whether the event happened or not, respectively. See Brier (1950) for the original introduction.

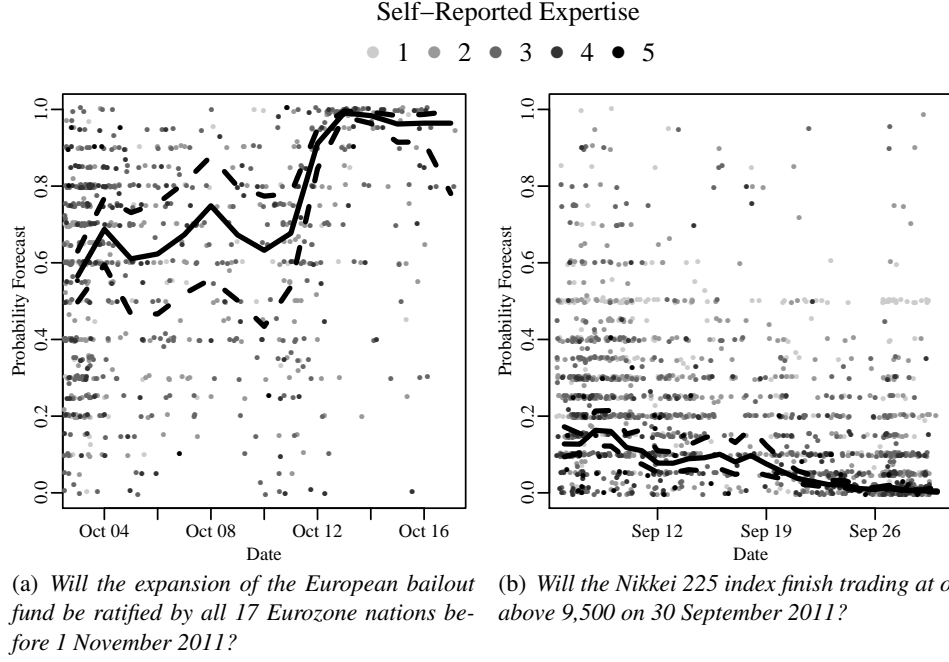


FIG 1. Scatterplots of the probability forecasts given for two questions in our dataset.

$k = 1, \dots, K$ . Denote the logit-probabilities with

$$Y_{i,t,k} = \text{logit}(p_{i,t,k}) = \log \left( \frac{p_{i,t,k}}{1 - p_{i,t,k}} \right) \in \mathbb{R}$$

and collect the logit-probabilities for question  $k$  at time  $t$  into a vector  $\mathbf{Y}_{t,k} = [Y_{1,t,k} \ Y_{2,t,k} \ \dots \ Y_{I_k,t,k}]^T$ . Partition the experts into  $J$  groups based on some individual feature, such as self-reported expertise, with each group sharing a common multiplicative bias term  $b_j \in \mathbb{R}$  for  $j = 1, \dots, J$ . Collect these bias terms into a bias vector  $\mathbf{b} = [b_1 \ b_2 \ \dots \ b_J]^T$ . Let  $\mathbf{M}_k$  be a  $I_k \times J$  matrix denoting the group-memberships of the experts in question  $k$ ; that is, if the  $i$ th expert participating in the  $k$ th question belongs to the  $j$ th group, then the  $i$ th row of  $\mathbf{M}_k$  is the  $j$ th standard basis vector  $\mathbf{e}_j$ . The bias vector  $\mathbf{b}$  is assumed to be identical across all  $K$  questions. Under this notation, the model for the  $k$ th question can be expressed as

$$(3.1) \quad \mathbf{Y}_{t,k} = \mathbf{M}_k \mathbf{b} X_{t,k} + \mathbf{v}_{t,k}$$

$$(3.2) \quad \begin{aligned} X_{t,k} &= \gamma_k X_{t-1,k} + w_{t,k} \\ X_{0,k} &\sim \mathcal{N}(\mu_0, \sigma_0^2) \end{aligned}$$

where (3.1) denotes the observed process, (3.2) shows the hidden process that is driven by the constant  $\gamma_k \in \mathbb{R}$ , and  $(\mu_0, \sigma_0^2) \in (\mathbb{R}, \mathbb{R}^+)$  are hyper-parameters fixed *a priori* to 0 and 1, respectively. The error terms follow

$$\begin{aligned} \mathbf{v}_{t,k} | \sigma_k^2 &\stackrel{i.i.d.}{\sim} \mathcal{N}_{I_k}(\mathbf{0}, \sigma_k^2 \mathbf{I}_{I_k}) \\ w_{t,k} | \tau_k^2 &\stackrel{i.i.d.}{\sim} \mathcal{N}(0, \tau_k^2), \end{aligned}$$

Therefore the parameters of the model are  $\mathbf{b}$ ,  $\sigma_k^2$ ,  $\gamma_k$ , and  $\tau_k^2$  for  $k = 1, \dots, K$ . Their prior distributions are chosen to be non-informative,  $p(\mathbf{b}, \sigma_k^2 | \mathbf{X}_k) \propto \sigma_k^2$  and  $p(\gamma_k, \tau_k^2 | \mathbf{X}_k) \propto \tau_k^2$ .

The hidden state  $X_{t,k}$  represents the aggregate logit-probability for the  $k$ th event given all the information available up to and including time  $t$ . To make this more specific, let  $Z_k \in \{0, 1\}$  indicate whether the event associated with the  $k$ th question happened ( $Z_k = 1$ ) or did not happen ( $Z_k = 0$ ). If  $\{\mathcal{F}_{t,k}\}_{t=1}^{T_k}$  is a filtration representing the information available up to and including a given time point, then  $\mathbb{E}[Z_k | \mathcal{F}_{t,k}] = \mathbb{P}(Z_k = 1 | \mathcal{F}_{t,k}) = \text{logit}^{-1}(X_{t,k})$ . It is reasonable to assume that this probability maximizes sharpness subject to calibration (for technical definitions of calibration and sharpness see [Ranjan and Gneiting \(2010\)](#); [Gneiting and Ranjan \(2011\)](#)) Even though a single expert is unlikely to have access to all the available information, a large and diverse group of experts may share a considerable portion of the available information. The collective wisdom of the group therefore provides an attractive proxy for  $\mathcal{F}_{t,k}$ .

Given that the experts may believe in false information, hide their true beliefs, or be biased for many other reasons, their probability assessments should be aggregated via a model that can detect potential bias, separate signal from noise, and use the collective opinion to estimate  $X_{t,k}$ . In our model the experts are assumed to be, on average, a multiplicative constant  $\mathbf{b}$  away from  $X_{t,k}$ . Therefore an individual element of  $\mathbf{b}$  can be interpreted as a group-specific *systematic bias* that labels the group either as over-confident ( $b_j \in (1, \infty)$ ) or as under-confident ( $b_j \in (0, 1)$ ). See Section 3.1 for a brief discussion on different bias structures. Any other deviation from  $X_{t,k}$  is considered *random noise*. This noise is measured in terms of  $\sigma_k^2$  and can be assumed to be caused by momentary over-optimism (or pessimism), false beliefs, or other misconceptions.

The *random fluctuations* in the hidden process are measured by  $\tau_k^2$  and are assumed to represent changes or shocks to the underlying circumstances that ultimately decide the outcome of the event. The *systematic component*  $\gamma_k$  allows the model to incorporate a constant signal stream that drifts the hidden process. If the uncertainty in the question diminishes ( $\gamma_k \in (1, \infty)$ ), the hidden process drifts to positive or negative infinity. Alternatively, the hidden process can drift to zero in which case any available information does not improve predictive accuracy

( $\gamma_k \in (0, 1)$ ). Given that all the questions in our dataset were resolved within a pre-specified timeframe, we expect  $\gamma_k \in (1, \infty)$  for all  $k = 1, \dots, K$ .

As for any future time  $T^* \geq t$

$$\begin{aligned} X_{T^*,k} &= \gamma_k^{T^*-t} X_t + \sum_{i=t+1}^{T^*} \gamma_k^{T^*-i} w_i \\ &\sim \mathcal{N} \left( \gamma_k^{T^*-t} X_{t,k}, \tau_k^2 \sum_{i=t+1}^{T^*} \gamma_k^{T^*-i} \right), \end{aligned}$$

the model can be used for time-forward prediction as well. The prediction for the aggregate logit-probability at time  $T^*$  is given by an estimate of  $\gamma_k^{T^*-t} X_{t,k}$ . Naturally the uncertainty in this prediction grows in  $T$ . To make such time-forward predictions it is necessary to assume that the past population of experts is representative of the future population. This is a reasonable assumption because even though the future population may consist of entirely different individuals, on average the population is likely to look very similar to the past population. In practice, however, social scientists are generally more interested in an estimate of the current probability than the probability under unknown conditions in the future. For this reason, our analysis focuses on probability aggregation only up to the current time  $t$ .

**3.1. Bias Structure.** For the sake of model identifiability, it is sufficient to share only one of the elements of  $\mathbf{b}$  among the  $K$  questions. In this paper, however, all the elements of  $\mathbf{b}$  are assumed to be identical across the questions because some of the questions in our real-world data set involve very few experts with the highest level of self-reported expertise. The model can be extended rather easily to estimate bias at a more general level. For instance, by assuming a hierarchical structure  $b_{ik} \sim \mathcal{N} \left( b_{j(i,k)}, \sigma_{j(i,k)}^2 \right)$ , where  $j(i, k)$  denotes the self-reported expertise of the  $i$ th expert in question  $k$ , the bias can be estimated at an individual-level. These estimates can then be compared across questions. Individual-level analysis was not performed in our analysis for two reasons. First, most experts gave only a single prediction per problem, which makes accurate bias estimation at the individual-level very difficult. Second, it is unclear how the individually estimated bias terms can be validated.

**3.2. Multinomial Outcomes.** If the future event can take upon  $M > 2$  possible outcomes, the hidden state  $X_{t,k}$  is extended to a vector of size  $M - 1$  and one of the outcomes, e.g., the  $M$ th one, is chosen as the base-case to ensure that the probabilities will sum to one at any given time point. Each of the remaining  $M - 1$  possible outcomes is represented by an observed process similar to (3.1). Given

that this multinomial extension is equivalent to having  $M - 1$  independent binary-outcome models, the estimation and properties of the model are easily extended to the multi-outcome case. This paper focuses on binary-outcomes because it is the most commonly encountered setting in practice.

**4. Model Estimation.** This section introduces a two-step procedure, called *Sample-And-Calibrate* (SAC), that captures a well-calibrated estimate of the hidden process without sacrificing the interpretability of our model.

**4.1. Sampling Step.** Given that  $(a\mathbf{b}, X_{t,k}/a, a^2\tau_k^2) \neq (\mathbf{b}, X_{t,k}, \tau_k^2)$  for any  $a > 0$  yield the same likelihood for  $\mathbf{Y}_{t,k}$ , the model as described by (3.1) and (3.2) is not identifiable. A well-known solution is to choose one of the elements of  $\mathbf{b}$ , say  $b_3$ , as the reference point and fix  $b_3 = 1$ . In Section 5 we provide a guideline for choosing the reference point. Denote the constrained version of the model by

$$\begin{aligned} \mathbf{Y}_{t,k} &= \mathbf{M}_k \mathbf{b}(1) X_{t,k}(1) + \mathbf{v}_{t,k} \\ X_{t,k}(1) &= \gamma_k(1) X_{t-1,k}(1) + w_{t,k} \\ \mathbf{v}_{t,k} | \sigma_k^2(1) &\stackrel{i.i.d.}{\sim} \mathcal{N}_{I_k}(\mathbf{0}, \sigma_k^2(1) \mathbf{I}_{I_k}) \\ w_{t,k} | \tau_k^2(1) &\stackrel{i.i.d.}{\sim} \mathcal{N}(0, \tau_k^2(1)), \end{aligned}$$

where the trailing input notation,  $(a)$ , signifies the value under the constraint  $b_3 = a$ . Given that this version is identifiable, estimates of the model parameters can be obtained. Denote the estimates by placing a hat on the parameter symbol. For instance,  $\hat{\mathbf{b}}(1)$  and  $\hat{X}_{t,k}(1)$  represent the estimates of  $\mathbf{b}(1)$  and  $X_{t,k}(1)$ , respectively.

These estimates are obtained by first computing a posterior sample via Gibbs sampling and then taking the average of the posterior sample. The first step of our Gibbs sampler is to sample the hidden states via the *Forward-Filtering-Backward-Sampling* (FFBS) algorithm. FFBS first predicts the hidden states using a Kalman filter and then performs a backward sampling procedure that treats these predicted states as additional observations (see, e.g., [Carter and Kohn \(1994\)](#); [Migon et al. \(2005\)](#) for details on FFBS). Given that the Kalman filter can handle varying numbers or even no forecasts at different time points, it plays a very crucial role in our probability aggregation under sparse data.

Our implementation of the sampling step is written in C++ and runs fast. For instance, to obtain a posterior sample of size 1,000 for 50 questions each with 100 time points and 50 experts takes about 215 seconds on the first author's computer (1.7 GHz Intel Core i5). See the Online Supplement for the technical details of the sampling steps, and, e.g., [Gelman et al. \(2003\)](#) for a discussion on the general principles of Gibbs sampling.



4.2. *Calibration Step.* Given that the model parameters can be estimated by fixing  $b_3$  to any constant, the next step is to search for the constant that gives an optimally sharp and calibrated estimate of the hidden process. This section introduces an efficient procedure that finds the optimal constant without requiring any additional runs of the sampling step. First, assume that parameter estimates  $\hat{\mathbf{b}}(1)$  and  $\hat{X}_{t,k}(1)$  have already been obtained via the sampling step described in Section 4.1. Given that for any  $\beta \in \mathbb{R}/\{0\}$ ,

$$\begin{aligned} \mathbf{Y}_{t,k} &= \mathbf{M}_k \mathbf{b}(1) X_{t,k}(1) + \mathbf{v}_{t,k} \\ &= \mathbf{M}_k (\mathbf{b}(1)\beta) (X_{t,k}(1)/\beta) + \mathbf{v}_{t,k} \\ &= \mathbf{M}_k \mathbf{b}(\beta) X_{t,k}(\beta) + \mathbf{v}_{t,k}, \end{aligned}$$

we have that  $\mathbf{b}(\beta) = \mathbf{b}(1)\beta$  and  $X_{t,k}(\beta) = X_{t,k}(1)/\beta$ . Recall that the hidden process  $X_{t,k}$  is assumed to be sharp and well-calibrated. Therefore  $b_3$  can be estimated with the value of  $\beta$  that simultaneously maximizes the sharpness and calibration of  $\hat{X}_{t,k}(1)/\beta$ . A natural criterion for this maximization is given by the class of *proper scoring rules* that combine sharpness and calibration (Gneiting et al. (2008); Buja, Stuetzle and Shen (2005)). Due to the possibility of *complete separation* in any one question (see, e.g., Gelman et al. (2008)), the maximization must be performed over multiple questions. Therefore,

$$(4.1) \quad \hat{\beta} = \arg \max_{\beta \in \mathbb{R}/\{0\}} \sum_{k=1}^K \sum_{t=1}^{T_k} S\left(Z_k, \hat{X}_{k,t}(1)/\beta\right)$$

where  $Z_k \in \{0, 1\}$  is the event indicator for question  $k$ . The function  $S$  is a strictly proper scoring rule such as the negative Brier score (Brier (1950))

$$S_{BRI}(Z, X) = -(Z - \text{logit}^{-1}(X))^2$$

or the logarithmic score (Good (1952))

$$S_{LOG}(Z, X) = Z \log(\text{logit}^{-1}(X)) + (1 - Z) \log(1 - \text{logit}^{-1}(X))$$

The estimates of the unconstrained model parameters are then given by

$$\begin{aligned} \hat{X}_{t,k} &= \hat{X}_{k,t}(1)/\hat{\beta} \\ \hat{\mathbf{b}} &= \hat{\mathbf{b}}(1)\hat{\beta} \\ \hat{\tau}_k^2 &= \hat{\tau}_k^2(1)/\hat{\beta}^2 \\ \hat{\sigma}_k^2 &= \hat{\sigma}_k^2(1) \\ \hat{\gamma}_k &= \hat{\gamma}_k(1) \end{aligned}$$

Notice that estimates of  $\sigma_k^2$  and  $\gamma_k$  are not affected by the constraint.

**5. Synthetic Data Results.** This section uses synthetic data to evaluate how accurately the SAC-procedure captures the hidden states and bias vector. The analysis is therefore not reflective of real-world performance but serves rather as a sanity check. The hidden process is generated from standard Brownian motion. More specifically, if  $Z_{t,k}$  denotes the value of a path at time  $t$ , then

$$\begin{aligned} Z_k &= \mathbb{1}(Z_{T_k,k} > 0) \\ X_{t,k} &= \text{logit} \left[ \Phi \left( \frac{Z_{t,k}}{\sqrt{T_k - t}} \right) \right] \end{aligned}$$

gives a sequence of  $T_k$  calibrated logit-probabilities for the event  $Z_k = 1$ . A hidden process is generated for  $K$  questions with a time horizon of  $T_k = 101$ . The questions involve 50 experts allocated evenly among five expertise groups. Each expert gives one probability forecast per day with the exception of time  $t = 101$  when the event resolves. The forecasts are generated by applying bias and noise to the hidden process as described by (3.1). Our simulation study considers a three-dimensional grid of parameter values:

$$\begin{aligned} \sigma^2 &\in \{1/2, 1, 3/2, 2, 5/2\} \\ \beta &\in \{1/2, 3/4, 1, 4/3, 2/1\} \\ K &\in \{20, 40, 60, 80, 100\}, \end{aligned}$$

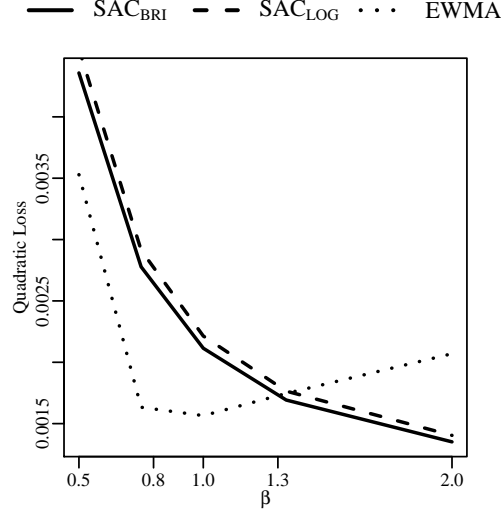
where  $\beta$  varies the bias vector by  $\mathbf{b} = [1/2, 3/4, 1, 4/3, 2/1]^T \beta$ . Forty synthetic datasets are generated for each combination of  $\sigma^2$ ,  $\beta$ , and  $K$  values. The SAC-procedure runs for 200 iterations of which the first 100 are used for burn-in.

SAC under the Brier ( $\text{SAC}_{\text{BRI}}$ ) and logarithm score ( $\text{SAC}_{\text{LOG}}$ ) are compared with *Exponentially Weighted Moving Average* (EWMA). EWMA, which serves as a baseline, can be understood by first denoting the (expertise-weighted) average forecast at time  $t$  for the  $k$ th question by

$$(5.1) \quad \bar{p}_{t,k} = \sum_{j=1}^J \omega_j \left( \frac{1}{|E_j|} \sum_{i \in E_j} p_{i,t,k} \right)$$

where  $E_j$  refers to an index set of all experts in the  $j$ th expertise group, and  $\omega_j$  denotes the weight associated with the  $j$ th expertise group. The EWMA forecasts for the  $k$ th problem are then constructed recursively from

$$\hat{p}_{t,k}(\alpha) = \begin{cases} \bar{p}_{1,k}, & \text{for } t = 1, \\ \alpha \bar{p}_{t,k} + (1 - \alpha) \hat{p}_{t-1,k}(\alpha), & \text{for } t > 1, \end{cases}$$

FIG 2. The marginal effect of  $\beta$  on the average quadratic loss.

where  $\alpha$  and  $\omega$  are learned from the training set by

$$(\hat{\alpha}, \hat{\omega}) = \arg \min_{\alpha, \omega_j \in [0,1]} \sum_{k=1}^K \sum_{t=1}^{T_k} (Z_k - \hat{p}_{t,k}(\alpha, \omega))^2 \quad \text{s.t.} \quad \sum_{j=1}^J \omega_j = 1$$

The accuracy of the estimated hidden process is measured with the quadratic loss in the probability space

$$(5.2) \quad \sum_{k=1}^K \sum_{t=1}^{100} (\text{logit}^{-1}(\hat{X}_{t,k}) - \text{logit}^{-1}(X_{t,k}))^2 / (100K)$$

The three competing methods, SAC<sub>BRI</sub>, SAC<sub>LOG</sub>, and EWMA, estimate the hidden process with great accuracy. Their quadratic losses (5.2) averaged over all simulations are 0.00245, 0.00257, and 0.00211, respectively. Even though EWMA outperforms SAC marginally in this synthetic and hence rather easy setup, it performs much worse under real-world data (see Section 6). Based on other performance measures that are not shown for the sake of brevity, all three methods suffer from an increasing level of noise in the expert logit-probabilities but can make efficient use of extra data.

Some interesting differences are found by inspecting Figure 2 that shows the marginal effect of  $\beta$  on the average quadratic loss. As can be expected, EWMA performs well when the experts are, on average, close to unbiased. Interestingly, SAC

estimates the hidden process more accurately when the experts are over-confident (large  $\beta$ ) rather under-confident (small  $\beta$ ). To understand this result, assume that the experts in the third group are highly under-confident. Their logit-probabilities are then expected to be closer to zero than the corresponding hidden states. After adding white noise to these expected logit-probabilities, they are likely to cross to the other side of zero. If the sampling step fixes  $b_3 = 1$ , as it does in our case, the third group is treated unbiased and some of the constrained estimates of the hidden states are likely to be on the other side of zero as well. Unfortunately, this discrepancy cannot be corrected by the calibration step that is restricted to shifting the constrained estimates either closer or further away from zero but not across it. To maximize the likelihood of having all the constrained estimates on the right side of zero and hence avoiding the discrepancy, the reference point in the sampling step should be chosen with care. A helpful guideline is to fix the element of  $\mathbf{b}$  that is apriori believed to be the largest.

The accuracy of the estimated bias vector is measured with the quadratic loss,  $\|\mathbf{b} - \hat{\mathbf{b}}\|^2/5$ . Unfortunately, EWMA does not produce an estimate of the bias vector. Therefore it cannot be used as a baseline for the accuracy in estimating the bias vector. Given that the quadratic losses averaged over all simulations for  $\text{SAC}_{\text{BRI}}$  and  $\text{SAC}_{\text{LOG}}$  are 0.104 and 0.100, respectively, both methods estimate the bias vector accurately.

**6. Geopolitical Data Results.** This section presents results for the real-world data described in Section 2. The goal is to provide application specific insight by discussing the specific research objectives itemized in Section 1. First, however, we discuss two practical matters that must be taken into account when aggregating real-world probability forecasts.

**6.1. Incoherent and Imbalanced Data.** The first matter regards human experts making probability forecasts of 0.0 or 1.0 even if they are not completely sure of the outcome of the event. For instance, all the 166 questions in our dataset contain both a zero and a one. Transforming such forecasts into the logit-space yields infinities that can cause problems in model estimation. To avoid this, [Ariely et al. \(2000\)](#) suggest changing  $p = 0.00$  and  $1.00$  to  $p = 0.02$  and  $0.98$ , respectively. This is similar to *winsorising* that sets the extreme probabilities to a specified percentile of the data (see, e.g., [Hastings et al. \(1947\)](#) for more details on winsorising). [Allard, Comunian and Renard \(2012\)](#), on the other hand, consider only probabilities that fall within a constrained interval, say  $[0.001, 0.999]$ , and discard the rest. Given that this implies ignoring a portion of the data, we adopt an approach similar to [Ariely et al. \(2000\)](#) by truncating  $p = 0.00$  and  $1.00$  to  $p = 0.01$  and  $0.99$ , respectively. Our results remain insensitive to the exact choice of truncation as long as this is done in a reasonable manner to keep the extreme probabilities from becoming

highly influential in the logit-space.

The second matter is related to the distribution of the class labels in the data. If the set of occurrences is much larger than the set of non-occurrences (or *vice versa*), the dataset is called *imbalanced*. On such data the modeling procedure can end up over-focusing on the larger class, and as a result, give very accurate forecast performance over the larger class at the cost of performing poorly over the smaller class (see, e.g., [Chen \(2009\)](#); [Wallace and Dahabreh \(2012\)](#)). Fortunately, it is often possible to use a well-balanced version of the data. The first step is to find a partition  $S_0$  and  $S_1$  of the question indices  $\{1, 2, \dots, K\}$  such that the equality  $\sum_{k \in S_0} T_k = \sum_{k \in S_1} T_k$  is as closely approximated as possible. This is equivalent to an NP-hard problem known in computer science as the *Partition Problem*: determine whether a given set of positive integers can be partitioned into two sets such that the sums of the two sets equal to each other (see, e.g., [Karmarkar and Karp \(1982\)](#); [Hayes \(2002\)](#)). A simple solution is to use a greedy algorithm that iterates through the values of  $T_k$  in descending order, assigning each  $T_k$  to the subset that currently has the smaller sum (see, e.g., [Kellerer, Pferschy and Pisinger \(2004\)](#); [Gent and Walsh \(1996\)](#) for more details on the *Partition Problem*). After finding a well-balanced partition, the next step is to assign the class labels such that the labels for the questions in  $S_x$  are equal to  $x$  for  $x = 0$  or  $1$ . Recall from [Section 4.2](#) that  $Z_k$  represents the event indicator for the  $k$ th question. To define a balanced set of indicators  $\tilde{Z}_k$  for all  $k \in S_x$ , let

$$\begin{aligned} \tilde{Z}_k &= x \\ \tilde{p}_{i,t,k} &= \begin{cases} 1 - p_{i,t,k}, & \text{if } Z_k = 1 - x, \\ p_{i,t,k}, & \text{if } Z_k = x, \end{cases} \end{aligned}$$

where  $i = 1, \dots, I_k$ , and  $t = 1, \dots, T_k$ . The resulting set

$$\left\{ \left( \tilde{Z}_k, \{ \tilde{p}_{i,t,k} | i = 1, \dots, I_k, t = 1, \dots, T_k \} \right) \right\}_{k=1}^K$$

is a balanced version of the data. This procedure was used to balance our real-world dataset both in terms of events and time points. The final output splits the events exactly in half ( $|S_0| = |S_1| = 83$ ) such that number of time points in the first and second halves are 8,737 and 8,738, respectively.

**6.2. Out-of-Sample Aggregation.** This section is motivated by decision-making. The goal is to evaluate the accuracy of the aggregate probabilities made by SAC and several other procedures. The models are allowed to utilize a training set before making aggregations on an independent testing set. To clarify some of the upcoming notation, let  $S_{train}$  and  $S_{test}$  be index sets that partition the data into

training and testing sets of sizes  $|S_{train}| = N_{train}$  and  $|S_{test}| = 166 - N_{train}$ , respectively. This means that the  $k$ th question is in the training set if and only if  $k \in S_{train}$ . Before introducing the competing models, note that all choices of thinning and burn-in made in this section are conservative and have been made based on pilot runs of the models. This was done to ensure a posterior sample that has low autocorrelation and arises from a converged chain. The competing models are as follows.

1. *Simple Dynamic Linear Model (SDLM)*. This is equivalent to the dynamic model from Section 3 but with  $\mathbf{b} = \mathbf{1}$  and  $\beta = 1$ . Thus,

$$\begin{aligned} \mathbf{Y}_{t,k} &= X_{t,k} + \mathbf{v}_{t,k} \\ X_{t,k} &= \gamma_k X_{t-1,k} + w_{t,k}, \end{aligned}$$

where  $X_{t,k}$  is the aggregate logit-probability. Given that this model does not share any parameters across different questions, estimates of the hidden process can be obtained directly for the questions in the testing set without fitting the model first on the training set. The Gibbs sampler is run for 500 iterations of which the first 200 are used for burn-in. The remaining 300 iterations are thinned by discarding every other observation, leaving a final posterior sample of 150 observations. The mean of this sample gives the final estimates.

2. *The Sample-And-Calibrate procedure both under the Brier ( $SAC_{BRI}$ ) and the logarithmic score ( $SAC_{LOG}$ )*. The model is first fit on the training set by running the sampling step for 3,000 iterations of which the first 500 iterations are used for burn-in. The remaining 2,500 observations are thinned by keeping every fifth observation. The calibration step is performed for the final 500 observations. The out-of-sample aggregation is done by running the sampling step for 500 iterations with each consecutive iteration reading in and conditioning on the next value of  $\beta$  and  $\mathbf{b}$  found during the training period. The first 200 iterations are used for burn-in. The remaining 300 iterations are thinned by discarding every other observation, leaving a final posterior sample of 150 observations. The mean of this sample gives the final estimates.
3. *A fully Bayesian version of  $SAC_{LOG}$  ( $BSAC_{LOG}$ )*. Denote the calibrated logit-probabilities and event indicators across all  $K$  questions with  $\mathbf{X}(1)$  and  $\mathbf{Z}$ , respectively. The posterior distribution of  $\beta$  conditional on  $\mathbf{X}(1)$  is given by  $p(\beta|\mathbf{X}(1), \mathbf{Z}) \propto p(\mathbf{Z}|\beta, \mathbf{X}(1))p(\beta|\mathbf{X}(1))$ . The likelihood is

$$(6.1) \quad p(\mathbf{Z}|\beta, \mathbf{X}(1)) \propto \prod_{k=1}^K \prod_{t=1}^{T_k} \text{logit}^{-1}(X_{t,k}(1)/\beta)^{Z_k} \times (1 - \text{logit}^{-1}(X_{t,k}(1)/\beta))^{1-Z_k}$$

As in [Gelman et al. \(2003\)](#), the prior for  $\beta$  is chosen to be locally uniform,  $p(1/\beta) \propto 1$ . Given that this model estimates  $X_{t,k}(1)$  and  $\beta$  simultaneously, it is a little more flexible than SAC. Posterior estimates of  $\beta$  can be sampled from (6.1) using generic sampling algorithms such as the Metropolis algorithm ([Metropolis et al. \(1953\)](#)) or slice sampling ([Neal \(2003\)](#)). Given that the sampling procedure conditions on the event indicators, the full conditional distribution of the hidden states is not in a standard form. Therefore the Metropolis algorithm is also used for sampling the hidden states. Estimation is made with the same choices of thinning and burn-in as described under *Sample-And-Calibrate*.

4. Due to the lack of previous literature on dynamic aggregation of expert probability forecasts, the main competitors are exponentially weighted versions of procedures that have been proposed for static probability aggregation:
  - (a) *Exponentially Weighted Moving Average (EWMA)* as described in Section 5.
  - (b) *Exponentially Weighted Moving Logit Aggregator (EWMLA)*. This is a moving version of the aggregator  $\hat{p}_G(\mathbf{b})$  that was introduced in [Satopää et al. \(2014\)](#). The EWMLA aggregate probabilities are found recursively from

$$\hat{p}_{t,k}(\alpha, \mathbf{b}) = \begin{cases} G_{1,k}(\mathbf{b}), & \text{for } t = 1, \\ \alpha G_{t,k}(\mathbf{b}) + (1 - \alpha)\hat{p}_{t-1,k}(\alpha, \mathbf{b}), & \text{for } t > 1, \end{cases}$$

where the vector  $\mathbf{b} \in \mathbb{R}^J$  collects the bias terms of the expertise groups, and

$$G_{t,k}(\nu) = \left( \prod_{i=1}^{N_{t,k}} \left( \frac{p_{i,t,k}}{1 - p_{i,t,k}} \right)^{\frac{b_j(i,k)}{N_{t,k}}} \right) / \left( 1 + \prod_{i=1}^{N_{t,k}} \left( \frac{p_{i,t,k}}{1 - p_{i,t,k}} \right)^{\frac{b_j(i,k)}{N_{t,k}}} \right)$$

The parameters  $\alpha$  and  $\mathbf{b}$  are learned from the training set by

$$(\hat{\alpha}, \hat{\mathbf{b}}) = \arg \min_{\mathbf{b} \in \mathbb{R}^J, \alpha \in [0,1]} \sum_{k \in S_{train}} \sum_{t=1}^{T_k} (Z_k - \hat{p}_{t,k}(\alpha, \mathbf{b}))^2$$

- (c) *Exponentially Weighted Moving Beta-transformed Aggregator (EWMBMA)*. The static version of the Beta-transformed aggregator was introduced in [Ranjan and Gneiting \(2010\)](#). A dynamic version can be obtained by replacing  $G_{t,k}(\nu)$  in the EWMLA description with  $H_{\nu,\tau}(\bar{p}_{t,k})$ , where  $H_{\nu,\tau}$  is the cumulative distribution function of the Beta distribution and

$\bar{p}_{t,k}$  is given by 5.1. The parameters  $\alpha$ ,  $\nu$ ,  $\tau$ , and  $\omega$  are learned from the training set by

$$\begin{aligned} (\hat{\alpha}, \hat{\nu}, \hat{\tau}, \hat{\omega}) &= \arg \min_{\nu, \tau > 0, \alpha, \omega_j \in [0,1]} \sum_{k \in S_{train}} \sum_{t=1}^{T_k} (Z_k - \hat{p}_{t,k}(\alpha, \nu, \tau, \omega))^2 \\ \text{s.t. } &\sum_{j=1}^J \omega_j = 1 \end{aligned}$$

The competing models are evaluated via a 10-fold cross-validation<sup>2</sup> that first partitions the 166 questions into 10 sets such that each set has approximately the same number of questions (16 or 17 questions in our case) and the same number of time points (between 1,760 and 1,764 time points in our case). The evaluation then iterates 10 times, each time using one of the 10 sets as the testing set and the remaining 9 sets as the training set. Therefore each question is used nine times for training and exactly once for testing. The testing proceeds sequentially one testing question at a time as follows: First, for a question with a time horizon of  $T_k$ , give an aggregate probability at time  $t = 2$  based on the first two days. Compute the Brier score for this probability. Next give an aggregate probability at time  $t = 3$  based on the first three days and compute the Brier score for this probability. Repeat this process for all of the  $T_k - 1$  days. This leads to  $T_k - 1$  Brier scores per testing question and a total of 17,475 Brier scores across the entire dataset.

Table 3 summarizes these scores in different ways. The first option, denoted by *Scores by Day*, weighs each question by the number of days the question remained open. This is performed by computing the average of the 17,475 scores. The second option, denoted by *Scores by Problem*, gives each question an equal weight regardless how long the question remained open. This is done by first averaging the scores within a question and then averaging the average scores across all the questions. Both scores can be further broken down into subcategories by considering the length of the questions. The final three columns of Table 3 divide the questions into *Short* questions (30 days or fewer), *Medium* questions (between 31 and 59 days), and *Long* Problems (60 days or more). The number of questions in these subcategories were 36, 32 and 98, respectively. The bolded scores indicate the best score in each column. The values in the parenthesis quantify the variability in the scores: Under *Scores by Day* the values give the standard errors of all the scores. Under *Scores by Problem*, on other hand, the values represent the standard errors of the average scores of the different questions.

<sup>2</sup>A 5-fold cross-validation was also performed. The results were, however, very similar to the 10-fold cross-validation and hence not presented in the paper.



TABLE 3

*Brier Scores based on 10-fold cross-validation. Scores by Day weighs a question by the number of days the question remained open. Scores by Problem gives each question an equal weight regardless how long the question remained open. The bolded values indicate the best scores in each column. The values in the parenthesis represent standard errors in the scores.*

Model	Scores by Day			
	All	Short	Medium	Long
SDLM	0.100 (0.156)	0.066 (0.116)	0.098 (0.154)	0.102 (0.157)
BSAC <sub>LOG</sub>	0.097 (0.213)	<b>0.053</b> (0.147)	0.100 (0.215)	0.098 (0.215)
SAC <sub>BRI</sub>	0.096 (0.190)	0.056 (0.134)	0.097 (0.190)	0.098 (0.192)
SAC <sub>LOG</sub>	<b>0.096</b> (0.191)	0.056 (0.134)	<b>0.096</b> (0.189)	<b>0.098</b> (0.193)
EWMB	0.104 (0.204)	0.057 (0.120)	0.113 (0.205)	0.105 (0.206)
EWML	0.102 (0.199)	0.061 (0.130)	0.111 (0.214)	0.103 (0.200)
EWMA	0.111 (0.146)	0.080 (0.101)	0.116 (0.152)	0.112 (0.146)
Model	Scores by Problem			
	All	Short	Medium	Long
SDLM	0.089 (0.116)	0.064 (0.085)	0.106 (0.141)	0.092 (0.117)
BSAC <sub>LOG</sub>	0.083 (0.160)	<b>0.052</b> (0.103)	0.110 (0.198)	0.085 (0.162)
SAC <sub>BRI</sub>	0.083 (0.142)	0.055 (0.096)	0.106 (0.174)	0.085 (0.144)
SAC <sub>LOG</sub>	<b>0.082</b> (0.142)	0.055 (0.096)	<b>0.105</b> (0.174)	<b>0.085</b> (0.144)
EWMB	0.091 (0.157)	0.057 (0.095)	0.121 (0.187)	0.093 (0.164)
EWML	0.090 (0.159)	0.064 (0.109)	0.120 (0.200)	0.090 (0.159)
EWMA	0.102 (0.108)	0.080 (0.075)	0.123 (0.130)	0.103 (0.110)

As can be seen in Table 3, SAC<sub>LOG</sub> achieves the lowest score across all columns except *Short* where it is outperformed by BSAC<sub>LOG</sub>. It turns out that BSAC<sub>LOG</sub> is overconfident (see Section 6.3). This means that BSAC<sub>LOG</sub> underestimates the uncertainty in the events and outputs aggregate probabilities that are typically too near 0.0 or 1.0. This results into highly variable performance. The short questions generally involved very little uncertainty. On such easy questions, overconfidence can pay off frequently enough to compensate for a few large losses arising from the overconfident and drastically incorrect forecasts.

SDLM, on other hand, lacks sharpness and is highly under-confident (see Section 6.3). This behavior is expected as the experts are under-confident at the group-level (see Section 6.4) and SDLM does not use the training set to explicitly calibrate its aggregate probabilities. Instead, it merely smooths the forecasts given by the experts. The resulting aggregate probabilities are therefore necessarily conservative, resulting into high average scores with low variability.

Similar behavior is exhibited by EWMA that performs the worst of all the competing models. The other two exponentially weighted aggregators, EWML and EWMB, make efficient use of the training set and present moderate forecasting performance in most columns of Table 3. Neither approach, however, appears to dominate the other. The high variability and average of their performance scores indicate that their performance suffers from over-confidence.

**6.3. In- and Out-of-Sample Sharpness and Calibration.** A calibration plot is a simple tool for visually assessing the sharpness and calibration of a model. The idea is to plot the aggregate probabilities against the observed empirical frequencies. Therefore any deviation from the diagonal line suggests poor calibration. A model is considered under-confident (or over-confident) if the points follow an S-shaped (or Z-shaped) trend. To assess sharpness of the model, it is common practice to place a histogram of the given forecasts in the corner of the plot. Given that the data were balanced, any deviation from the the baseline probability of 0.5 suggests improved sharpness.

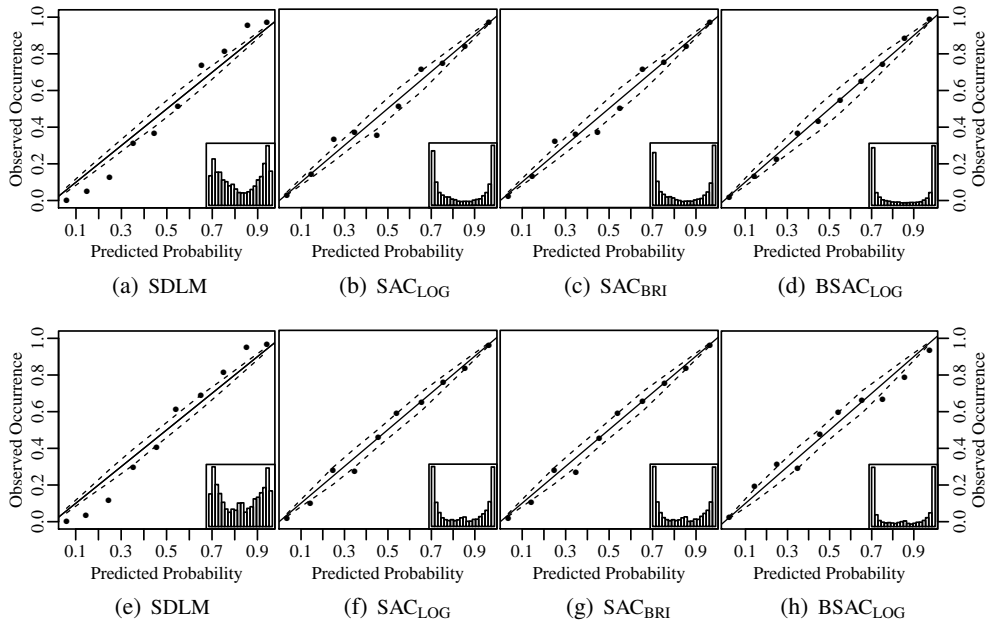


FIG 3. The top and bottom rows show in- and out-of-sample calibration and sharpness, respectively.

The top and bottom rows of Figure 3 present calibration plots for SDLM, SAC<sub>LOG</sub>, SAC<sub>BRI</sub>, and BSAC<sub>LOG</sub> under in- and out-of-sample probability aggregation, respectively. Each setting is of interest in its own right: Good in-sample calibration is crucial for model interpretability. In particular, if the estimated crowd belief is well-calibrated, then the elements of the bias vector  $\mathbf{b}$  can be used to study the amount of under- or over-confidence in the different expertise groups. Good out-of-sample calibration and sharpness, on other hand, are necessary properties in decision making. To guide our assessment, the dashed bands around the diagonal connect the point-wise, Bonferroni-corrected (Bonferroni (1936)) 95% lower and upper critical values under the null hypothesis of calibration. These have been com-

puted by running the bootstrap technique described in Bröcker and Smith (2007) for 10,000 iterations. The in-sample predictions were obtained by running the models for 10,200 iterations, leading to a final posterior sample of 1,000 observations after thinning and using the first 200 iterations for burn-in. The out-of-sample predictions were given by the 10-fold cross-validation discussed in Section 6.2.

Overall, SAC is sharp and well-calibrated both in- and out-of-sample with only a few points barely falling outside the *point-wise* critical values. Given that the calibration does not change drastically from the top to the bottom row, SAC can be considered to present robustness against over-fitting. This is, however, not the case with  $\text{BSAC}_{\text{LOG}}$  that is well-calibrated in-sample but presents over-confidence out-of-sample. Figures 3(a) and 3(e) serve as baselines by showing the calibration plots for SDLM. Given that this model does not perform any explicit calibration, it is not surprising to see most points outside the critical values. The pattern in the deviations suggests strong under-confidence. Furthermore, the inset histogram reveals drastic lack of sharpness. Therefore SAC can be viewed as a well-performing compromise between SDLM and  $\text{BSAC}_{\text{LOG}}$  that avoids over-confidence without being too conservative.

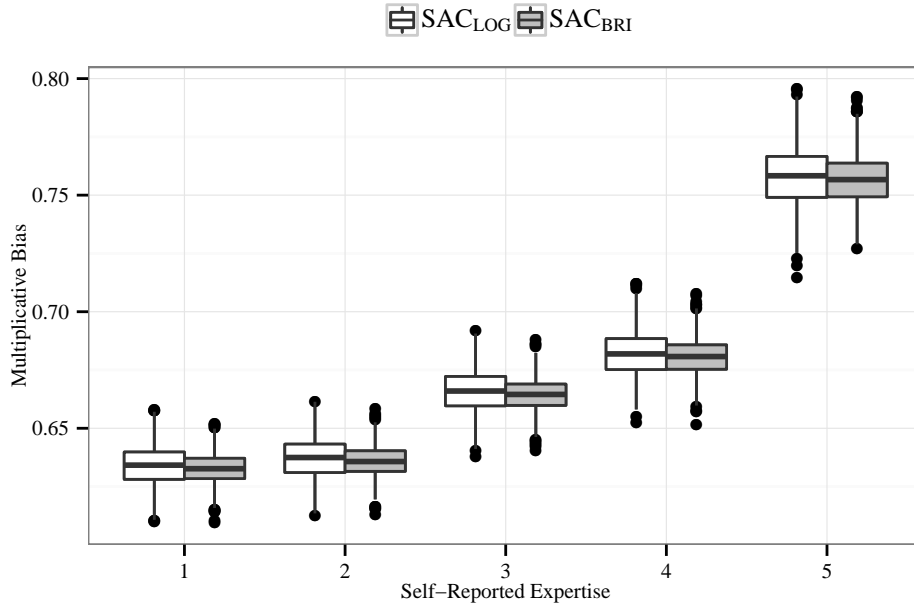


FIG 4. Posterior distributions of  $b_j$  for  $j = 1, \dots, 5$ .

**6.4. Group-Level Expertise Bias.** This section explores the bias among the five expertise groups in our dataset. Figure 4 compares the posterior distributions of the

individual elements of  $\mathbf{b}$  with side-by-side boxplots. Given that the distributions fall completely below the *no-bias* reference-line at 1.0, all the expertise groups are deemed under-confident. Even though the exact level of under-confidence is affected slightly by the extent to which the extreme probabilities are truncated (see Section 6.1), the qualitative results in this section remain insensitive to different levels of truncation.

From Figure 4 it is clear that the under-confidence decreases as expertise increases. The posterior probability that the most expert group is the least under-confident is approximately equal to 1.0, and the posterior probability of a strictly decreasing level of under-confidence is approximately 0.87. The latter probability is driven down by the inseparability of the two groups with the lowest levels of self-reported expertise. This inseparability suggests that the experts are poor at assessing how little they know about a topic that is strange to them. If these groups are combined into a single group, the posterior probability of a strictly decreasing level of under-confidence is approximately 1.0.

The decreasing trend in under-confidence can be reasoned by viewing the process of making a subjective probability as Bayesian updating: a completely ignorant expert aiming to minimize a reasonable loss function, such as the Brier score, has no reason to give anything but 0.5 as his probability forecast. However, as soon as the expert gains some knowledge about the event, he produces an updated forecast that is a compromise between his initial forecast and the new information acquired. The updated forecast is therefore conservative and too close to 0.5 as long as the expert remains only partially informed about the event. If most experts fall somewhere on this spectrum between ignorance and full information, their average forecast tends to fall strictly between 0.5 and the most-informed probability forecast (see Baron et al. (2013) for more details). Given that expertise is to a large extent determined by subject-matter knowledge, the level of under-confidence can be expected to decrease as a function of the group’s level of self-reported expertise.

Finding under-confidence in all the groups is a rather surprising result given that many previous studies have shown that experts are often over-confident (see, e.g., Lichtenstein, Fischhoff and Phillips (1977); Morgan (1992); Bier (2004) for a summary of numerous calibration studies). It is worth emphasizing two points: First, our result is a statement about groups of experts and hence does not invalidate the possibility of the individual experts being overconfident. To make conclusions at the individual-level based on the group-level bias terms would be considered an *ecological inference fallacy* (see, e.g., Lubinski and Humphreys (1996)). Second, the experts involved in our dataset are overall very well calibrated (Mellers et al. (2013)). A group of well-calibrated experts, however, can produce an aggregate forecast that is under-confident.

**6.5. Question Difficulty and Other Measures.** One advantage of our model arises from its ability to produce estimates of interpretable question-specific parameters  $\gamma_k$ ,  $\sigma_k^2$ , and  $\tau_k^2$ . These quantities can be combined in many interesting ways to answer questions about different groups of experts or the questions themselves. For instance, being able to assess the difficulty of a question could lead to more principled ways of aggregating performance measures across questions or to novel insight on the kind of questions that are found difficult by experts (see, e.g., a discussion on the *Hard-Easy Effect* in [Wilson \(1994\)](#)). To illustrate, recall that higher values of  $\sigma_k^2$  suggest greater disagreement among the participating experts. Given that experts are more likely to disagree over a difficult question than an easy one, it is reasonable to assume that  $\sigma_k^2$  has a positive relationship with question difficulty. An alternative measure is given by  $\tau_k^2$  that quantifies the volatility of the underlying circumstances that ultimately decide the outcome of the event. Therefore a high value of  $\tau_k^2$  can cause the outcome of the event to appear unstable and difficult to predict.

As a final illustration of our model, we return to the two example questions introduced in Figure 1. Given that  $\hat{\sigma}_k^2 = 2.43$  and  $\hat{\sigma}_k^2 = 1.77$  for the questions depicted in Figures 1(a) and 1(b), respectively, the first question provokes more disagreement among the experts than the second one. Intuitively this makes sense because the target event in Figure 1(a) is determined by several conditions that may change radically from one day to the next while the target event in Figure 1(b) is determined by a relatively steady stock market index. Therefore it is not surprising to find that in Figure 1(a)  $\hat{\tau}_k^2 = 0.269$ , which is much higher than  $\hat{\tau}_k^2 = 0.039$  in Figure 1(b). We may conclude that the first question is inherently more difficult than the second one.

**7. Discussion.** This paper began with an introduction of a rather unorthodox but nonetheless realistic time-series setting where probability forecasts are made very infrequently by a heterogeneous group of experts. The resulting data is too sparse to be modeled well with standard time-series methods. In response to this lack of appropriate modeling procedures, our work introduces an interpretable time-series model that incorporates self-reported expertise to capture a sharp and well-calibrated estimate of the crowd belief. To the best of our knowledge, this procedure extends the forecasting literature into rather unexplored areas of probability aggregation.

Our model preserves parsimony while addressing the main challenges in modeling sparse probability forecasting data. Therefore it can be viewed as a basis for many future extensions. To give some ideas, recall that most of the model parameters were assumed constant over time. It is intuitively reasonable, however, that these parameters behave differently during different time intervals of the question.

For instance, the level of disagreement (represented by  $\sigma_k^2$  in our model) among the experts can be expected to decrease towards the final time point when the question resolves. This hypothesis could be explored by letting  $\sigma_{t,k}^2$  evolve dynamically as a function of the previous term  $\sigma_{t-1,k}^2$  and random noise.

This paper modeled the bias separately within each expertise group. This is by no means restricted to the study of bias or its relation to self-reported expertise. Different parameter dependencies could be constructed based on many other expert characteristic, such as gender, education, or specialty, to produce a range of novel insight on the forecasting behavior across different groups of experts. It would also be useful to know how expert characteristics interact with question types, such as economic, domestic, or international. This way the researcher can gain insight about the kind of experts who generally perform well on certain types of questions. The results would be of interest to the decision-maker who could use the information as a basis for hiring only a high-performing subset of the available experts.

Given that decision-makers can have different preferences on calibration and sharpness, it may also be of interest to study hidden processes with other goals besides maximizing sharpness subject to calibration. For instance, a government official may want to sacrifice some calibration for extra sharpness. This can be easily achieved by changing the optimization criterion in (4.1) to an appropriate function that meets the new goal.

Other future directions could aim to remove some of the obvious limitations of our model. For instance, recall that the random components are assumed to follow a normal distribution. This is a strong assumption that may not always be justified. Logit-probabilities, however, have been modeled with the normal distribution before (see, e.g., [Erev, Wallsten and Budescu \(1994\)](#)). Furthermore, the normal distribution is a rather standard assumption in psychological models (see, e.g., signal-detection theory in [Tanner Jr and Swets \(1954\)](#)). A second limitation resides in the assumption that both the observed and hidden processes are expected to grow linearly. This assumption could be relaxed, for instance, by adding higher order terms to the model. A more complex model, however, is likely to sacrifice interpretability. Given that our model can detect very intricate patterns in the crowd belief (see [Figure 1](#)), compromising interpretability for the sake of facilitating non-linear growth is hardly necessary.

**8. Acknowledgements.** This research was supported by a research contract to the University of Pennsylvania and the University of California from the Intelligence Advanced Research Projects Activity (IARPA) via the Department of Interior National Business Center contract number D11PC20061. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright annotation thereon. Disclaimer: The views and con-

clusions expressed herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of IARPA, DoI/NBC, or the U.S. Government.

We deeply appreciate the project management skills and work of Terry Murray and David Wayrynen, which went far beyond the call-of-duty on this project.

## References.

- ALLARD, D., COMUNIAN, A. and RENARD, P. (2012). Probability Aggregation Methods in Geoscience. *Mathematical Geosciences* **44** 545-581.
- ARIELY, D., AU, W. T., BENDER, R. H., BUDESCU, D. V., DIETZ, C. B., GU, H., WALLSTEN, T. S. and ZAUBERMAN, G. (2000). The Effects of Averaging Subjective Probability Estimates between and within Judges. *Journal of Experimental Psychology: Applied* **6** 130-147.
- BAARS, J. A. and MASS, C. F. (2005). Performance of National Weather Service Forecasts Compared to Operational, Consensus, and Weighted Model Output Statistics. *Weather and Forecasting* **20** 1034-1047.
- BARON, J., UNGAR, L. H., MELLERS, B. A. and TETLOCK, P. E. (2013). Two Reasons to Make Aggregated Probability Forecasts More Extreme. Manuscript submitted for publication (A copy can be requested by emailing Lyle Ungar at [ungar@cis.upenn.edu](mailto:ungar@cis.upenn.edu)).
- BATCHELDER, W. H., STRASHNY, A. and ROMNEY, A. K. (2010). Cultural Consensus Theory: Aggregating Continuous Responses in a Finite Interval. In *Advances in Social Computing* 98-107. Springer.
- BIER, V. (2004). Implications of the Research on Expert Overconfidence and Dependence. *Reliability Engineering & System Safety* **85** 321-329.
- BONFERRONI, C. E. (1936). Teoria Statistica Delle Classi e Calcolo Delle Probabilità. *Pubblicazioni del R Istituto Superiore di Scienze Economiche e Commerciali di Firenze* **8** 3-62.
- BRIER, G. W. (1950). Verification of Forecasts Expressed in Terms of Probability. *Monthly Weather Review* **78** 1-3.
- BRÖCKER, J. and SMITH, L. A. (2007). Increasing the Reliability of Reliability Diagrams. *Weather and Forecasting* **22** 651-661.
- BUJA, A., STUETZLE, W. and SHEN, Y. (2005). Loss Functions for Binary Class Probability Estimation and Classification: Structure and Applications. Manuscript available at [www-stat.wharton.upenn.edu/buja](http://www-stat.wharton.upenn.edu/buja).
- CARTER, C. K. and KOHN, R. (1994). On Gibbs Sampling for State Space Models. *Biometrika* **81** 541-553.
- CHEN, Y. (2009). Learning Classifiers from Imbalanced, Only Positive and Unlabeled Data Sets. *Department of Computer Science Iowa State University*.
- CLEMEN, R. T. and WINKLER, R. L. (2007). Aggregating Probability Distributions. *Advances in Decision Analysis* 154-176.
- COOKE, R. M. (1991). *Experts in Uncertainty: Opinion and Subjective Probability in Science*. Oxford University Press, New York, NY, USA.
- EREV, I., WALLSTEN, T. S. and BUDESCU, D. V. (1994). Simultaneous Over- and Underconfidence: The Role of Error in Judgment Processes. *Psychological Review* **66** 519-527.
- GELMAN, A., CARLIN, J. B., STERN, H. S. and RUBIN, D. B. (2003). *Bayesian Data Analysis*. CRC press.
- GELMAN, A., JAKULIN, A., PITTAU, M. G. and SU, Y.-S. (2008). A Weakly Informative Default Prior Distribution for Logistic and Other Regression Models. *The Annals of Applied Statistics* 1360-1383.

- GEMAN, S. and GEMAN, D. (1984). Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images. *Institute of Electrical and Electronics Engineer (IEEE) Transactions on Pattern Analysis and Machine Intelligence* **6** 721–741.
- GENEST, C. and ZIDEK, J. V. (1986). Combining Probability Distributions: A Critique and an Annotated Bibliography. *Statistical Science* **1** 114–148.
- GENT, I. P. and WALSH, T. (1996). Phase Transitions and Annealed Theories: Number Partitioning as a Case Study. In *Proceedings of European Conference on Artificial Intelligence (ECAI 1996)* 170–174. John Wiley & Sons.
- GNEITING, T. and RANJAN, R. (2011). Combining Predictive Distributions. *arXiv preprint arXiv:1106.1638*.
- GNEITING, T., STANBERRY, L. I., GRIMIT, E. P., HELD, L. and JOHNSON, N. A. (2008). Rejoinder on: Assessing Probabilistic Forecasts of Multivariate Quantities, with an Application to Ensemble Predictions of Surface Winds. *Test* **17** 256–264.
- GOOD, I. J. (1952). Rational Decisions. *Journal of the Royal Statistical Society. Series B (Methodological)* 107–114.
- HASTINGS, C., MOSTELLER, F., TUKEY, J. W. and WINSOR, C. P. (1947). Low Moments for Small Samples: A Comparative Study of Order Statistics. *The Annals of Mathematical Statistics* **18** 413–426.
- HAYES, B. (2002). The Easiest Hard Problem. *American Scientist* **90** 113–117.
- KARMARKAR, N. and KARP, R. M. (1982). *The Differencing Method of Set Partitioning*. Computer Science Division, University of California Berkeley.
- KELLERER, H., PFERSCHY, U. and PISINGER, D. (2004). *Knapsack Problems*. Springer.
- LICHTENSTEIN, S., FISCHHOFF, B. and PHILLIPS, L. D. (1977). *Calibration of Probabilities: The State of the Art*. Springer.
- LUBINSKI, D. and HUMPHREYS, L. G. (1996). Seeing the Forest from the Trees: When Predicting the Behavior or Status of Groups, Correlate Means. *Psychology, Public Policy, and Law* **2** 363.
- MELLERS, B. A., UNGAR, L., BARON, J., RAMOS, J., GURCAY, B., FINCHER, K., SCOTT, S., MOORE, D., ATANASOV, P., SWIFT, S., MURRAY, T. and TETLOCK, P. (2013). Improving Predictions in a Political Forecasting Tournament. Manuscript under review.
- METROPOLIS, N., ROSENBLUTH, A. W., ROSENBLUTH, M. N., TELLER, A. H. and TELLER, E. (1953). Equation of State Calculations by Fast Computing Machines. *The Journal of Chemical Physics* **21** 1087–1092.
- MIGON, H. S., GAMERMAN, D., LOPES, H. F. and FERREIRA, M. A. (2005). Dynamic Models. *Handbook of Statistics* **25** 553–588.
- MILLS, T. C. (1991). *Time Series Techniques for Economists*. Cambridge University Press.
- MORGAN, M. G. (1992). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge University Press.
- MURPHY, A. H. and WINKLER, R. L. (1987). A General Framework for Forecast Verification. *Monthly Weather Review* **115** 1330–1338.
- NEAL, R. M. (2003). Slice Sampling. *Annals of Statistics* 705–741.
- PEPE, M. S. (2003). *The Statistical Evaluation of Medical Tests for Classification and Prediction*. Oxford University Press Oxford.
- PRIMO, C., FERRO, C. A., JOLLIFFE, I. T. and STEPHENSON, D. B. (2009). Calibration of Probabilistic Forecasts of Binary Events. *Monthly Weather Review* **137** 1142–1149.
- RAFTERY, A. E., GNEITING, T., BALABDAOUI, F. and POLAKOWSKI, M. (2005). Using Bayesian Model Averaging to Calibrate Forecast Ensembles. *Monthly Weather Review* **133** 1155–1174.
- RANJAN, R. and GNEITING, T. (2010). Combining Probability Forecasts. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **72** 71–91.
- SANDERS, F. (1963). On Subjective Probability Forecasting. *Journal of Applied Meteorology* **2** 191–201.



- SATOPÄÄ, V. A., BARON, J., FOSTER, D. P., MELLERS, B. A., TETLOCK, P. E. and UNGAR, L. H. (2014). Combining Multiple Probability Predictions Using a Simple Logit Model. *International Journal of Forecasting*. In press.
- SHLYAKHTER, A. I., KAMMEN, D. M., BROIDO, C. L. and WILSON, R. (1994). Quantifying the Credibility of Energy Projections from Trends in Past Data: The US Energy Sector. *Energy Policy* **22** 119–130.
- TANNER JR, W. P. and SWETS, J. A. (1954). A Decision-Making Theory of Visual Detection. *Psychological Review* **61** 401.
- TETLOCK, P. E. (2005). *Expert Political Judgment: How Good Is It? How Can We Know?* Princeton University Press.
- UNGAR, L., MELLERS, B., SATOPÄÄ, V., TETLOCK, P. and BARON, J. (2012). The Good Judgment Project: A Large Scale Test of Different Methods of Combining Expert Predictions. In *The Association for the Advancement of Artificial Intelligence 2012 Fall Symposium Series*.
- VISLOCKY, R. L. and FRITSCH, J. M. (1995). Improved Model Output Statistics Forecasts Through Model Consensus. *Bulletin of the American Meteorological Society* **76** 1157–1164.
- WALLACE, B. C. and DAHABREH, I. J. (2012). Class Probability Estimates Are Unreliable for Imbalanced Data (and How to Fix Them). In *Institute of Electrical and Electronics Engineers (IEEE) 12th International Conference on Data Mining (International Conference on Data Mining)* 695–704. Institute of Electrical and Electronics Engineers (IEEE).
- WALLSTEN, T. S., BUDESCU, D. V. and EREV, I. (1997). Evaluating and Combining Subjective Probability Estimates. *Journal of Behavioral Decision Making* **10** 243–268.
- WILSON, A. G. (1994). *Cognitive Factors Affecting Subjective Probability Assessment*. Citeseer.
- WILSON, P. W., DAGOSTINO, R. B., LEVY, D., BELANGER, A. M., SILBERSHATZ, H. and KANNEL, W. B. (1998). Prediction of Coronary Heart Disease Using Risk Factor Categories. *Circulation* **97** 1837–1847.
- WINKLER, R. L. and JOSE, V. R. R. (2008). Comments on: Assessing Probabilistic Forecasts of Multivariate Quantities, with an Application to Ensemble Predictions of Surface Winds. *Test* **17** 251–255.
- WINKLER, R. L. and MURPHY, A. H. (1968). “Good” Probability Assessors. *Journal of Applied Meteorology* **7** 751–758.
- WRIGHT, G., ROWE, G., BOLGER, F. and GAMMACK, J. (1994). Coherence, Calibration, and Expertise in Judgmental Probability Forecasting. *Organizational Behavior and Human Decision Processes* **57** 1–25.

PHILADELPHIA, PA 19104- 6340, USA  
E-MAIL: [satopaa@wharton.upenn.edu](mailto:satopaa@wharton.upenn.edu)