Forecaster Performance Characteristics*

Jonathan Benchimol,† Makram El-Shagi‡ and Yossi Saadon§

July 2, 2019

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Preliminary version

Abstract

More than 480 experts provide forecasts about the next inflation or central bank interest rates. We characterize experts with respect to their education, experience, gender, affiliation characteristics to show how these characteristics influence their behaviors, i.e., their forecasting performance, courage, and instability. We show the level and quality of the education, the localization, and type of their affiliation and their experience as a forecaster are critical characteristics for improving these behaviors. Some behavioral interpretations and policy recommendations are derived from these results.

Keywords: TBC, TBC.

JEL Classification: TBC, TBC.

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*This paper does not necessarily reflect the views of the Bank of Israel. The authors thank Lahcen Bounader and participants at the Bank of Israel research seminar for their useful comments.

†Bank of Israel, POB 780, 91007 Jerusalem, Israel. Email: jonathan.benchimol@boi.org.il

‡Center for Financial Development and Stability, Henan University, Keifeng, China. Corresponding author. Email: makram.el-shagi@cfds.henu.education

§Bank of Israel, POB 780, 91007 Jerusalem, Israel. Email: yosis@boi.org.il

1 Introduction

Expert forecasts of inflation and central bank interest rates influence economic agents Boubakri et al. (2015); Piotroski and Roulstone (2004). Institutions and governments use these forecasts extensively, usually aggregate them in the most simplistic way (simple average) and use standard forecast quality measures (root mean square error, RMSE) to rank them without considering the expert characteristics.

By constructing two original databases about expert forecast characteristics and performances over the two last decades, our approach assesses which expert and institution characteristics matter in their US inflation (CPI) and Fed fund rates forecasting quality over time. Our first database includes the key characteristics of an expert forecast such as its experience (place, type and time), gender, education (level, type and quality), and affiliation (type and place). Our second database covers all the US inflation and Fed fund rates expert forecast loss functions by expert's name and institutional affiliation over time covering the performance, courage, and instability of the forecasts.

Investors and central banks use forecasts to plan or justify their decisions and the performance of these decisions depends on the accuracy of the forecasts. These agents rely on various sources to formulate their forecasts. Since expert forecasts are generally better than market-based forecasts Adeney et al. (2017); Benchimol and El-Shagi (2017), they essentially rely on the average of expert forecasts Genre et al. (2013). Identifying the characteristics of the best experts could help firms and policymakers to efficiently achieve their objectives.

Accurate predictions are also important for financial stability. As forecasts constitute an essential information channel leading to investment portfolio decisions, the more accurate the forecast, the less a surprise could occur, minimizing the required adjustment costs of the investment portfolio and the corresponding market volatility when the data will be made public. The more money is spent relative to these inaccurate forecasts, the more volatile the markets. In other words, helping economic agents to identify and rely on good experts contributes to improving financial stability.

In addition to personal expert characteristics, our study tracks the institutional affiliation type of each expert, be they a financial,[1] academic, monetary, or private non-financial institution.

The characteristics of financial analysts and their forecast quality was analyzed in the finance literature. Bae et al. (2008) examine, over 32 countries,

[1] Including all compagnies managing money, brokerage, and insurance.

whether analysts resident in a country make more precise earnings forecasts for firms in that country than analysts who are not resident in that country. They find that the earnings forecasts of local financial experts are more precise–the *local analyst advantage*.

Bae et al. (2008) interpret this local advantage as evidence that local analysts are better informed than foreign analysts because of their proximity to their covered firm. They also find that the local analyst advantage is strong in countries that are more underweighted in U.S. portfolios relative to their share in the float world market portfolio.[2]

Mitchell and Pearce (2007) analyze the forecast performance of economists surveyed biannually by the Wall Street Journal. They find evidence that predictions of some economists are systematically above the survey mean, while those of others are systematically below. They also find support for strategic models that predict that the absolute deviations of economists' forecasts from the consensus depend on the industry of the economists' employers.

Interestingly, Mitchell and Pearce (2007) find that as economists age their forecasts about interest and exchange rates deviate less from the consensus. Their precursor study shows that individual characteristics could matter in terms of forecasting accuracy.

Berger et al. (2009) use a novel database on the forecasts of ECB policy decisions of 120 financial institutions in 24 countries since1999. They show that differences in their ability to understand and anticipate policy decisions by the ECB are substantially explained by geography and country-specific economic conditions. Berger et al. (2009) find that financial institutions based in Frankfurt (or subsidiary in Frankfurt, perform substantially better in predicting ECB interest rate decisions. This suggests that geography plays a significant role in information asymmetries about the macroeconomic forecasts.

Berger et al. (2009) find that country-specific economic conditions are also relevant, with the accuracy of forecasts depending on the levels of inflation in the institutions' host countries. experts in countries with higher (lower) than Eurozone inflation tend to produce more hawkish (dovish) forecasts, suggesting that the national inflation environment biases experts' views of ECB monetary policy.

Veress and Kaiser (2017) show that, depending on their affiliation, economists are systematically biased towards being overly optimistic or pessimistic. They are not able to forecast the correct direction nor the range of magnitude of future

[2]So that the underlying information asymmetries that lead to the local analyst advantage also contribute to the home bias.

returns. They find lower forecasting quality for most affiliations compared to 6-month ahead predictions.

Veress and Kaiser (2017) find that economists fulfilling a public mission (academics, Fed and government employees) demonstrate a tendency towards being pessimistic, whereas bankers in general are overly optimistic about future stock-market developments. They show that these characteristics are of particular relevance and statistically significant during economic recessions and stock market downturns. Whilst investment bankers have always shown a tendency towards being optimistic, other affiliations are increasingly following their footsteps and most dominantly so for short-term forecasts. Especially during the GFC, their expectations of fast rebounds remained largely unsatisfied.

Our research questions relating to expert forecasts about US inflation and Fed fund rates to personal and institutional characteristics are multiple. Due to the importance of expert forecasts in portfolio management, various investment decisions (i.e., not only from firms) and monetary policy in general, and financial stability in particular, we examine the courage and instability of the expert forecasts in addition to its forecasting performance (quality) through various panel estimations.

The existence, or absence, of expert personal and institutional characteristics influencing the quality, courage or volatility of the expert forecasts are relevant to financial stability monitoring and its vulnerability. The RMSE (quality), median deviation (courage), and volatility (instability) of expert forecasts are estimated as a function of their gender, education (field, place, ranking and level), experience (the one as an active expert, type and place), and affiliation (type and place).

We also identify experts who predicted the *difficult* US inflation and Fed fund rates cases–i.e., provided predictions different from the consensus of experts when this consensus failed. Competent experts are thus identified against follower ones. Which characteristics make the expert more *courageous*?

Besides, we determine which characteristics led to more volatile forecasts. Indeed, economic and financial decisions based on volatile forecasts, thus generating more surprises, should increase market and economic (implied) volatility, thus instability by reflecting uncertainty which therefore sharpens exogenous shocks. Beyond the financial effects, real effects are expected due to the global rational behavior of economic agents to change their economic decisions for less risky (or more protected, thus involving additional costs to hedge their decisions) ones during such a period. More protected–less risky–economic decisions and changing economic agent behaviors under uncertainty periods finally mean less yield.

As the GFC played a significant role in shaping economic behaviors, including expert ones, we test our research questions over the full sample (two last decades), pre- and post-GFC subsamples to catch potential expert forecast changes and their changed relation to the characteristics above described.

Our study contributes to the exciting debate in cognitive sciences and behavioral economics about the role of education, its level, field, and quality of expert behaviors. It also contributes to the debates in human resources about how experience within or between institution types matters in terms of forecasting performance, courage, or volatility.

The remainder of the paper is organized as follows. Section 2 describes a simplistic theoretical model embedding our research question and justifying its intuition. Section 3 presents the methodologies used to obtain our datasets and empirical results presented in Section 4. Section 5 provides an interpretation of the results which lead to some policy implications presented in Section 6. Section 7 presents the concluding remarks, and Section 7 presents some robustness checks.

2 Model

As we assume that only institutions use expert forecasts to shape their economic decisions, each institution i should minimizes a specific and simple loss function, denoted by $\mathcal{L}_{t,i}$, to fulfill their respective objectives.

For instance, a central bank (cb) minimizes a simple loss function such as

$$\mathcal{L}_{t,cb} = \left(\pi^* - \mathbb{E}^e_{t-1}\left[\pi_t\right]\right)^2 \tag{1}$$

where π_t is the inflation rate in period t, $\mathbb{E}^e_{t-1}\left[\pi_t\right]$ the expected inflation in t knowing the full information set until $t-1$, and π^* the inflation target (central bank objective).

The interest rate forecasts are also key for the central bank credibility, a central bank surprising the expected central bank interest rate path cannot be reliable. Consequently, we can assume that another simple central bank credibility (ccb) loss function can be expressed as

$$\mathcal{L}_{t,ccb} = \left(r_t - \mathbb{E}^e_{t-1}\left[r_t\right]\right)^2 \tag{2}$$

where r_t is the central bank interest rate rate in period t, $\mathbb{E}^e_{t-1}\left[r_t\right]$ the central bank expected interest rate in t knowing the full information set until $t-1$.

Both inflation and interest rates expectations could affect the central bank losses.

A private institution ($firm$) maximizes its benefits, which is translated through the following loss function

$$\mathcal{L}_{t,firm} = c_t - s_t \tag{3}$$

where $\forall u \in \{s, c\}$, $x_t = f_x\left(L_{t,\pi}, L_{t,r}, O_{t,x}\right)$ represents the sales (s) and costs (c) of the firm at time t. Both sales and costs are dependent of US inflation expectation losses, $L_{t,\pi} = \left(\pi_t - \mathbb{E}^e_{t-1}\left[\pi_t\right]\right)^2$, and Fed fund rate expectation losses, $L_{t,r} = \left(r_t - \mathbb{E}^e_{t-1}\left[r_t\right]\right)^2$. $O_{t,s}$ and $O_{t,c}$ are the sales and costs independent from $L_{t,\pi}$ and $L_{t,r}$, respectively.

In both settings, the expert provides $\mathbb{E}^e_{t-1}\left[r_t\right]$ and $\mathbb{E}^e_{t-1}\left[r_t\right]$. In other words, the expert forecasts in $t-1$ the US inflation and Fed fund rates that should prevail in t.

$\forall x \in \{\pi, r\}$, $\mathbb{E}^e_{t-1}\left[x_t\right]$ crucially depends on the performance and courage of the expert. The volatility of the expert forecast provides an additional (second order) layer to this theoretical framework by penalizing these loss function for volatile forecasts.

Our aim is to assess the characteristics influencing $\mathcal{L}_{t,i} = F_i\left(L_{t,\pi}, L_{t,r}, O_{t,c}, O_{t,s}\right)$. Given the available data described in Section 3.1, we assume that $L_{t,\pi}$ and $L_{t,r}$ dynamics depend on institutional and personal characteristics rather than time effect like a crisis, business cycles and other time-related phenomena that could affect this assumption.

$\forall x \in \{\pi, r\}$, the main measure influencing $L_{t,x}$ is the standard expert-specific forecasting performance measured as the RMSE and presented in Eq. 4. However, each expert could be tempted to follow each other in order to avoid deviating from the consensus–measured as the median of the forecasts at each time-period t (see Eq. 5). Among the fact that $L_{t,x}$ is influenced by followers and courageous experts, decision makers are particularly attentive to any information or characteristics influencing this behavior (herding). Some of these decision makers, like policymakers or government, prefer to rely on credible and stable forecasts to build economic scenarios and justify their decisions. Hence, volatile expert forecasts affect the second-order of the previous loss functions leading these decision makers to monitor the expert forecast instability (see Eq. 6).

Does the Fed decide with respect to expert forecasts ? No one (can) knows the answer, the true one at least. Yet, a simple exercise can led us to such an assumption: the Fed strongly takes into account the expert forecasts since the GFC, among other indicators, in their decision and communication processes. The Federal Open Market Committee (FOMC) Meeting Minutes details the record of the committee's policy-setting meeting held and offer detailed insights regarding the FOMC's stance on monetary policy. They mention the word "forecaster" only 6 times over the pre-GFC decade (88 minutes) while it is 4 times more over the post-GFC decade (25 times over 82 minutes). The word "survey" does not appear over the pre-GFC decade interest rate announcements while it appears 29 times over the pre-GFC decade. The governor speeches are more spectacular. The word "forecaster" appeared only 8 times in the 216 pre-GFC governor speeches during the pre-GFC decade. However, it appeared 58 times in only 160 governor speeches over the post-GFC decade–it is almost 10 times more than during the pre-GFC decade.

3 Methodology

3.1 Data

Our databases are constructed through manual and automated procedures. For the database of forecasts, most of the data, including the name and the affiliation of the experts, come from Bloomberg. Although most of the collecting procedure was automated, some manual checking and adjustments were processed to make this database readable from any econometric software.

For the database of the characteristics, we scrapped automatically and manually LinkedIn and other websites collecting personal information of experts. As this process cannot be perfect (the internet still not collect all the required information for all our experts), a substantial amount of adjustment was made manually to complete missing information. Some of these information were collected after manually reading CV or biographies available on the internet.

In essence, the data we collected about experts concerns around 480 experts and 440 institutions that published at least one time a forecast about inflation or Fed fund rates.

For each expert, we collected data about crucial characteristics of an expert forecast such as its experience (type and time), gender, education (level, type, and quality), and affiliation (type and place).

The collected experience data indicate the type of accumulated working experience, considering the experience in academia, a central bank, and financial institution. Other collected personal data indicate the gender (assuming only male and female possibilities) and education of each expert. The level (Bachelor, Master, Ph.D. diploma or other), the field (economics, finance, both or other) and the Shanghai ranking of the corresponding institution of the highest diploma.[3]

Although we classified these diplomas for three different rankings (General, Economics and Finance), we only rely on the two most popular Shanghai University Rankings, General and Economics. The Shanghai University Ranking in Finance is, unfortunately too small to become useful in our study.

The data about the affiliation of the expert describe the type of institution and its main localization. Although we built a deep database separating several relevant hosting institution types,[4] we rely only upon the simple (and more relevant) difference between private financial, academic, monetary institutions.

Concerning the Bloomberg expert forecasts, each expert can send its forecasts about the US CPI inflation and Fed fund rates to Bloomberg until several days before the publication of the effective corresponding data.[5] We assume that an expert not updating its forecasts according to additional information received before the publication of the effective data is not rational. Consequently, all the expert forecasts we collected are the best ones for each forecaster.

3.2 Dependent variable

The variables under study, dependent variables, are defined in this section. Although we studied various dependent variables, we choose to focus on three key behaviors related to forecasters.

The first one is the most popular measure of performance, RMSE. The loss function representing the **performance** dependent variable (p) is

$$L_{i,t}^{p} = \left(x_t - \mathbb{E}_{t-1}^{i}\left[x_t\right]\right)^2 \tag{4}$$

where i is the specific forecaster.

The second *loss* function representing the **courage** of the forecaster (c), its

[3] In details, we also collected the exact name of each most important diploma earned by each expert.

[4] Retail, investment, or private bank, insurance, economic and financial analysis, fund, loan, investment management, brokerage, credit union, savings, academia, a central bank, and others.

[5] The ability for a forecaster, recognized as an expert forecast by Bloomberg, to communicate (and update) through Bloomberg its forecasts exists for almost all countries and all macroeconomic variables of interest for the Bloomberg users (traders, brokers, analysts, governement, policy institutions etc.) according to the countru-specific supply from expert forecasts. Obviously, the US expert forecasts are the richer dataset, in terms of both historical and amount of experts, currently available.

ability to publish forecasts different from the consensus measured by the median over all expert forecasts, is

$$L_{i,t}^{c} = \left(m\left(x_{i,t}\right) - \mathbb{E}_{t-1}^{i}\left[x_t\right]\right)^2 \tag{5}$$

where $m\left(x_{i,t}\right)$ represents the median over all the published forecasts i by each forecaster at time t.

The third loss function represents the **instability** of the expert forecasts (v) and is measured by the volatility of the forecasts

$$L_{i,t}^{v} = \left(\Delta\mathbb{E}_{t-1}^{i}\left[x_t\right]\right)^2 \tag{6}$$

where Δ is the standard delta shift-equivariant linear operator.

3.3 Survival

How likely will an expert submit another forecast in the future based on the current (and past) performance? The model is specified as the proportional hazards model, i.e., high coefficients imply a high chance of being removed from the sample (i.e., not providing another forecast).

This hazard model predicts the risk of being removed from the sample. For most applications, the term removed relates to death, but in our case, it mostly relates to being fired, retired (or forced to), or transferred in another job.

The hazard function is $h = \lambda_t \exp\left(\beta X\right)$ where the vector X contains the explanatory variables and β the coefficient vector. The time-specific risk can be captured by λ_t while β represents the risk of the X factors.

The probability for the event (remove) is proportional to $\exp\left(\beta X\right)$, which is why both the coefficient and its exponent are reported. A positive coefficient means a higher risk to be removed from the sample. We compute the z-value which is similar to popular t-stat, and $\Pr\left(> |z|\right)$ is the p-value (low means significant). All our detailed quantitative results are available upon request.

We explain the hazard mostly through the past forecast performance. Raw is the last periods' performance, MA5 a five-period moving average (backward looking) and wMA5 a weighted moving average where most recent periods have a higher weight. Positive coefficients mean that high errors correspond to an increased risk to be removed from the sample.

3.4 Cross section

Although we include forecaster and institutional controls in the panel model without fixed effects, we focus on a simple *between* model for the assessment of those effects. However, instead of looking at raw average forecast performance, we first adjust forecast performance for its period average.[6] Since the number of forecasts provided by different forecasters differs hugely, and the average performance is thus subject to different degrees of uncertainty, we use a weighted least squares approach in this estimation.

Although we could process the empirical tests related to this methodology easily, the low theoretical and empirical relevance of these results, coupled with the sake of simplicity, incited us not to present them in this paper. However, the detailed results are available upon request.

3.5 Panel

To assess the role of experience, we run several simple panel regressions. In all those regressions, we include time fixed effects to control for the possibility of time-varying uncertainty in our sample period.

However, the inclusion of time fixed effects comes at a cost. When we also control for expert fixed effects in order to allow persistent differences in quality, the effect of simple linear measures of experience (that increase by a constant amount each month) is no longer identified.

Consequently, we follow two different approaches to identify the impact of the experience.

First, we focus on a measure of experience that is based on the number of forecasts provided by a single expert. This regression does not allow any inference regarding job experience (or economic expertise) in general but focuses on the specific type of knowledge required to provide accurate forecasts accumulated on the job. Since the frequency of forecast differs quite dramatically between experts, the effect of the *forecast-count*–the total number of previously provided forecasts–is still identified even though both time and fixed effects are included.

Second, we consider a model without fixed effects. Given that there is some competition between forecasting institutions that should erode persistent quality differentials, this model has some plausibility in particular for forecasts provided by private institutions. We now can test for the impact of total job experience (or experience in a specific profession) measured in months (rather than the

[6] This is equivalent to using the residuals from a panel regression that uses time fixed effects as only regressors.

number of forecasts provided). Since we do no longer include fixed effects, we do, however, have to control for the initial experience which is obtained from CV data for all experts. Additionally, we add a range of nontime-varying, expert, and institution-specific controls.

Our canonical panel estimation model is

$$y_{i,t} = x'_{i,t}\beta + \alpha_i + \theta_t + \varepsilon_{i,t} \tag{7}$$

where the individual effect is α_i, and θ_t represents the time effect. This model is considered as a *two-way* model if both individual and time effects are present. Thus, α_i captures effects that are specific to some panel unit but constant over time, whereas θ_t captures effects that are specific to some time-period but constant over panel units.

4 Results

This section presents the quantitative results of our survival (Section 4.1) and panel analyses (Section 4.2).

4.1 Survival estimation

4.1.1 Inflation

Table 1 presents the survival estimates for US CPI experts. Positive significant coefficients in this table show that a high dependent variable (Raw, MA5, wMA5) increases risk to be removed.

Table 1 shows that a low inflation past performance (MA5) increases the probability to be removed. It also shows that having an economics education strongly immunizes the expert from being removed after low forecasting performances or courageous forecasts.[7] This result is less significant for instable experts. Interestingly, a finance education does not protect the expert from being removed as being graduated in economics.

Being graduated from a top-ranked university (general ranking) significantly immunizes the expert from low forecasting performances and courageous forecasts, but this characteristic does not significantly influence instable experts.

[7] The presented results use the exact partial likelihood. Under the Breslow and Chatterjee (1999) approximation, a low past performance in forecasting inflation (MA5) increases the probability to be removed. See Appendix A.1 for robustness checks presenting the same estimation without interactions. It appears that working in a financial institution protects experts providing volatile forecasts from being removed.

	Performance			Courage			Instability		
	Raw	MA5	wMA5	Raw	MA5	wMA5	Raw	MA5	wMA5
Dependent variable	1.299	5.005*	3.340	0.3835	4.4247	3.3218	0.3375	-0.697	0.1417
Local expert	-0.3238	-0.293	-0.303	-0.3375	-0.3375	-0.3374	-0.0089	-0.0081	-0.0183
Local institution	-0.1721	-0.1852	-0.1818	-0.1582	-0.1748	-0.1649	-0.7644	-0.7845*	-0.7598
Financial institution	-0.4699	-0.4663	-0.469	-0.4304	-0.4228	-0.4311	-0.573	-0.565	-0.5686
Experience in central bank	0.0191	0.0277	0.023	0.0139	0.029	0.0308	-0.2306	-0.2205	-0.2223
Experience in academia	0.374	0.3782	0.3805	0.3631	0.3591	0.3665	0.6278	0.6055	0.6189
Gender	0.1513	0.1845	0.1652	0.1488	0.1524	0.1433	0.0746	0.0714	0.0673
Master	-0.0583	-0.0792	-0.0658	-0.0425	-0.0377	-0.0396	0.0808	0.1012	0.0726
Ph.D.	-0.3097	-0.5317	-0.3516	-0.282	-0.3561	-0.306	0.1972	0.1901	0.192
Economics education	-1.2882**	-1.2396**	-1.2135*	-1.3373**	-1.3039**	-1.2981**	-1.4958*	-1.5143*	-1.4889*
Finance education	-1.0154	-0.9737	-0.9379	-1.0906*	-1.0577	-1.0546	-1.1564	-1.1779	-1.1407
Economics and finance education	0.6904	0.7965	0.7727	0.649	0.7016	0.7031	17.8835	17.866	17.8749
Shanghai Ranking : Economics	0.3899	0.4218	0.4095	0.3962	0.4048	0.3996	0.6235*	0.616*	0.621*
Shanghai Ranking : General	-0.2918**	-0.289**	-0.2906**	-0.2897**	-0.2863**	-0.288**	-0.1195	-0.1076	-0.1144
Financial institution and economics education	-0.0872	-0.1078	-0.0947	-0.1005	-0.1118	-0.1026	-0.4304	-0.4358	-0.4308
Ph.D. in economics	0.1403	0.3594	0.1868	0.1187	0.2037	0.147	0.0575	0.1002	0.0554

Table 1: Survival estimates for US CPI experts.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Raw stands for the last periods performance, MA5 for five-period moving average (backward looking) and wMA5 for weighted moving average where the most recent periods have a higher weight.

4.1.2 Interest rate

Table 2 presents the survival estimates for Fed fund experts. Here again positive significant coefficients show that a high dependent variable increases risk to be removed.

Table 1 shows that the most significant result concerns the forecasters graduated in economics and affiliated to a financial institution that increases there probability to be removed for any behavior. However, this result should be balanced with the financial affiliation only that lead, at least for non-performing and courageous experts, to decrease the probability to be removed. Nevertheless, being graduated in finance increases the probability to be removed in almost all expert behaviors, while the probability is higher (almost twice more than for low performance and courage) in the case of volatile forecasts.

4.2 Panel estimation analysis

4.2.1 Inflation

Table 3 presents the panel estimations for the US inflation expert forecasts with time fixed effects.

Table 3 shows that the over the full sample, experience, localization (local), institution type (financial) and education (top university in economics) significantly contribute to increasing the expert performance while having a Ph.D. contributes to affect its forecasting performance (RMSE).

The results before and after the GFC are different. Before the GFC, working in a local or financial institution improved expert forecasting performance more than having experience in a central bank. However, this results is balanced by the interaction showing that working at a local and financial institution decreases the expert forecasting quality (but the global effect is still in favor of the positive impact on the performance of these effects). Interestingly, only the general university ranking contributed to better forecasting performance while after the GFC and over the full sample, the field-specific university ranking in economics was impactful. However, these results are also balanced by the interaction showing that working at a financial institution and being graduated from a top university in economics could increase your forecasting errors. Being a man seems to improve the forecasting quality before the GFC. Our interpretation will develop more in-depth this result (Section 5).

The results about expert courage display a radical and probably structural change in the expert behavior between our two subsamples. While working at

	Performance			Courage			Instability		
	Raw	MA5	wMA5	Raw	MA5	wMA5	Raw	MA5	wMA5
Dependent variable	-3.3195	-6.0839	-5.7772	-0.538	-2.3844	-1.1666	-1.0204	-3.1607	-1.9377
Local expert	0.1388	0.1371	0.1359	0.1643	0.1627	0.1655	0.243	0.2303	0.2404
Local institution	-0.2959	-0.2865	-0.2881	-0.2599	-0.2561	-0.2596	-0.4521*	-0.4387*	-0.4475*
Financial institution	-0.5152**	-0.5181**	-0.5178**	-0.4179**	-0.418**	-0.4187**	-0.3244	-0.3228	-0.3231
Experience in central bank	0.2483	0.2501	0.2491	0.2084	0.2089	0.2078	0.2456	0.2601	0.2517
Experience in academia	0.1683	0.1662	0.1674	0.1562	0.1549	0.1565	0.1999	0.1784	0.1965
Gender	0.0346	0.0334	0.0327	0.0349	0.0335	0.0355	-0.0125	0.0006	-0.0114
Master	-0.1189	-0.1264	-0.1237	-0.0354	-0.0371	-0.0351	0.1075	0.1196	0.1099
Ph.D.	-0.5721	-0.5805	-0.5787	-0.4324	-0.438	-0.4345	-0.2392	-0.2342	-0.2413
Economics education	-0.5294*	-0.5292*	-0.5325*	-0.4439*	-0.4484*	-0.4456*	0.0573	0.0734	0.0655
Finance education	0.6487**	0.6535**	0.6504**	0.6198***	0.6185***	0.6195***	1.1876***	1.1923***	1.1927***
Economics and finance education	0.6705	0.6875	0.6755	0.6724*	0.6704*	0.6721*	0.7987	0.8418	0.8156
Shanghai Ranking : Economics	-0.2593**	-0.2594**	-0.2585*	-0.1954*	-0.1952*	-0.195*	-0.2075	-0.2112	-0.2069
Shanghai Ranking : General	-0.0759	-0.0766	-0.0758	-0.0852	-0.0845	-0.0854	-0.0934	-0.0848	-0.0927
Financial institution and economics education	0.5175***	0.5192***	0.5193***	0.4268***	0.4259***	0.4277***	0.5305***	0.5108**	0.5256***
Ph.D. in economics	0.4957	0.4978	0.499	0.393	0.3965	0.3955	0.1595	0.1518	0.1618

Table 2: Survival estimates for Fed fund rates experts.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Raw stands for the last periods performance, MA5 for five-period moving average (backward looking) and wMA5 for weighted moving average where the most recent periods have a higher weight.

	Performance			Courage			Instability		
	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC
Experience as an expert	-0.0003***	-0.0008	-0.0004***	-0.0001***	0.0002	-0.0001***	-0.0047***	-0.0101	-0.0052***
Local expert	-0.0153***	-0.0287	-0.0175***	-0.0026*	-0.0165	-0.0033**	-0.0817**	0.2455	-0.1051***
Local institution	-0.0019	-0.0455**	0.008	-0.0018	-0.0239*	0.0029	0.0595	-0.2417	0.1314
Financial institution	-0.018***	-0.0927***	-0.0112*	-0.0053**	-0.0469***	-0.0022	-0.018	-0.3319	0.0056
Experience in central bank	-0.018***	-0.0298*	-0.0169***	-0.0077***	-0.0147	-0.0063***	-0.1499***	0.1049	-0.174***
Experience in academia	-0.0052	-0.0052	-0.0059	-0.0033**	-0.0013	-0.004***	-0.0486	0.3957**	-0.0668
Gender	0.0006	0.0543***	-0.0128	0.0098**	0.0345***	0.001	-0.2561	0.0287	-0.3233
Master	0.024	0.0056	0.0303	0.0244***	0.0106	0.0229	0.1331	0.1406	0.057
Ph.D.	0.0612**	0.0033	0.0686	0.0337***	-0.0298	0.0445***	0.1596	0.102	-0.0373
Economics education	0.0147	0.0351	0.0245	0.0171**	0.018	0.0187	0.2071	-0.1044	0.1364
Finance education	-0.0067	-0.0011	-0.0062	-0.0099***	0.0034	-0.0103***	0.0313	-0.0406	0.047
Economics and finance education	-0.0233	-0.0025	-0.0213	-0.0208**	0.0005	-0.0162	0.0283	0.1589	-0.3618
Shanghai Ranking : Economics	-0.0184***	-0.0177	-0.0205***	-0.0041***	-0.0055	-0.005***	-0.1011**	-0.4624*	-0.1212***
Shanghai Ranking : General	0.0008	-0.0166**	0.001	0	-0.0092**	0.0002	0.023	0.1505	0.0189
Interactions									
Master in Economics	-0.0214	-0.0139	-0.0313	-0.0244***	-0.0067	-0.0256*	-0.0963	0.131	-0.0173
Ph.D. in Economics	-0.0633**	-0.044	-0.0697	-0.0375***	0.008	-0.0479***	-0.0674	0.1103	0.1314
Local financial institution	0.0117	0.1012***	-0.0006	0.0066**	0.0589***	0.0005	-0.058	0.202	-0.1285
Experience with a Master	-0.0001	-0.0001	0	-0.0001*	-0.0008	0	0.0007	0.0099	0.0008
Ranked university in a financial institution	0.0133***	0.0302*	0.0136***	0.0031*	0.016	0.0032*	0.028	0.3564	0.0392
Experience and gender	0.004	-0.0124	0.0083*	-0.0012	-0.0087	0.0012	0.1077**	-0.0751	0.1312**
Observations	3115	363	2752	3115	363	2752	2672	229	2443
Adjusted R^2	0.041	0.0954	0.0465	0.0292	0.105	0.0307	0.0298	0.0039	0.0334

Table 3: Panel estimates for the US CPI expert forecasts with time fixed effect.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

a financial institution led to less courage before the GFC, working at a local financial institution led to more courage. With gender and university ranking, no other characteristics seem to have been played a role in the expert courage before the GFC. The picture drastically changed after the GFC. Being an experienced expert in forecasting, in academia or a central bank, living in the US (local), having a financial education and being graduated from a top university in economics led to less courageous experts. More specifically, having a Ph.D. in economics led to substantially less courageous experts, twice less than having a master in economics. This is compensated by the fact that having a Ph.D., whatever the field, led to more courageous expert forecasts.

The results about instability are also very insightful. Having experience in academia led to more volatile forecasts before the GFC. However, experience as an active forecaster, or in a central bank, the localization (local) or the field-specific (economics) university ranking led to significantly less volatile forecasts after the GFC. Interestingly, being a woman and having experience led to more volatile forecasts after the GFC (and over the full sample).

Note that substantial trade-offs occurred between the periods for all our loss functions, indicating that the GFC significantly influenced the expert behavior.

4.2.2 Interest rate

Table 4 presents the panel estimations for the Fed fund rates expert forecasts with time fixed effects.

Table 3 shows that over the full and all subsamples, experience as a forecaster significantly improve the Fed fund rates forecasts. However, working in a US institution affects these expert forecasts after the GFC–while it is a bit balanced by the financial and local institution interaction. After the GFC, having experience in academia led to better expert forecasts. Besides, getting a master or a Ph.D. also led to better forecasts. Interestingly, having a Ph.D. from a top-ranked university led to lower forecasting performance after the GFC compared to before the latter. Over the full sample, only experience as a forecaster or experience in academia characteristics significantly improved expert forecasts.

Over the full sample, the expert courage was mainly influenced by its education. Being Ph.D. graduated led to opposite influences on the expert courage depending if the expert was Ph.D. graduated in a top-ranked university or not. Whatever over the full sample or after the GFC, the compensation between the Ph.D. characteristic and its interaction with a ranked university led to the conclusion that overall, an expert having a Ph.D. is generally less courageous (in his

	Performance			Courage			Instability		
	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC
Experience as an expert	-0.0001***	-0.0001***	-0.0001***	0***	-0.0001***	0***	-0.0003***	-0.0001	-0.0002***
Local expert	0.0003	0.0005	0.0005	0.0003	0.0009	0.0003	0.0024	-0.0005	0.0038
Local institution	0.0026*	-0.0002	0.0038**	0.0013	-0.0016	0.0031**	0.0106	0.0025	0.0134
Financial institution	0.0009	-0.0017	0.0019	0.0006	-0.0017	0.0016	0.0062	-0.0023	0.0066
Experience in central bank	0.0012	0.0017	0.001	0.0006	0.0007	0.0012	0.0087**	0.007	0.0076
Experience in academia	-0.0016**	-0.0005	-0.0021**	-0.0008	-0.0002	-0.0012	-0.0108***	-0.004	-0.0126*
Gender	-0.0004	0.0011	-0.0016	0.0001	0.0019*	-0.0013	-0.0025	0.0094*	-0.0137
Master	-0.0024	-0.0001	-0.0048***	-0.0019*	-0.0009	-0.0037**	-0.0154**	0.0061	-0.0336***
Ph.D.	-0.0017	0.0008	-0.0047***	-0.0021**	-0.0006	-0.0043***	-0.0117*	0.0038	-0.0293***
Economics education	-0.0016	-0.0001	-0.0029*	-0.0009	0.002*	-0.0036***	-0.0008	-0.0021	-0.0035
Finance education	-0.0002	-0.0005	0.0006	0.0006	0.0021	-0.0003	0.0034	0.0006	0.0036
Shanghai Ranking : General	-0.0001	0.0019	-0.0016*	-0.0007	-0.0004	-0.0012	-0.0055	0.0008	-0.0096*
Interactions									
Master in a ranked university	0.0001	-0.0017	0.0016	0.0004	0.0002	0.0008	0.0068	-0.002	0.0116*
Ph.D. in a ranked university	0.0008	-0.0015	0.0027***	0.0016***	0.0011	0.0023***	0.007*	-0.0016	0.0139**
Financial and local institution	-0.0027*	0	-0.004**	-0.0019	0.0007	-0.0035**	-0.014*	-0.0015	-0.0175
Observations	8113	3970	4143	8113	3970	4143	5793	2826	2967
Adjusted R^2	0.008	0.0047	0.0076	0.005	0.0059	0.0075	0.0073	0.0018	0.0034

Table 4: Panel estimates for the Fed fund rate expert forecasts with time fixed effect.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

forecasts) than without a Ph.D. After the GFC, it appears that expert education and localization played a significant role in its behavior. Working at a local institution led to more courageous forecasts, but the interaction with a financial institution (i.e., local financial institution) led to less courageous forecasts. Being graduated (Master or Ph.D.), especially in economics, generally, lead to less courageous expert forecasts.

Concerning the volatility of the expert forecasts, experience as a forecaster or in academia appears to reduce this instability, at least over the full sample. Interestingly, before the GFC, almost not characteristic influenced the forecasting volatility of the experts. The picture is more evident after the GFC where experience as a forecaster or graduation (Master of Ph.D.) led to less volatile expert forecasts while having a Ph.D. from a top-ranked university in economics led to more unstable expert forecasts. Here again, the GFC played a key role by changing the expert behaviors in their relationship between their characteristics and expectation formation.

5 Interpretation

Our results indicate that several expert characteristics are of prior importance related to expert behavior: performance, courage, and instability. While in terms of the probability to be removed, educational factors and affiliation are significant. The characteristics are more varied in terms of the panel estimation with time fixed effects. Indeed, the performance of an expert is significantly affected by its experience, its localization, its affiliation, and its education (level and quality) in economics. The forecaster characteristics also influence its herding behavior, which is in line with the literature about financial analysts (Hong et al., 2000).

The GFC changed the forecaster behaviors, and consequently, their characteristics explaining these behaviors changed between the pre- and post-GFC periods. Our interpretation resides in the fact that institutions, mainly US ones, recruited experts with a higher level educational background where the field and quality played an essential role.

The education level did not seem to play a significant role when comparing MA to Ph.D. graduated expert behaviors. However, the experts graduated with a Ph.D. in economics or from a top-ranked university appear to be more courageous but also less performing after the GFC compared to MA graduated experts. We established a clear relationship between performance, courage, and instability, and the educational level and field about economic expert forecasts, a result in line with the recent literature linking cognitive sciences to financial analysts background and behaviors Poore et al. (2014).

The outcomes in many competitive tasks depend upon both skill, including education and experience, environment, including localization and institution type, and luck, and illuminating their relative contributions has long attracted attention in the psychological literature Atkinson (1957). As Clement and Tse (2003) shown, the experience as a forecaster particularly characterizes the expert performance, courage and instability. In addition, we show that other characteristics influence economic experts which are close to the ones identified for financial analysts. Forecasts that deviate widely from the consensus—which is observable by the forecaster—potentially carry career-related rewards but also reputational risks, we find that the expert courage (deviation from consensus) exhibited by forecasters of different skill levels (measured by both past forecasting accuracy and education) in different market conditions increases as the economic state change (pre- and post-GFC periods). A result completely in line with Evgeniou et al. (2013) which also showed that low-skilled financial analysts exhibit larger increases in deviations from consensus than high-skilled analysts. One can interpret our results as a consequence for the high-skilled experts to feel more confident with a high level or quality of education compared to others, changing their professional behaviors and outcomes.

Our finding linking the herding behavior with the institutional type and the education adds a layer to the past debate about how financial institutions and mutual fund managers who lag behind their competitors in a given period have been observed to increase the riskiness of their portfolios in the next period in attempts to outperform competitors Chevalier and Ellison (1999). Similarly, as we have shown with economic expert forecasts, Denrell and Fang (2010) illustrate that non-performing financial analysts make more extreme predictions and, as a result, they conclude that ex-post are overrepresented among those who can see the *next big thing*.

6 Policy implications

The policy implications that could be extracted from the results and interpretations are straightforward. A decision maker, be they a government, policy, or private institution should select the right subsample of experts to focus on their forecasts. Not because on average this strategy could lead to similar forecasting performance or volatility, but also because economic uncertainty (and hence the level of luck in outcomes) could affect most of the expert forecasts in relation to the expert characteristics over several periods.

Specifically, central banks that extensively rely on the expert forecasts for both having a clue about the CPI in the future periods and their ability to surprise the economic agents could build subgroups of relevant forecasters according to their experience, education, and localization. This strategy could be used in parallel (and compared) with the other existing methodologies such as the median and average of expert forecasts. Such use (and comparison) could provide some clues about the perception of agents about their communication or monetary policy, which are key central banks tools Benchimol et al. (2019) and their optimality could depend on behavioral or cognitive biases Benchimol and Bounader (2018).

Private institutions can also use our results for their management and human resources purposes. Among the fact that our study allows these institutions to select the best candidates among their characteristics for a targeted profession, economic forecaster, the localization and environment these (financial) institutions provide is essential for their future outcomes and reputation related to these forecasting outcomes.

7 Conclusion

TBD

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Appendix

A Robustness checks

A.1 Inflation

Table 5 presents the survival estimates for US CPI experts without interactions.

Table 5 shows that providing volatile forecasts from a financial institution decreases the probability of being removed while coming from academia increases the probability of being removed if the expert provides such forecasts. Interestingly, being graduated in economics significantly reduces the probability to be removed, whatever the expert forecasting behavior. Having a finance education protects from being removed the courageous experts, but this result is less significant for non-performing or instable forecasters.

Table 6 presents the panel estimations for the US CPI inflation expert forecasts with time fixed effects but without interactions.

Table 6 shows that our conclusions drawn in Section 4.2 hold and are mostly not dependant of the interactions.

A.2 Interest rate

Table 7 presents the survival estimates for the Fed fund rates experts without interactions.

Table 7 shows that the most significant result concerns the economics education that seems to protect the low performance and highly courageous Fed fund rate experts from being removed. However, being courageous or volatile forecaster increase the probability to be removed.

Table 8 presents the panel estimations for the Fed fund rates expert forecasts with time fixed effects but without interactions.

Table 8 also shows that our conclusions drawn in Section 4.2 hold and are mostly not dependant of the interactions.

	Performance			Courage			Instability		
	Raw	MA5	wMA5	Raw	MA5	wMA5	Raw	MA5	wMA5
Dependent variable	0.6346	4.3103	2.4521	-0.0947	4.0153	2.4698	0.3062	-0.716	0.0959
Local expert	-0.4785	-0.4655	-0.466	-0.4808	-0.4852	-0.4821	-0.1295	-0.1226	-0.138
Local institution	-0.0631	-0.0554	-0.0658	-0.056	-0.0611	-0.0579	-0.5869	-0.6095	-0.583
Financial institution	-0.5298	-0.5226	-0.5283	-0.4983	-0.4939	-0.4986	-0.9344***	-0.9295***	-0.9301***
Experience in central bank	0.0642	0.0767	0.0708	0.0599	0.0805	0.0771	-0.1913	-0.1843	-0.1837
Experience in academia	0.3011	0.2913	0.3025	0.2926	0.2897	0.2961	0.6778*	0.6618*	0.6694*
Gender	0.237	0.264	0.2465	0.2327	0.2309	0.2265	0.1483	0.1405	0.1413
Master	0.0554	0.0441	0.0518	0.0684	0.0732	0.0705	0.1399	0.161	0.1315
Ph.D.	-0.2391	-0.2476	-0.2366	-0.2273	-0.2188	-0.2233	0.1131	0.1503	0.1064
Economics education	-1.304***	-1.2166***	-1.2404***	-1.3271***	-1.2837***	-1.2953***	-1.6353***	-1.648***	-1.6295***
Finance education	-1.1326**	-1.0516*	-1.066*	-1.1877**	-1.1442**	-1.1562**	-1.3403*	-1.3611*	-1.3284*
Shanghai Ranking : General	-0.1812	-0.1732	-0.1754	-0.1778	-0.1738	-0.1752	0.0184	0.0275	0.0219

Table 5: Survival estimates for US CPI experts.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Raw stands for the last periods performance, MA5 for five-period moving average (backward looking) and wMA5 for weighted moving average where the most recent periods have a higher weight.

	Performance			Courage			Instability		
	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC
Experience as an expert	-0.0003***	-0.0015***	-0.0004***	-0.0001***	-0.0008***	-0.0001***	-0.0039***	-0.0036	-0.0043***
Local expert	-0.0135***	0.0069	-0.0156***	-0.0028*	0.0022	-0.0028**	-0.0696*	0.2909*	-0.0906**
Local institution	0.005	0.0037	0.0044	0.0036**	0.0079	0.0026*	-0.0017	-0.1423	0.0058
Financial institution	-0.0023	-0.0096	-0.001	0.0001	-0.0018	0.0003	-0.0242	-0.0179	-0.026
Experience in central bank	-0.0173***	-0.03**	-0.016***	-0.0074***	-0.0145*	-0.006***	-0.1503***	0.0324	-0.1781***
Experience in academia	-0.0062*	-0.0038	-0.007*	-0.0036**	-0.0003	-0.0041***	-0.0471	0.3173**	-0.0641
Gender	0.0108***	0.0154	0.014***	0.0044***	0.0099	0.0046***	0.1063**	-0.1154	0.1493***
Master	0.0012	0.0067	0.0009	-0.0014	0.0073	-0.0025	0.0866*	0.2516	0.0931*
Ph.D.	0	-0.0275	0.0016	-0.0033*	-0.0161	-0.0026	0.1115**	0.1234	0.1155**
Economics education	-0.005	0.0487*	-0.0081	-0.0038	0.027*	-0.0074**	0.1321	0.1344	0.1274
Finance education	-0.0059	0.029	-0.0084	-0.0069*	0.0183	-0.0109***	0.0473	0.0022	0.0554
Economics and finance education	0.0064	0.0459	-0.0214	-0.0094	0.01	-0.0163	0.0534	0.2892	-0.3398
Shanghai Ranking : Economics	-0.0064***	0.0065	-0.0083***	-0.0015**	0.0052	-0.002***	-0.072***	-0.1292*	-0.081***
Shanghai Ranking : General	0	-0.025***	0.0007	-0.0002	-0.0136***	0.0001	0.0264	0.0868	0.0247
Observations	3115	363	2752	3115	363	2752	2672	229	2443
Adjusted R^2	0.0356	0.0564	0.0428	0.0235	0.063	0.0286	0.0292	0.0067	0.0323

Table 6: Panel estimates for the US CPI expert forecasts with time fixed effect and without interactions.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Performance			Courage			Instability		
	Raw	MA5	wMA5	Raw	MA5	wMA5	Raw	MA5	wMA5
Dependent variable	-3.1248	-5.0781	-5.1018	-0.2209	-1.03	-0.5489	-0.3029	-2.545	-0.9284
Local expert	0.0752	0.0731	0.072	0.0897	0.0893	0.0907	0.1378	0.1376	0.1384
Local institution	-0.2728	-0.2659	-0.2665	-0.242	-0.2405	-0.2425	-0.4404*	-0.4279*	-0.4372*
Financial institution	0.0379	0.0363	0.0367	0.0256	0.0254	0.0253	0.1899	0.1894	0.1922
Experience in central bank	0.2469	0.2482	0.2471	0.2199	0.2201	0.2194	0.2502	0.2638	0.2531
Experience in academia	0.2134	0.2113	0.2123	0.1952	0.195	0.1955	0.1889	0.1881	0.1923
Gender	0.0626	0.0618	0.0619	0.0775	0.0769	0.079	0.0813	0.0798	0.0789
Master	-0.0922	-0.0973	-0.0958	-0.0244	-0.0251	-0.024	0.181	0.1868	0.1815
Ph.D.	-0.2266	-0.2307	-0.2297	-0.1526	-0.1537	-0.1527	-0.111	-0.1086	-0.1103
Economics education	-0.5648***	-0.5664***	-0.5674***	-0.4744***	-0.4756***	-0.4747***	-0.028	-0.016	-0.0236
Finance education	0.4136*	0.4137*	0.4129*	0.4515*	0.4514*	0.4516*	0.9385***	0.95***	0.9422***
Shanghai Ranking : General	-0.0857	-0.0859	-0.0851	-0.0816	-0.0814	-0.0817	-0.0849	-0.0835	-0.0857

Table 7: Survival estimates for Fed fund rates experts.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Raw stands for the last periods performance, MA5 for five-period moving average (backward looking) and wMA5 for weighted moving average where the most recent periods have a higher weight.

	Performance			Courage			Instability		
	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC	Full sample	Pre-GFC	Post-GFC
Experience as an expert	-0,0001***	-0,0001***	-0,0001***	0***	-0,0001***	0***	-0,0003***	-0,0001	-0,0002***
Local expert	0,0001	0,0004	-0,0001	0,0004	0,0011	-0,0001	0,0014	-0.0007	0.001
Local institution	0.0006	-0.0003	0.0016	0	-0.001	0.0011	0.0018	0.001	0.0052
Financial institution	-0.0012*	-0.0017	-0.001	-0.0008*	-0.001	-0.0009	-0.0039	-0.0035	-0.0055
Experience in central bank	0.0009	0.0017	0.0005	0.0002	0.0004	0.0007	0.0075*	0.0069*	0.0055
Experience in academia	-0.0016**	-0.0005	-0.0019*	-0.0007	-0.0002	-0.0011	-0.0104***	-0.004	-0.0117*
Gender	-0.0003	0.0007	-0.0013	0.0002	0.0017*	-0.0012	-0.0001	0.0091*	-0.0111
Master	-0.0023***	-0.0021	-0.0025**	-0.0015**	-0.0007	-0.0025**	-0.0069	0.0037	-0.0163**
Ph.D.	-0.0009	-0.0008	-0.0016	-0.0005	0.0005	-0.0017	-0.0032	0.0021	-0.0115
Economics education	-0.0014	0.0002	-0.0027*	-0.0007	0.0018*	-0.0032**	-0.0002	-0.0014	-0.0023
Finance education	0	-0.0001	0.0004	0.0007	0.0019	-0.0002	0.003	0.0013	0.0021
Shanghai Ranking : General	0.0003	0.0005	0.0002	0.0001	0.0002	0.0002	0.0004	-0.0007	0.0012
Observations	8113	3970	4143	8113	3970	4143	5793	2826	2967
Adjusted R^2	0.0079	0.0051	0.0061	0.0041	0.006	0.0058	0.0068	0.0008	0.0025

Table 8: Panel estimates for the Fed fund rates expert forecasts with time fixed effect and without interactions.

***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.