

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

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This version: January 2008

Abstract

The paper shows that there is a substantial degree of heterogeneity in the ability of Fed watchers to forecast US monetary policy decisions. Based on a novel database for 268 professional forecasters since 1999, the average 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. Moreover, the paper shows that such heterogeneity is economically important as it leads to greater financial market volatility after FOMC meetings. Finally, policy-makers are not impotent in influencing such heterogeneity as Fed communication is found to affect forecast accuracy significantly.

JEL No.: E52, E58, G14

Keywords: monetary policy; forecast; Federal Reserve; FOMC; geography; skills; heterogeneity; survey data; communication; United States.

* We would like to thank Jan Marc Berk, Sharon Kozicki, Ken Kuttner, Tao Zha, seminar participants at the San Francisco Fed, the Board of Governors, the European Central Bank, Magyar Nemzeti Bank, the Bundesbank/ZEW Conference on “Monetary Policy and Financial Markets,” and the 2008 AEA Meetings in New Orleans, as well as a referee of the ECB’s Working Paper Series for helpful comments and suggestions, and Alexander Bick for excellent research assistance. This paper presents the authors’ personal opinions and does not necessarily reflect the views of the European Central Bank.

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 be responsible for the 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 and heterogeneous beliefs seem of particular importance in the area of monetary policy, 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.

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 remarkably high, having substantial economic costs. To understand this heterogeneity, we concentrate on forecaster asymmetries in information processing related to skill differences 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.

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

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 (2006) for a discussion of the difference between disagreement and uncertainty.

analytical framework of forecasters or analysts with certain given skill sets cluster in particular localities.²

Finally, *communication* by the Federal Reserve may also shape the understanding of future action. However, whether Federal Reserve communication will lead forecasters to act homogeneously or – similar to other information processing – heterogeneously depending on, for instance, location and skill levels, is open to discussion. In what follows, we will treat this mostly as an empirical matter.

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 2006) and given the frequency of forecasters' participation cannot be the result of pure chance.

Another important result is that the observed differences in forecasting ability are relevant for financial market behavior, which has potentially important policy implications. We show that the larger the observed heterogeneity of monetary policy expectations, the higher is financial market volatility. This poses a challenge for central banks' efforts to enhance transparency. Reducing uncertainty will reduce possible distortions in investment decisions, facilitate firms' access to funds, and, more generally, increase the efficient allocation of capital in the economy.

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.

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

² Our paper is also related to the literature on information and geography. One strand of this literature emphasizes the role of information asymmetries for international capital flows (e.g., Ahearne, Grier, 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).

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.

Finally, we investigate how Federal Reserve *communication* affects the cross-sectional dispersion of interest rates forecasts in an extension to the main analysis. We find that more frequent as well as more informative communication reduces disparities in forecast performance across analysts stemming from differences in regional economic conditions. However, the impact of communication may not be homogenous across analysts. An intriguing result is that the superior forecast accuracy of some analysts appears to be related to their ability to extract relatively more or better information from existing Fed communication.³

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 analyses the effectiveness of Federal Reserve communication to address the heterogeneity in expectations across analysts. Section 5 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 many major 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.⁴ 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

³ These results are of relevance for the literature on the role of communication for monetary policy, underlining the importance of transparency. Central banks have a keen interest in guiding expectations of economic agents, in particular in financial markets; Blinder (1998) and Bernanke (2004), among others, stress the key role of communication in this regard. An emerging empirical literature, summarized in Blinder et al. (2007), suggests that communication is indeed a powerful tool for this purpose.

⁴ The forecast horizon is therefore generally rather short (with a median of 5, an average of 11, and a maximum of 57 days). While uncertainty about upcoming decisions at this short horizon is certainly smaller than about the future path of interest rates at a longer horizon, we believe that similar determinants are likely to explain the diversity of longer-horizon forecasts.

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 must 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 is independent from the number of participants.⁵ 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).⁶ 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.

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. How large and variable is this heterogeneity over time? Figure 1 shows the standard deviation of forecast errors across analysts for each FOMC meeting and the underlying average forecast mistake. While there is some variability in this measure over time, there is no clear trend or large outliers that can be identified.

This leads us to an important question for the empirical analysis: How large is the heterogeneity in forecast performance across individual analysts? Ranking all forecasters by their average absolute forecast errors over the full sample period, we find 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 for all FOMC meetings where forecasters deviated in their predictions (and dropping observations for FOMC meetings without dissent), 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 in decile 1 to the 10% with the largest mistakes in decile 10.

⁵ Regressing the average absolute forecast error across analysts for each FOMC meeting \bar{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:

$$\bar{s}_t = \frac{1.6267}{(0.5281)} + \frac{0.0598}{(0.0981)} F_t + \varepsilon_t,$$

where the absolute forecast error for each individual $s_{i,t}$ is defined as the absolute difference between the individual’s forecast $r_{i,t}^e$ 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 forecast error across agents.

⁶ Regressing the absolute forecast error $s_{i,t}$ for each analyst on FOMC meetings on the lead time, in number of days ($L_{i,t}$) with which he or she gives the forecasts, we find:

$$s_{i,t} = -0.0175 L_{i,t} + \varepsilon_{i,t},$$

(0.0046)

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.

⁷ Additional results available on request.

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 with regard to 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 (i.e., time fixed effects), 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 Economic relevance of forecast heterogeneity

Why is the analysis of forecast heterogeneity important? The presence of systematic forecaster heterogeneity has potentially important consequences for the real economy. If differing forecast accuracy ex ante leads to greater financial market volatility and uncertainty ex post, firms may find it more difficult to make investment decisions or to raise funds. As a consequence, the allocation of capital to its most efficient uses in investment or production may be distorted.

Thus, before moving to the analysis of the determinants of this heterogeneity, it is worthwhile investigating the link between forecast heterogeneity and financial market behavior. The most natural way to address this issue is by testing whether heterogeneity matters for the way financial markets respond to the release of the monetary policy decisions by the Federal Reserve. Our hypothesis is that more heterogeneity ex ante, if reflected in trading positions, should lead to more volatility in financial markets ex post, as there are more positions that need adjusting.

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

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).

expectations, measured as the standard deviation of the surprises calculated across survey participant (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 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:

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

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 R² 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 R² 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.

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. 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.

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 very similar 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:

$$L_i \equiv |E_i(\theta) - \theta|, \quad (2)$$

with θ representing the upcoming interest rate decision and $E(\cdot)$ the expectations operator. In line of our earlier discussion, we should think of individuals i as differing with regard to their skill levels 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

¹¹ As mentioned earlier, differences in information availability – the second principle source of forecasting heterogeneity highlighted in the literature (Hong and Stein 2007) – seems 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 relevant information. 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). As we argue below, 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.

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

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

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

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

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

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

which illustrates that forecast accuracy depends on the stochastics of the information process, $|x - y|$, 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 , $|\hat{\gamma}_i - \gamma|$.

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, agents 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. Pointing in the same directions is the fact that some information may only be available in certain locations or, equivalently, prohibitively priced elsewhere.¹⁴ In addition, geographically close forecasters may share certain

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.

¹⁴ As is common in the literature on trade in goods and financial assets, we approximate the availability and costliness of information through various measures of geographic "proximity".

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 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.¹⁵ 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.¹⁶

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

¹⁵ 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).

¹⁶ 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.

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
Income growth difference	Absolute difference between current regional income growth and its sample average	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
Employment growth difference	Absolute difference between current regional growth in non-farm payrolls and its sample average		
Location:		Individual background:	
		<i>Institution:</i>	
Distance to Federal Reserve	Distance from Washington DC (in 1000 km)	Investment bank	D=1 if analyst works for such institution; D=0 otherwise
Washington DC	D=1 if analyst is located in Washington DC; D=0 otherwise	Commercial bank	D=1 if analyst works for such institution; D=0 otherwise
New York City	D=1 if analyst is located in New York City; D=0 otherwise	Forecast institution	D=1 if analyst works for such institution; D=0 otherwise
Financial center ¹⁷	D=1 if analyst is located in Chicago, Boston, London, HK, Paris, Frankfurt, Madrid or S.Francisco	<i>Job position:</i>	
USA	D=1 if analyst is located in neither DC, NYC or a US financial center, but resides in the US; D=0 otherwise	Economist	D=1 if analyst holds this job title; D=0 otherwise
English language	D=1 if foreign analyst is located in Canada, UK, Ireland or Australia; D=0 otherwise	Senior Economist	D=1 if analyst holds this job title; D=0 otherwise
Northeast, Midwest, South, West	Regional dummies each for the four US census regions	Chief Economist	D=1 if analyst holds this job title; D=0 otherwise
		<i>Education:</i>	
		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

¹⁷ 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.

		highest degree; D=0 otherwise
PhD degree		D=1 if analyst has this as highest degree; D=0 otherwise
<i>Employment history:</i>		
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

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 – which obviously rather indirect ways of approximating the skills and ability of analysts –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

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

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

$$\begin{aligned} s_{i,t} = 0 & \quad \text{if} & \quad \hat{s}_{i,t} \leq \kappa_0 \\ s_{i,t} = 25 & \quad \text{if} & \quad \kappa_0 < \hat{s}_{i,t} \leq \kappa_1 \\ s_{i,t} = 50 & \quad \text{if} & \quad \hat{s}_{i,t} > \kappa_1. \end{aligned}$$

The κ 's are unknown parameters to be estimated with the coefficient vector β , and $\varepsilon_{i,t}$ is a well-behaved error term.¹⁸

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

¹⁸ 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.

elsewhere.¹⁹ 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 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.²⁰

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 disproportionately 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

¹⁹ 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.

²⁰ 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.

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 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, those who have a Master’s degree as their last degree may have an MBA, which in turn may signal something specific about the effort and qualifications of these analysts.

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 disproportionately, 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.²¹

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.

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. The Role of Fed Communication

There is a rapidly growing literature on the importance of communication for the predictability of the Federal Reserve and other central banks (see Blinder et al. 2007). However, almost all of the studies in this literature concentrate on the mean or consensus expectations of financial markets. By contrast, our objective in this section is to analyze the effect of communication on the heterogeneity of expectations across individual market participants.

Heterogeneity of expectations is at least in part undesirable from a monetary policy perspective as it may create significant differences in the understanding of FOMC policy decisions and thus the transmission process of policy. A key question therefore is: what can a central bank do to affect this heterogeneity in expectations? In particular, what role does communication play in this regard? Communication is potentially a powerful tool not only to convey a particular policy message and alter the consensus or mean of expectations, but may also be used to influence the degree of heterogeneity among market participants. This section analyses to what extent Fed communication has exerted such an influence on the heterogeneity of expectations in the past, and through what channels this effect has functioned. More precisely, we ask whether communication policy can be used in a systematic manner so as to reduce this heterogeneity stemming from differences in geography and skills, and thus promote a more homogenous understanding of monetary policy. Note that there are clear indications that communication is a powerful tool in this regard: during the period of explicit forward guidance by the FOMC through the so-called “measured pace”-statements, cross-forecaster heterogeneity has basically vanished from our dataset (see Figure 1).

A more detailed identification of effects of Fed communication on heterogeneity in forecast accuracy is not without difficulties. Traditional measures of Fed communication do not entail a geographic component (see below). As a result, the empirical approach has to rely on interaction

²¹ 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.

terms – that is, we ask whether the effect of the variables explaining the heterogeneity of forecast accuracy varies as the Fed communicates. However, identification through interaction terms is an indirect approach that may or may not be sufficient to capture all effects of Fed communication. Ultimately, of course, this is an empirical question.

For this purpose, we take the data on communication by FOMC members developed in Ehrmann and Fratzscher (2007), which is available until the FOMC meeting in May 2004, and investigate the effect on the heterogeneity of expectations and its channels. Based on newswire service reports of statements about the monetary policy inclination by FOMC members during the inter-meeting period, two measures of Fed communication policy can be distinguished.²²

First, we employ the frequency of Fed communication (measured as the number of statements recorded in the dataset during an inter-meeting period) as a proxy for the information content of Fed communication for each inter-meeting period. The hypothesis is as follows: more information provided by the Federal Reserve should not only enhance the ability of market participants to anticipate the subsequent FOMC decision, but also reduce the heterogeneity in expectations across agents if this information is understood and processed by all agents in a similar way.

Second, we analyze the effect of communication dispersion, i.e. the extent of disagreement across individual FOMC members in an inter-meeting period (measured as

$$\Omega_t = \frac{\sum_{i=1}^{N-1} \sum_{j=i+1}^N |C_i - C_j|}{\frac{1}{2} \cdot (N^2 - D)},$$

with N the number of statements in the inter-meeting period that

ends on meeting day t, C the statements classified as dovish, neutral or hawkish as $\{-1,0,+1\}$, and a dummy D with D=0 if N is an even number and D=1 if it is odd. This normalization allows us to obtain a dispersion measure that lies strictly between zero (no dispersion) and one. Our prior is that if there is a high degree of disagreement, then it should raise uncertainty about the upcoming FOMC policy decision and thus also increase the heterogeneity in expectations.

To test whether communication policy helps reduce the effects that differences in geography and skills have on the heterogeneity of expectations, we estimate an extension of model (6) which adds interaction variables of geography and skills/ability ($x_{k,i,t}$) with communication (c_t):

$$\hat{s}_{i,t} = \alpha_t + \sum_{k=1}^K \beta_k x_{k,i,t} + \sum_{k=1}^K \gamma_k x_{k,i,t} c_t + \varepsilon_{i,t} \quad (7)$$

Note that the communication variable c_t alone cannot be included in model (7) due to the inclusion of the time fixed effects α_t . Our key hypothesis of interest is $H_0: \gamma_k = 0$. Whenever γ_k is different from zero, the model identifies that Fed communication affects forecast heterogeneity; if the sign of a γ_k is opposite of the sign of the corresponding β_k (where k refers to the k th explanatory variable included in $X_{i,t}$), communication reduces heterogeneity; in the case of equally signed coefficients, it tends to enhance it instead. Recall from Tables 6-8 that most of the coefficients β_k of the benchmark models are negative – for instance, being located in a financial center reduces the forecast error $s_{i,t}$ of an analyst. This means that $\gamma_k > 0$ implies that a particular communication policy reduces or even eliminates the impact of a particular geographic or skill-related characteristic on the absolute forecast error. By contrast, $\gamma_k < 0$ entails that communication has the opposite effect of widening the information asymmetries and thus the dispersion in forecast accuracy. For the variables measuring regional macroeconomic disparities, the interpretation is reversed, as these yielded positive coefficients β_k in model (6).

²² A detailed outline and explanation of the data and its underlying methodology is provided in Ehrmann and Fratzscher (2007).

Table 9

Table 9 shows the results for the interaction coefficients γ_k . A first central finding is that Fed communication appears to be successful in *reducing* the heterogeneity in forecast accuracy stemming from disparities in regional economic conditions. For instance, a higher frequency of communication reduces the effect of regional income growth differentials on the heterogeneity of forecast errors. Somewhat surprisingly, also a more dispersed communication flow from the Fed to the public helps analysts overcome some of the confusion stemming from diverging regional economic conditions. We interpret this result as being indicative that Fed communication indeed succeeds in reducing information asymmetries that come from the differences in regional economic conditions which influence agents' expectations about FOMC policy decisions.

A second finding is that Fed communication mostly *raises* the heterogeneity in forecast performance that stems from differences in the skills and abilities of individual analysts, as suggested by the mostly negative coefficients. For instance, communication reduces the forecast error of analysts working at investment banks, commercial banks and forecast institutions, i.e. those analysts who on average show lower forecast errors of US monetary policy decisions. Similar evidence is found for differences in education: analysts with Master's degrees benefit relatively more from Fed communication in terms of improved forecast performance. An interpretation of this result is that those analysts who are relatively good in anticipating FOMC policy decisions obtain these superior forecast skills at least partly from their ability to better extract information from Fed communication.

Finally, there is also some limited evidence that communication plays a role for geographic characteristics of analysts. In fact, Fed communication improves the forecast performance of analysts based in New York City or the United States; though in other cases the point estimates are not statistically significant.

In summary, Fed communication appears to reduce information asymmetries along some dimensions, but may increase it along others. On the one hand, the results suggest that communication can indeed be effective in reducing disparities in forecast performance across analysts stemming from differences in regional economic conditions. Thus communication in some instances appears successful in reducing information asymmetries across market participants. On the other hand, at least part of the superior forecast accuracy stemming from analysts' individual background appears to be related to their ability to extract more or better information from Fed communication.

5. 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 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).

The paper has demonstrated that this heterogeneity is economically meaningful as it has repercussions for trading behavior, by significantly increasing financial market volatility. This could distort investment decisions of firms, make it more difficult for firms to raise funds for investment or production, and could decrease the efficient allocation of capital.

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.

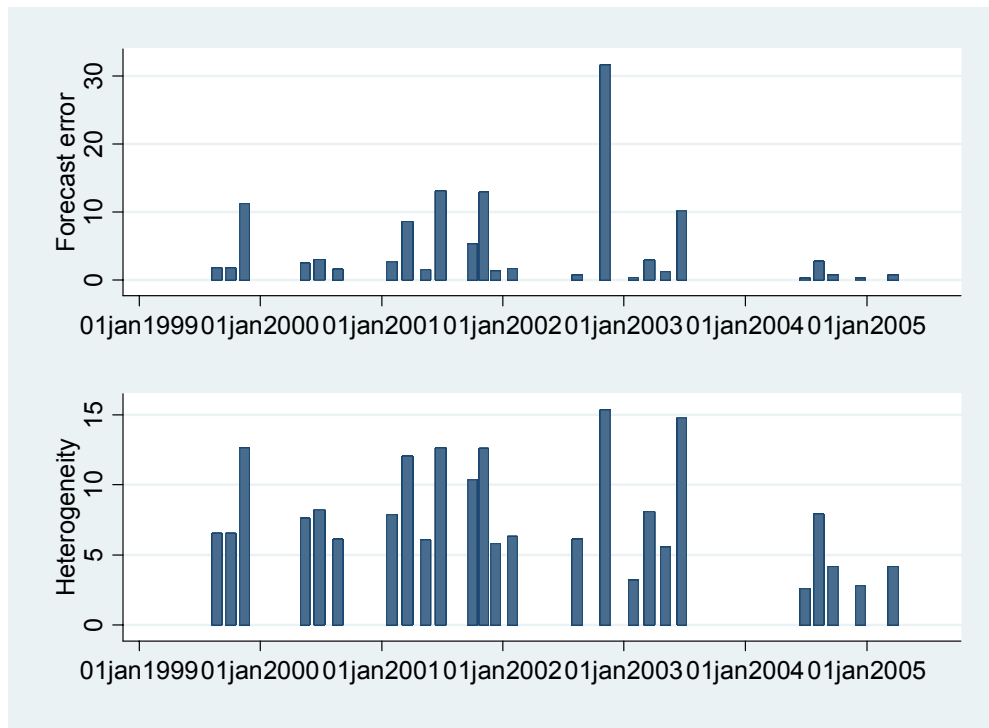
At the same time, some of the analysis has also normative implications, though these can be no more than tentative and suggestive. Clearly, it is desirable for central banks to disseminate information and knowledge as equally as possible across agents not least because a high degree of heterogeneity is likely to result in financial market uncertainty and volatility. Our empirical findings indicate that Fed communication policies have indeed been successful in reducing disparities in forecast performance stemming from differences in regional economic conditions. However, communication appears to have been less successful in addressing those disparities that stem from differences in skills of analysts. 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.

References

- Andersen, T., T. Bollerslev, F.X. Diebold and P. Labys (2003). Modelling and Forecasting Realized Volatility. *Econometrica* 71, 529-626.
- Ahearne, Alan G., William L. Grier, and Francis E. Warnock (2004). Information Costs and Home Bias: An Analysis of US Holdings of Foreign Equities, *Journal of International Economics*, 62: 313-36.
- Bae, Kee-Hong, René Stulz, and Hongping Tan (2008). Do Local Analysts Know More? A Cross-Country Study of the Performance of Local Analysts and Foreign Analysts. Forthcoming, *Journal of Financial Economics*.
- Bauer, A., Eisenbeis, R., Waggoner, D. and T. Zha (2006). Transparency, Expectations, and Forecasts. *Federal Reserve Bank of Atlanta Economic Review* Q1, 1-25.
- Berger, Helge, Michael Ehrmann and Marcel Fratzscher (2006). Forecasting ECB monetary policy: accuracy is (still) a matter of geography, ECB Working Paper No. 578, January 2006.
- Bernanke, Ben (2004). FedSpeak. Remarks at the Meetings of the American Economic Association, San Diego, California, January 3, 2004, available at www.federalreserve.gov/boarddocs/speeches/2004/200401032/default.htm.
- Blinder, Alan (1998). *Central Banking in Theory and Practice*. MIT Press, Cambridge MA.
- Blinder, A., M. Ehrmann, M. Fratzscher, D. de Haan and D.J. Jansen (2007). Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence. Mimeo.
- Coval, J. D. and Moskowitz, T. J. (1999). Home bias at home: local equity preference in domestic portfolios. *Journal of Finance* 54 (6): 2045 – 2073.
- Coval, J. D. and Moskowitz, T. J. (2001). The geography of investment: informed trading and asset pricing. *Journal of Political Economy* 109(4): 811 – 841.
- D’Amico, S. and A. Orphanides (2006). Uncertainty and Disagreement in Economic Forecasting. Mimeo, Board of Governors, <http://www.athanasiosorphanides.com/ud054.pdf>.
- Della Vigna, S. (2007). Psychology and Economics: Evidence from the Field. NBER Working Paper No. 13420.
- Diether, K.B., C.J. Malloy and A. Scherbina (2002). Differences of Opinion and the Cross Section of Stock Returns. *Journal of Finance* 57(5): 2113 – 2141.
- Dvorak, Tomas, (2005). Do Domestic Investors Have an Information Advantage? Evidence from Indonesia. *Journal of Finance* 60(2): 817 – 839.
- Ehrmann, Michael and Marcel Fratzscher (2007). Communication and decision-making by central bank committees: different strategies, same effectiveness?, *Journal of Money, Credit and Banking* 39, 509-541.
- Gürkaynak, Refet, Sack, Brian and Eric Swanson (2005). Do Actions Speak Louder than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking* 1: 55-94.
- Gürkaynak, Refet, Sack, Brian and Eric Swanson (2007). Market-Based Measures of Monetary Policy Expectations. *Journal of Business and Economic Statistics* 25(2), 201-212.
- Hamilton, J.D. (2007). Daily Changes in Fed Funds Futures Prices. NBER Working Paper No. 13112.
- Harris, M. and A. Raviv (1993). Differences in Opinion Make a Horse Race. *Review of Financial Studies* 6(3), 473-506.
- Hau, Harald (2001). Location Matters: An Examination of Trading Profits, *Journal of Finance* 56(5): 1959-1983.
- Hirshleifer, D. and S.H. Teoh (2003). Limited Attention, Information Disclosure, and Financial Reporting. *Journal of Accounting and Economics* 36(1-3), 337-386.
- Hong, H. and J.C. Stein (2007). Disagreement and the Stock Market. *Journal of Economic Perspectives* 21(2), 109-128.
- Hong, H., J.C. Stein and J. Yu (2007). Simple Forecasts and Paradigm Shifts. *Journal of Finance* 62(3), 1207-1242.
- Kandel, E. and N.D. Pearson (1995). Differential Interpretation of Public Signals and Trade in Speculative Markets. *Journal of Political Economy* 103(4), 831-872.

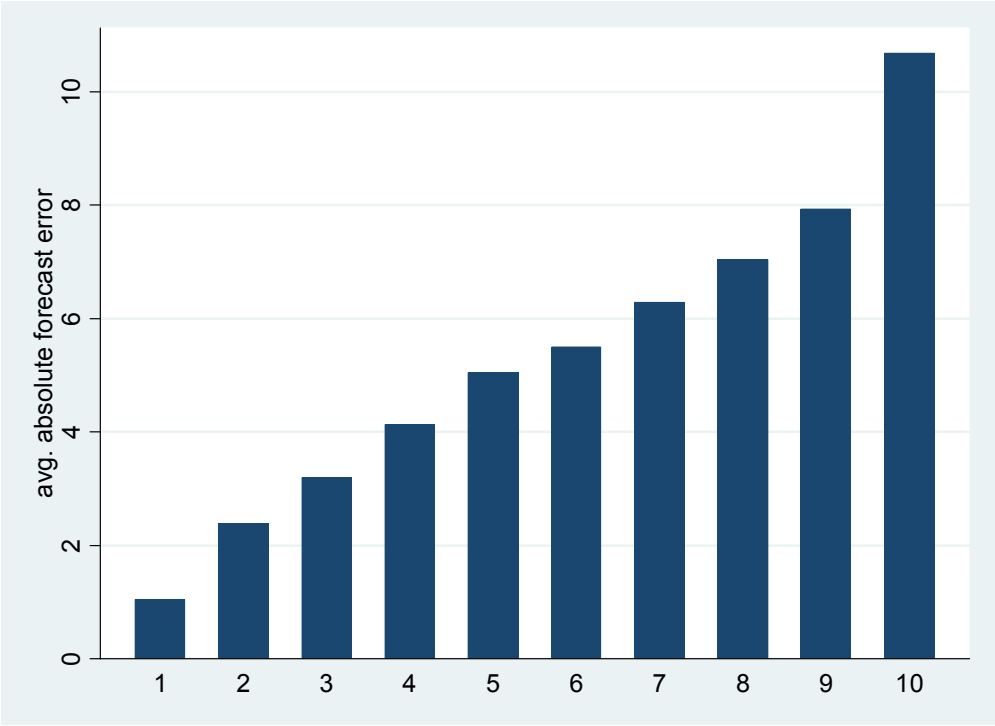
- Kang, Jun-Koo and René Stulz (1997). Why Is There a Home Bias? An Analysis of Foreign Portfolio Equity Ownership in Japan, *Journal of Financial Economics*, 46: 3-28.
- Kuttner, K. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market, *Journal of Monetary Economics* 47, 523–544.
- Lange, Joe, Brian Sack, and William Whitesell (2003). Anticipations of Monetary Policy in Financial Markets, *Journal of Money, Credit, and Banking*, 35, 889-909.
- Laster, D., P. Bennett and I.S. Geoum (1999). Rational Bias in Macroeconomic Forecasts. *Quarterly Journal of Economics* 114(1), 293-318.
- Mankiw, N.G., R. Reis and J. Wolfers (2004). Disagreement About Inflation Expectations, in: M. Gertler and K. Rogoff (eds.), *NBER Macroeconomics Annual*, 209-248.
- Peng, L. and W. Xiong (2006). Investor Attention, Overconfidence and Category Learning. *Journal of Financial Economics* 80, 563-602.
- Poole, William, Robert Rasche, and Daniel Thornton (2002). Market Anticipations of Monetary Policy Actions, *Federal Reserve Bank of St. Louis Economic Review*, July/August, 65-94.
- Portes, Richard and Helene Rey (2005). The Determinants of Cross Border Equity Flows, *Journal of International Economics* 65: 269-96.
- Swanson, Eric (2006). Have Increases in Federal Reserve Transparency Improved Private Sector Interest Rate Forecasts? *Journal of Money, Credit, and Banking*, 38, 791-819.
- Tversky, A. and D. Kahneman (1973). Availability: A heuristic for judging frequency and availability, *Cognitive Psychology* 5, 207-232.

Figure 1: Forecast error heterogeneity and distribution of forecast errors over time



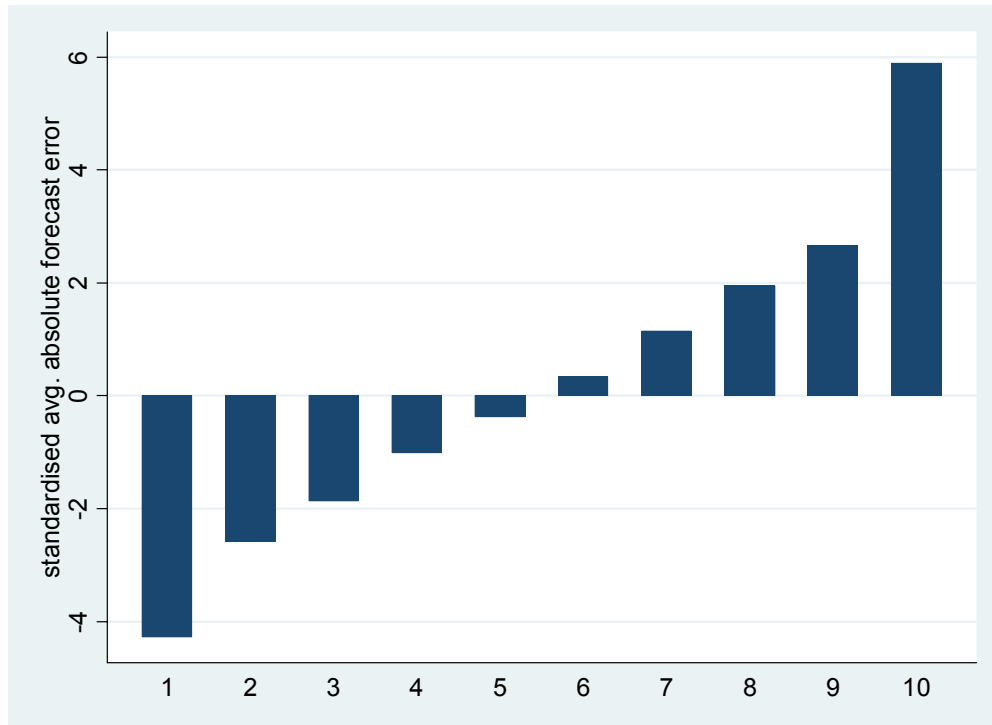
Note: The upper panel shows the average absolute forecast error (in b.p.) across individual forecasters for each FOMC meeting. The lower panel shows the standard deviation of the absolute forecast errors across individual forecasters.

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: The effect of monetary policy surprises and heterogeneity in expectations on 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	0.725
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					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									
<i>Institution:</i>									
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
<i>Job position:</i>									
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	268	0.36	0.48	0	1	194	0.34	74	0.42
<i>Education:</i>									
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	268	0.56	0.50	0	1	194	0.46	74	0.82
<i>Employment history:</i>									
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	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: "No information" means that individuals have not provided any entry for a particular item.

Table 5: Summary statistics, 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								
<i>Institution:</i>								
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
<i>Job position:</i>								
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	100	0.31	32	0.25	45	0.42	17	0.40
<i>Education:</i>								
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	100	0.42	32	0.50	45	0.47	17	0.73
<i>Employment history:</i>								
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	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: "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)	(8)	(9)	(10)	(11)	
	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								
New York City			-0.427 ***	0.110								
Financial center			-0.437 ***	0.127								
USA			-0.010	0.147								
English language			-0.037	0.213								
Regional conditions:												
CPI inflation difference					0.353 **	0.171			0.310 *	0.175		
Income growth difference					-1.491	5.472			10.029 *	5.911		
Employment growth difference					9.712 *	5.127			14.623 ***	5.582		
# of observations	1323		1323		1323				1323		1323	
McFadden's adj. R ²	0.326		0.328		0.328				0.339		0.463	
Cragg-Uhler (Nagelkerke) adj. R ²	0.494		0.509		0.498				0.518		--	
McKelvey & Zavoina's R ²	0.496		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 - OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)			
	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.	coef.	std. err.
Individual background										
<i>Institution:</i>										
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
<i>Job position:</i>										
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
<i>Employment history:</i>										
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
<i>Education:</i>										
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	-1.633 ***	0.631
Industrial production forecast							0.082	0.154	0.589	0.692
# of observations	1323	1323	1323	1323	1323	1323	1323	1323	1323	1323
McFadden's adj. R ²	0.333	0.330	0.326	0.327	0.329	0.335	0.329	0.335	0.463	0.463
Cragg-Uhler (Nagelkerke) adj. R ²	0.503	0.502	0.497	0.498	0.498	0.524	0.498	0.524	--	--
McKelvey & Zavoina's R ²	0.511	0.510	0.500	0.501	0.503	0.542	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						
<i>Institution:</i>						
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
<i>Job position:</i>						
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
<i>Employment history:</i>						
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
<i>Education:</i>						
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.

Table 9: The role of Federal Reserve communication policy for geography and skills

	Number of Fed statements		Fed communication dispersion	
	coef.	std. err.	coef.	std. err.
Location:				
Washington DC	-0.345	0.400	-1.199	1.462
New York City	-0.363 **	0.168	-0.570	0.703
Financial center	-0.099	0.171	-0.532	0.749
USA	-0.410 **	0.198	-1.434	0.892
English language	0.149	0.272	1.221	1.333
Regional economic conditions:				
CPI inflation difference	-0.025	0.166	-0.336	0.981
Income growth difference	-0.897 **	0.422	-2.782 **	1.198
Employment growth difference	-0.029	0.169	0.318	0.730
Individual background				
<i>Institution:</i>				
Investment bank	-0.538 ***	0.210	-2.961 ***	0.799
Commercial bank	-0.848 ***	0.229	-3.757 ***	0.934
Forecast institution	-0.596 ***	0.232	-2.751 ***	0.933
<i>Job position:</i>				
Economist	0.684 **	0.271	2.265 *	1.166
Senior Economist	0.296	0.237	1.195	0.914
Chief Economist	0.356 *	0.198	1.142	0.802
No information	0.309	0.217	0.410	0.866
<i>Employment history:</i>				
Fed Board of Governors	-0.186	0.239	-1.078	0.880
Fed New York	-0.152	0.168	-0.179	0.726
No information	-0.178	0.148	-0.043	0.610
<i>Education:</i>				
Bachelor's degree	0.021	0.291	-1.240	1.098
Master's degree	-0.378 ***	0.145	-1.751 ***	0.594
No information	-0.167	0.154	-0.730	0.602
Macro forecast performance				
CPI inflation forecast	-0.106	0.138	-0.953	0.602
Industrial production forecast	-0.115	0.171	0.651	0.486
# of observations	868		868	
McFadden's adj. R ²	0.309		0.316	
Cragg-Uhler (Nagelkerke) adj. R ²	0.584		0.590	
McKelvey & Zavoina's R ²	0.633		0.620	

Notes: The table shows the coefficients for the listed variables, interacted with the corresponding communication variable in each column from model (7), obtained from ordered probit estimates. See tables 7 and 8 for the definition of the non-interacted variables. ***, **, and * indicate significance at the 99%, 95%, and 90% levels, respectively. Sample period: February 1999 – May 2004.