Assessing Amazon turker and automated machine forecasts in the Hybrid Forecasting Competition

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Abstract

The Hybrid Forecasting Competition (HFC) is an ongoing project to develop hybrid geopolitical forecasting systems that combine human- and machine-generated forecasts. The first project trial period took place in 2018, during the course of which volunteer participants, Amazon Mechanical Turkers, and an automated time series forecasting module we developed provided forecasts for more than 150 questions covering a diverse set of topics. We investigate two questions: (1) how does the performance of turker forecasters compare to volunteers, and (2) what impact did access to the machine forecasts have on forecaster accuracy?

The Hybrid Forecasting Competition (HFC)[1] is an IARPA program that seeks to develop methods for hybrid geopolitical forecasting system that combine human and machine forecasts to answer a broad range of questions about economic, political, health, and other events and trends. The first trial period, or RCT, took place in 2018, during the course of which hundreds of volunteer and Amazon Mechnial Turk forecasters, as well as automated machine models, answered more than 150 questions covering a broad range of issues.

We worked on one of the competition teams, and specifically by contributing a time series forecasting module. Out of the large set of interesting questions one could examine with the results so far, given our specific focus on this project, we will try to examine in this paper two questions: (1) how does the accuracy of turker forecasters compare to volunteer forecasters, and (2) what was the impact of the machine forecasts on human forecaster accuracy?

The Hybrid Forecasting Competition

The goal of the HFC is to find ways to optimally combine human and machine forecasts. For example, machine forecasts can be reliable and scalable, but are constrained by available data, idiosyncratic questions, and cold start problems when a corpus of historical data is not available. Human-generated forecasts on the other hand are more flexible, but also more costly to scale and subject to various cognitive biases.(e.g. Kahneman and Egan 2011).

The competition is organized around Good Judgement-style forecasting tournaments (P. Tetlock 2005, P. E. Tetlock, Mellers, and Scoblic (2017)), where forecasters answer and are scored on a diverse pool of questions. Examples from the first trial period, RCT-A, include:

- What will be the long-term interest rate for South Africa (ZAF) in July 2018?
- How many deaths perpetrated by Boko Haram will the Council on Foreign Relations report for June 2018?
- What will be the daily closing spot price of Brent crude oil (USD per barrel) on 31 May 2018, according to the U.S. EIA?

Each question includes 2 to 5 answer options to which forecasters must assign weights summing to 1. Performance for a single forecast is then based on an ordered multinomial Brier score.

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In addition to this basic "human forecaster" tournament, competitors were expected to implement features that would in some fashion or agument these human forecasts with machine-generated tools and forecasts. An explicity requirement for the latter is that they are automated systems, e.g. an ad-hoc hand-tuned and expert-implemented machine model to forecast on a question would not be allowed, rather it would have to be a system that can generate such a model. On the other hand, if a forecaster has the skills and inclination to use data and model as a forecasting tool, that is perfectly allowed.

SAGE approach

One of the distinguishing features of our team's approach was a system that could automatically associate some of the RCT-A questions with a clearly corresponding time series and display these to a forcaster. This is based on a data platform which automatically collects and updates data from a variety of sources, and which can associate questions, based on their title, to an appropriate transformation of a data set if it is in the platform and matches a known, pre-specified pattern or template. If data is found for a question, it can then be shown to users as a simple time series chart accompanying the relevant question.

Additionally, we could use the time series to generate a machine forecast based on a univariate ARIMA model, and which then would either be shown to a user, and/or submitted seperately as a standalone forecast. The module generating these forecasts, "basil-ts", was based on the Auto ARIMA model in Hyndman and Khandakar (2008), which consists of a ARIMA-family model with an automated algorithm for determining a reasonble specific model structure, e.g. whether and how many differencing orders to apply, AR and MA orders, and some other parameters. This is wrapped in additional functionality needed to meet the automation requirements, e.g. recognizing how far a forecast needs to extend, data pre-processing, converting time series to answer option forecasts, updating forecasts with additional information if available, etc.

Research design for RCT-A

Since the scientific goal of HFC is to evaluate various hybrid forecasting techniques, the pripmary aspect of our research design for RCT-A was designed to assess what impact exposure to the time series charts and model forecasts would have on human forecaster accuracy. Incoming forecasters were assigned to one of three experimental conditions. The first group, A, served as control group and only had access to a basic version of the online platform showin the question information and tools to enter weights for the answer options. The second group, B, could also see the time series charts, and the third group, C, could see the chart and machine forecast. All forecasters, regardless of group, were forecasting on the same set of questions.

There were elements in the research design to assess other design choices but they are not relevant to the set of questions we seek to examine here, thus we will not discuss them.

Table 1: Summary of original research design.

Condition	Treatment
A	None; control
B	Chart
C	Chart and machine forecast

Comparison of groups A and B should have shown the effect of seeing a time series chart, and of groups B and C for the effect of seeing a model forecast. In practice, there were issues that complicated the effective design or forecaster groupings and treatments:

- **Amazon Mechanical Turk forecasters**. Due to lower than expected activity levels, turker forecasters started to be provided several weeks intot he first trial period. Given activity levels at that time, a decision was made to assign turkers to either condition A or C, but not B. This mean that the group whose treatment was to only see charts (B) consisted only of volunteers, while the other two groups contained mixed populations of volunteers and turkers, thus adding a confounding factor for assessing the impact of charts and machine models.

- **Gaps in data and machine coverage**. Only about 1/3 of IFPs had time series data available, meaning that within each condition group, most questions did not have a chart nor model. There was also a small number of instances where data was available, but a machine forecast was not. One example were questions related to FluNet influenza case counts, where a change in the data source broke the ability to update chart data, which would have required models to forecast over excessive time horizons. Since the availability of data was related to the type of question, it is not possible to rule out the possibility that questions with data were systematically different in their difficulty from questions without data.
- **Changes in the data and machine forecasting platforms over time**. Both the data platform and the machine forecasting system suffered from various bugs and related issues, especially during the earlier portions of RCT-A. These problems in some cases resulted in incorrectly aggregated or otherwise inaccurate data, insufficient updating which led to data in the platform falling behind source availability and thus requiring forecasts over longer time periods than neccessary, and bugs in the machine forecaster that led to no or bad forecasts. The quality of the data and machine forecasts displayed to some users thus varied over time and IFPs, in ways that are difficult to reconstruct in retrospective.

In respect to the first two problems, which we can quantify, the effective treatment groups were more complicated and are showin in Table 2.

Table 2: Effective treatments by group after addition of turkers to conditions A and C.

Group	Condition	Forecaster	IFP_Group	Sees chart?	Sees model?
1	A: no chart	Turker	No TS data		
2	A: no chart	Turker	Chart only		
3	A: no chart	Turker	Chart and model		
4	A: no chart	Volunteer	No TS data		
5	A: no chart	Volunteer	Chart only		
6	A: no chart	Volunteer	Chart and model		
7	B: chart only	Volunteer	No TS data		
8	B: chart only	Volunteer	Chart only	X	
9	B: chart only	Volunteer	Chart and model	X	
10	C: chart and model	Turker	No TS data		
11	C: chart and model	Turker	Chart only	X	
12	C: chart and model	Turker	Chart and model	X	X
13	C: chart and model	Volunteer	No TS data		
14	C: chart and model	Volunteer	Chart only	X	
15	C: chart and model	Volunteer	Chart and model	X	X
16	Machine	Machine	Chart and model		

Design, data, and method

DGP

Question comes from T&E to our platform.

Now on two tracks:

1. Human

- sees question, and depending on condition the chart and machine forecast
- forecasts, possibly multiple times per day
- Mean daily Brier score

Table 3: Average Brier score by forecaster group

Forecaster	avg_Brier	n
Machine	0.39	1975
Turker	0.43	39140
Volunteer	0.32	7816

Table 4: Average Brier score by forecaster group

Forecaster	A: no chart	B: chart only	C: chart and model	Machine
Machine				0.39
Turker	0.44		0.43	
Volunteer	0.30	0.25	0.37	

2. Platform

- parses question, finds associated data
- sends question and data to forecaster
- forecaster parses question and data, TS forecast, convert to MN forecast
- mean daily Brier score and/or shown to user

Data

RCT-A lasted from March 7th to September 7th 2018. However, Turkers did not enter until May 2nd, and for an unrelated reason we also discard data after August 2nd. This leaves a total of 48,931 forecasts—7,816 from volunteer forecasters, 39,140 from Turkers, and 1,975 from machine—for 156 IFPs, of which 101 did not have TS data, 6 had TS data but not a machine forecast, and 49 had both TS data and a machine forecast.

Results

Volunteers who had only charts did the best

Table 5 summarizes the average Brier scores for all 16 treatment/forecaster/IFP groups in Table XX. As it is quite unwieldy, we include it for reference and will discuss specific insights in more details below.

Turkers generally did worse

Turkers overall had worse forecast accuracy than either the machine models or volunteers. To rule a spurious relationship, we can compare the accuracy in directly comparable pairs, e.g. rows 1 and 4 in Table 5 consists of the average Brier scores for questions without TS data and in condition A treatment group for turkers and volunteers respectively, and show a difference of 0.14.

Figure shows the results of pairwise comparisons of the average Brier scores for all groups relative to Turker forecasters. Each row in the plot corresponds to a linear model for forecasters from the corresponding condition and IFP group, and the pointranges show coefficient estimates and 95% confidence intervals for Turkers, Machine, and Volunteer forecasters. The Turker values correspond to the average Brier for them in this grouping, while the Machine and Volunteer estimates indicate the *relative* performance. I.e. for them, values below zero indicate an improvment. Note that the x-scale is reversed, so that better is further to the right.

In most groups volunteers have an advantage sufficient to generate p-values below 0.05, although the effects are minute in comparison to general between-forecaster differences: all models have very small adjusted Rˆ2

Table 5: Average Brier scores for all 15 distinct human IFP/treatment groups, as well as the machine forecasts

Group	Condition	Forecaster	IFP_Group	avg_Brier	sd_Brier	n
1	A: no chart	Turker	No TS data	0.45	0.50	6690
2	A: no chart	Turker	Chart only	0.55	0.56	304
3	A: no chart	Turker	Chart and model	0.39	0.40	2907
4	A: no chart	Volunteer	No TS data	0.31	0.54	510
5	A: no chart	Volunteer	Chart only	0.36	0.46	18
6	A: no chart	Volunteer	Chart and model	0.28	0.34	274
7	B: chart only	Volunteer	No TS data	0.26	0.48	1702
8	B: chart only	Volunteer	Chart only	0.42	0.42	57
9	B: chart only	Volunteer	Chart and model	0.23	0.31	973
10	C: chart and model	Turker	No TS data	0.45	0.50	19502
11	C: chart and model	Turker	Chart only	0.56	0.52	990
12	C: chart and model	Turker	Chart and model	0.38	0.40	8747
13	C: chart and model	Volunteer	No TS data	0.38	0.60	3090
14	C: chart and model	Volunteer	Chart only	0.59	0.57	73
15	C: chart and model	Volunteer	Chart and model	0.32	0.40	1119
16	Machine	Machine	Chart and model	0.39	0.36	1975

Figure 1: Pairwise comparisons of turker versus machine and volunteer forecast accuracy. Each row shows estimates from a linear regression model with turkers as reference group, for different groupings of the experimental conditions and IFP data/model availability. The turker estimates (red dots) correspond to the average Brier for turker forecasters, while the other estimates correspond to the relative difference from the turker average for other forecasters. Points further to the right correspond to lower Brier scores, i.e. better peformance. Volunteers on average performed better than turker forecasters in all conditions and question groups, except on the small number of charts-only IFPs, where estimates are uncertain.

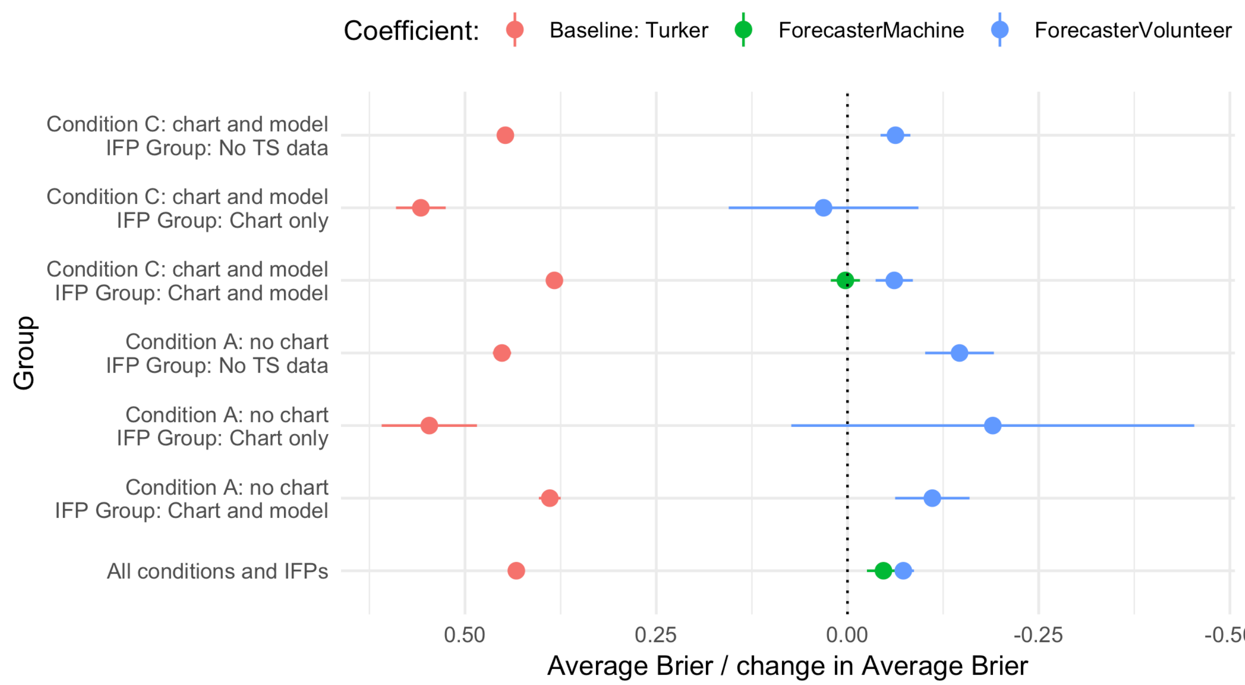


Table 6: Model summary statistics

Model	Statistic	Value
Model 1: Linear model	N	46956
	R^2	0.01
	Adj. R^2	0.01
Model 2: Linear model with IFP random intercepts	N	46956
	Marginal R^2	0.01
	Conditional R^2	0.28

values, below 0.01.

Chart and model effects

Teasing out the chart and model effects is a bit harder through pairwise comparison. Instead, we directly coded whether a forecaster saw a chart or model forecast. Forcasters in conditions B and C and for questions that had a chart saw a chart, and forecasters in condition C looking at a question which had a machine forecast will have seen a model forecast. We also leave out the machine forecasts from the data, leaving almost 47,000 forecasts, of which about 25% were made with a chart available, and 21% also had a model forecast available.

We estimated two linear models to predict Brier scores for a forecast. The first has the specifiction:

$$
\begin{aligned}
\text{Brier} = \; & \alpha + \beta_1 \text{SeesModel} + \beta_2 \text{SeesChart} + \beta_3 \text{IFPGroupChartOnly} + \beta_4 \text{IFPGroupChartAndModel} \\
& + \beta_5 \text{ForecasterVolunteer}
\end{aligned}
$$

All variables are dummy terms. The intercept α corresponds to the average Brier score for a Turker forecasting on an IFP that did not have chartable data, and who neither saw a chart nor machine forecast.

The second model includes random intercepts for IFP to account for the possibility that seeings charts or models may make users differentially willing to forecast on harder IFPs, i.e. those with higher average Brier scores. Otherwise the specification of covariates is the same.

$$
\begin{aligned}
\text{Brier} = \; & \alpha_{\text{Global}} + \alpha_{\text{IFP}} + \beta_1 \text{SeesModel} + \beta_2 \text{SeesChart} + \beta_3 \text{IFPGroupChartOnly} \\
& + \beta_4 \text{IFPGroupChartAndModel} + \beta_5 \text{ForecasterVolunteer}
\end{aligned}
$$

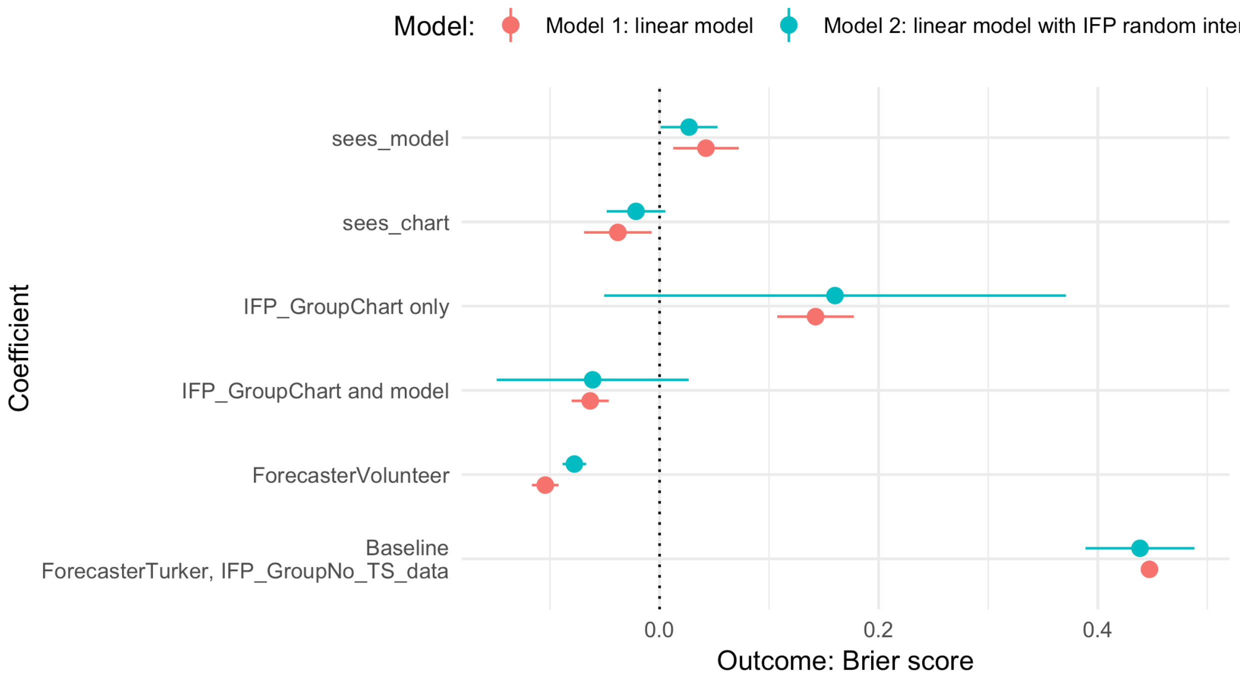
Figure 2 plots the coefficient estimates from both models. The results are consistent. Seeing a chart slightly helps, seeing a model slightly hurts forecast performance. However, the effects are small and not as important as whether a forecasters was a volunteer or turker. In addition, the models themselves capture only a small portion of the variation in Brier scores overall. Table 6 shows R^2 statistics for both models. The covariates account for less than 0.01 of the variation in Brier scores; the inclusion of random IFP intercepts in model 2 increases this to 0.28 (conditional R^2), but the fraction explained by the covariates together is still 0.01 (marginal R^2). Most of the variation remains either between forecasters or due to other random factors.

Thus, while we find that exposure to charts and model forecasts has a small impact on forecast quality, the effect sizes are small in comparison to other systematic factors in the model, and small relative to unsystematic and random factors not in the model.

Models generally were disappointing, but did they do well in certain areas?

Although the machine models overall underperformed, it is possible that they performed well relative to human forecasters in certain areas. To examine this we looked at all forecasts for questions that had a

Figure 2: Model estimates for the direct effects of seeing a chart and machine forecast.



machine forecast. This leaves us with 15,995 forecasts, approximately 2,000 of which were machine and volunteer forecasts, respectively, and the remaining 12,000 from turkers.

To estimate the relative performance of different forecasters, we again estimated a simple linear model, similar to those used for the turker pariwise comparisons. The model has the general form:

$$\text{Brier} = \beta_i \text{DataSource} + \beta'_{ij}(\text{DataSource} \times \text{Forecaster})$$

Data source is a discrete variable with $i = 14$ levels for the different data sources reflected in the set of IFPs. Based on previous exploratory analysis, we separated one data source, ACLED questions, by whether a question was binary with two answer options ("yes"/"no"), or not (3 or 5 options). Forecaster is also a discrete variable with 3 levels, but we leave out "Machine" as reference category, giving us $j = 2$ different levels. Thus, each of the β coefficients corresponds to the average Brier score for machine forecasts for that group of IFPs, and each β'_i coefficient is the relative difference of the average volunteer and turker Brier score compared to the corresponding baseline in β_i.

Figure 3 shows the coefficient estimates. The left panel shows the baseline machine forecast performance. The right panel shows the relative difference in average Brier scores for turker and volunteer forecasts; points to the left of the dotted 0 line indicate that volunteer or turker forecasters on average outperformed the machine forecasts.

The machine forecasts did better than human forecasts on ACLED 5-option, Boko Haram killings ("nigeria-security"), and hacking ("privacyrights") questions. All three data sources consist of count data derived from original event datasets, i.e. they require data aggregation before one can see a time series relevant to the question at hand, which might be a factor in the relative performance on these questions. On the other hand, human forecasters consistently did better on ACLED 2-option, food price index ("FAO-FPI"), financial ("fred"), and oil production ("opec") questions. The results for ACLED 2-option questions might be influenced by the particular mechanism by which time series forecasts were converted to answer option probabilities, which may explain the inconsistency with ACLED 5-option questions.

Figure 3: Linear model estimates for the relative performance of machine to volunteer and turker forecasts by data source. The left panel shows the baseline machine performance for each data source, the right panel shows the relative difference of the volunteer and turker forecasts to the corresponding baseline. The outcome variable is a forecasts's Brier score.

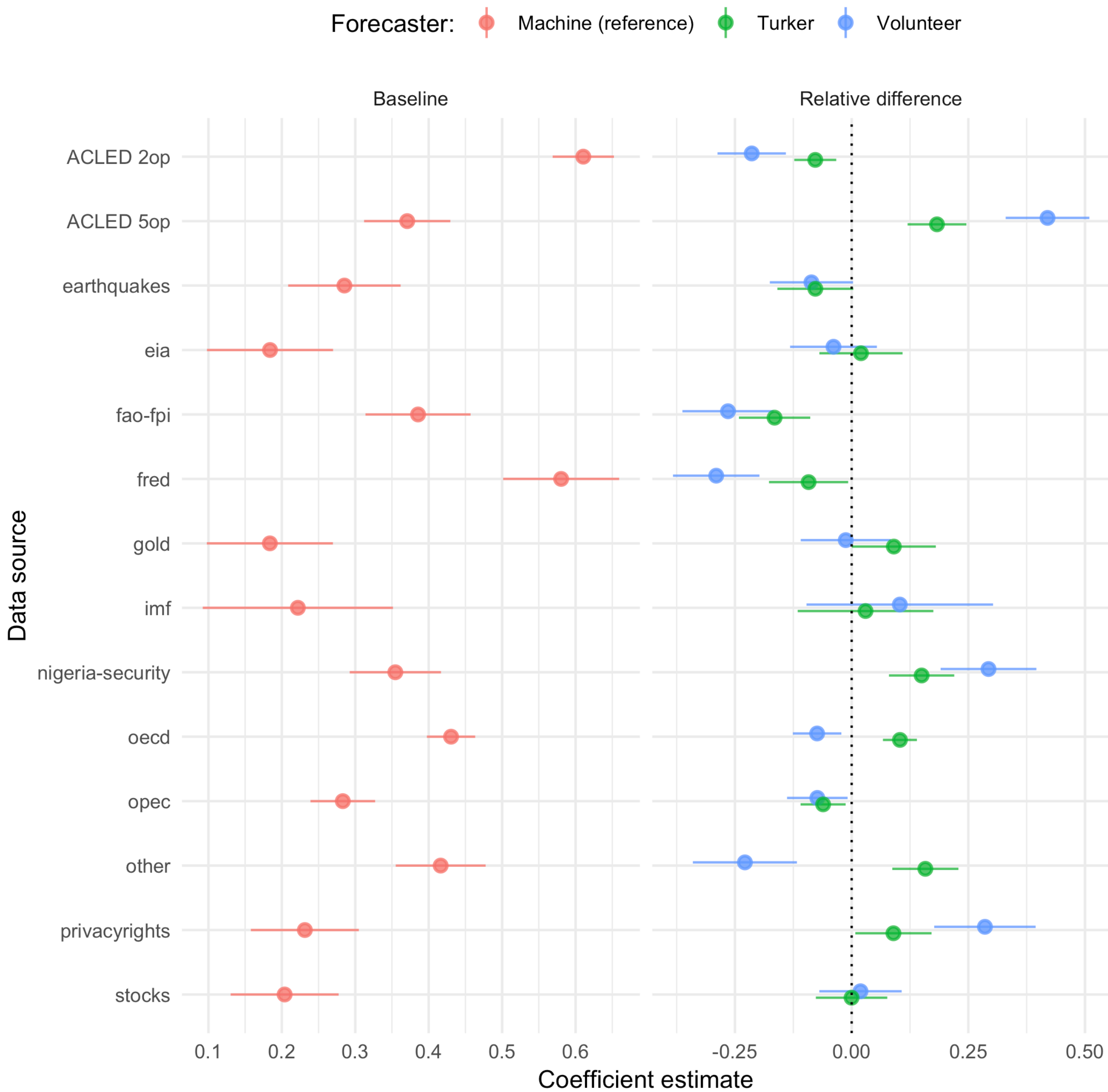


Table 7: Condition B advantage

Group	Condition	IFP_Group	avg_Brier	sd_Brier	n
7	B: chart only	No TS data	0.26	0.48	1702
4	A: no chart	No TS data	0.31	0.54	510
13	C: chart and model	No TS data	0.38	0.60	3090
8	B: chart only	Chart only	0.42	0.42	57
5	A: no chart	Chart only	0.36	0.46	18
14	C: chart and model	Chart only	0.59	0.57	73
9	B: chart only	Chart and model	0.23	0.31	973
6	A: no chart	Chart and model	0.28	0.34	274
15	C: chart and model	Chart and model	0.32	0.40	1119

There are some hard to quantify factors that may explain some of the variation in human to machine performance:

1. As mentioned, some data sources (ACLED, privacyrights, nigeria-security) required relatively complicated data aggregation to derive usable count series, and which therefore may not have been accessible to all human forecasters.
2. Not all data sources are equally easy to automatically download and update, and at least in some of the data sources it was the case that models had to forecast over much longer time horizons due to outdated data, while a human forecaster would have been able to access more recent data.
3. Due to obstacles in data acquisition, in at least one case–OPEC oil production rates–a secondary and less accurate source was substituted. OPEC production values are delivered in monthly PDF reports that are difficult to automatically extract data from, and the alternative data source in some instances significantly deviated from the OPEC values. Thus models for these questions would have been forecasting with incorrect input data.
4. For questions in which the data source is at a monthly (or higher) resolution, humans have an advantage over univariate time series models in that they can incorporate sub-monthly information into their forecast. For many of these questions, if they were open for a period of one or two months, there would in fact have only been one or two distinct time series forecasts (barring practical live system issues and bugs).

A caveat to these trends is that the number of IFPs and forecasts for each data source are small and the results may thus be due to random variation. Results from future RCTs should test this.

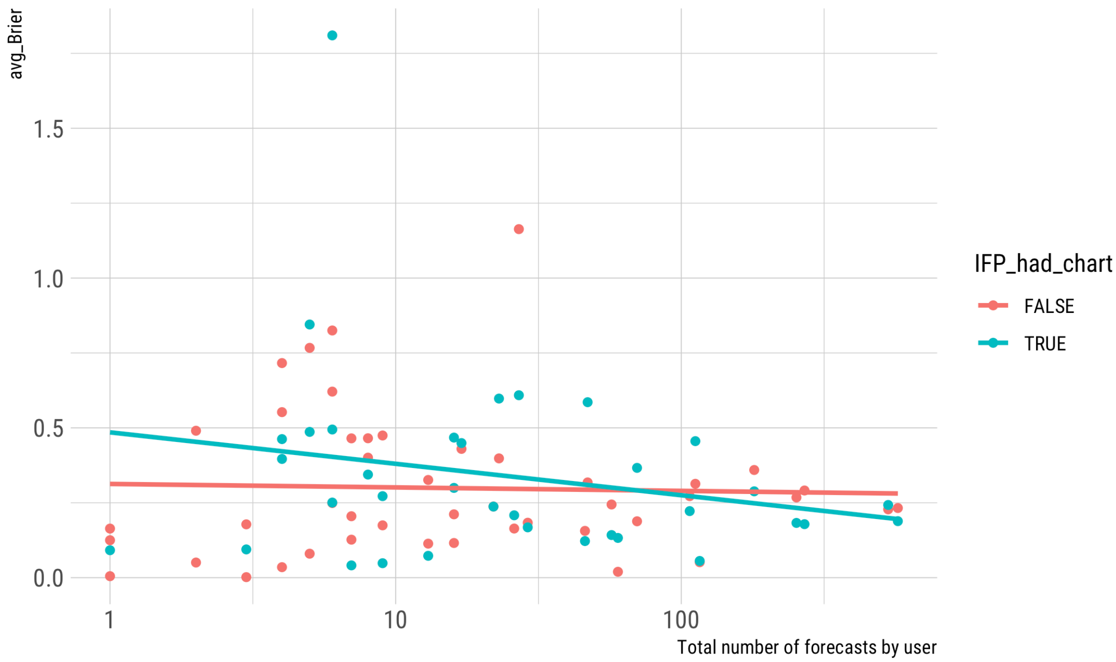
Why did condition B volunteers do so well?

Condition B volunteers had the best overall performance out of the 16 groups shown in Table 5. Considering that the machine forecasts were relatively bad, one possible explanation is that the charts overall had a positive impact on human forecast accuracy, while seeing machine forecasts had a negative impact.

However, there are several additional patterns that are either inconsistent with this simple explanation or at least suggest the need for a more complex alternative. The first is that condition B forecasters did not only do better than other groups on questions that had a chart, but also on questions that did not have a chart. Table 7 shows the relevant rows from the average Brier scores for all forecaster groups in Table 5. With the partial exception of the few chart-only questions, condition B forecasters' advantage on questions without a chart is as pronounced as their advantage in questions that did have a chart. Considering that there were two to three times as many forecasts on questions without chartable data, most of the condition B volunteer advantage is driven by doing better on questions that did not have a chart.

We could exlain this if there is, in addition to the direct beneficial effect of seeing a chart, but not a potentially misleading machine forecast, a spillover effect whereby exposure to charts also improves a volunteer

Figure 4: Average Brier for condition B volunteers by user and by whether a IFP had a chart. Intensive users are slightly more accurate than novice users on questions with a chart, but no more accurate on questions without a chart.



forecaster's ability to forecast on other questions without charts.

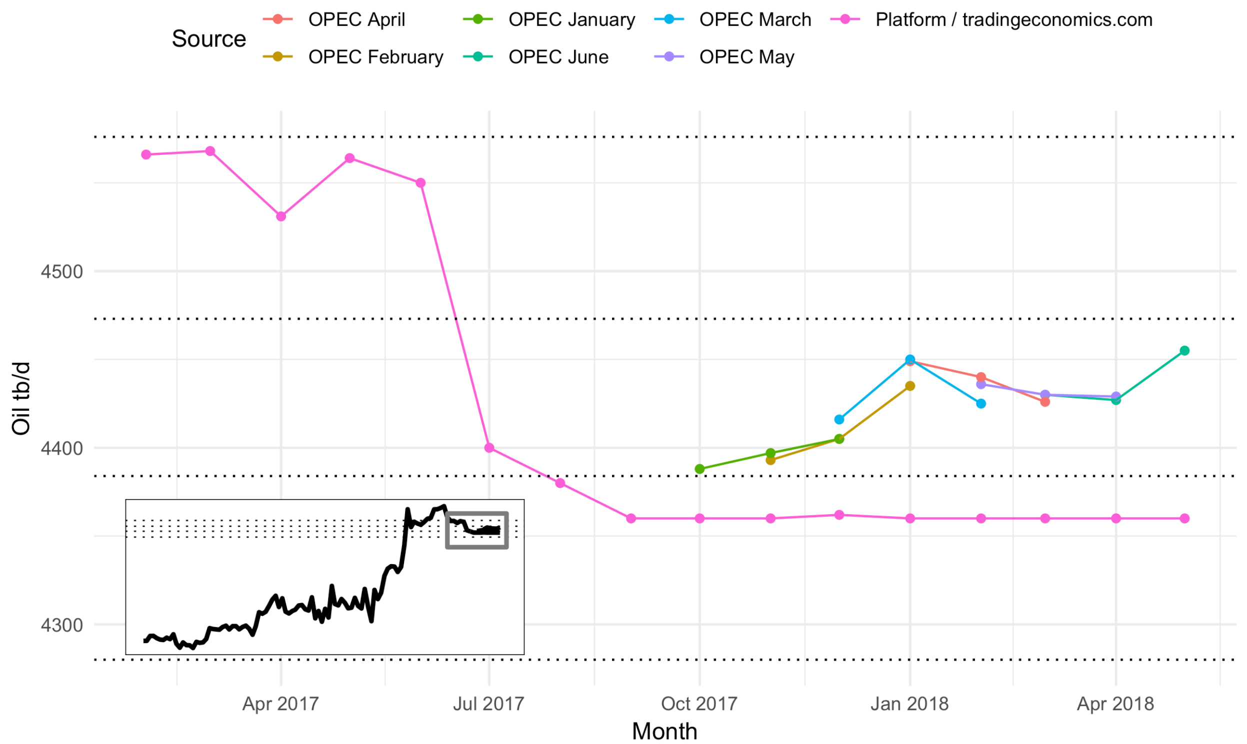
Curious inconsistencies remain:

There appears to be no chart spillover effect for condition C human and volunteer forecasters. Tabe 5 shows that condition C volunteers did worse on questions without time-series data than the condition A control group. Condition C turkers also did not do better than their condition A control group counterparts. Unlike condition B forecasters, they were exposed to machine forecasts as well, so maybe there is an equal but opposite negative machine spillover effect.

Condition B volunteers who forecast a lot do no better on non-chart questions than novices. Figure 4 show average Brier scores as a function of the total number of forecasts a user has. The data consist of only forecasts from condition B volunteers. Each point is the average Brier score for a user's forecasts on the set of questions that did (blue) or did not have a chart (red). Novice users tend to be as accurate as intensive users on non-chart questions. This implies that the condition B volunteer advantage on non-chart questions is not related to how active a user was. If there is a spillover effect, even very inactive users seem to somehow benefit from it.

Condition C volunteers do well on questions where we know that data displayed was wrong. There were several instances where we know that the data displayed in a chart were inaccurate. Figure 5 shows the first example, oil production figures for Iraq. The main chart shows several teim series depicting oil production in Iraq, according to different sources. The canonical data are contained in monthly OPEC oil market reports, each of which contains production figures for the past 3 months. Those are shown in the sequence of short time series on the mid-right part of the main chart–the figures are somewhat inconsistent between reports, but this is another peculiarity. Because this data is difficult to obtain programatically, an alternative data source is used instead. This is what would have been shown in the charts, and what

Figure 5: Iraq oil production



informed the machine forecast. Obviously it is incorrect data. The dotted lines show the values separating the answer options for this question. The chart placed the production values in an entirely incorrect answer category.

Curiously, the condition B volunteers performed better on this question than any other forecaster. The number of forecasts here are low, and only the last three groups, starting from the machine forecasts, have pairwise statistically significant differences in average Brier score from the condition B volunteers.

Forecaster	condition	avg_Brier	n
Volunteer	b	0.07	5
Volunteer	a	0.11	5
Turker	c	0.18	87
Machine	n/a	0.25	14
Turker	a	0.35	23
Volunteer	c	0.45	21

Another example with incorrect data is an early ICEWS question that fell outside the common period and thus did not have forecasts from turkers. Condition B volunteers also outperformed all other groups on this question, although the pairwise differences with the other groups are not statistically significant.

Forecaster	condition	avg_Brier	n
Volunteer	b	0.92	14
Machine	n/a	1.00	18
Volunteer	a	1.11	7
Volunteer	c	1.11	25

Even when the machine predictions were good, condition B volunteers did better than their C counterparts. If bad machine predictions influence human forecasts and are the reason why the beneficial chart effecgt is only apparent in condition B forecasters, and not condition C forecasters, then it should also be the case that condition C forecasters do well on those questions where the machine forecasts were good. This is no the case. The table below shows the subset of forecasts on questions that had a machine forecast (and thus chart) and where the machine forecast average Brier was lower than the average Brier score for the forecasts from all other forecaster × condition groups. Condition B volunteers beat their condition C counterparts even when the machine model should have improved their forecasts because they happened to be accurate.

Forecaster	Condition	avg_Brier	n_fcasts
Machine	Machine	0.39	1975
Turker	A: no chart	0.39	2810
Turker	C: chart and model	0.38	8482
Volunteer	A: no chart	0.28	267
Volunteer	B: chart only	0.23	958
Volunteer	C: chart and model	0.32	1094

One possibility that we should not discard with these apparent inconsistencies is that we are digging in noise. All of the effects—for turkers versus other forecasts, for the disappointing performance of the machine forecasts, for conditions or different groupings of IFPs—pale in comparison to differences in accuracy between individual forecasters and between forecasts for different IFPs. But on the other hand there are several inconsistencies so it also is a stretch to write all of them off to random coincidence. Condition B volunteers clearly did better than all other forecasters/condition groups, but it is not clear why.

Conclusion

Are we digging in noise?

Many of the questions involve monthly time series but are only open for periods spanning a single or few months. Some of the advantage of the human forecasters may thus have been due to operating on a sub-monthly time scale.

We also know that model performance suffered from issues related to automation. Were we able to run the RCT-A questions with the current system and with a data platform that optimally ingests data sources on the bleeding edge of their own updates, our forecasts would have been . . .

[**check with updated results from test bed what the performance gain would have been, i think the site visit stats were not accurate anymore**]

Additional information

Table 11: Average Brier scores for machine and other forecasts by question data source.

Data_source	N_IFPs	Machine	Turker	Volunteer
ACLED 2op	7	0.611	0.533	0.396
ACLED 5op	4	0.371	0.554	0.790
earthquakes	2	0.285	0.207	0.199
eia	5	0.184	0.204	0.145
fao-fpi	3	0.386	0.220	0.121
fred	2	0.580	0.488	0.290

Data_source	N_IFPs	Machine	Turker	Volunteer
gold	3	0.184	0.274	0.171
imf	1	0.222	0.252	0.325
nigeria-security	2	0.355	0.504	0.648
oecd	7	0.430	0.534	0.356
opec	5	0.283	0.222	0.209
other	2	0.416	0.574	0.188
privacyrights	2	0.231	0.321	0.517
stocks	4	0.204	0.204	0.223

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