Geography or Skills: What Explains Fed Watchers' Forecast Accuracy of US Monetary Policy? *

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Abstract

The paper shows that there is a substantial degree of heterogeneity in the ability of Fed watchers to forecast U.S. monetary policy decisions. Based on a novel database for 268 individual professional forecasters since 1999, the average absolute forecast error of FOMC decisions varies 5 to 10 basis points between the best and worst-performers across the sample. This heterogeneity is found to be related to both the skills of analysts – such as their educational and employment backgrounds – and to geography. In particular, forecasters located in regions which experience more idiosyncratic economic conditions perform worse in anticipating monetary policy. This evidence is indicative that limited attention and heterogeneous priors are present even for anticipating important events such as monetary policy decisions.

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1. Introduction

Over the last two decades, a major evolution has taken place in the world of central banking towards a transparent conduct of monetary policy and away from a monetary policy that had often largely surprised the public. In light of this development, central banks have repeatedly stressed the importance of predictability of their decisions, which has indeed improved remarkably over time (e.g., Poole, Rasche and Thornton 2002; Lange, Sack and Whitesell 2003).

While much of the empirical work has focused on predictability based on the financial market consensus (Kuttner 2001, Hamilton 2007, Gürkaynak, Sack and Swanson 2007), others have documented the role of disagreement and heterogeneity among agents in forecasting monetary policy (Bauer, Eisenbeis, Waggoner and Zha 2006, Swanson 2006). The latter papers suggest that the increasingly transparent monetary policy of the Federal Reserve has not only led to a better prediction by financial markets in general, but is also reflected in more synchronized forecasts of monetary policy decision. Nonetheless, these papers also document that a remarkable degree of disagreement among forecasters about future central bank actions seems to persist.

The literature suggests a number of factors that may generate disagreement among economic forecasters. Hong and Stein (2007), surveying the discussion on financial market forecasting, stress asymmetries in information availability and information processing. An example relating to information availability is the notion of "gradual information flow", where the arrival of information is staggered across agents. Examples relating to information processing include limited attention (where agents neglect or overweight information because of limits in their information processing capabilities) and heterogeneous prior beliefs (where agents receive the same information, yet interpret it differently).[1] Differences in information processing seem of particular importance in the area of monetary policy forecasts, where, as a rule, the relevant macroeconomic information governing central bank decisions, as well as all relevant central bank communication is available to all forecasters.[2]

The present paper focuses on the heterogeneity among forecasters of monetary policy decisions by the U.S. Federal Reserve, and its determinants. The paper is motivated by the fact, as we will show, that such heterogeneity is surprisingly high, even at a very short forecasting horizon. To understand this heterogeneity, we concentrate on forecaster asymmetries in information processing related to skills and geography. Given an abundance of potentially relevant data, a major challenge in forecasting monetary policy decisions is to make an appropriate selection of information and apply proper weights. Limited attention as well as heterogeneous priors can therefore easily generate disagreement. Both mechanisms suggest that *skills* have an important role to play, as better skilled forecasters devote the appropriate attention to the relevant signals, or have priors which more closely reflect the actual FOMC behavior.

[1] Hong, Stein and Yu (2007) develop a model where financial market participants simplify a forecasting problem by selecting a small subset of the available data, and provide empirical support for the model's predictions. Further evidence in favor of limited attention of investors is provided, e.g., in Hirshleifer and Teoh (2003) and Peng and Xiong (2006). Other studies have provided evidence in favor of heterogeneous priors, (e.g., Harris and Raviv 1993, Kandel and Pearson 1995, Diether, Malloy and Scherbina 2002). Focusing on economic forecasting, Mankiw, Reis and Wolfers (2004) provide evidence that the nature of information (in the form of "sticky information") can explain disagreement in surveys of inflation expectations. See D'Amico and Orphanides (2008) for a discussion of the difference between disagreement and uncertainty.

[2] Monetary policy decisions are obviously largely made on the basis of expected future fundamentals. Differences in the ability of analysts to anticipate policy decisions may thus, in part, stem from differences in their ability to forecast future fundamentals. In our terminology, we refer to such differences as differences relating to the processing of information, rather than information asymmetries, since salient information for such forecasts are publicly available, yet analysts may weight and process them differently.

Another important implication is that *geographical location* matters. This is because local information is salient, which, in the presence of limited attention might bias information processing and distract forecasters' attention from other signals. In addition, geographical location could influence priors, for instance, because the salience of local information shapes the analytical framework of forecasters or analysts with certain given skill sets cluster in particular localities. Our paper is also related to the literature on information and geography,[3] including Berger, Ehrmann and Fratzscher (2009), who find evidence that geographic factors play a role for the predictability of ECB monetary policy decisions. The present paper is substantially wider in scope.[4]

The paper uses a novel dataset of 268 professional forecasters – covering many major investment banks, commercial banks and forecasting institutions – who are located across 98 cities in 15 countries, for FOMC decisions between February 1999 and September 2005. The dataset is very rich, containing not only each forecaster's survey expectations for FOMC decisions, but also information about the individual's forecasts of other economic variables, such as inflation and economic activity. Moreover, the data includes information related to analysts' skills, e.g. the type of institution, his or her position within that institution, employment record and educational background. We combine this dataset with information about the economic conditions specific to the region in which each individual is located.

As a key stylized fact, the degree of heterogeneity in the forecast performance across individuals is large: after grouping forecasters by performance over the full sample period, the absolute forecast error by the group of the 10% of the worst forecasters is 5 basis points (b.p.) higher than that of the best decile of analysts, when measured across all FOMC meetings. This difference rises to 10 b.p. when analyzing only those FOMC meetings that had some degree of heterogeneity across forecasters. This is of the same order of magnitude we have found for the heterogeneity of forecasts of ECB monetary policy decisions (Berger, Ehrmann and Fratzscher 2009) and given the frequency of forecasters' participation cannot be the result of pure chance. Interestingly, the observed differences in forecasting ability are mirrored in financial market data: We show that the larger the observed heterogeneity of monetary policy expectations, the higher is financial market volatility.

Next, we find that a significant part of the heterogeneity in forecasting accuracy is systematic. That is, there is compelling empirical evidence that skills *and* geography play a significant and substantial role. As to *geography*, we find that a number of locational factors systematically influence the ability of forecasters to anticipate US monetary policy. For instance, forecasters located in New York City or in other financial centers, either in the USA or abroad, as well as those located in Washington DC, i.e. in immediate proximity of the Board of Governors of the Federal Reserve, perform better on average. Moreover, we find that forecasters take a local perspective in the sense that regional economic developments shape their forecasting ability for US monetary policy. We take this as evidence that salience of information is an important factor in the forecasting process.

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[3] One strand of this literature emphasizes the role of information asymmetries for international capital flows (e.g., Ahearne, Griever, and Warnock 2004, Portes and Rey 2005, Dvorak 2005). A different strand stresses the importance of the geographic location of analysts in determining the profitability of investment (e.g. Coval and Moskowitz 1999 & 2001, Hau 2001, Bae et al. 2008).

[4] First, our data set in the present paper includes much broader and better measures for geographic factors, in particular on regional economic conditions. Second, given that we are able to identify the individual forecaster rather than just the forecasting institution, we are in a position to condition on a different and much larger set of forecaster characteristics such as the skills of analysts, which allows us to draw much clearer conclusions about the role of information processing and the role central banks play in this process. Finally, while some might argue that a relatively new monetary region with a diverse historical and political background such as the euro area can be expected to (still) show some heterogeneity in beliefs, asking whether geography plays a role in the U.S. means setting the empirical bar significantly higher.

As to *skills*, there are a number of factors that affect forecasters' performance. For instance, analysts who work for investment banks do better than those in other financial and non-financial companies. Second, it is intriguing that analysts who have the position of Economist in their institution do better than forecasters with higher-ranking titles, in particular executives. Our interpretation is that executives are less specialized and can devote less time and resources to following the Fed. The results seem to support the limited attention hypothesis. Third, professional experience and education matter for forecast accuracy. We find that analysts who previously worked for the Federal Reserve's Board of Governors perform better, as do analysts with a Master's degree. A related result of the empirical analysis is that forecasters who do well in predicting monetary policy also do well in anticipating other economic variables.

The paper is structured as follows. Section 2 discusses in detail the data for the monetary policy forecasts. Section 3 starts by outlining our hypotheses before presenting the empirical results. Section 4 concludes.

2. Data on Monetary Policy Expectations

This paper is based on a novel and fairly rich dataset that allows us to analyze the disagreement among forecasters of FOMC decisions. The data contain a large amount of relevant background information on the individual forecasters. In this section, we describe the dataset before proceeding to discuss the economic relevance of the heterogeneity across forecasters for financial market outcomes.

2.1 Data characteristics

Our database consists of time-series information on monetary policy expectations and other variables for 268 professional forecasters, covering a broad set of investment banks, commercial banks and forecasting institutions. The data comes from Bloomberg, which chooses which institutions and individuals to include in its survey of monetary policy expectations of the Federal Reserve. The survey consists of a simple question about what the analysts think will be the most likely policy decision of the FOMC in a given meeting.[5] We have available forecasts for all scheduled FOMC meetings starting in 1999 until September 2005.

Even though the expectations data is survey-based, its quality is high. One potential concern is about the effort individual analysts put into providing their input. However, there are a number of reasons suggesting that this is not a major concern. Most importantly, analysts are bound in their survey answers by their recommendations to clients. Hence an analyst for an investment bank, for instance, may find it hard to justify why he or she gave a recommendation different to the one of the survey. And indeed, a series of tests discussed below indicates that the forecasts surveyed by Bloomberg are significantly linked to financial market behavior.

There is also little evidence of selection bias in the cross-section. The way the survey works is that analysts can (but need not) provide their forecasts online at any time before the meeting. Thus, self selection could occur if, for instance, in times of heightened uncertainty "bad" forecasters decided to either systematically delay their participation in the survey or abstain completely. However, we find that the average forecasting errors made by participating analysts

[5] The forecast horizon is therefore generally rather short (with a median of 5, an average of 11, and a maximum of 57 days). Given that uncertainty about upcoming decisions at this short horizon is certainly smaller than about the future path of interest rates at a longer horizon, the amount of heterogeneity which we discover is all the more surprising, and suggests that the issue is likely to be even more pronounced for longer-horizon forecasts.

is independent from the number of participants.[6] In addition, across forecasters for a given meeting, there is no systematic relationship between the precision of individual forecasts and the lead time of an individual forecast submission (i.e., the time between when the forecast is filed and the relevant FOMC decision). What we do find, for individuals over time, is a negative correlation between lead time and forecasting accuracy.[7] This suggests that, as a group, analysts provide their forecasts at an earlier stage when decisions are easier to anticipate, while they enter their forecasts later, when FOMC decisions are harder to foresee. The empirical work in the main body of the paper will control for such common swings in overall forecasting behavior by introducing fixed time (or FOMC meeting) effects.

Another potential issue relates to herding among the survey participants when providing their forecasts to Bloomberg. Welch (2007), for instance, has provided evidence that security analysts show herding behavior, and it might well be that this is the case also in our dataset. Survey entries can be made at any time, and all responses available at that point in time are already displayed on Bloomberg. Even more, respondents can revise their forecasts. Unfortunately, what is available to us is only the final forecast, along with the date when it was entered into the system, such that we do not know to what extent revisions actually take place. On the other hand, institutions participating in the forecasts tend to be bound by their forecasts and advise to their clients, so that it appears unlikely that institutions fundamentally alter their forecasts at short horizons. For the purposes of this paper, we analyze the forecaster heterogeneity that remains in the sample after possible herding and revisions. The heterogeneity in our sample should thus be considered as a lower bound for the true degree of heterogeneity in the sample.

Figure 1

The main interest of the paper lies in understanding and explaining the cross-sectional differences across analysts' forecast performance of US monetary policy. Figure 1 shows the standard deviation of forecast errors across analysts for each FOMC meeting and the underlying average forecast mistake. To understand the magnitude of the heterogeneity in forecast performance across individual analysts, we rank all forecasters by their average absolute forecast errors over the full sample period. Doing so shows that the 10% with the best performance have on average a forecast error that is about 5 b.p. lower than the worst-performing 10%. However, as some decisions have been perfectly predicted by all market participants, a more informative comparison might look at forecast performance for the more difficult cases. Repeating this analysis therefore only for for those FOMC meetings in which there was heterogeneity in expectations across individual forecasters, Figure 2 ranks all forecasters by their average absolute forecast errors over the full sample period, starting from the 10% with the lowest average errors

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[6] Regressing the average absolute forecast error across analysts for each FOMC meeting $\overline{s_t}$ on the number of survey participants F_t for that FOMC meeting (participation varies from a minimum of 11 to a maximum of 54 forecasters, with an average of 32) yields:

$$\overline{s_t} = \underset{(0.5281)}{1.6267} + \underset{(0.0981)}{0.0598}\, F_t + \varepsilon_t ,$$

where the absolute forecast error for each individual $s_{i,t}$ is defined as the absolute difference between the individual's forecast $r^e_{i,t}$ and the actual Fed funds target rate set by the FOMC r_t. The OLS standard errors (in parentheses) indicate no significant relationship in the data between participation and the average absolute forecast error across agents.

[7] Regressing the absolute forecast error $s_{i,t}$ for each analyst on the lead time $L_{i,t}$ (in number of days) with which he or she gives the forecasts, we find:

$$s_{i,t} = \underset{(0.0046)}{-0.0175}\, L_{i,t} + \varepsilon_{i,t} .$$

Given the discrete nature of this variable, which changes in steps of 25 b.p., an ordered probit model is used for the above regression. The finding implies that a longer lead time is associated with a lower forecast error. Also note that all results below are robust to the inclusion of the lead time of a given forecast as an additional explanatory variable.

in decile 1 to the 10% with the largest mistakes in decile 10. The figure shows a remarkable degree of heterogeneity that, in the light of the frequency of participation of forecasters, cannot be explained by chance alone: the best forecasters have on average a forecast error that is about 10 b.p. lower than the worst-performing analysts.[8]

Figures 2 – 3

In order to obtain a measure of cross-sectional heterogeneity robust to possible self-selection (i.e., variations in participation of good or bad forecasters over time), we extract the time fixed effects. In other words, the time-corrected forecast errors are obtained as the residuals of regressing the absolute forecast error on a comprehensive set of time dummies, which in essence just subtracts from each individual's error the average error across all individuals for each meeting. Figure 3 shows the distribution of these time-corrected forecast errors across analysts. It confirms the large degree of heterogeneity, which remains unchanged at roughly 10 b.p. between the best and the worst forecast performers.

2.2 Is forecast heterogeneity reflected in financial markets?

An important question is whether such heterogeneity is reflected in financial markets. If survey participants take market positions according to their expectations about an upcoming FOMC decision, we should observe increased market volatility in response to the announcement of monetary policy decisions in the presence of larger heterogeneity, as a more substantial rebalancing of market positions may be required in such a case. This would provide strong evidence in favor of the above argument that the survey data are of high quality, and at the same time suggest that heterogeneity in expectations, in particular if it is systematic, has effects on financial markets.

For that purpose, we test whether market volatility around the release of the FOMC decision, and in its aftermath, is related to the heterogeneity of the expectations expressed in the Bloomberg survey. Starting from tick-by-tick data, we calculate realized volatility for the S&P 500 futures as described in Andersen et al. (2003) as the sum of the squared minutely returns over four separate time windows.[9] The first window precedes the release of the monetary policy decision at 14:15, ranging from 12:45 to 13:45. During the second window, which ranges from 13:45 to 14:45, the decision is released. The other two windows range from 14:45 to 15:30 and from 15:30 to the close of the market, which is usually at 16:00, and thus capture trading in the aftermath of the decision. In this fashion, we construct one observation for our dependent variable per time window per FOMC meeting.

If t denotes the day of the FOMC meeting, and τ the time window analyzed, we aim to explain market volatility ($\sigma_{t,\tau}$) in response to the release of monetary policy decisions. Two determinants are of interest in our context: first, the *magnitude* of the surprise, as measured by the absolute mean forecast error reported in Bloomberg ($\bar{s}_t$), and second, the *heterogeneity* of market expectations, measured as the standard deviation of the surprises calculated across survey participants (ψ_t). In order to control for time variations in market volatility that are unrelated to monetary policy, we add another regressor, namely market volatility observed in the same time

[8] To verify the robustness of these differences, we exclude those forecasters from the sample who have participated in less than 25% of the forecasts over the sample period.
[9] We opt for S&P 500 futures rather than, e.g., 10-year U.S. Treasury Notes Futures, as the former is traded until 16:15 Eastern Time (as opposed to 15:00 for the latter), thus allowing for an extended analysis of market effects. Data for the S&P 500 futures are from TickData Inc. Starting from tick data, we calculate price data on a minute-by-minute frequency by linear interpolation of the two tick prices immediately before and after the full minute. From these price data, we calculate minutely returns, and finally realized volatility as the sum of the squared returns over the relevant time windows (see Andersen et al. 2003).

window on the preceding day, ($\sigma_{t-1,\tau}$).[10] By using this particular time window, we ensure that our benchmark variable is not affected by time-of-the-day patterns in volatility. The model to be estimated is therefore as follows:

$$\sigma_{t,\tau} \quad = \quad \alpha + \beta\, \sigma_{t-1,\tau} + \gamma\, \bar{s}_t + \delta\, \psi_t + \varepsilon_{t,\tau}\,. \tag{1}$$

Note that the magnitude of the surprise and its heterogeneity are strongly correlated, with a correlation coefficient of 0.47. Accordingly, we perform regressions in three steps, by first including either one of the two explanatory variables $\bar{s}_t$ and ψ_t, and then both jointly.

Table 1

Table 1 reports the results of the various estimated OLS models. Neither the magnitude of the monetary policy surprise, nor the heterogeneity affects market volatility in the time window prior to the release of the decision, as suggested by the adjusted R^2 measures: model (1), which includes neither regressor, performs best. For the subsequent time window, which surrounds the release of the FOMC decision, the magnitude of the monetary policy surprise affects market volatility. With larger surprises, market volatility increases. In addition, however, also heterogeneity increases market volatility, in line with our hypothesis. As a matter of fact, the best model, judged by the adjusted R^2 measure, contains both regressors. This picture changes for the remaining trading day, however. As of 14:45, the only relevant factor is the heterogeneity in expectations, explaining roughly 6% of the variation in market volatility, whereas the magnitude of the policy surprise is no longer a relevant factor.

Looking at the estimated parameters for realized volatility in the same time window on the preceding day, it is apparent that markets wait for the release of the decision (as volatility is substantially lower just before the release), then react strongly to the release, with volatility increasing by a factor of 1.5 in the time window surrounding the release, and a factor of nearly 2 in the window from 14:45 to 15:30 (in case the monetary policy decision has been perfectly predicted by all participants – otherwise, volatility increases by even more). Only in the last time window is volatility roughly back to what it was on preceding days, with an estimate near one.

Overall, these findings suggest that more heterogeneity in expectations raises market volatility, significantly so and persistently so for the entire remaining trading day after the release of a monetary policy decision.

3. What explains heterogeneity in forecast accuracy?

The present section contains the core analysis of the paper. We start by discussing our hypotheses related to the role of geography and skills in influencing monetary policy forecasts, and continue by outlining the empirical methodology. We then turn to the empirical findings and robustness checks.

[10] The value for realized volatility on the preceding day can be seen as a proxy for market uncertainty and volatility in general. Adding additional proxies for uncertainty, such as the surprise component contained in recent macroeconomic announcements (e.g. non-farm payrolls, CPI, industrial production and consumer confidence), the lead time by which Fed watchers make their forecasts of FOMC decisions, or the number of participants in a given survey, does not affect results. Results are not reported here for brevity, but available upon request.

3.1 Hypotheses and methodology

How should we expect differences in information processing across analysts to shape their forecasting performance? For illustrative purposes, consider a limited attention model that departs from the assumption that individuals make decisions using all available information (e.g. Della Vigna 2007). In an attempt to simplify complex decisions, agents are likely to process only a subset of information. This might imply neglecting or overweighting of information. For instance, the availability heuristic (Tversky and Kahneman 1973) suggests that individuals tend to place too much weight on information that is easily recalled – i.e., information that is especially salient or vivid. At the same time, heterogeneous priors can generate equivalent results. Indeed, whether or not an agent disregards some information because she thinks that it is not important for the forecasting problem at hand, or whether she neglects it due to limited attention, is, in general, observationally equivalent.[11]

To portray the decision problem we are interested in, assume that forecasters of monetary policy decisions derive disutility if their forecast deviates from the actual decisions. This could be because of reputational concerns (in relation to customers, peers, current or potential future employers), or because they trade based on this forecasts in financial markets, such as the Fed funds futures market.[12] Accordingly, the loss function of individual forecaster *i* is described as:

$$L_i \equiv \left| E_i(\theta) - \theta \right| , \tag{2}$$

with θ representing the upcoming interest rate decision and E(.) the expectations operator. In line of our earlier discussion, we should think of individual *i* as differing with regard to her skill level and/or location.

Obviously, θ is ex ante unobservable and uncertain. However, agents receive signals which allow them to make informed forecasts about θ. For simplicity of exposition, let us restrict the number of signals to two. We assume that both signals are unbiased, but imperfect, as they contain some noise. The first signal is $x = \theta + \varepsilon$, where ε is i.i.d. with zero mean and variance σ_ε^2. The second signal is $y = \theta + \eta$, where η is also normally distributed with zero mean and variance σ_η^2. Defining the relative precisions of the signals as $\alpha \equiv 1/\sigma_\varepsilon^2$ and $\beta \equiv 1/\sigma_\eta^2$ implies that the expected value of the fundamental θ is

$$E(\theta) = (\alpha x + \beta y)/(\alpha + \beta) = \gamma\, x + (1-\gamma)\, y , \tag{3}$$

with $\gamma = \alpha/(\alpha + \beta)$. We assume that the central bank receives the same signals, but knows their relative precision. In this case, the expectation will ex post be realized, i.e. $\theta = E(\theta)$. Agents, on

[11] As mentioned earlier, differences in information availability – the second principle source of forecasting heterogeneity highlighted in the literature (Hong and Stein 2007) – seem less relevant in our context. Survey participants decide themselves at which point in time they enter their forecast. This allows them to wait until they have collected all information they deem relevant. Furthermore, it is obvious that forecasters in a Bloomberg poll have access to financial newswire services. Given that these report on all aspects related to monetary policy as well as on relevant macroeconomic announcements in real time, we can assume that all agents have access to the same information at the same point in time, making gradual information a less interesting candidate for our case.

[12] This assumption excludes the possibility of a rational bias, whereby forecasters in certain institutions posit a biased forecast in order to attract publicity, as e.g. illustrated in Laster et al. (1999). This seems less of an issue in our dataset, where we find that forecast heterogeneity is mirrored in financial market positions. In addition, our empirical models include information about institutional affiliation, which should effectively capture any remaining rational bias.

the other hand, do not know the precision of both signals, but must estimate them. Identifying estimated values with a hat, equation (3) becomes

$$E_i(\theta) = (\hat{\alpha}_i x + \hat{\beta}_i y)/(\hat{\alpha}_i + \hat{\beta}_i) = \hat{\gamma}_i x + (1-\hat{\gamma}_i) y \,. \tag{4}$$

Finally, substituting equations (3) and (4) into (2) yields

$$\left|E_i(\theta) - \theta\right| \quad = \quad \left|\hat{\gamma}_i - \gamma\right|\left|x - y\right|, \tag{5}$$

which illustrates that forecast accuracy depends on the stochastics of the information process, $\left|x-y\right|$, and, for our purpose more importantly, on the precision with which a forecaster processes the various signals that he or she receives or, more precisely, on the magnitude of the estimation error of γ, $\left|\hat{\gamma}_i - \gamma\right|$.

The last result illustrates how differences in the ability to process information may generate disagreement among forecasters.[13] Obviously, different skill sets across forecasters can result in differing priors. This will allow $\hat{\alpha}_i \neq \hat{\alpha}_j$, $\hat{\beta}_i \neq \hat{\beta}_j$, and, ultimately, differing forecasting errors according to equation (5). Also, in the presence of limited attention, agents may overweight salient information resulting in, for instance, $\hat{\beta}_i > \hat{\beta}_j$ if y is salient for i, but not for j. To give an extreme example, agent i in a particular location might focus on x and neglect y, choosing $\hat{\beta}_i = 0$, which clearly leads to an inefficient forecast of θ, while elsewhere agents choose $\hat{\alpha}_j = 0$, resulting in an equally inefficient but different forecast.

In what follows, we will identify and explain cross-sectional differences across analysts' forecast performance of US monetary policy along these lines. The key focus is on analyzing how much of this heterogeneity in expectations can be attributed to geography and how much to the skills of individual analysts.

Turning to the explanatory variables and the underlying hypotheses, *geography* provides a specific economic and informational environment in which individuals operate, with potentially important consequences for forecasting performance. As to the informational environment, local information is bound to be relatively salient, and we would therefore expect that it enters the forecasting problem with large (and perhaps too large) weights. In addition, geographically close forecasters may share certain priors, for instance, because dedicated "central bank watchers" tend to cluster in financial centers or close to the central bank.

One implication is that analysts who are located close to the Board of Governors, i.e. in or close to Washington DC, or in large financial centers such as New York City may have an information advantage and should be expected to perform better in forecasting US monetary policy than others. The information advantage could stem from more direct contacts or interactions with the Federal Reserve, but it could also be related to the fact that Washington DC and financial centers have a high concentration of institutions focused on issues related to monetary policy, which allows more efficient information sharing and improves the forecast performance of analysts. More generally, it is possible that analysts located in the United States have better information about US monetary policy, e.g. through the easier and more diverse availability of various media, than analysts located abroad. Similarly, language may matter as one would expect that analysts

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[13] A possible extension of this model could consist in the existence of indirect signals for θ, such as $y = \delta_0 + \delta_1\theta + \xi$, which would add parameter uncertainty to the model. Such an extension would not affect the main conclusions of our stylized model.

working in an English-language environment have an information advantage over those working primarily in a foreign-language environment. As English is, however, widespread as a working language in particular among financial institutions also in non-English speaking countries, an English-language environment may in practice not provide much of a gain.

We use various locational variables to capture this type of geographic proximity. First, the geographic coverage of the data is large, as our dataset includes 268 forecasters located across 98 cities in 15 countries. Tables 2 and 3 provide an overview of the geographic coverage.

Tables 2 – 3

A second way in which geography may play an important role for forecasting accuracy is through the specific local or regional economic environment analysts are operating in. Location choices of institutions often imply that their businesses are more strongly connected to regional clients or partners. Thus information about the immediate geographic surroundings may be better and more ample. Institutions may therefore (consciously or unconsciously) use this regional or local knowledge to help make inferences about overall economic developments. For the anticipation of monetary policy, this means that analysts may be significantly influenced by their regional economic conditions when making predictions about US monetary policy. We have three such regional economic indicators – CPI inflation for the four US census regions (Northeast, Midwest, South and West), as well as personal income growth and employment growth for all US states – and can match these to the location of the analysts in our sample.[14] To control for persistent differences in regional developments, we assume that analysts pay particular attention to deviations of regional developments from their respective long-term average. As any regional focus is likely to deviate from the aggregate perspective taken by policy makers in the FOMC (because analysts are putting too much weight on the economics information close to home), we would expect larger absolute deviations of current regional conditions from the regional norm to lead an analyst to make larger forecast errors.[15]

Tables 4 – 5

Tables 4 and 5 give summary statistics for all of these variables, as well as a breakdown of the information between the USA and abroad (Table 4), and across the individual regions of the United States (Table 5). Out of the 268 analysts, 194 are located in the United States and 74 abroad. There are a number of interesting and noteworthy characteristics in the data. For instance, about one third of all forecasters are based in financial centers, in particular New York City, but also major financial hubs such as Chicago, London, Hong Kong, Frankfurt or Boston.

Geography		**Skills**	
Regional economic conditions:		**Macro forecast performance:**	
CPI inflation difference	Absolute difference between current regional inflation and its sample average	CPI inflation forecast	D=1 if the individual's average inflation forecast error is below sample median; D=0 otherwise or if no forecast is available

[14] Regional CPI data, while providing less cross-sectional variance than metropolitan area CPI data, poses fewer matching problems with forecaster locations across the US. CPI inflation and nonfarm payroll data (Source: Bureau of Labor Statistics) are available real time, on a monthly frequency. Personal income growth data are quarterly (Source: Bureau of Economic Analysis).

[15] Ideally, we would like to test the same hypothesis for US national aggregate data. Unfortunately, this is not possible in the framework of model (1), as any variable which varies only across time, and not across analysts is wiped out by the set of time dummies. We however include below the absolute deviation of current US economic developments from their long-term average for non-US residents in the sample.

Income growth difference	Absolute difference between current regional income growth and its sample average
Employment growth difference	Absolute difference between current regional growth in non-farm payrolls and its sample average
Location:	
Distance to Federal Reserve	Distance from Washington DC (in 1000 km)
Washington DC	D=1 if analyst is located in Washington DC; D=0 otherwise
New York City	D=1 if analyst is located in New York City; D=0 otherwise
Financial center[16]	D=1 if analyst is located in Chicago, Boston, London, HK, Paris, Frankfurt, Madrid or S.Francisco
USA	D=1 if analyst is located in neither DC, NYC or a US financial center, but resides in the US; D=0 otherwise
English language	D=1 if foreign analyst is located in Canada, UK, Ireland or Australia; D=0 otherwise
Northeast, Midwest, South, West	Regional dummies each for the four US census regions
Industrial production forecast	D=1 if the individual's average industrial production forecast error is below sample median; D=0 otherwise or if no forecast is available
Individual background:	
Institution:	
Investment bank	D=1 if analyst works for such institution; D=0 otherwise
Commercial bank	D=1 if analyst works for such institution; D=0 otherwise
Forecast institution	D=1 if analyst works for such institution; D=0 otherwise
Job position:	
Economist	D=1 if analyst holds this job title; D=0 otherwise
Senior Economist	D=1 if analyst holds this job title; D=0 otherwise
Chief Economist	D=1 if analyst holds this job title; D=0 otherwise
Executive	D=1 if analyst holds this job title; D=0 otherwise
Education:	
Bachelor's degree	D=1 if analyst has this as highest degree; D=0 otherwise
Master's degree	D=1 if analyst has this as highest degree; D=0 otherwise
PhD degree	D=1 if analyst has this as highest degree; D=0 otherwise
Employment history:	
Fed Board of Governors	D=1 if analyst worked for this institution before; D=0 else
Fed New York	D=1 if analyst worked for this institution before; D=0 else
Neither Board nor NY Fed experience	D=1 if analyst has worked for neither at the Board nor the Fed New York before; D=0 else

[16] Note that the definition of financial centers here is clearly not all encompassing, and one could also argue for alternative definitions. However, the empirical findings presented below are robust to changing the set of cities defined as financial centers, i.e. when extending the set of cities or when reducing it – for instance, when including Philadelphia or excluding San Francisco etc.

Another possible determinant of analysts forecasting performance suggested by equation (5) are their *skills*. Higher skilled analysts either possess the correct priors as to what information to incorporate at which weights, or they focus their limited attention on the appropriate information. Therefore, we expect that the professional experience and employment record of analysts will have a significant effect on their performance in predicting Fed policy. In particular, someone who has previously worked for the Federal Reserve's Board of Governors, or possibly the New York Fed, may have a superior understanding of the functioning of the FOMC and its communication. In addition, technical expertise is likely to give analysts with a Master's or Ph.D. degree as an educational background an edge in the forecasts. Also, we would expect that the forecast performance of analysts is linked to the resources their institutions provide them with. Accordingly, the type of institution an analyst works for may matter. For instance, anticipating monetary policy decisions may be even more important for investment banks or specialized forecast institutions than for other financial or non-financial institutions. Finally, the degree of specialization might matter – individuals who conduct a number of other tasks on their job have less attention to devote to the FOMC forecast, which could affect their forecasting performance.

In addition to personal characteristics, we also have a more direct measure of their forecasting skills. In particular, our dataset includes the forecasts of other economic variables – CPI inflation and industrial production – made by many of the analysts in our sample. As both variables are also highly relevant for monetary policy decisions, we would expect that analysts who perform well in predicting US inflation and industrial production are also better in anticipating US monetary policy decisions at that particular point in time. To capture the overall quality or skill level in the empirical implementation we focus on the relative quality of forecasters compared to the sample median across time and individuals.

Tables 4 and 5 offer some summary statistics for these skills-related variables. Some interesting features of the data emerge. For instance, there is some concentration of analysts across institutions as almost half of them work for investment banks. We also find that a relatively large share of analysts hold a Ph.D. or Master's degree, while the distribution across job positions is relatively even. It should be noted that employment and education backgrounds are not available for several analysts. We therefore created a separate variable for these, included under "no information".

Turning to the empirical methodology, we want to explain the absolute forecast error $s_{i,t}$ for each FOMC meeting by each individual analyst. We restrict the analysis to those individuals who have participated in the survey more than 10 times. As $s_{i,t}$ is discrete, taking either the value of 0, 25 or 50 b.p., we model the effect of our explanatory variables, $x_{k,i,t}$, using an ordered probit model of the form

$$\hat{s}_{i,t} = \alpha_t + \sum_{k=1}^{K} \beta_k x_{k,i,t} + \varepsilon_{i,t}, \tag{6}$$

where $\hat{s}_{i,t}$ is an unobserved latent variable that relates to the observable forecast error according to the rule

$$\begin{array}{llr} s_{i,t} = 0 & \textit{if} & \hat{s}_{i,t} \le \kappa_0 \\ s_{i,t} = 25 & \textit{if} & \kappa_0 < \hat{s}_{i,t} \le \kappa_1 \\ s_{i,t} = 50 & \textit{if} & \hat{s}_{i,t} > \kappa_1. \end{array}$$

The κ's are unknown parameters to be estimated with the coefficient vector β, and $\varepsilon_{i,t}$ is a well-behaved error term.[17]

The model controls for time fixed effects by including a full set of time dummies α_t. As mentioned above, our focus is on the cross-sectional differences across analysts' forecast performance. We therefore want to control for the fact that some FOMC decisions may be more difficult to predict than others, and to avoid the resulting potential self-selection bias. Note that this also implies that the empirical findings are effectively based only on those FOMC meeting in which there was some cross-section heterogeneity.

3.2 Empirical results

Our modeling strategy is to start by analyzing the role of geography in explaining forecast errors of US monetary policy, then to move to skills and finally to combine both sets of variables in a single model.

3.2.1 Geography

Table 6 presents the results for the geography variables in the ordered probit model, using different specifications. Model (1) shows the influence of distance, an often used proxy for information costs in the literature on trade in goods and financial assets. However, we find that greater distance from Washington DC, the seat of the Federal Reserve's Board of Governors, is not associated with a statistically significantly higher forecast error. In model (2), we ask whether there are differences across the four US regions and indeed find that analysts located in the Northeast and the Midwest perform significantly better than those of the excluded group from the model, in this case all non-US analysts. Part of the reason for this better performance may be that the Northeastern and Midwestern regions include most of the major financial centers of the United States, which may have an information advantage as major financial hubs.

Table 6

In model (3), we therefore test the role of specific locations. We find that analysts based in Washington DC, in New York City, and in other financial centers do better than analysts located elsewhere.[18] By contrast, forecasters in other US locations, or those based in countries with English as the main language do not appear to make smaller forecast errors than other foreign analysts (model (4)). What this suggests is that there are indeed strong information advantages in financial hubs, pointing to an important role of geographic "proximity" (recall that all analysts have access to financial newswire services, such that unequal access to information should not generate this result).

The second proxy for the role of geography is the regional economic environment analysts operate in. Model (5) shows the point estimates for the absolute difference of CPI inflation, income growth and employment growth from their averages over the whole sample period. The

[17] Interpreting β can be difficult, especially when using explanatory dummy variables. For instance, depending on the cut-off points, a negative dummy coefficient could indicate that a 50 basis-point error is less likely but a 25 basis-point error is more likely when the variable takes the value 1. However, this case is not relevant in our sample. As a robustness check and to ease interpretation, we will report OLS results in addition to ordered probit estimates in what follows.

[18] Note that it is not straightforward to interpret the coefficients, due to the non-linear nature of the ordered probit model, as the coefficients give only the marginal effects at each variable's mean. We will return to a more detailed discussion of the marginal effects and their interpretation further below.

results indicate that regional conditions indeed play a role, with larger deviations in inflation and employment growth leading to significantly higher forecast errors about US monetary policy.[19]

Finally, model (6) combines the various location and regional conditions variables in a single estimation. The results are generally robust to this extension, though the effect of financial centers other than New York City does not remain statistically significant. On the other hand, the combined model identifies an additional, albeit only marginally significant, effect of deviations in regional income growth, with larger absolute deviations pointing to larger forecast errors. Estimates of the same model by OLS (i.e., ignoring the discrete nature of the forecast error) confirm the findings of the ordered probit models, with slight changes in the significance level of regional macroeconomic differences.

3.2.2 Skills

Table 7 gives the empirical results for the effects of various measures of analysts' skills and ability on forecast performance; first only for each category, then by combining the different skill proxies in a single model.

Table 7

Regarding institutional affiliations, in model (1) we find that analysts who work for investment banks have significantly lower forecast errors of FOMC decisions compared to the excluded benchmark group, namely analysts working for other financial or non-financial institutions and academics. The coefficient for individuals working for forecast institutions is slightly insignificant in this specification, although such analysts are found to perform marginally better in the more complete specification of model (6).

As to job classifications, forecasters with the job title of Economist, Senior Economist or Chief Economist appear to perform significantly better than analysts who are executives in their institutions and form the excluded category in the regression. This may seem somewhat surprising as one may expect that executives have more experience and thus should be able to predict US monetary policy decisions at least equally well. One interpretation is that executives have a multitude of tasks and therefore have less time to acquire or maintain the specific expertise to do well in anticipating FOMC decisions. The results may also be influenced by an omitted variable bias as, for instance, forecasters who have the title of an executive may disproportionally work for specific institution types, such as small think tanks or non-financial institutions, and thus do worse merely because of their affiliation. However, model (6) shows that the findings with regard to the superior performance of economists and chief economists are robust when controlling for the full set of institutional and other analyst characteristics.

In addition, the employment history matters for forecast performance. Model (3) shows that individuals who have worked for the Board of Governors in the past do a significantly better job in anticipating FOMC decisions. Again, this finding is robust to controlling for the full set of skill determinants, as shown in model (6). This result suggests that having first-hand knowledge in the functioning and thinking of the Federal Reserve should provide an analyst with a valuable advantage compared to other analysts in predicting FOMC decisions.

Fourth, the educational background appears to also play a significant role. Interestingly, analysts with a Ph.D. – the excluded category in model (4) – do significantly worse than those with a Master's degree. Two possible explanations come to mind for this result. On the one hand, it may imply that specific technical expertise may not be crucial for being a good forecaster of US

[19] These results are generated by a bias, whereby higher than normal inflation leads to an overestimation of interest rates, and (to some extent) higher than normal real developments to an underestimation.

monetary policy. On the other hand, it may indicate that it is not the level of the degree, but the quality or type of degree – for which we do not have information – that explains this effect. For instance, we cannot exclude the possibility that most of those with a Master's degree have an MBA, whereas many of those with a PhD obtained their degree in Economics.

Finally, a much more direct proxy for the skills of analysts is their ability to forecast other economic variables, such as US inflation and industrial production developments. While there is no effect of the quality of industrial production forecasts on the accuracy of forecasts of monetary policy decisions, model (5) indicates that indeed analysts who are, on average, better in predicting the next inflation figure after an FOMC meeting than the sample median are also better in correctly anticipating the FOMC decision. Overall, this finding is probably the strongest direct evidence that skills matter for the forecast accuracy of US monetary policy.

Controlling for the robustness of results by re-estimating the combined model (6) using OLS corroborates the findings in general, as shown in column (7), with only one change: the superior performance of chief economists turns insignificant.

3.2.3 Geography versus skills

As the final part of the analysis, we include the various proxies for geography and for individual skills in the same model specification. It is important to combine the different categories in order to counter the possibility that geography and skills of analysts are not independent from one another. This may imply that what we measure as the effect of geography could at least in part reflect differences in the skill set of analysts, or vice versa effects of skills may represent the impact of geography. If, for instance, skilled analysts tended to move to New York City disproportionally, then the geography variable for New York City may pick up this concentration of skills, rather than information alone. However, the causality of this relationship could also be the reverse in that institutions move their analysts to New York or another major financial center precisely *because* of the information advantage they obtain from being there.

Table 8

Table 8 provides the empirical findings for this combined model. Overall, the results are mostly robust as most of the variables retain their statistical significance. In only a few cases do variables lose their statistical significance. For instance, the professional experience of having worked for the Federal Reserve before does enter the expanded ordered probit model only marginally significant. Only minor changes are apparent when non-US residents are dropped from the sample, as shown in the second set of results in Table 8. In this case, professional Fed experience regains its significance, whereas regional inflation differences become statistically insignificant. [20]

In order to obtain a more direct proxy for the quantitative effect of each of the variables on the monetary policy forecast error, we estimate the same model using OLS. The results shown in the right-hand side columns of Table 8 support the previous qualitative and statistical findings for the geography variables. Quantitatively, according to the linear model, analysts based in New York or in another financial center perform on average about 2 b.p. better than others. This gain is even more pronounced for analysts based in Washington DC, who have on average a forecast error that is 4 b.p. lower.

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[20] Results are furthermore robust to the inclusion of a variable that measures the lead time of a given forecast, to including the number of forecasts an individual had previously filed in the Bloomberg survey, to separating forecasters into those that make a good macro forecasts, those whose forecast are below the median, and those who do not make forecasts at all. The estimates for regional economic conditions are robust to estimation of a model with full sets of forecaster and meeting fixed effects.

The significance of most of the skill variables is also confirmed in the combined model. Institutions, job position and educational background all continue to exert a substantial impact on forecast accuracy. Equally importantly, analysts who do well in predicting the next inflation figure are also more accurate in predicting the next FOMC meeting. In fact, analysts who are better than the mean in forecasting inflation have a roughly 1.7 b.p. lower forecast error.

In summary, both geography and individual skills play a substantial role for the forecast accuracy of US monetary policy decisions. In particular the magnitude of the effects of several of the geography and skill proxies underline the overall large importance they have in explaining the heterogeneity in the ability of agents to anticipate policy decisions by the Federal Reserve.

4. Conclusions

The monetary policy of the Federal Reserve has become increasingly predictable over time, also given its remarkable progress towards more transparency. This process has not only led to fewer monetary policy actions that have surprised the public, it has also synchronized the views of individual Fed watchers. However, disagreement among market participants remains, and is still sizable. Based on a novel dataset of 268 individual professional forecasters located across 98 cities in 15 countries, we found that the degree of heterogeneity in the forecast performance across individuals is large: the average absolute forecasts error by the group of the 10% of the worst forecasters is 5 b.p. higher than that of the best decile of analysts (10 b.p. if we focus on FOMC meetings where not all forecasters agreed). This heterogeneity has repercussions for trading behavior, by significantly increasing financial market volatility.

As to the determinants of forecast heterogeneity, we have shown the relevance of locational factors. Importantly, the paper has found that monetary policy expectations exhibit a significant and systematic regional pattern in the United States, in that regional economic developments shape their forecasting ability about monetary policy. In particular, forecasters make larger errors the more economic developments in their home region differ from their average. As to the role of skills, a revealing point of the empirical analysis is that forecasters that are good in forecasting inflation also perform well in predicting monetary policy decisions. Moreover, analysts who work for investment banks or specialized forecast institutions, have a graduate degree or have an employment history with the Federal Reserve's Board of Governors all conduct better forecasts.

What do these findings imply for policy? First of all, it should be stressed that not all heterogeneity in expectations is necessarily undesirable from a policy perspective, in particular if such differences are the result of different degrees of investment in information gathering by analysts' institutions. Moreover, differential expectations about policy decisions may at times also provide useful information to policy-makers. Therefore, the primary nature of the analysis of the paper is a positive one, i.e. to document the magnitude and understand the determinants of the heterogeneity in monetary policy expectations.

At the same time, some of the analysis has also normative implications, though these can be no more than tentative and suggestive. Clearly, it is desirable for central banks to disseminate information and knowledge as equally as possible across agents not least because a high degree of heterogeneity is likely to result in unwanted financial market uncertainty and volatility. In particular the fact that such heterogeneity is linked to regional factors, which significantly influence forecasters' expectations, raises many issues for policy-makers, such as the choice of communication tools and strategies to enhance a more homogenous understanding of monetary policy. This may be particularly relevant in periods like the present, where some economic regions – and in particular financial centers – are facing a more uncertain and volatile environment than others.

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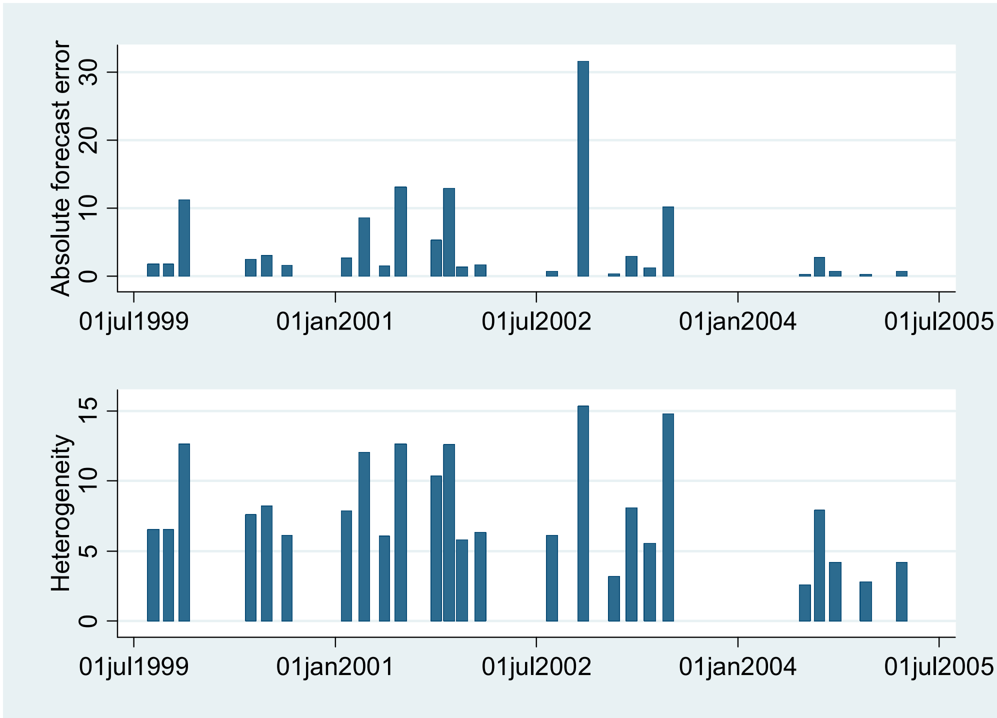
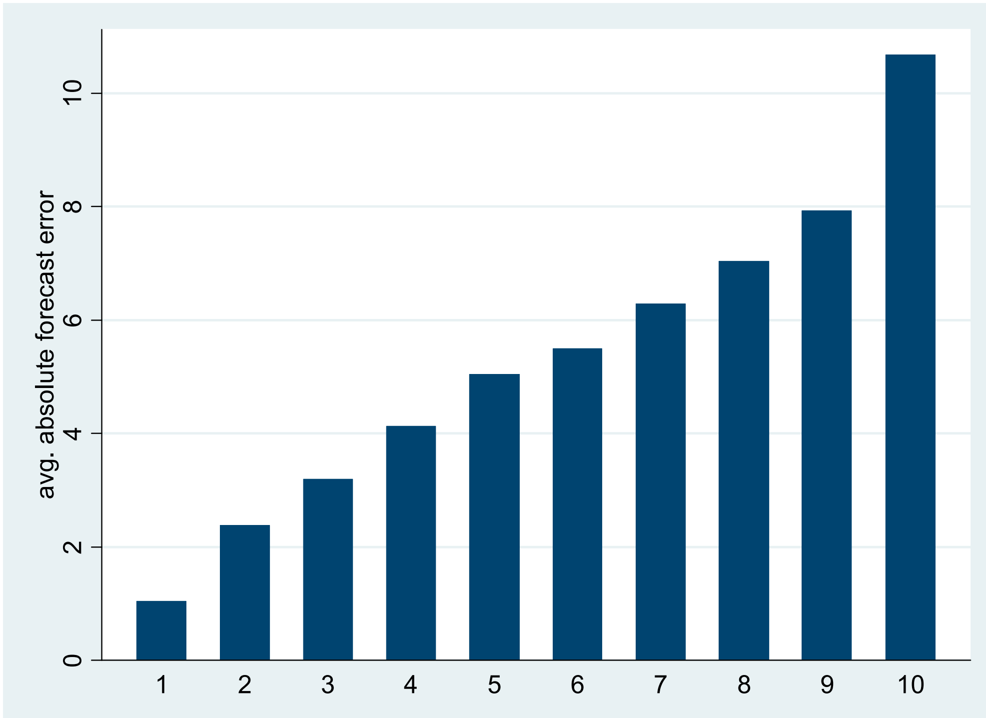
Figure 1: Distribution of forecast errors and forecast error heterogeneity over time



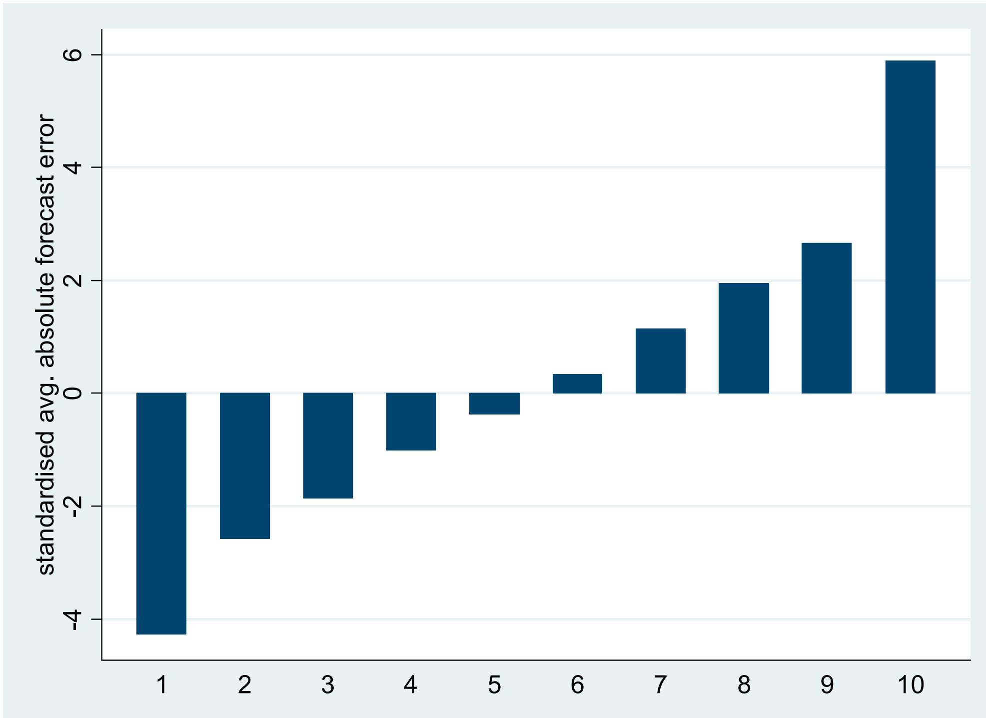
Note: The upper panel shows the average absolute forecast error (in b.p.) across individual forecasters for each FOMC meeting. The lower panel shows the standard deviation of the absolute forecast errors across individual forecasters.

Figure 2: Distribution of forecast errors across individual forecasters



Note: The figure shows the average absolute forecast error in b.p. by individual forecaster, ranging from the decile with the lowest forecast errors in decile 1 to those 10% with the highest prediction error in decile 10, for those FOMC meetings in which there was heterogeneity in expectations across individual forecasters.

Figure 3: Distribution of *time-corrected* forecast errors across individual forecasters, FOMC meetings with expectations heterogeneity



Note: The figure shows the average absolute *time-corrected* forecast error in b.p. by individual forecaster, ranging from the decile with the lowest forecast errors in decile 1 to those 10% with the highest prediction error in decile 10, for those FOMC meetings in which there was heterogeneity in expectations across individual forecasters.

Table 1: Monetary policy surprises, heterogeneity in expectations and the S&P 500 futures

	(1)		(2)		(3)		(4)	
	coef.	*std. err.*	coef.	*std. err.*	coef.	*std. err.*	coef.	*std. err.*
					12:45-13:45			
Absolute surprise	--	--	-0.016	*0.025*	--	--	-0.005	*0.029*
Heterogeneity	--	--	--	--	-0.037	*0.046*	-0.034	*0.054*
Volatility, preceding day	0.327 **	*0.124*	0.326 **	*0.125*	0.327 **	*0.126*	0.326 **	*0.127*
# observations	54		54		54		54	
Adjusted R^2	0.390		0.380		0.382		0.370	
					13:45-14:45			
Absolute surprise	--	--	1.381 **	*0.614*	--	--	0.874	*0.556*
Heterogeneity	--	--	--	--	2.143 ***	*0.697*	1.544 **	*0.635*
Volatility, preceding day	1.388 **	*0.665*	1.471 **	*0.624*	1.442 ***	*0.527*	1.479 ***	*0.544*
# observations	54		54		54		54	
Adjusted R^2	0.055		0.221		0.249		0.292	
					14:45-15:30			
Absolute surprise	--	--	0.332 *	*0.187*	--	--	0.128	*49.725*
Heterogeneity	--	--	--	--	0.709 ***	*0.250*	0.622 **	*0.261*
Volatility, preceding day	1.902 ***	*0.510*	1.906 ***	*0.512*	1.887 ***	*0.490*	1.890 ***	*0.497*
# observations	54		54		54		54	
Adjusted R^2	0.435		0.458		0.497		0.491	
					15:30-16:00			
Absolute surprise	--	--	0.052	*0.061*	--	--	-0.035	*0.049*
Heterogeneity	--	--	--	--	0.236 ***	*0.072*	0.260 ***	*0.077*
Volatility, preceding day	0.930 ***	*0.178*	0.909 ***	*0.189*	0.919 ***	*0.169*	0.932 ***	*0.177*
# observations	54		54		54		54	
Adjusted R^2	0.426		0.422		0.488		0.480	

Note: The table explains volatility of the S&P 500 futures returns on FOMC announcement days through the magnitude of the monetary policy surprise (measured by the absolute mean forecast error in the Bloomberg survey), the heterogeneity in market expectations (measured by the standard deviation of the individual forecast errors) and volatility during the identical time window on the preceding trading day. FOMC releases are made at 14:15. Standard errors are robust to heteroskedasticity. ***, **, and * indicate significance at the 99%, 95%, and 90% levels, respectively.

Table 2: Country coverage

Australia	Germany	Sweden
Canada	Ireland	Switzerland
China	Italy	The Netherlands
Denmark	Portugal	United Kingdom
France	Spain	United States

Table 3: City coverage

Albany	Copenhagen	Jupiter	New Canaan	Saint Louis
Amsterdam	Danville	Kennesaw	New Haven	Saint Petersburg
Ann Arbor	Detroit	King of Prussia	New York City	Salt Lake City
Arlington	Dublin	Leeds	Newport Beach	San Francisco
Atlanta	East Lansing	Lexington	Northville	Silicon Valley
Baltimore	El Paso	Lisbon	Oakland	Stamford
Berlin	Essen	Lisle	Omaha	Stockholm
Birmingham	Fairfield	Little Rock	Ottawa	Stuttgart
Bonn	Frankfurt am Main	London	Paris	Sydney
Boston	Greenwich	Los Angeles	Pasadena	Tempe
Boulder	Hamburg	Lugano	Pepper Pike	Toronto
Bridgeport	Hannover	Madrid	Philadelphia	Utrecht
Burlington	Hoboken	McLean	Phoenixville	Valhalla
Calabasas	Holland	Menomonee Falls	Pittsburgh	Vineland
Chapel Hill	Hong Kong	Milan	Potomac	Washington DC
Charlotte	Honolulu	Milwaukee	Princeton	West Chester
Chicago	Houston	Minneapolis	Raleigh	Wilmington
Cleveland	Islandia	Montreal	Richmond	Zug
College Park	Jacksonville	Muenchen	Rome	
Columbus	Jersey City	Murfreesboro	Rye	

Table 4: Summary statistics, US and foreign forecasters

	All					Of which:			
						USA		Foreign	
	# obs	mean	std. dev.	min.	max.	# obs	mean	# obs	mean
Dependent variable:									
Monetary policy forecast error	268	3.17	4.49	0	25	194	3.40	74	2.56
Location:									
Distance to Federal Reserve	268	2.06	2.70	0	13.11	194	0.75	74	5.71
Washington DC	268	0.05	0.22	0	1	194	0.07	74	0.00
New York City	268	0.26	0.44	0	1	194	0.35	74	0.00
Financial center	268	0.17	0.37	0	1	194	0.13	74	0.27
USA	268	0.72	0.45	0	1	194	1.00	74	0.00
English language	268	0.81	0.40	0	1	194	1.00	74	0.30
Foreign	268	0.28	0.45	0	1	194	0.00	74	1.00
Regional economic conditions:									
CPI inflation difference	268	0.571	0.211	0.030	1.496	194	0.580	74	0.547
Income growth difference	268	0.021	0.010	0.001	0.063	194	0.023	74	0.017
Employment growth difference	268	0.014	0.007	0.000	0.040	194	0.015	74	0.011
Individual background									
Institution:									
Investment bank	268	0.47	0.50	0	1	194	0.51	74	0.35
Commercial bank	268	0.23	0.42	0	1	194	0.12	74	0.51
Forecast institution	268	0.15	0.36	0	1	194	0.19	74	0.04
Other institution	268	0.16	0.36	0	1	194	0.18	74	0.09
Job position:									
Economist	268	0.12	0.33	0	1	194	0.08	74	0.24
Senior Economist	268	0.07	0.26	0	1	194	0.08	74	0.05
Chief Economist	268	0.26	0.44	0	1	194	0.30	74	0.15
Executive	268	0.18	0.38	0	1	194	0.20	74	0.14
No information [1)]	268	0.36	0.48	0	1	194	0.34	74	0.42
Education:									
Bachelor's degree	268	0.04	0.20	0	1	194	0.04	74	0.04
Master's degree	268	0.19	0.39	0	1	194	0.22	74	0.09
PhD degree	268	0.21	0.41	0	1	194	0.27	74	0.04
No information [1)]	268	0.56	0.50	0	1	194	0.46	74	0.82
Employment history:									
Fed Board of Governors	268	0.04	0.20	0	1	194	0.06	74	0.00
Fed New York	268	0.02	0.15	0	1	194	0.03	74	0.00
Neither Board nor Fed NY	268	0.59	0.49	0	1	194	0.60	74	0.57
No information [1)]	268	0.35	0.48	0	1	194	0.31	74	0.43
Macro forecast performance									
CPI inflation forecast	121	0.001	0.007	-0.002	0.069	76	0.000	45	0.003
Industrial production forecast	126	0.000	0.001	-0.006	0.004	77	0.000	49	-0.001

Note: 1) "No information" means that individuals have not provided any entry for a particular item.

Table 5: Summary statistics for US forecasters, by US region

	Northeast		Midwest		South		West	
	# obs	mean	# obs	mean	# obs	mean	# obs	mean
Dependent variable:								
Monetary policy forecast error	100	3.05	32	3.13	45	3.55	17	6.13
Location:								
Distance to Federal Reserve	100	0.36	32	0.97	45	0.48	17	3.70
Washington DC	100	0.00	32	0.00	45	0.29	17	0.00
New York City	100	0.68	32	0.00	45	0.00	17	0.00
Financial center	100	0.10	32	0.34	45	0.00	17	0.27
USA	100	1.00	32	1.00	45	1.00	17	1.00
English language	100	1.00	32	1.00	45	1.00	17	1.00
Foreign	100	0.00	32	0.00	45	0.00	17	0.00
Regional economic conditions:								
CPI inflation difference	100	0.541	32	0.680	45	0.597	17	0.571
Income growth difference	100	0.027	32	0.014	45	0.022	17	0.019
Employment growth difference	100	0.016	32	0.012	45	0.014	17	0.014
Individual background								
Institution:								
Investment bank	100	0.65	32	0.34	45	0.27	17	0.67
Commercial bank	100	0.11	32	0.22	45	0.07	17	0.07
Forecast institution	100	0.15	32	0.22	45	0.29	17	0.13
Other institution	100	0.09	32	0.22	45	0.38	17	0.13
Job position:								
Economist	100	0.10	32	0.03	45	0.07	17	0.07
Senior Economist	100	0.11	32	0.09	45	0.02	17	0.07
Chief Economist	100	0.32	32	0.31	45	0.27	17	0.27
Executive	100	0.16	32	0.31	45	0.20	17	0.20
No information [1)]	100	0.31	32	0.25	45	0.42	17	0.40
Education:								
Bachelor's degree	100	0.04	32	0.06	45	0.04	17	0.00
Master's degree	100	0.24	32	0.28	45	0.13	17	0.20
PhD degree	100	0.30	32	0.16	45	0.36	17	0.07
No information [1)]	100	0.42	32	0.50	45	0.47	17	0.73
Employment history:								
Fed Board of Governors	100	0.08	32	0.03	45	0.04	17	0.00
Fed New York	100	0.06	32	0.00	45	0.00	17	0.00
Neither Board nor Fed NY	100	0.61	32	0.63	45	0.58	17	0.53
No information [1)]	100	0.25	32	0.34	45	0.38	17	0.47
Macro forecast performance								
CPI inflation forecast	56	0.000	8	0.000	7	0.000	5	0.000
Industrial production forecast	56	0.000	8	-0.001	8	0.000	5	-0.002

Note: 1) "No information" means that individuals have not provided any entry for a particular item.

Table 6: The role of *geography* for the accuracy of forecasts of FOMC monetary policy decisions

	Location								Regional conditions		Combined		Combined - OLS	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Location:														
Distance	0.029	*0.021*												
Western US region			-0.120	*0.285*										
Southern US region			0.148	*0.179*										
Midwestern US region			-0.266 *	*0.158*										
Northeastern US region			-0.264 **	*0.118*										
Washington DC					-0.823 **	*0.391*	-0.832 **	*0.402*			-1.139 ***	*0.415*	-3.659 ***	*1.232*
New York City					-0.427 ***	*0.110*	-0.436 ***	*0.144*			-0.585 ***	*0.162*	-2.658 ***	*0.816*
Financial center					-0.437 ***	*0.127*	-0.441 ***	*0.152*			-0.530 ***	*0.161*	-2.137 ***	*0.823*
USA							-0.010	*0.147*			-0.063	*0.152*	-0.488	*0.786*
English language							-0.037	*0.213*			-0.011	*0.219*	0.070	*1.027*
Regional conditions:														
CPI inflation difference									0.353 **	*0.171*	0.310 *	*0.175*	2.706 **	*1.186*
Income growth difference									-1.491	*5.472*	10.029 *	*5.911*	32.04	*31.67*
Employment growth difference									9.712 *	*5.127*	14.623 ***	*5.582*	70.81 **	*27.73*
# of observations	1323		1323		1323		1323		1323		1323		1323	
McFadden's adj. R^2	0.326		0.328		0.338		0.335		0.328		0.339		0.463	
Cragg-Uhler (Nagelkerke) adj. R^2	0.494		0.500		0.509		0.509		0.498		0.518		--	
McKelvey & Zavoina's R^2	0.496		0.506		0.521		0.521		0.502		0.536		--	

Notes: The table shows results of the ordered probit model (6) in columns (1) to (6), and of a corresponding OLS model in column (7). The variable USA denotes forecasters located in the US, but neither in Washington DC, New York City or another financial center. The variable English language captures non-US forecasters residing in an English-speaking country. The variables for regional economic conditions are calculated as the absolute deviation of regional conditions from the respective regional average over the sample period. ***, **, and * indicate significance at the 99%, 95%, and 90% levels, respectively.

Table 7: The role of *individual skills* for the accuracy of forecasts of FOMC monetary policy decisions

	Individual background								Macro forecast performance		Combined		Combined - OLS	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Individual background														
Institution:														
Investment bank	-0.492 ***	*0.150*									-0.386 **	*0.162*	-1.822 **	*0.829*
Commercial bank	-0.165	*0.162*									-0.122	*0.165*	-0.551	*0.903*
Forecast institution	-0.223	*0.170*									-0.306 *	*0.182*	-1.516 *	*0.964*
Job position:														
Economist			-0.550 **	*0.252*							-0.572 **	*0.261*	-2.509 **	*1.181*
Senior Economist			-0.405 **	*0.197*							-0.220	*0.218*	-1.035	*1.084*
Chief Economist			-0.397 **	*0.157*							-0.311 *	*0.167*	-1.441	*0.912*
No information			-0.123	*0.168*							-0.068	*0.184*	-0.249	*0.994*
Employment history:														
Fed Board of Governors					-0.423 *	*0.237*					-0.522 **	*0.256*	-2.391 **	*0.952*
Fed New York					-0.120	*0.181*					-0.104	*0.210*	-0.588	*1.025*
No information					0.026	*0.125*					-0.066	*0.140*	-0.689	*0.716*
Education:														
Bachelor's degree							-0.151	*0.254*			-0.179	*0.285*	-0.869	*1.320*
Master's degree							-0.244 **	*0.124*			-0.417 ***	*0.140*	-1.905 ***	*0.673*
No information							0.049	*0.113*			-0.030	*0.136*	-0.058	*0.698*
Macro forecast performance														
CPI inflation forecast									-0.437 ***	*0.156*	-0.447 ***	*0.162*	-1.633 ***	*0.631*
Industrial production forecast									0.082	*0.154*	0.126	*0.157*	0.589	*0.692*
# of observations	1323		1323		1323		1323		1323		1323		1323	
McFadden's adj. R^2	0.333		0.330		0.326		0.327		0.329		0.335		0.463	
Cragg-Uhler (Nagelkerke) adj. R^2	0.503		0.502		0.497		0.498		0.498		0.524		--	
McKelvey & Zavoina's R^2	0.511		0.510		0.500		0.501		0.503		0.542		--	

Notes: The table shows results of the ordered probit model (6) in columns (1) to (6), and of a corresponding OLS model in column (7). The variables for the macro forecast performance are dummies, taking the value of one if the absolute difference is *smaller* than the mean across all observations over the whole sample period and for all individuals, and the value of zero if this difference is *larger*. ***, **, and * indicate significance at the 99%, 95%, and 90% levels, respectively.

Table 8: *Geography* versus *individual skills*: explaining the accuracy of forecasts of FOMC monetary policy decisions

	Ordered probit		Ordered probit, excluding foreigners		OLS	
	coef.	std. err.	coef.	std. err.	coef.	std. err.
Location:						
Washington DC	-1.148 **	*0.452*	-0.961 **	*0.411*	-4.023 ***	*1.447*
New York City	-0.380 **	*0.192*	-0.288 **	*0.146*	-2.090 **	*0.976*
Financial center	-0.459 ***	*0.173*	-0.398 **	*0.185*	-2.196 ***	*0.853*
USA	-0.089	*0.190*			-0.752	*0.963*
English language	0.101	*0.236*			0.421	*1.089*
Regional economic conditions:						
CPI inflation difference	0.379 **	*0.181*	0.207	*0.190*	2.806 **	*1.161*
Income growth difference	10.596 *	*6.026*	11.182 *	*5.930*	32.597	*32.043*
Employment growth difference	13.482 **	*5.691*	13.151 **	*5.756*	62.426 **	*27.536*
Individual background						
Institution:						
Investment bank	-0.429 **	*0.178*	-0.378 **	*0.189*	-1.916 **	*0.896*
Commercial bank	-0.181	*0.195*	-0.097	*0.223*	-0.859	*0.992*
Forecast institution	-0.355 *	*0.193*	-0.311	*0.202*	-1.541	*0.966*
Job position:						
Economist	-0.480 *	*0.270*	-1.132 **	*0.504*	-2.047 *	*1.194*
Senior Economist	-0.137	*0.233*	-0.241	*0.268*	-0.673	*1.089*
Chief Economist	-0.165	*0.184*	-0.413 **	*0.203*	-0.765	*0.943*
No information	0.014	*0.201*	-0.257	*0.216*	0.127	*1.027*
Employment history:						
Fed Board of Governors	-0.409	*0.258*	-0.496 **	*0.252*	-1.820 *	*0.969*
Fed New York	-0.087	*0.210*	-0.091	*0.213*	-0.402	*1.036*
No information	-0.086	*0.142*	0.020	*0.185*	-0.810	*0.704*
Education:						
Bachelor's degree	-0.140	*0.291*	0.225	*0.341*	-0.760	*1.317*
Master's degree	-0.398 ***	*0.147*	-0.359 **	*0.148*	-1.744 **	*0.684*
No information	-0.030	*0.145*	-0.102	*0.157*	0.041	*0.708*
Macro forecast performance						
CPI inflation forecast	-0.459 ***	*0.166*	-0.525 ***	*0.190*	-1.733 ***	*0.641*
Industrial production forecast	0.157	*0.160*	0.121	*0.178*	0.647	*0.708*
# of observations	1323		1056		1323	
McFadden's adj. R^2 (OLS: adj. R^2)	0.339		0.299		0.470	
Cragg-Uhler (Nagelkerke) adj. R^2	0.540		0.511		--	
McKelvey & Zavoina's R^2	0.567		0.540		--	

Notes: See tables 6 and 7 for the definition of the variables. ***, **, and * indicate significance at the 99%, 95%, and 90% levels, respectively.