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Uncertainty measures from partially rounded probabilistic forecast surveys

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Although survey-based point predictions have been found to outperform successful forecasting models, corresponding variance forecasts are frequently diagnosed as heavily distorted. Professional forecasters who report inconspicuously low ex ante variances often produce squared forecast errors that are much larger on average. In this paper, we document the novel stylized fact that this variance misalignment is related to the rounding behavior of survey participants. Rounding may reflect the fact that some survey participants employ a rather judgmental approach to forecasting as opposed to using a formal model. We use the distinct numerical accuracies of panelists' reported probabilities as a way to propose several alternative and easily implementable corrections that (i) can be carried out in real time, that is, before outcomes are observed, and (ii) deliver a significantly improved match between ex ante and ex post forecast uncertainty. According to our estimates, uncertainty about inflation, output growth and unemployment in the U.S. and the Euro area is higher after correcting for the rounding effect. The increase in the share of nonrounded responses in recent years also helps to understand the trajectory of survey-based average uncertainty during the years since the financial and sovereign debt crisis.

Keywords. Survey data, probabilistic forecasting, rounding, uncertainty.

JEL classification. C32, C52, C53, C83.

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1. Introduction

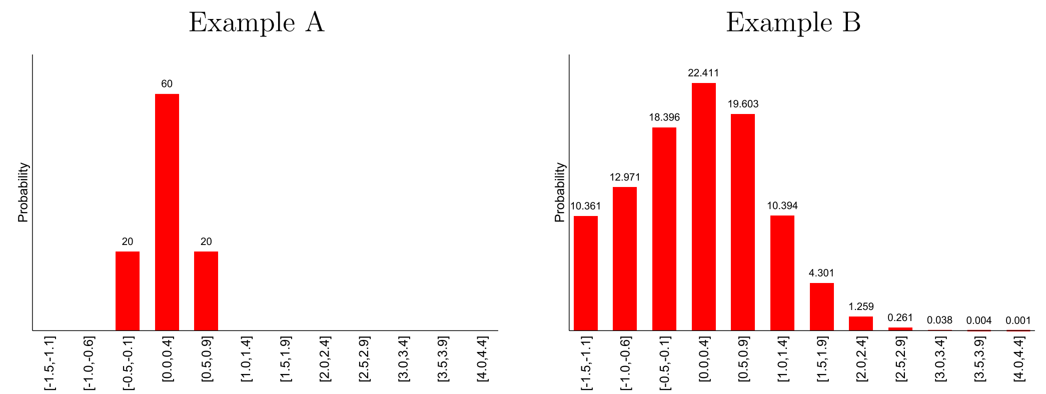
Forecasts that dispense with uncertainty bands are increasingly regarded as incomplete. It has been argued that to express how strongly a point prediction is expected to deviate from the ex post observed outcome, point forecasts should be complemented by a quantification of ex ante uncertainty (Dawid (1984) and Bruine de Bruin et al. (2010)). While it has been documented that survey forecasts for inflation, GDP growth or unemployment outperform model-based forecasts (cf. Ang et al. (2007) and Faust and Wright (2009)), the informative content of survey predictions for the conditional variance has been recently contested, for example, by Clements (2018). In case of the Survey of Professional Forecasters (SPF) that is conducted by the Federal Reserve Bank of Philadelphia (FED) and the European Central Bank (ECB), point forecasts are elicited along with probabilistic forecasts in the form of histograms. A measure of ex ante uncertainty can be computed as the variance of these histograms. Several desirable properties of this index have been documented. For example, Lahiri and Sheng (2010) show that the cross-sectional average variance increases with the forecast horizon. However, it has been found that the ex ante variance (in our terms, "uncertainty") deviates considerably from the average squared ex post forecast error. This finding is sometimes interpreted as evidence for "over- or underconfidence" (Kenny et al. (2014, 2015) and Clements (2014)). The term "overconfidence" in this context typically refers to an ex ante variance that is small compared to a predefined benchmark such as the ex post squared forecast error.[1] This finding suggests that the average variance of the SPF histograms as proposed by Zarnowitz and Lambros (1987) has to be interpreted with caution.

In this paper, we ask under which conditions the second moments from the SPF data are relatively well aligned with the variability of prediction errors. The derivation of an ex ante measure of forecast uncertainty that takes potential distortions into account is difficult since the survey data does not contain any covariates that might help to understand forecasters' behavior.[2] Thus, hypotheses about the dependence of individuals' reported ex ante uncertainty on misperceptions of their own capability to forecast cannot be easily examined empirically. Against the background of these difficulties, we propose to relate the ex ante variance of forecasters to the properties of the predictions themselves, which are observed prior to the outcome.

A misalignment of ex ante and ex post forecast variances has been documented by Giordani and Söderlind (2003, 2006), Kenny et al. (2014, 2015), Clements (2014), and Casey (2021). Our main finding is that these deviations of panelists' forecast uncertainty prior to and after the outcome can partially be ascribed to the response pattern of a large group of forecasters that provide their histogram predictions in a particular form. A striking feature of this group is that their forecasts are conveyed in a rather coarse form, with apparently strongly rounded numbers and a relatively low number of probability categories that are assigned nonzero numbers. An example of this is depicted in Figure 1.

[1] As Clark et al. (2020) show, functions of past squared forecast errors might also be employed to estimate the ex ante variance.

[2] One notable exception is a categorical variable in the FED-SPF data that reports whether forecasters are employed in the financial services industry, a research institute or any other employer.



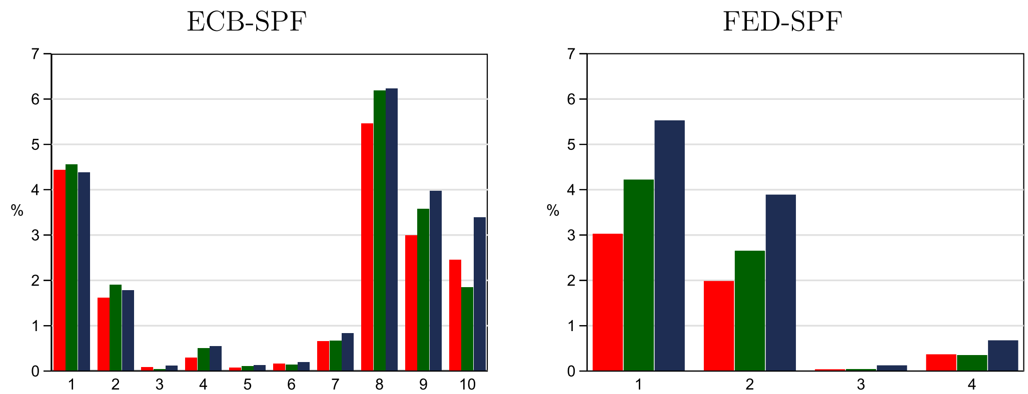
Notes: The graphs depict two examples of one-quarter-ahead histogram forecasts for the annual inflation rate in the Euro area in 2016. Both predictions are taken from the 2016Q4 wave of the ECB-SPF. The histograms have been submitted by the forecasters with identification numbers 102 and 95. In the right subfigure, the decimal numbers attached to the probabilities are cut off at the third decimal after the comma, that is, the original histogram contains additional decimal numbers.

Figure 1. Two examples of histogram forecasts for the inflation rate from the ECB-SPF.

The subfigures show histogram forecasts for the annual inflation rate in 2016 reported by two participants in the 2016Q4 survey wave of the ECB-SPF. Two differences are apparent. First, the forecasted probabilities in Example A are multiples of 10%, whereas those in Example B do not seem to have a common divisor. Second, the number of outcome intervals that contain nonzero probability numbers is considerably smaller in the left graph. In other words, the right histogram exhibits larger variance. Moreover, Figure 2 summarizes the share of probabilities that contain between one and ten decimal numbers out of all reported probability numbers in the SPF data, pooled across forecasters, time periods, and forecast horizons.[3] To improve the readability, those bins that are assigned a nonzero probability yet have no decimals are omitted from the graph.

The left panel of Figure 2 shows that the ECB-SPF contains two clearly separated groups of forecasters that are distinguished both in terms of the number of bins for which they fill in nonzero numbers and the number of decimals in their numerical values. The right part of the figure shows the counterpart for the case of the FED-SPF. As it is suggested in Figure 1, separating the two groups, we find that the ex ante variances of those forecasters who report more strongly rounded numbers are substantially smaller than those of survey participants who appear to round less or not at all. Moreover, the ex ante and ex post uncertainties of the nonrounding group of forecasters are clearly more in line with each other than in the case of the group which reports strongly rounded histogram probabilities. This is the outcome of the comparison between rounded and nonrounded forecasts both within the ECB-SPF and within the FED-SPF. However, the number of responses that entail a large number of decimals is substantially larger in the former than in the latter.

[3]In the following, the term “decimals” refer to digits after the comma.



Notes: The graphs depict the share of probabilities that contain $d \in \{1, \dots, 10\}$ decimal numbers out of all reported probabilities in the SPF data for inflation (first bar), output growth (second bar), and unemployment (third bar). Those bins that are assigned a nonzero probability yet have no decimals are omitted to improve the readability. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 2. Relative frequencies of the number of decimals reported in the SPF.

There are several potential explanations for this finding. First, the degree of coarseness of the probability numbers might be related to individuals' choices whether to employ a formal model to derive the histogram forecasts or to rely primarily on less formal considerations. In the latter case, one might speak of "judgmental forecasting." This possibility is discussed in Section 5, where we examine the results from two special questionnaires of the ECB-SPF that indicate that two groups of survey participants can be separated based on the degree to which they rely on formal models to arrive at forecasts. Interestingly, the size of the group which relies on models as opposed to judgment roughly equals the size of the nonrounding group. Although different degrees of formalization in forecasters' conceptual frameworks might be the most intuitive explanation, other reasons for the observed data patterns may also play a role. In particular, a second explanation is that the coarseness of the reported numbers may reflect specifics of the survey design. The FED-SPF is elicited in a rather traditional way by asking respondents to fill in the questionnaire by means of paper-and-pencil. In contrast, the ECB-SPF questions can be answered on the computer via an excel spreadsheet. Hence, it is conceivable that respondents find it easier to report numbers with many decimals in the case of the ECB-SPF.

As mentioned above, it is difficult to test such hypotheses empirically due to the absence of explanatory variables in the SPF data. Instead, this paper aims at establishing a reliable means to adjust a measure of aggregate uncertainty for the marked influence of coarse histogram forecasts. We show that there exists a pervasive correlation between the rounding behavior of individuals and their respective variance misalignment. Thus, rounded probability numbers are a pertinent indicator for the subgroup of histogram forecasts that show the sort of coarseness, which gives rise to suspiciously low ex ante variances at certain forecast horizons. This provides a reliable way to single out these forecasts since the classification is essentially unaffected by distinct ways to define rounding.

Besides the influence of rounding, we find that ex ante uncertainty is also affected by the width of the histogram bins that are filled in by panelists. A comparison between the ECB-SPF and the FED-SPF shows that the bin width is in most cases twice as large for the latter. Interestingly, we find that this does not seem to affect the number of bins that SPF participants assign nonzero numbers to. Consequently, this results in a higher ex-ante uncertainty in the FED-SPF. We summarize several changes in this pattern over time and across variables which suggest that the different magnitudes of ex ante uncertainty across the two surveys can indeed be partly ascribed to the width of histogram bins.

Our findings have three important implications for users of histogram-based uncertainty measures. First, the distortion of an index of overall uncertainty that is computed as the average across the individual variances (Lahiri and Sheng (2010) and Lahiri et al. (2015)) can be reduced ex ante by focusing on forecasts that are nonrounded. As the share of nonrounded histograms is relatively small, this would imply a considerable loss of observations. However, since the number of nonrounders was small mainly in the early survey waves, this problem has been partly mitigated during more recent years. Second, the trajectory of average uncertainty during recent years is at least partly affected by the overall increase in the share of forecasters who do not report strongly rounded numbers. Third, an improvement in the identification of rounders and nonrounders would be possible if survey participants were given the opportunity to state if their responses were rounded or not by asking them to comment on this issue in the questionnaire as it has been suggested by Manski and Molinari (2010). We conclude that uncertainty is likely higher than what is reflected by the average forecast variance due to the presence of considerable rounding.

The remainder of this paper is structured as follows. After briefly reviewing the related literature in Section 2, the data are introduced in Section 3. We discuss the categorizations that are used to classify survey participants as rounders or nonrounders in Section 4. In Section 5, we analyze the size of both groups in the SPF data and examine the potential connection between rounding and judgmental forecasting. Moreover, the findings regarding the variance misalignment and the performance of the histogram forecasts are presented. Based on our results we discuss potential deficiencies of aggregate forecast uncertainty as it is measured with the SPF data and highlight a way to derive a more meaningful uncertainty measure. Section 6 examines the influence of interval definitions in the survey questionnaire on our results and provides a comparison of our findings with those from a related study by Binder (2017). Section 7 summarizes and concludes.

2. Rounding and the information content of histogram forecasts in the related literature

Though surveys like the SPF have become a popular data source to quantify forecast uncertainty, it is not well understood to what extent numerical inaccuracies such as rounded numbers may distort the variance of histogram forecasts. Heitjan and Rubin

(1991) discuss the implications of rounding and similar forms of incomplete survey responses on the likelihood of parameter estimates that are based on survey data. They suggest that rounding can be understood as a form of information loss that should optimally be corrected for. According to Heitjan and Rubin (1991), this might be accomplished by discarding rounded observations if more sophisticated correction methods are not available. The absence of covariates in the SPF data sets renders the omission of rounded observations the most promising way to address the problem of distorted histogram forecasts in our case. Similarly, Tay and Wallis (2002) note that the communication of uncertainty from survey-based density forecasts faces several distinct problems.[4] Some of the crucial steps like the design of the survey questionnaire, the timing of the elicitation process, the production and reporting of forecasts by survey participants as well as the interpretation and evaluation by users of the survey may introduce distortions in the conveyed information. In general, the performance of survey participants in probabilistic surveys may also be assessed in terms of the coverage of the entire histogram forecast. This is often accomplished by means of the probability integral transform (Dawid (1984), Diebold et al. (1998), and Clements (2006)). Due to the prominence of second moment statistics in applied economic research such as the construction of forecast intervals or the influence of uncertainty on investment and consumption decisions, we focus on this particular feature of histogram forecasts in this paper.

The question we address in this paper is how rounding may affect ex ante and ex post measures of forecast uncertainty. We are particularly interested in the implications of the observation that forecasters who provide strongly rounded responses also show a tendency to provide narrow histograms with only a small number of outcomes to which they attach nonzero probabilities. It has been previously noted that such response behavior may affect conditional second moment statistics from survey data. For example, Boero et al. (2015) interpret the decision of forecasters to round the probabilities of surveys histograms as an expression of what they call "uncertain uncertainty." Other studies such as Manski and Molinari (2010) also highlight the importance of rounding choices on the outcomes of histogram forecasts as they are provided by the SPF.

A distinct approach is taken by Binder (2017), who derives an index of inflation uncertainty based on rounding outcomes in a survey of consumer expectations. The construction of this index is based on the assumption that rounding can be seen as an expression of uncertainty. This is also reflected in Bruine de Bruin and Carman (2012) or Ruud et al. (2014). These hypotheses regarding the link between rounding and uncertainty connect to the more general literature which discusses rounding and other forms of *data coarsening* (Heitjan and Rubin (1991) and Ruud et al. (2014)). We do not employ rounding as the single source of information regarding uncertainty, but derive a direct measure of uncertainty based on the SPF histograms. This enables us to discuss potential distortions from rounding in the computation of the resulting uncertainty index.

Clements (2018) examines the informative content of density forecasts in terms of their capability to deliver variance forecasts and concludes that the SPF data provided by the ECB contain little reliable information beyond the forecast for the conditional

[4]We use the terms "density forecast" and "histogram forecast" synonymously throughout.

mean. In the current study, we draw upon such findings and examine to what extent the misalignment between ex ante uncertainty and ex post forecast performance can be linked to the tendency to concentrate the entire probability mass in a small share of the outcome intervals from the survey questionnaire. In a related study, Clements (2011) documents that the mismatch between the reported probabilities of a decline in output growth and corresponding probabilities derived from the histogram forecasts can be partially explained by the rounding choices of the forecasters in the FED-SPF. Since more than 75% of the SPF participants' responses appear to be rounded to some extent, it is important to investigate the implications of this particular data feature for the assessment of macroeconomic uncertainty.

3. Data

In this section, the data used to quantify ex ante and ex post uncertainty are described. The survey data are provided by the SPF of the ECB and the Federal Reserve Bank of Philadelphia. Both surveys elicit point and density forecasts of future inflation, real GDP growth and unemployment rates in the Euro area and the U.S. at the quarterly frequency. For inflation and output growth, the outcome variable x_t refers to year-on-year growth rates, that is,

$$x_t = 100 \times \left(\frac{X_t}{X_{t-1}} - 1 \right), \tag{1}$$

where X_t denotes the annual average of either the respective price index or real GDP in year $t = 1, \ldots, T$.[5] In the case of the unemployment rate, x_t is calculated as the annual average over the civilian unemployment rates that are observed at the monthly frequency, that is, $x_t = X_t$. Data on the realizations for the Euro area and the U.S. are drawn from the Statistical Data Warehouse of the ECB and the Real-Time Data Set for Macroeconomists of the Federal Reserve Bank of Philadelphia, respectively.[6,7] Both databases provide data vintages for all outcome variables. For each vintage, we calculate X_t in all cases where consecutive observations for each month (Harmonized Index of Consumer Prices, unemployment rate) or quarter (GDP price index, real GDP) of year t are available and compute x_t. In the empirical analysis, we employ the first-releases of x_t, which are most closely related to the information available to forecasters when they produce their predictions.[8] Moreover, Jo and Sekkel (2019) show that ex post forecast variances based on the most recent data vintage tend to be underestimated.

[5]The ECB-SPF inflation forecasts refer to the monthly Harmonized Index of Consumer prices. For the FED-SPF, we use the quarterly chain-weighted GDP price index. We prefer GDP inflation over CPI inflation because density forecasts for the latter are available only since 2007 in the FED-SPF, whereas predictions for the former are available for the entire sample period. For the computation of output growth, we use quarterly real GDP.

[6]http://sdw.ecb.europa.eu/

[7]https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/real-time-data-set-for-macroeconomists

[8]Meyler (2020) uses second-release data for GDP in his analysis of the ECB-SPF. Our results are basically unchanged when using second-release data instead of first release data to calculate real GDP growth. To facilitate the comparison of results across outcome variables, we consistently use first-releases throughout the analysis. Alternative results will be provided upon request.

TABLE 1. Horizon structure of fixed-event forecasts.

Survey Period	Forecast Horizon h "Current Year"	"Next Year"
Q1	4	8
Q2	3	7
Q3	2	6
Q4	1	5

Note: This table depicts the structure of the forecast horizons associated with the predictions for the current and the next calendar year from the SPF data.

The survey data from the SPF consist of so-called "fixed-event" density forecasts, which are characterized by a fixed target year t and a quarterly forecast horizon h. As noted by Binder et al. (2021), the ECB-SPF also provides fixed-horizon density forecasts. To facilitate the comparison of our findings for the ECB- and FED-SPF, we focus on the fixed-event forecasts in our analysis. The nature of these forecasts implies that h diminishes in each consecutive quarter in which the survey is conducted until the arrival of the realization in t. We consider predictions for the current and the next year. This obtains a sequence of individual h-step-ahead density forecasts with forecast horizons $h \in \{8, 7, \dots, 1\}$ as depicted in Table 1.

In case of the inflation rate and output growth, forecasters in our sample target the years 2000 to 2017. This means that the time period when forecasts are made and collected ranges from 1999Q1 to 2017Q4.[9] Density forecasts for the unemployment rate in the FED-SPF are available only since 2009Q2, whereas the responses in the ECB-SPF are available for the entire sample period. For the U.S., we thus focus on the unemployment rates in the years 2011 to 2017, for which predictions are available for each horizon.

In the questionnaire, survey participants $i = 1, \dots, N$ are requested to assign probabilities to a prespecified number of outcome intervals, the so-called "bins." Let $p_{i,k,t,h} \in [0, 100]$ for $k = 1, \dots, K$ denote the probability number assigned to the kth bin. The maximum range covered by the bins differs across surveys, outcome variables, and time instances. The bins have a width of 0.4 percentage point in case of the ECB-SPF as can be seen in Figure 1. In the FED-SPF, the bin width is 0.9 percentage point except in a few cases. Since 2014Q1, the bin width for inflation has been reduced to 0.4 percentage point. Similarly, the majority of the interior bins for the unemployment rate have a width of 0.4 percentage point throughout the sample period. The relevance of the bin width as well as the impact of adjustments to the bin definitions for quantifications of ex ante uncertainty will be discussed below. As in Abel et al. (2016), the gaps between the interior bins are closed by extending the lower and upper bound of each bin by 0.05 percentage point. This seems to be in line with how most SPF participants interpret their reporting

[9]Forecasts for inflation and output growth in the U.S. are available since 1968Q4. However, we prefer to focus on a common sample period for both the ECB- and FED-SPF and exclude these earlier predictions. This also helps to avoid various methodological changes in the FED-SPF such as the switch from gross national product to gross domestic product. Since no five- to eight-step-ahead forecasts for the year 1999 are available in the ECB-SPF data, we exclude the current year predictions from the surveys conducted between 1999Q1 and 1999Q4.

task, as it is documented in a special survey conducted by the ECB in 2008, where 76% of the respondents stated that they interpret an interval like 1.5%–1.9% to actually indicate a range as given by 1.45%–1.95% (ECB, 2009). The bins at the lower and upper end of the support are assumed to have twice the width of the interior intervals, that is, one or two percentage points depending on the survey and variable. The bounds of the individual histograms are fixed at the leftmost and rightmost bin with nonzero probability mass.

We exclude observations from the sample whenever the sum over the reported probabilities deviates by at least 0.9 percentage point from the required 100% overall probability in absolute terms.[10] Moreover, there is a small group of forecasters that assign 100% to a single bin.[11] To find out if this affects our conclusions, we conducted the analysis with and without these histograms and found the difference in results to be negligible in most cases. Thus, we present our findings based on the full sample unless stated otherwise.[12]

The participants in both surveys include employees of research institutes and the financial services industry. The occupation of the anonymous survey participants is provided in case of the FED-SPF. Depending on the survey period under consideration, 22–50% of the participants of the FED-SPF are classified as "financial service providers" and 39–70% as "nonfinancial service providers." A third category of unclassified "others" is also included, which amounts to 0–15% of the cross-section. This information is not provided for the ECB-SPF. An identification number allows to track the anonymous individual forecasters. We observe a relatively large number of entries and exits of SPF participants in each survey round. In order to analyze whether participation varies systematically across forecast horizons, we define the participation indicator variable $D^{\mathcal{P}}_{i,t,h}$, which is equal to unity if forecaster i issues an h-step-ahead density forecast for x_t, and zero else.[13] For each forecast horizon $h \in \{8, 7, \dots, 1\}$, Table 2 presents the number of density forecasts reported in both versions of the SPF, that is, $\sum_{i=1}^{N} \sum_{t=1}^{T} D^{\mathcal{P}}_{i,t,h}$.

The sample size is roughly constant across variables and forecast horizons in both surveys with the obvious exception of the unemployment rate in the FED-SPF. This suggests that the cross-section of forecasters is relatively similar. Although the total number of participants is higher in the FED-SPF than in the ECB-SPF (116 vs. 104), the sample size for inflation and real GDP growth is considerably larger in the latter case. In other words, average participation is lower in the FED-SPF. The average number of forecasters who contribute to each wave of the ECB-SPF has declined from approximately 60 during the early survey rounds to 50 in recent periods. In contrast, the average number of participants in the FED-SPF has remained relatively constant at a level of 30–35.

In order to compute first and second moments of the histograms, it is common to assume that the entire probability mass within each bin is located at the midpoint (Lahiri et al. (1988) and Kenny et al. (2015)). Alternatively, one may compute the moments of a smoothed density function as it is described in Engelberg et al. (2009). This

[10] We permit small deviations in order to keep the nonrounded histograms in the sample. In such cases, the probabilities may not add up to exactly 100%.

[11] Approximately 1% of the histograms submitted to the ECB-SPF and around 2% in the FED-SPF.

[12] Results based on a sample that excludes all single-bin histograms will be provided upon request.

[13] The symbol "D" is meant to indicate that this and similar statistics may be thought of as dummy variables in the following empirical analyses.

Table 2. Number of density forecasts provided by SPF participants.

SPF	Variable	Forecast Horizon h								$\sum_h$
		8	7	6	5	4	3	2	1	
ECB	Inflation	942	955	863	967	967	961	877	966	7498
	GDP growth	948	956	867	973	972	963	878	972	7529
	Unemployment	908	916	825	914	925	919	830	910	7147
FED	Inflation	626	654	635	663	654	662	637	657	5188
	GDP growth	652	676	654	685	677	685	659	680	5368
	Unemployment	263	255	257	264	258	251	254	254	2056

Note: For each outcome variable, this table presents the number of reported histograms per forecast horizon, that is, $\sum_i \sum_t D^{\mathcal{P}}_{i,t,h}$, as well as the total number of observations across all horizons. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

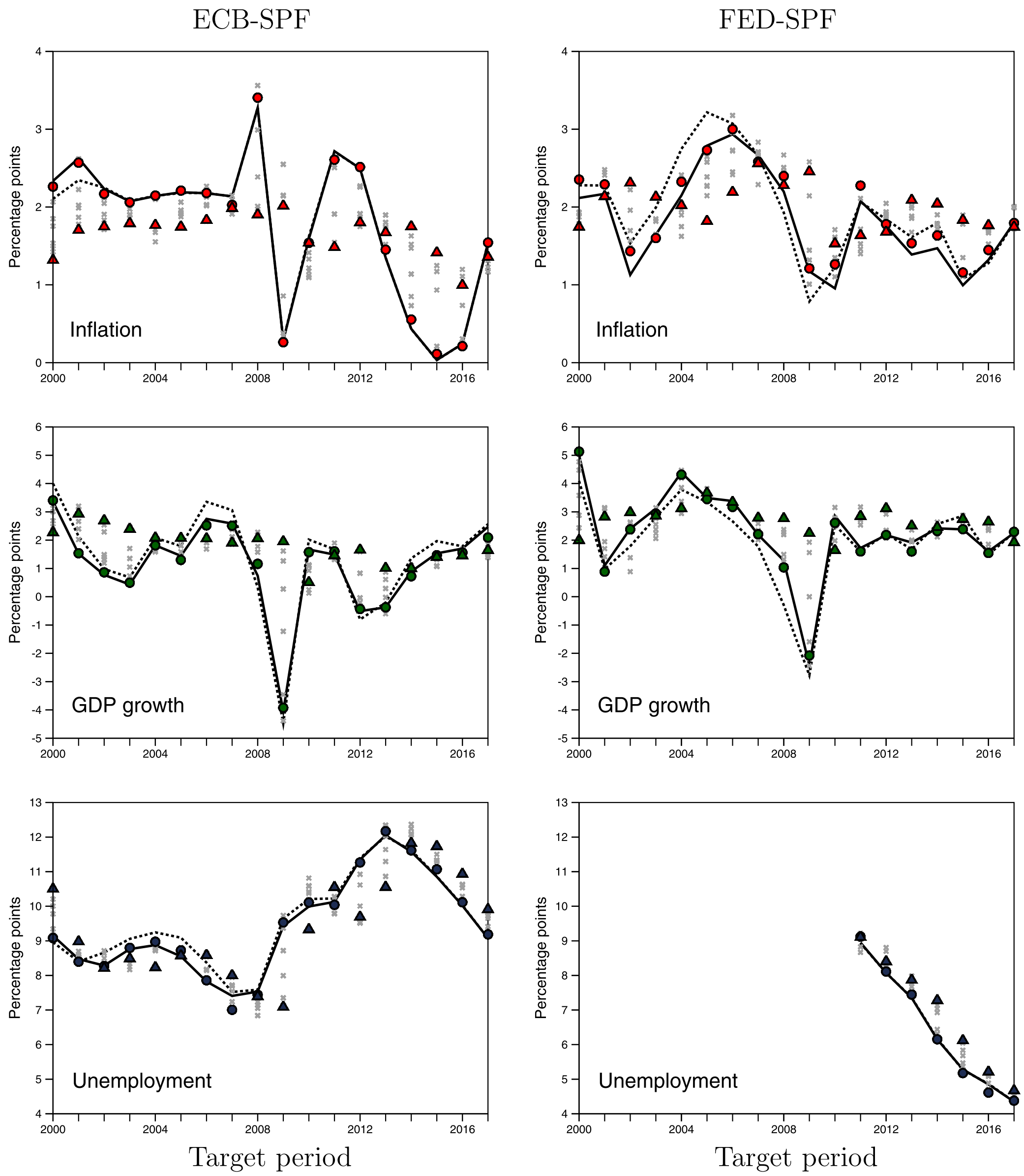
choice has little impact on the first moment. However, Glas (2020) shows that the variance estimates from beta distributions tend to be somewhat smaller than those from the "mass-at-midpoint" approach. Moreover, fitting beta distributions to histogram forecasts should at least partially alleviate the influence of the definition of bin widths on moment statistics, since this approach entails to fit a smooth function between the boundaries of the histogram support (for details, see Engelberg et al. (2009)). In contrast, the mass-at-midpoint approach has the advantage that the same probability numbers are used for both the distinction between rounders and nonrounders on the one hand and the quantification of moment statistics on the other hand. To retain the advantage to base both classification of forecasts and the computation of moments on the same numerical values, we proceed by using the mass-at-midpoint assumption as the primary means to derive ex-ante variances and compare the results to those based on the beta distribution approach in the relevant cases. Based on the mass-at-midpoint approach, the mean of forecaster i's histogram is given by

$$\mu_{i,t,h} = \frac{1}{100} \sum_{k=1}^{K} p_{i,k,t,h} \times \mathfrak{m}_k, \tag{2}$$

with $\mathfrak{m}_k$ denoting the midpoint of the kth bin. The h-step-ahead "consensus" forecast is calculated as the equally-weighted average over the individual histogram means, that is,

$$\bar{\mu}_{t,h} = \frac{1}{N} \sum_{i=1}^{N} \mu_{i,t,h}. \tag{3}$$

In order to analyze which data release is predicted by the SPF participants, Figure 3 depicts the realizations of each outcome variable in the Euro area and the U.S. using observations from both the first release (solid line) and the most recent data vintage (dashed line). Moreover, each plot includes the consensus forecasts, that is, $\bar{\mu}_{t,h}$ from equation (3), for horizons $h \in \{8, 7, \dots, 1\}$. The one- and eight-step-ahead predictions are highlighted distinctly from the other forecast horizons.



Notes: The graphs depict the time series of the annual realizations x_t for inflation (first row), output growth (second row), and unemployment (third row) in the Euro area and the U.S. based on first-release (solid black lines) and last-release (dashed black lines) data vintages. In addition, each plot shows the cross-sectional average across the means of the individual h-step-ahead histogram forecasts, that is, $\bar{\mu}_{t,h}$ from equation (3). Triangles "$\triangle$" and bullets "$\bullet$" indicate the eight- and one-step-ahead consensus forecasts, respectively. Crosses "$\times$" indicate the predictions for the intermediate forecast horizons. The horizontal axis depicts the target year. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

Figure 3. Realizations and consensus forecasts from the SPF.

Figure 3 shows that the accuracy of the average forecast improves as the target period approaches. In other words, forecast errors decline with h. In particular, the deviation between x_t and $\bar{\mu}_{t,1}$ is smaller than the difference between x_t and $\bar{\mu}_{t,8}$ in almost all cases. Moreover, in cases where the first and last data releases deviate substantially, $\bar{\mu}_{t,1}$ is more closely associated with the former. This finding suggests that SPF participants predict the first release of the respective outcome variable and supports our choice of focusing on this particular data release in the empirical analysis.

To compare the mismatch between ex ante and ex post uncertainty, we need a quantification of the variances of the reported histograms that enables us to retain the information regarding the rounding choices of forecasters. Based on the mean from equation (2), we calculate the individual variance as

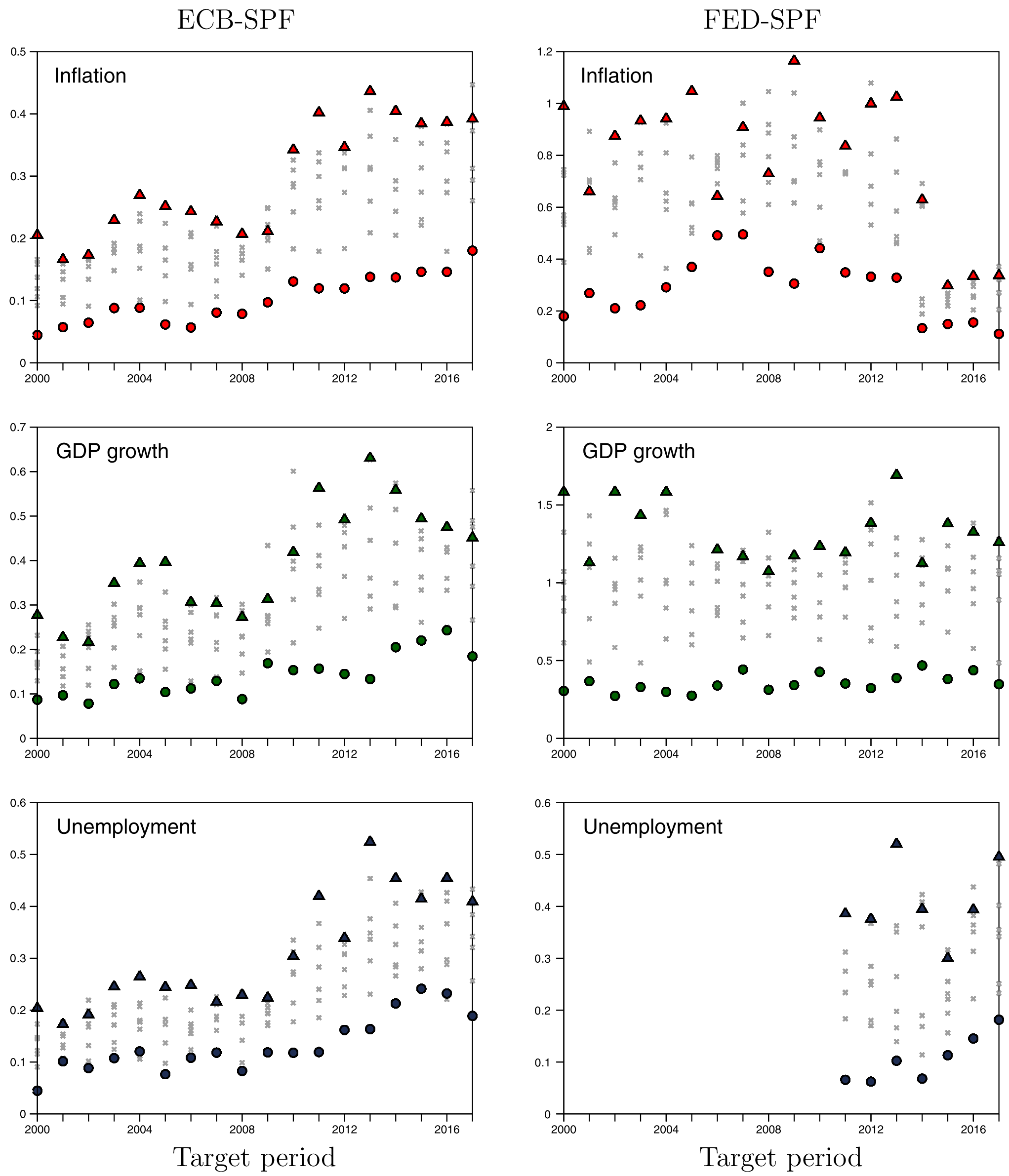
$$\sigma^2_{i,t,h} = \frac{1}{100} \sum_{k=1}^{K} p_{i,k,t,h} \times (\mathfrak{m}_k - \mu_{i,t,h})^2. \tag{4}$$

This variable serves as a measure of forecaster i's ex ante uncertainty. To obtain an indicator of aggregate uncertainty, we follow Lahiri and Sheng (2010) and compute the cross-sectional average of the h-step-ahead variances from equation (4),

$$\overline{\sigma^2_{t,h}} = \frac{1}{N} \sum_{i=1}^{N} \sigma^2_{i,t,h}. \tag{5}$$

Analogously to Figure 3, Figure 4 depicts the time series of the h-step-ahead average forecast variances. Average ex ante uncertainty declines with the forecast horizon, that is, the average forecaster becomes increasingly more confident as the target period approaches and more information about the realization is available. After the beginning of the financial crisis in 2008, average uncertainty is markedly higher, especially in the ECB-SPF. Moreover, there is a break in the forecast uncertainty of inflation in the FED-SPF. In this case, the decrease in uncertainty is likely related to the adjustment of the bin width from 0.9 to 0.4 percentage point in 2014Q1. Note that after this change, the width of the bins in the FED-SPF is the same as that in the ECB-SPF. If forecasters have a fixed range of inflation outcomes in mind when stating their histogram forecast, it may be expected that the number of bins with nonzero probability increases markedly in response to the smaller bin width. However, it may also be the case that some panelists prefer to report probability numbers for a fixed number of bins regardless of their precise definition. Interestingly, when comparing the number of bins used by FED-SPF participants to predict inflation before and after 2014Q1, we find only a modest increase from four to five bins on average. This finding suggests that forecasters do not automatically use twice as many bins when the bin width is cut in half. As a result, inflation uncertainty in the FED-SPF drops to levels similar to those observed in the ECB-SPF.[14]

[14]Figure A.1 in the Online Supplementary Material (Glas and Hartmann (2022)) shows that average uncertainty based on the variances from the beta distributions, denoted as $\overline{\sigma^2_{B,t,h}}$, tends to be smaller in magnitude than that based on the mass-at-midpoint assumption. However, the break in the inflation uncertainty series is still present.



Notes: The graphs depict the time series of the cross-sectional average across the h-step-ahead variances from the individual histograms for inflation (first row), output growth (second row), and unemployment (third row) in the Euro area and the U.S., that is, $\overline{\sigma^2_{t,h}}$ from equation (5). Triangles "△" and bullets "•" indicate the eight- and one-step-ahead average variances, respectively. Crosses "×" indicate the average variances for the intermediate forecast horizons. The horizontal axis depicts the target year. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 4. Average ex ante uncertainty.

So far, we have described the characteristics of the entire cross-section of SPF participants in both the U.S. and the Euro area. However, it may be that panelists differ systematically with respect to the coarseness of their predictions. In the next step, we aim to isolate two distinct groups of forecasters based on the way that individual survey participants decide to round (or not to round) the reported probability numbers.

4. Classification of survey participants

In this section, we discuss alternative classification schemes that serve as a means to distinguish nonrounders from rounders based on their reporting behavior. Though rounding is one of the most striking characteristics of the histogram forecasts in the SPF, an unambiguous classification into rounders and nonrounders is not possible. Since the coarseness of the responses appears to vary across individual forecasters, we propose several distinct categorization schemes in order to assess the robustness of our findings. Due to the anonymous nature of participation in the SPF, reputational concerns should not play an important role in the decision whether or not to round a prediction. In most empirical research on rounding of survey-based forecasts, the participants are classified as rounders based on whether the point forecast is a multiple of a particular integer number (for example, Binder (2017)). In contrast, we analyze the histograms reported in the SPF. Thus, the employed rounding schemes are based on multiple reported numbers for each individual instead of just a single one. Moreover, we consider two distinct types of categorizations that differ in terms of what constitutes a rounded probability.

4.1 *Decimal-based categorization*

The first type of categorization is based on the number of decimals of each probability number, $p_{i,k,t,h}$, which is denoted as $d_{i,k,t,h}$. For notational convenience, we suppress all subscripts except for i and k in the following subsections.[15] Let $K_i \in \{1, \dots, K\}$ denote the number of bins to which forecaster i assigns nonzero probability (that is, cases where $p_{i,k} > 0$) and $K_i^\star \in \{0, \dots, K_i\}$ indicate the number of bins with nonzero probability that contain decimals numbers (that is, cases where both $p_{i,k} > 0$ and $d_{i,k} > 0$). The share of probabilities in forecaster i's histogram with nonzero decimals numbers is given by

$$\rho_i = \frac{K_i^\star}{K_i}. \tag{6}$$

Based on ρ_i, we define distinct classification schemes that are introduced here in terms of how strictly we delineate the definition of a nonrounder. That is, each of the rules that are successively introduced below is less likely to classify a forecaster as a nonrounder than the previous one. The first approach is to treat a forecaster as a nonrounder if *any* of the individually reported probability numbers are stated with decimals, that is,

$$D_i^{\text{any}} = \begin{cases} 1 & \text{if } \rho_i > 0 \text{ and} \\ 0 & \text{else.} \end{cases} \tag{7}$$

[15] This does not mean that we assume that variation across time or forecast horizons plays no role. We analyze the importance of these factors in Section 5.

It is likely that this indicator will classify some forecasters as nonrounders even though the majority of reported numbers entail a rather strong degree of rounding. Consider an example where five bins are available, that is, $K = 5$, and a survey participant reports probabilities $(p_{i,1}, \dots, p_{i,5})' = (0.5\%, 30\%, 39\%, 30\%, 0.5\%)'$, such that $K_i = 5$ and $K_i^\star = 2$. Despite the fact that only the probabilities in the tails include decimals, such a forecaster is considered as a nonrounder based on D_i^{any} since $\rho_i = 0.4$. A more restrictive rule to single out nonrounders is obtained if a panelist is regarded as a nonrounder if *most* of the probabilities are reported with nonzero decimal numbers, that is,

$$D_i^{\text{most}} = \begin{cases} 1 & \text{if } \rho_i > 0.5 \text{ and} \\ 0 & \text{else.} \end{cases} \tag{8}$$

This approach categorizes forecasters as nonrounders if more than 50% of the probabilities reported in a given histogram contain decimal numbers. Note that if K_i is even and half of the probabilities contain decimals while the other half do not, that is, if $K_i^\star = K_i/2$, the scheme in equation (8) classifies a survey participant as a rounder. Based on this categorization, the forecaster from the example above is considered to be a rounder because only 40% of the probabilities contain decimal numbers. The most restrictive approach is to classify a forecaster as a nonrounder if *all* probabilities are stated by means of nonzero decimal numbers, that is,

$$D_i^{\text{all}} = \begin{cases} 1 & \text{if } \rho_i = 1 \text{ and} \\ 0 & \text{else.} \end{cases} \tag{9}$$

In this case, forecasters are considered to be nonrounders only if each probability number is stated with nonzero decimal numbers, that is, cases where $K_i^\star = K_i$. Based on the scheme in equation (9), the forecaster from the example above is considered as a rounder because three out of five probabilities do not contain decimal numbers.

To summarize, the categorizations described in equations (7)–(9) classify survey participants as rounders if any, most or all of the probabilities are stated with nonzero decimal numbers. It follows that $\sum_{i=1}^N D_i^{\text{any}} \geq \sum_{i=1}^N D_i^{\text{most}} \geq \sum_{i=1}^N D_i^{\text{all}}$.

4.2 *Integer-based categorization*

In a preliminary part of her empirical analysis, Binder (2017) classifies consumers as rounders based on whether their point forecast is a multiple of five. Similarly, Manski (2004) notes that probabilistic survey forecasts are frequently multiples of an integer number. For example, D'Amico and Orphanides (2008), Engelberg et al. (2009), or Clements (2011) observe that the probabilities reported in the FED-SPF tend to be multiples of five or ten. Boero et al. (2015) document similar evidence for the predictions in the Survey of External Forecasters. A similar integer-based approach is considered here, which contrasts with the previous categorization that classifies survey participants based on whether the reported probabilities contain decimal numbers. In order to analyze whether the decimal- and integer-based approaches yield comparable results in isolating rounders and nonrounders, we analyze whether the probability in the kth bin of forecaster i's histogram is a multiple of integer $\tau \in \mathbb{N}$ by defining

$$\tilde{D}_{i,k}^{\mathrm{m}\tau} = \begin{cases} 1 & \text{if } \tau \cdot \left\lfloor \dfrac{p_{i,k}}{\tau} \right\rfloor = p_{i,k} \text{ and} \\ 0 & \text{else,} \end{cases} \tag{10}$$

where $\lfloor p_{i,k}/\tau \rfloor$ is the integer part of $p_{i,k}/\tau$ and the superscript "m" stands for "multiple." Based on the bin-specific indicator variables from equation (10), forecasters are classified as rounders according to the following rule:

$$\tilde{D}_{i}^{\mathrm{m}\tau} = \begin{cases} 1 & \text{if } \operatorname{mode}\big(\tilde{D}_{i,1}^{\mathrm{m}\tau}, \dots, \tilde{D}_{i,K}^{\mathrm{m}\tau}\big) = 1 \text{ and} \\ 0 & \text{else.} \end{cases} \tag{11}$$

Thus, a survey participant is treated as a rounder if the majority of the probabilities are multiples of τ. If the modal value in equation (11) is not uniquely defined, we set $\tilde{D}_{i}^{\mathrm{m}\tau}$ to zero. Thus, if half of the probabilities are multiples of τ, but the other half are not, the corresponding forecaster is considered a nonrounder. Note that the integer-based categorization identifies rounders, as opposed to nonrounders as in the decimal-based classifications in equations (7)–(9). This complementarity is highlighted by the symbol '$\sim$' in $\tilde{D}_{i}^{\mathrm{m}\tau}$. In order to facilitate the comparison between both approaches, we use

$$D_{i}^{\mathrm{m}\tau} = 1 - \tilde{D}_{i}^{\mathrm{m}\tau} \tag{12}$$

in most cases instead of $\tilde{D}_{i}^{\mathrm{m}\tau}$. Thus, forecasters are considered to be nonrounders if most of the probabilities are *not* multiples of τ. In reference to the evidence documented in Boero et al. (2015) that many of the probabilities submitted to the SPF are multiples of five or ten, the forecaster considered in the example from the previous subsection is classified as a nonrounder based on both $D_{i}^{\mathrm{m}5}$ and $D_{i}^{\mathrm{m}10}$ since only two out of the five probabilities are multiples of either five or ten.

5. Rounding patterns and variance misalignment

In this section, we characterize and distinguish the groups of rounders and nonrounders in the SPF based on the methodology from Section 4. We document that this categorization helps to understand the finding of a mismatch between the ex ante and ex post uncertainties of forecasters. In order to test if variance misalignment and rounding choices are systematically related, inferential results regarding the differences in the histogram characteristics of rounders and nonrounders are reported.[16]

5.1 *Rounders and nonrounders in the SPF data*

To investigate which reasons can be considered as viable explanations for the observation that survey responses are coarse in distinct ways, we first employ the cross-sectional

[16]Results based on a smaller sample that ends in 2016Q4 are reported in Chapter 5 of Glas (2019).

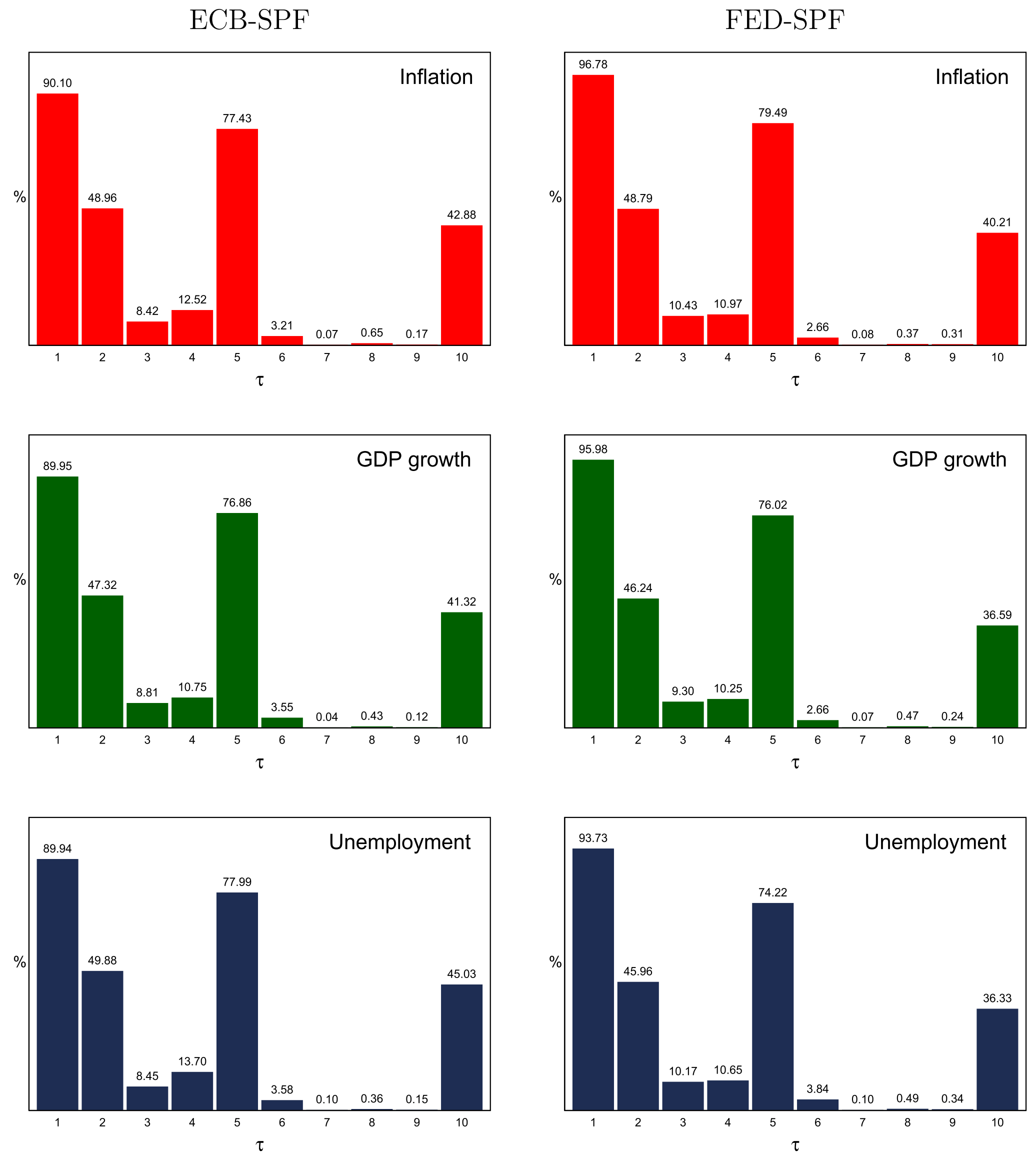
dimension to examine how pervasive the habit of reporting rounded probability numbers is among the SPF panelists. Comparing the relative size of the rounding versus nonrounding categories, as well as conditioning on time periods or forecast horizons, provides tentative explanations for the observed response patterns. Moreover, special survey questions that are provided in the ECB-SPF regarding the use of formal models versus judgment can be related to the relative size of the two groups of forecasters. For the sake of brevity, we choose to focus on one of the decimal-based categorizations and consider the integer-based approach for one particular value of τ in the following subsections. However, the results from the empirical analysis are robust to the choice of the considered categorization.

Figure 2 shows that relatively few participants in the FED-SPF state their probabilities in terms of decimal numbers. In contrast, the share of probabilities that contain decimal numbers is considerably larger in the ECB-SPF. Moreover, the participants in the FED-SPF use a relatively narrow range of at most four decimals, whereas the panelists in the ECB-SPF use up to ten. This may be due to systematic differences in either the cross-section or the structure of both surveys such as the differences in the bin width. Based on the small number of probabilities with $d_{i,k,t,h} > 0$ in case of the FED-SPF, we choose to focus on $D^{\text{any}}_{i,t,h}$ as the preferred decimal-based classification scheme. This is recommendable since the explanatory power of the distinction between rounders and nonrounders may be reduced due to the smaller number of forecasters that are classified as nonrounders based on $D^{\text{most}}_{i,t,h}$ and $D^{\text{all}}_{i,t,h}$.

The choice of τ for the integer-based categorization is guided by the evidence from Figure 5, which depicts the share of rounded histograms in the SPF data based on equation (11) for a pooled sample of observations across all time periods and forecast horizons in the case of inflation (first row), output growth (second row) and unemployment rates (third row). This share is calculated as 100 times the number of rounded histograms that are classified via $\tilde{D}^{\text{m}\tau}_{i,t,h}$ for $\tau \in \{1, \dots, 10\}$ divided by the total number of predictions, that is,

$$\tilde{S}^{\text{m}\tau} = 100 \times \frac{\sum_i \sum_t \sum_h \tilde{D}^{\text{m}\tau}_{i,t,h}}{\sum_i \sum_t \sum_h D^{\mathcal{P}}_{i,t,h}}. \tag{13}$$

The results are remarkably similar across all outcome variables and both versions of the SPF. The majority of survey participants are classified as rounders if we set τ to unity, that is, most histogram forecasts consist of probabilities that almost exclusively do not contain decimal numbers. This is not surprising given that Figure 2 shows that only a small fraction of the SPF participants reports probabilities with decimal numbers. There are two notable spikes in the cases where τ is set to either five or ten. This squares with the evidence documented in Engelberg et al. (2009) and Boero et al. (2015), who show that many of the probabilities reported in surveys of macroeconomic expectations are multiples of five or ten. In particular, 74–79% of all histograms in the SPF data consist of probabilities that are for the most part multiples of five. Similar numbers are reported in Clements (2011). Thus, we isolate nonrounders by setting τ to five and use $D^{\text{m5}}_{i,t,h}$ in



Notes: The graphs depict the share of rounded histogram forecasts classified via the integer-based categorization from equation (12), that is, $\tilde{S}^{m\tau} = 100 \times (\sum_i \sum_t \sum_h \tilde{D}^{m\tau}_{i,t,h})/(\sum_i \sum_t \sum_h D^{\mathcal{P}}_{i,t,h})$ for $\tau \in \{1, \ldots, 10\}$, based on a pooled sample of observations across all forecast horizons for inflation (first row), output growth (second row), and unemployment (third row). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 5. Share of rounded histograms (integer-based categorization).

TABLE 3. Share of nonrounded observations across horizons.

SPF	Variable	Scheme	Forecast Horizon h							
			8	7	6	5	4	3	2	1
ECB	Inflation	D^{any}	14.12	13.82	14.14	12.93	13.24	12.80	12.77	11.28
		D^{m5}	23.46	23.14	22.83	22.34	22.96	22.89	22.69	20.29
	GDP growth	D^{any}	13.82	14.33	14.42	13.77	12.96	12.56	12.30	11.63
		D^{m5}	23.84	24.69	22.95	23.12	24.38	24.20	22.10	19.75
	Unemployment	D^{any}	12.67	13.21	12.85	12.47	12.76	12.51	13.49	11.65
		D^{m5}	22.80	21.94	21.82	23.74	21.84	21.87	22.77	19.34
FED	Inflation	D^{any}	4.15	4.13	4.72	4.07	4.28	4.53	5.02	4.11
		D^{m5}	21.57	22.94	21.42	20.21	18.35	20.39	21.19	18.11
	GDP growth	D^{any}	6.13	6.80	6.42	7.30	6.50	6.57	6.53	5.00
		D^{m5}	24.69	24.70	23.55	23.50	23.63	23.80	22.91	25.00
	Unemployment	D^{any}	9.51	7.84	8.17	7.95	8.53	7.17	7.87	5.12
		D^{m5}	23.19	24.71	26.85	25.38	28.29	25.10	28.35	24.41

Note: For each forecast horizon, this table presents the share of nonrounded observations in the sample, that is, $S_h^{\mathcal{R}} = 100 \times (\sum_i \sum_t D_{i,t,h}^{\mathcal{R}})/(\sum_i \sum_t D_{i,t,h}^{\mathcal{P}})$ for the preferred decimal- and integer-based classification schemes $D_{i,t,h}^{\mathcal{R}} \in \{D_{i,t,h}^{\text{any}}, D_{i,t,h}^{\text{m5}}\}$ from equations (7) and (12). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

the following analysis due to the fact that the share of rounded histograms is particularly large in this case.[17]

One explanation for the decision to round a forecast may be the amount of information that is available to all forecasters at the time a prediction is made rather than systematic differences between certain groups of panelists. In a fixed-event setting, the information set of a survey participant increases as h declines. In order to analyze the size of the groups of rounders and nonrounders, Table 3 summarizes the share of nonrounded observations in the SPF data for each forecast horizon, that is,

$$S_h^{\mathcal{R}} = 100 \times \frac{\sum_i \sum_t D_{i,t,h}^{\mathcal{R}}}{\sum_i \sum_t D_{i,t,h}^{\mathcal{P}}}, \tag{14}$$

where $D_{i,t,h}^{\mathcal{R}} \in \{D_{i,t,h}^{\text{any}}, D_{i,t,h}^{\text{m5}}\}$ denotes either the preferred decimal- or integer-based scheme for nonrounding described in equations (7) and (12), respectively.

[17] Depending on the outcome variable, 86–87% (81–84%) of all histograms in the ECB-SPF (FED-SPF) are unanimously classified as either rounded or nonrounded by $D_{i,t,h}^{\text{any}}$ and $D_{i,t,h}^{\text{m5}}$. The classification of forecasters is also consistent across outcome variables. For the ECB-SPF (FED-SPF), the share of predictions that are classified as either rounded or nonrounded across all three outcome variables is 94% (95%) for $D_{i,t,h}^{\text{any}}$ and 88% (79%) for $D_{i,t,h}^{\text{m5}}$. Our findings suggest that the choice of the employed categorization or variable-specific considerations have little impact on the status of individual panelists. Moreover, Table A.1 in the Online Supplementary Material shows that the correlation between the rounding status of FED-SPF participants and their industry classification is close to zero.

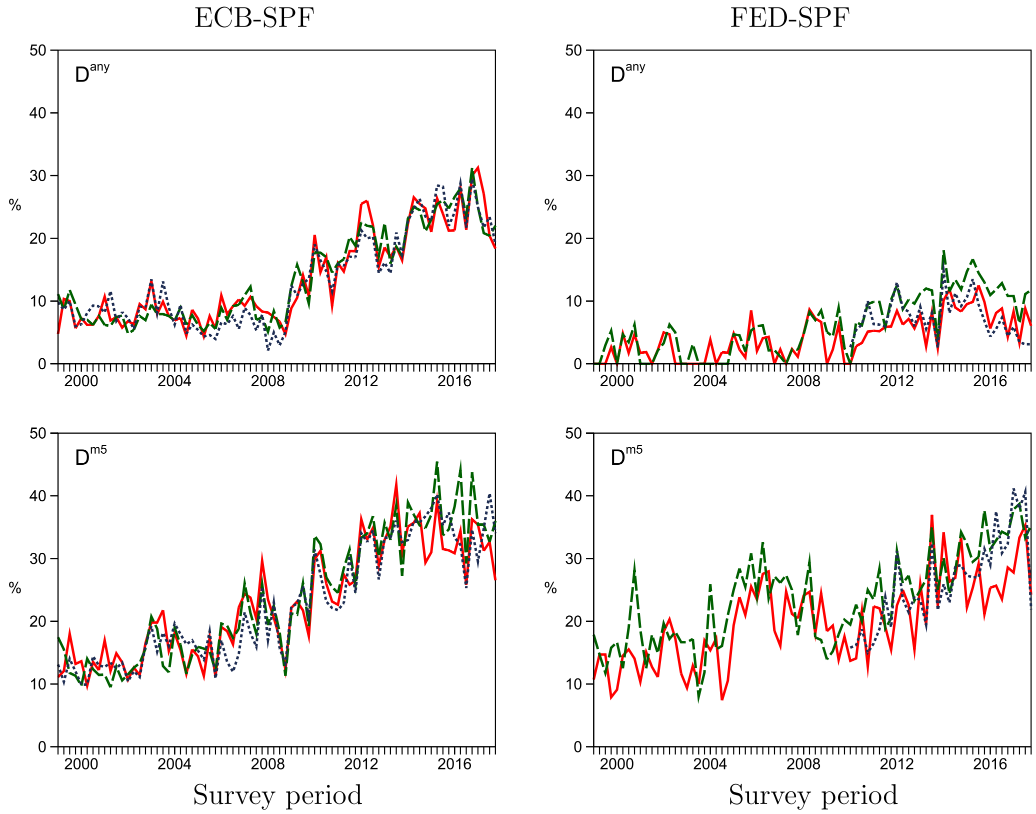
Table 3 shows that the share of nonrounded observations indicated by $D^{\text{any}}_{i,t,h}$ is relatively small in both surveys. Between 11–14% (ECB-SPF) and 4–10% (FED-SPF) of all histograms consist of probabilities that are stated with decimal numbers and are thus classified as being nonrounded. As expected, the share of nonrounded histograms based on $D^{\text{m5}}_{i,t,h}$ is considerably larger and relatively similar in both versions of the SPF. In particular, S^{m5}_{h} lies between 19–25% (ECB-SPF) and 18–28% (FED-SPF). Notably, the share of nonrounders is stable across forecast horizons. This suggests that the decision not to round is not merely the result of more information being available as the target period approaches.

As a means to analyze the fluctuations in the status of active forecasters, Figure 6 depicts the time variation in the share of nonrounders across the predictions for both the current and the next year (defined analoguously to equation (14)). As before, nonrounders are classified in terms of either $D^{\text{any}}_{i,t,h}$ (first row) or $D^{\text{m5}}_{i,t,h}$ (second row).

For each variable, the share of nonrounders in the ECB-SPF has increased considerably from approximately 5–15% of the cross-section during the initial years to 30–45% in recent survey periods. Over the same time period, the share of nonrounders in the FED-SPF has also increased, although it rarely exceeds 15% in the case of the classification via $D^{\text{any}}_{i,t,h}$. In contrast, the series based on $D^{\text{m5}}_{i,t,h}$ are relatively similar in both versions of the SPF. These observations are in line with the previously documented evidence from Figures 2 and 5, which show that participants in the FED-SPF rarely provide probabilities with decimal numbers, but are relatively more often classified as nonrounders based on cases where they provide probabilities that are not multiples of five.

Overall, Figure 6 shows an increase in the share of nonrounded histogram forecasts over time. This is partly the result of an increasing number of new entrants to both surveys who are classified as nonrounders. However, incumbent participants' transitions from the rounding to the nonrounding group are also more frequent than transitions in the other direction. In general, such changes in the response pattern for a given identification number might be either due to changes in personnel or reorganizations of the forecasting process within the institutions that participate in the SPF. In particular, it may be the case that rounding choices reflect the fact that some survey participants use formal models to arrive at their forecasts, whereas others rely more on judgment and intuition.

In order to shed light on the reporting practices of its participants, the ECB-SPF conducted two special surveys in 2008 and 2013 (cf. ECB, 2009, 2014). Among other questions, respondents were asked if their probability distributions are based on a model, judgment, or a mixture of the two. In the first special survey, 79% of the survey participants answered that their reported probabilities are judgment-based, whereas the remaining panelists replied that they are derived from a formal model or a functional form. Interestingly, the fraction of forecasters who stated that they rely entirely on judgment is very close to the relative frequency of rounded observations classified by means of $\tilde{D}^{\text{m5}}$ (cf. Table 3). In the second survey, the share of forecasters who indicated that their reported probabilities are based on judgment varies between 68% for the medium-term inflation and GDP growth forecasts and 79% for the short-term unemployment rate forecasts. On average, the predominance of forecasters who rely on judgment has



Notes: The graphs depict the share of nonrounded histogram forecasts for inflation (solid), output growth (dashed) and unemployment (dotted) based on $D^{\text{any}}_{i,t,h}$ (first row) and $D^{\text{m5}}_{i,t,h}$ (second row) for a pooled sample of observations across the predictions for the current ($h \leq 4$) and the next year ($h \geq 5$). The horizontal axis depicts the quarter during which predictions are reported. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 6. Time-variation in the share of nonrounders.

slightly declined compared to the first special survey. This squares with the increase in the share of nonrounders in recent survey periods depicted in Figure 6.[18] Notably, the share of forecasters who replied that they compute their probabilities specifically for the SPF (79%), as opposed to producing them for purposes related to their regular work, is the same as the fraction of forecasters who stated that they rely on judgment. Consequently, it is also very similar to the share of rounders as measured by $\tilde{S}^{\text{m5}}$.

It is tempting to examine the link between the results from the special surveys and the rounding choices in the quarterly ECB-SPF questionnaires. The questions in the special surveys refer to fixed-horizon forecasts, that is, predictions with a constant forecast horizon. Thus, we consider the share of nonrounders for the fixed-horizon forecasts reported in the surveys that correspond to the dates when the special surveys were sent

[18]The share of cases where judgment is applied to the point forecasts is considerably smaller and rarely exceeds 50% in the first special survey. In the second special survey, this share has declined even further.

out, that is, 2008Q3 and 2013Q2. Note, however, that the number of forecasters in the 2013Q2 survey (39) does not match the number of responses from the second special survey in all cases (35-40). The share of nonrounders in 2008Q3 based on D^{m5} (17–30% depending on the variable and horizon; 21% on average) closely mirrors the share of forecasters who reported that they use some sort of model when they report their probabilities (21%).[19] The share of nonrounders classified via D^{m5} in 2013Q2 (34–47%; 38% on average) is relatively similar to the fraction of forecasters who replied that they use either a model or a combination of model and judgment in the second special survey (26–33%). Thus, it appears that there is a close association between our distinction of rounders and nonrounders on the one hand and the judgment- versus nonjudgment-based forecast grouping documented in the special surveys of the ECB on the other hand. A more thorough analysis is not possible because the individual responses from the special surveys are not publicly available.

5.2 *Analysis of variance misalignment*

In this section, we compare the ex ante and ex post uncertainties of the SPF participants and document the differences in the degree of the variance misalignment between rounders and nonrounders. In the case of fixed-event forecasts, the survey participants should become better informed as the forecast horizon shrinks during successive survey rounds. If this is the case, the differences in the variance misalignment may be related to the forecast horizon. This hypothesis is examined next. We measure the ex ante uncertainty of forecaster i at forecast horizon h by means of the individual-specific average variance, which is defined as

$$\overline{\sigma^2_{i,h}} = \frac{1}{T_{i,h}} \sum_{t=1}^{T_{i,h}} \sigma^2_{i,t,h}, \tag{15}$$

where $T_{i,h} = \sum_{t=1}^{T} D^{\mathcal{P}}_{i,t,h}$ indicates the number of times forecaster i has reported h-step-ahead histogram forecasts and $\sigma^2_{i,t,h}$ denotes the variance from equation (4). In order to analyze the degree of the variance misalignment in the SPF, the ex ante uncertainty from equation (15) is compared to the mean squared error (MSE), as given by

$$\mathrm{MSE}_{i,h} = \frac{1}{T_{i,h}} \sum_{t=1}^{T_{i,h}} e^2_{i,t,h}, \tag{16}$$

which serves as a quantification of ex post uncertainty. The MSE in Eqn. (16) is based on the individual forecast errors,

$$e_{i,t,h} = x_t - \mu_{i,t,h}, \tag{17}$$

with x_t denoting the realization of the outcome variable and $\mu_{i,t,h}$ indicating the mean of forecaster i's histogram as defined in equation (2). To compare ex post and ex ante

[19] We consider both the category "econometric model" and what is referred by the ECB as a "functional form" as cases where forecasters employ some generic form of model.

uncertainty across all survey participants, we compute the average misalignment ratio,

$$m_h = \frac{1}{N_h} \sum_{i=1}^{N_h} \frac{\mathrm{MSE}_{i,h}}{\overline{\sigma_{i,h}^2}}, \tag{18}$$

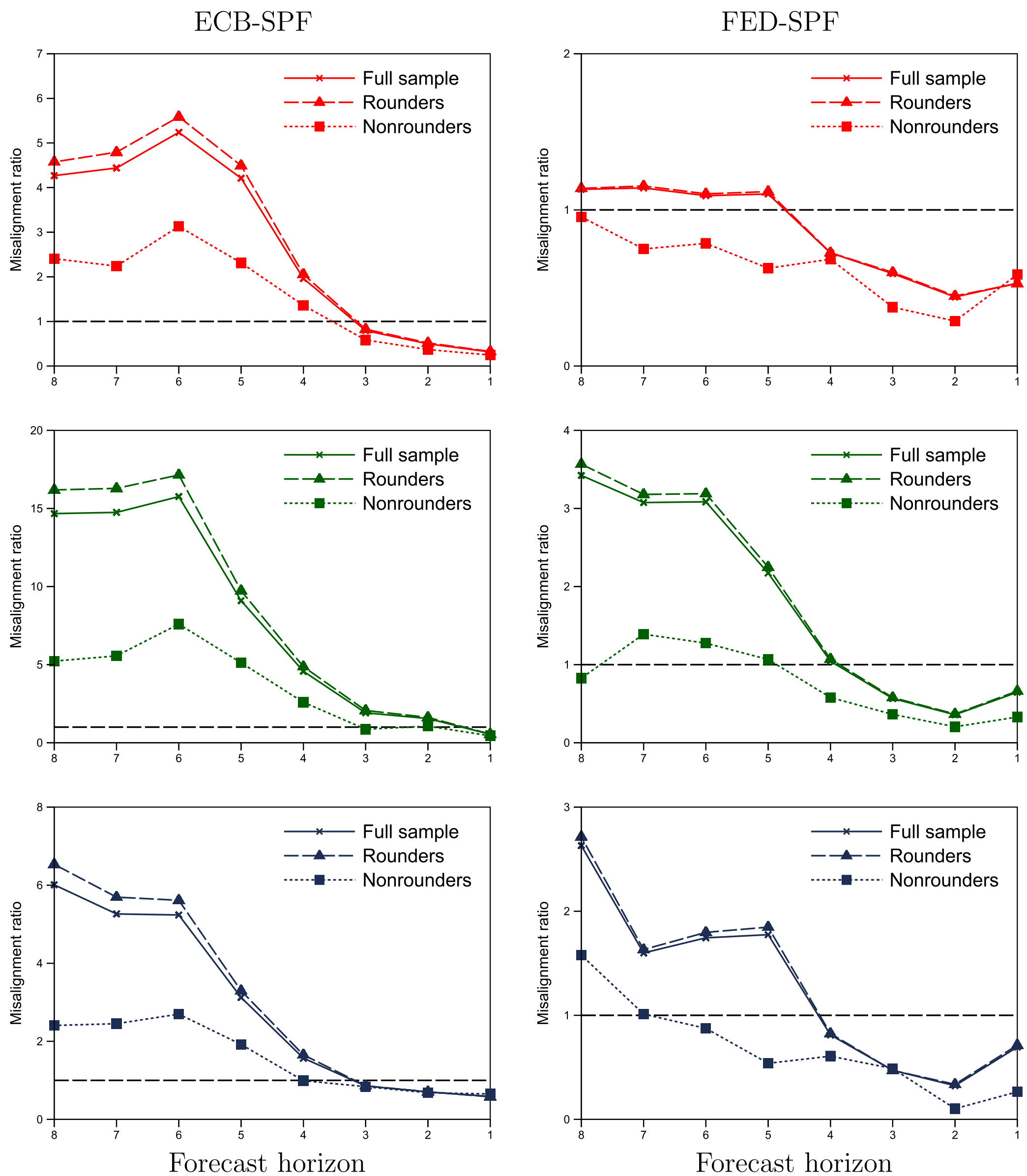
for each forecast horizon, where N_h denotes the number of survey participants who report h-step-ahead histogram forecasts for outcome variable x_t. If forecasters provide an accurate ex ante quantification of the average size of their forecast errors, the value of the statistic in equation (18) equals unity.[20] Values above unity are typically interpreted as evidence of "overconfidence," that is, cases where ex ante uncertainty is, on average, too small compared to ex post uncertainty. We compute the m_h-series across all forecasters as well as separate ratios for the rounders and nonrounders. The corresponding series do not include histograms with 100% probability in a single bin to avoid excessively large ratios of ex post to ex ante uncertainty. In extreme cases where forecasters set *all* their h-step-ahead variances to zero by assigning 100% probability to only one bin, the denominator of equation (18) is zero. Thus, it seems advisable to exclude these observations from the calculation of the m_h-series.[21] Figures 7 and 8 present the results based on $D^{\mathrm{any}}_{i,t,h}$ and $D^{\mathrm{m5}}_{i,t,h}$, respectively.

The evidence for the entire cross-section shows that the variance misalignment can be diagnosed in both surveys. The values of the m_h-ratios tend to be substantially larger than unity at forecast horizons of one year or more, that is, ex post and ex ante uncertainty are better aligned as the target period approaches. In particular, there is a notable drop in m_h as the forecast horizon diminishes from five to four quarters ahead. As discussed in Lahiri and Sheng (2008), this may be related to the availability of first releases of data for x_t for the respective year or alternative sources of information about the outcome. At the shortest forecast horizons, the ex ante variances are frequently larger than the MSE statistics. In these cases, forecasters overstate their ex ante uncertainty compared to the squared forecast errors and should, on average, reduce the variance of their histogram close to the target. Overall, these results square with similar evidence documented in Giordani and Söderlind (2003, 2006) and Clements (2014, 2018) for the FED-SPF and in Kenny et al. (2014), Krüger (2017), and Casey (2021) for the ECB-SPF. In particular, our findings support the result of Clements (2014) that the ex ante uncertainty of SPF participants exceeds ex post uncertainty at short forecast horizons.

While empirical studies on the variance misalignment in surveys of macroeconomic expectations typically evaluate the entire cross-section of forecasters, we isolate

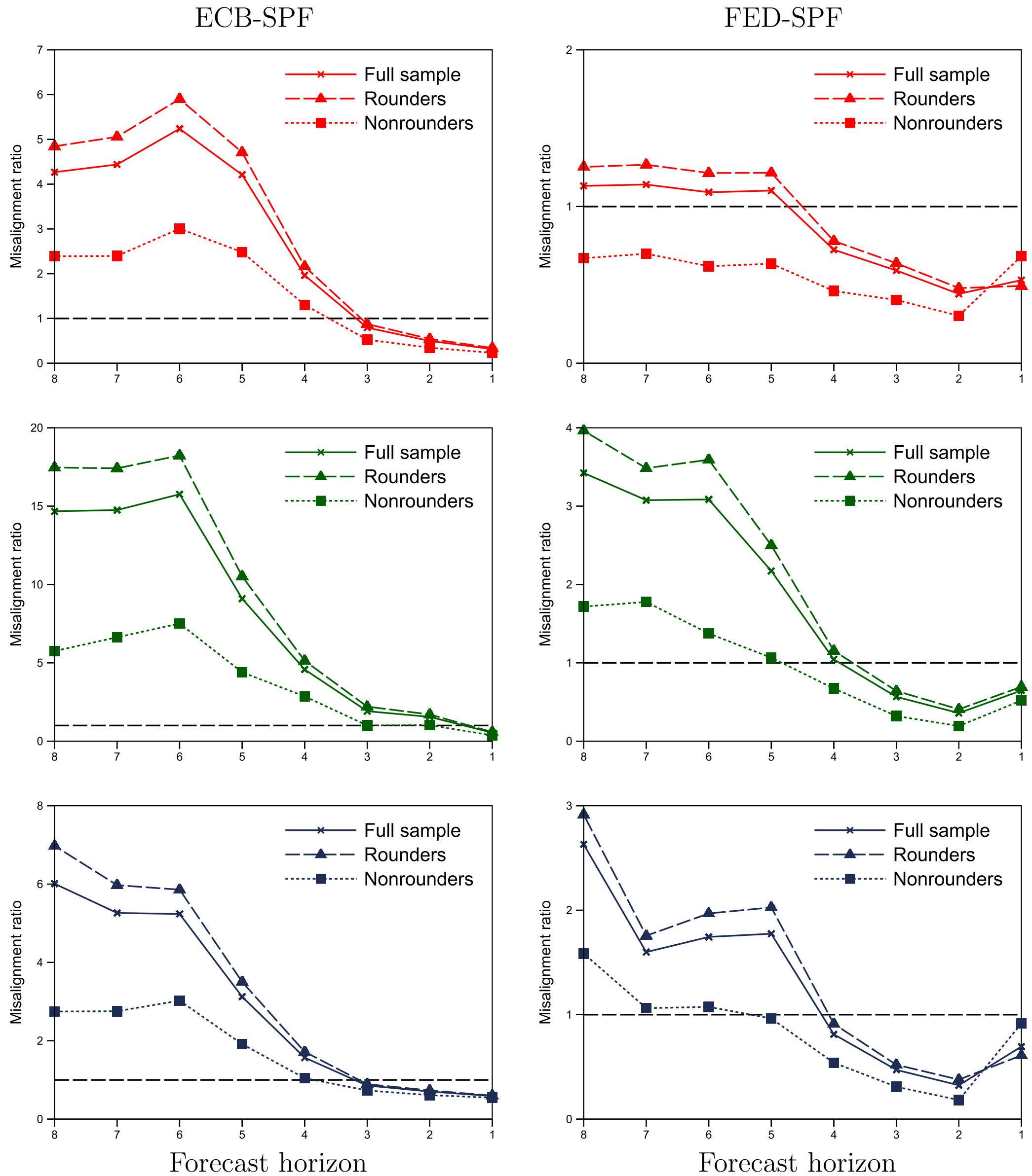
[20]Note that the statistic in equation (18) differs from the one employed in Clements (2014) where the root MSE and the standard deviations are used to compute a similar ratio. Due to the nonlinearity of this transformation, the two statistics cannot be directly compared. Lahiri et al. (2015) discuss the distinct interpretations that arise due to the ordering by means of which aggregation and the root-transformation are applied. To avoid this type of ambiguity, we opt for employing the variance and the MSE instead.

[21]We also exclude the forecaster with identification number 563 from the FED-SPF sample for the analysis in this section. This survey participant is classified as a nonrounder and reports relatively small one-quarter-ahead ex ante uncertainty compared to his/her one-quarter-ahead ex post uncertainty, which disproportionately affects the magnitude of our findings for this particular forecast horizon. However, including this forecaster does not affect the qualitative conclusions of our analysis.



Notes: Each plot depicts the misalignment ratio m_h from equation (18) for inflation (first row), output growth (second row), and unemployment (third row) in the ECB- (first column) and FED-SPF (second column). In addition to the average ratio for the entire cross-section (solid line), each plot depicts separate ratios for rounders (dashed line) and nonrounders (dotted line). Nonrounders are classified by means of $D^{\text{any}}_{i,t,h}$. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 7. Variance misalignment in the SPF data (decimal-based categorization).



Notes: Each plot depicts the misalignment ratio m_h from equation (18) for inflation (first row), output growth (second row), and unemployment (third row) in the ECB- (first column) and FED-SPF (second column). In addition to the average ratio for the entire cross-section (solid line), each plot depicts separate ratios for rounders (dashed line) and nonrounders (dotted line). Nonrounders are classified by means of $D^{\text{m5}}_{i,t,h}$. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 8. Variance misalignment in the SPF data (integer-based categorization).

rounders and nonrounders as a next step. Thereby we find that the average ratios of the nonrounders are much closer to unity at forecast horizons of one year or more. These are also the horizons for which the studies listed above tend to find the most substantial evidence of "overconfidence." In contrast, the average ratios of the rounders and nonrounders are relatively similar as the target period approaches.[22]

The observed patterns are remarkably similar across variables. However, in most cases the degree of the variance misalignment is larger in the ECB-SPF than in the FED-SPF. These differences may be related to varying degrees of forecastability of macroeconomic variables in the Euro area and the U.S. economy. It seems likely that for the unemployment rate it is indeed the numerator of m_h that drives the difference between the two surveys. Evidence in favor of this this explanation is provided in Table A.2 in the Online Supplementary Material, which shows differences in the MSE across surveys and variables. For the unemployment rate, the average MSE across all survey participants and time instances is considerably lower in the FED-SPF. Hence, the stronger alignment between variance forecasts and the MSE for the unemployment rate in the FED-SPF is likely due to higher overall forecastability. Comparing MSE statistics across ECB-SPF and FED-SPF for inflation and GDP growth shows that the forecast performance for these variables is much more similar across surveys, especially when excluding the Great Recession. In these cases, the differences in the level of the misalignment ratios may be related to specific details in the design of the survey questionnaires of the ECB-SPF and FED-SPF. In particular, the width of the bins for real GDP growth and inflation (until 2014Q1) in the FED-SPF is almost twice as large as that in the ECB-SPF. However, as we show below, the average number of bins used by panelists is remarkably similar across surveys and outcome variables. As a result, average ex ante uncertainty for inflation and GDP growth is considerably higher in the FED-SPF (see Figure 4). This can help to explain why the misalignment ratios are markedly smaller in the this case. The inflation rate forecasts in the FED-SPF are particularly noteworthy since they are relatively well aligned even at long forecast horizons.

As a robustness check, we examine if the influence of bin widths on the variance misalignment can be mitigated by fitting beta distributions to the histograms. Glas (2020) shows that the beta distribution tends to compress the variance of probabilistic forecasts to some extent. Hence, it might pay to assess how this type of smoothing can change the results. Figures A.2 and A.3 in the Online Supplementary Material show the misalignment ratios based on the variances from the beta distributions. While the results are nearly identical for the ECB-SPF, we observe higher misalignment ratios in case of the FED-SPF. In particular, the pattern for the inflation rate in this case more closely resembles the one that is depicted in the other plots. However, comparing results with and without the beta distribution clearly shows that this type of smoothing cannot entirely neutralize the effect of the bin width definition on the elicitation process. We examine the influence of the bin width on misalignment ratios in more detail in Section 6.1.

In sum, the results indicate that the ex ante and ex post uncertainties of the nonrounders are better aligned than those of the rounders at forecast horizons of one year

[22] Our findings for the variance misalignment do not change if we use point forecasts instead of the histogram means to compute prediction errors (results not shown).

or more. Thus, it appears that rounding choices of the SPF participants can be employed as an indicator of variance misalignment. Rounding may affect both the numerator and the denominator of the statistic in equation (18). On the one hand, the histogram mean can be affected. This has an impact on the size of the prediction errors. On the other hand, rounding may be related to the ex ante uncertainty as measured by the variance of the histogram. These potential channels are analyzed in the next subsection.

5.3 *Differences in histogram characteristics*

In this section, we investigate in which aspects the reported histograms of the nonrounders differ from those of the rounders. In a first step, we focus on two features of the histograms which are related to the histogram width, and thus ex ante uncertainty. First, the number of bins to which a forecaster assigns a nonzero probability as represented by the count statistic $K_{i,t,h}$. For both nonrounders and rounders, we calculate the average number of bins used by the individuals in each group,

$$\overline{K} = \frac{\sum_i \sum_t \sum_h K_{i,t,h} \times D^{\mathcal{R}}_{i,t,h}}{\sum_i \sum_t \sum_h D^{\mathcal{R}}_{i,t,h}} \tag{19}$$

and

$$\overline{\tilde{K}} = \frac{\sum_i \sum_t \sum_h K_{i,t,h} \times \tilde{D}^{\mathcal{R}}_{i,t,h}}{\sum_i \sum_t \sum_h \tilde{D}^{\mathcal{R}}_{i,t,h}}, \tag{20}$$

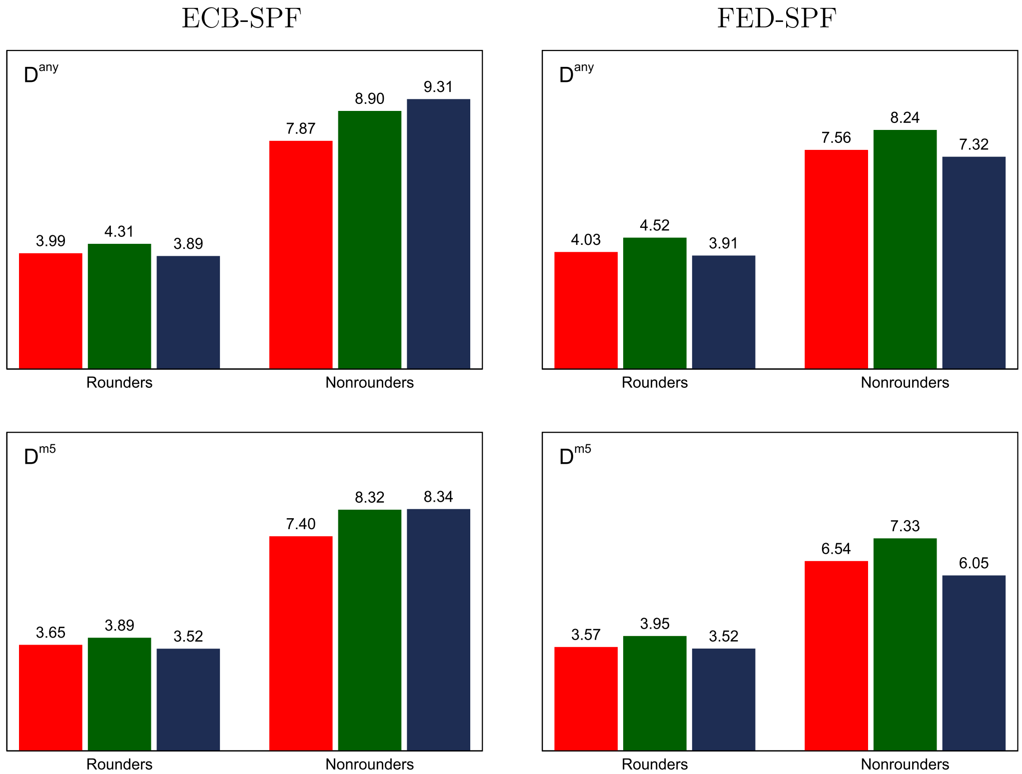
where $\tilde{D}^{\mathcal{R}}_{i,t,h} = 1 - D^{\mathcal{R}}_{i,t,h}$ indicates rounders. Second, we consider the variance of the individual histograms, that is, $\sigma^2_{i,t,h}$ from equation (4). We compute the average variance of each group, that is,

$$\overline{\sigma^2} = \frac{\sum_i \sum_t \sum_h \sigma^2_{i,t,h} \times D^{\mathcal{R}}_{i,t,h}}{\sum_i \sum_t \sum_h D^{\mathcal{R}}_{i,t,h}} \tag{21}$$

and

$$\overline{\tilde{\sigma^2}} = \frac{\sum_i \sum_t \sum_h \sigma^2_{i,t,h} \times \tilde{D}^{\mathcal{R}}_{i,t,h}}{\sum_i \sum_t \sum_h \tilde{D}^{\mathcal{R}}_{i,t,h}}. \tag{22}$$

Note that it is unclear from an ex ante point of view whether nonrounders or rounders report histograms with a higher variance. Figures 9 and 10 show the results based on the decimal- and integer-based categorizations for the average number of bins and variances, respectively.

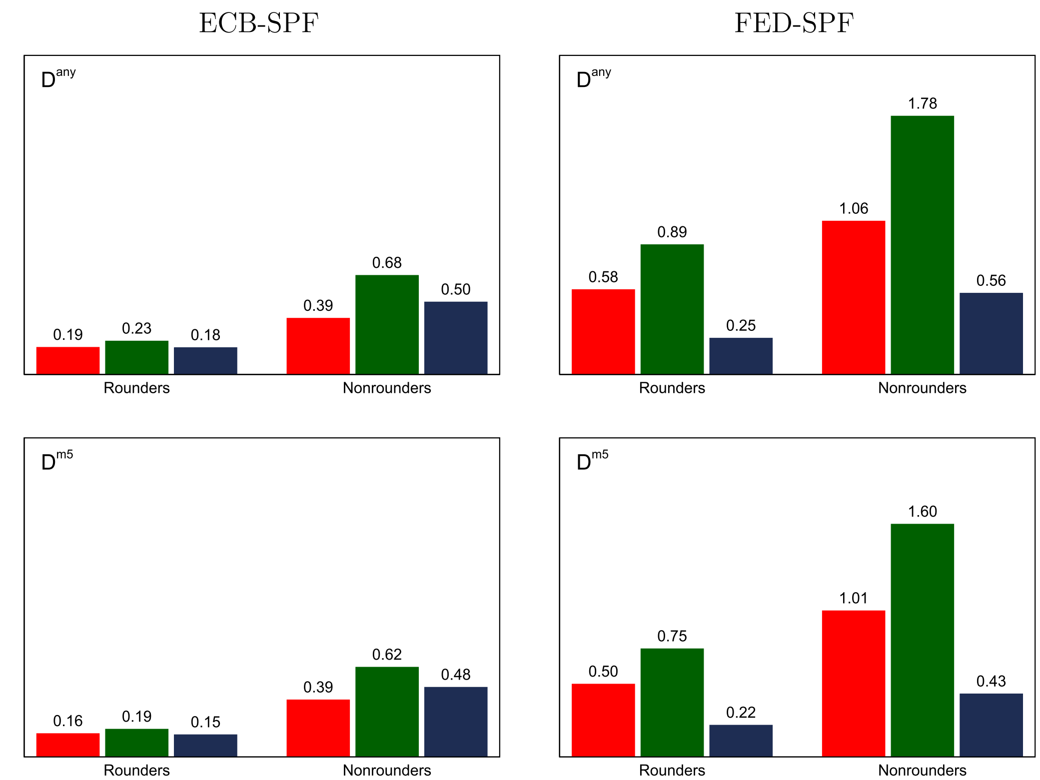


Notes: The graphs depict the average number of bins used by rounders and nonrounders based on the predictions for inflation (first bar), output growth (second bar), and unemployment (third bar) for a pooled sample of observations across forecasters, time periods, and forecast horizons. Nonrounders are classified by means of $D^{\text{any}}_{i,t,h}$ (first row) or $D^{\text{m5}}_{i,t,h}$ (second row). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 9. Average number of bins used by rounders and nonrounders.

Figure 9 shows that the rounders in both surveys assign nonzero probabilities to four bins on average, whereas the nonrounders use twice as many in most cases. Similarly, Figure 10 shows that the variances of the nonrounders are, on average, approximately twice as large as those of the rounders. These findings are remarkably robust across outcome variables and the employed categorization.[23] However, Figure 10 shows that there is substantial heterogeneity in the level of ex ante uncertainty across surveys and outcome variables. This is in line with the evidence from Figure 4. As discussed in the

[23]To disentangle the effect of rounding on the ex-ante variance from any other influence like the (unobserved) individual characteristics of the anonymous survey participants, we conducted an artificial rounding exercise: For each histogram with $D^{\text{m5}}_{i,t,h} = 1$, we rounded the reported probabilities to multiples of five. After excluding observations where the artificially rounded probabilities do not sum to 100% we found that the average variance from equation (21) reduces by 7–10% (ECB-SPF) and 10–11% (FED-SPF), depending on the outcome variable. The average variance based on the artificially rounded histograms remains higher than that of the rounders from equation (22), which suggests that other factors besides rounding explain part of the differences in the reported level of uncertainty.



Notes: The graphs depict the average across the ex ante variances reported by rounders and nonrounders based on the predictions for inflation (first bar), output growth (second bar), and unemployment (third bar) for a pooled sample of observations across forecasters, time periods and forecast horizons. Nonrounders are classified by means of $D^{\text{any}}_{i,t,h}$ (first row) or $D^{\text{m5}}_{i,t,h}$ (second row). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 10. Average ex ante variances reported by rounders and nonrounders.

previous subsection, an explanation for the difference in ex ante uncertainty between the ECB-SPF and the FED-SPF might be that the bins of the histogram forecasts for GDP growth and inflation are about twice as large in the latter, in contrast to the case of the unemployment rate where the bin width equals 0.4 in both surveys. As Figure 9 shows that the number of bins that are used by the survey participants is relatively similar across variables in both surveys, it is clear that the FED-SPF forecasts cover a considerably broader range of these variables' support. This explanation is also suggested by the reduction in ex ante uncertainty of the inflation forecasts in the FED-SPF during and after 2014 that can be seen in the upper right panel of Figure 4. Note that comparing the average ex ante uncertainty for unemployment forecasts in Figure 10 reveals similar numbers for both surveys. This can be expected since the bin width is equal across surveys for this variable.

To shed further light on the implications of distinguishing rounded from nonrounded histogram forecasts, Figure 11 depicts the trajectory of ex ante uncertainty over time, separately for both groups. To avoid seasonality effects that stem from the fixed-event structure, we focus on the approximate one-year-ahead forecasts from the Q1-surveys, that is, the resulting series are obtained at the annual frequency. Evidently, the level of ex ante uncertainty is considerably higher for the nonrounders. Moreover, the dynamics of both series are clearly distinct. This is particularly visible when the trajectories for ex ante uncertainty in the ECB-SPF are compared around the time of the Great Recession.

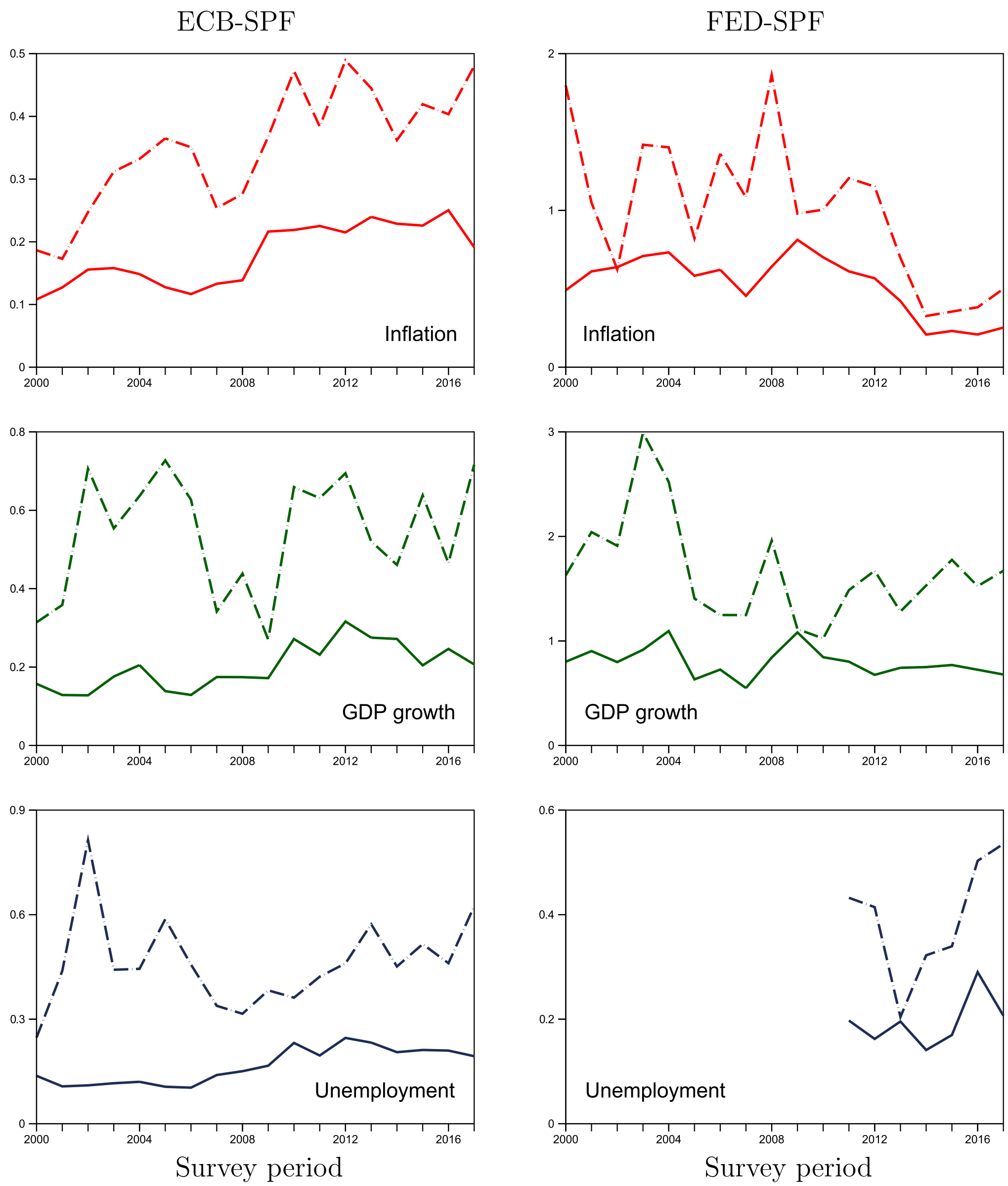
5.3.1 *Horizon-specific regression analysis* It may be the case that rounders and nonrounders update their information sets at different frequencies, for example, due to heterogeneity in the level of information stickiness or differences in the horizons forecasters are concerned with as part of their principal occupation. Hence, the differences between rounders and nonrounders may vary with the forecast horizon h. To better understand the potential reasons for the misalignment of variances, we analyze the forecast performance and histogram characteristics of rounders and nonrounders at distinct forecast horizons. To evaluate the impact of nonrounding, we estimate horizon-specific regressions of the form

$$y_{i,t,h} = \alpha_h + \beta_h D^{\mathcal{R}}_{i,t,h} + \gamma_{2,h} D^{t=2}_{t,h} + \cdots + \gamma_{T,h} D^{t=T}_{t,h} + \varepsilon_{i,t,h}, \tag{23}$$

where $y_{i,t,h} \in \{K_{i,t,h}, \sigma^2_{i,t,h}, |e_{i,t,h}|, e^2_{i,t,h}\}$ denotes distinct histogram characteristics, variation measures and loss functions, respectively, $D^{\mathcal{R}}_{i,t,h}$ indicates the employed categorization for nonrounding and $\varepsilon_{i,t,h}$ is the error term. The first group of histogram characteristics consists of variables that capture the histogram width, that is, the number of bins used by forecasters, $K_{i,t,h}$, and the individual variance defined in equation (4). These variables are observable ex ante and affect the denominator of equation (18). The second group captures the individual ex post forecast performance based on the realizations and the histogram means. In particular, we consider the absolute forecast errors, $|e_{i,t,h}| = |x_t - \mu_{i,t,h}|$, as well as the squared forecast errors, $e^2_{i,t,h} = (x_t - \mu_{i,t,h})^2$. Both are related to the numerator of the ratio in equation (18). In order to capture unobserved time variation, equation (23) includes time-fixed effects $D^{t=2}_{t,h}, \dots, D^{t=T}_{t,h}$. For example, the unobserved sources of heterogeneity include adjustments to the bin definitions.

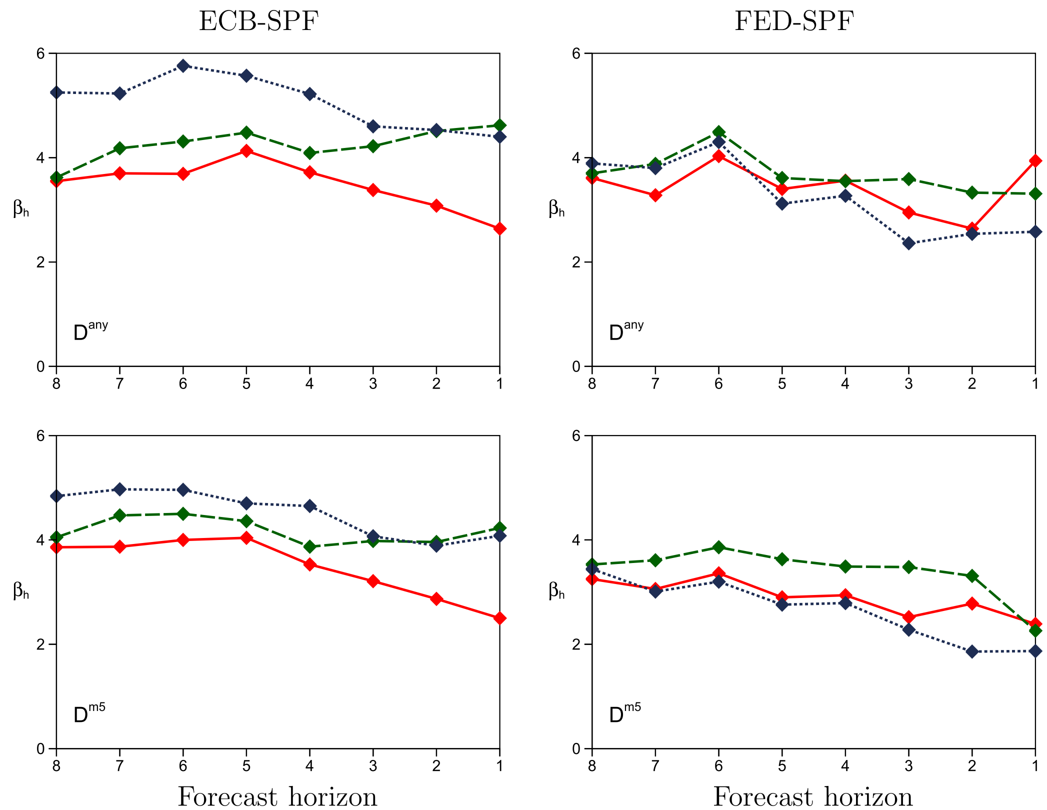
In equation (23), each candidate variable for $y_{i,t,h}$ is regressed on $D^{\mathcal{R}}_{i,t,h}$, that is, the indicator for nonrounding. The slope coefficients $\beta_8, \dots, \beta_1$ capture the differences in the histogram characteristics of nonrounders and rounders at distinct forecast horizons $h \in \{8, 7, \dots, 1\}$. The parameter vector $(\alpha_h, \beta_h, \gamma_{2,h}, \dots, \gamma_{T,h})'$ is estimated via ordinary least squares (OLS). Table 2 presents the sample size used in the estimation for each h. Since the data used in each regression are observed at the annual frequency, the error terms in equation (23) are correlated across time periods due to the overlapping forecast horizons in cases where $h > 4$. In order to account for the autocorrelation patterns in the data, we apply the variance-covariance estimator by Newey and West (1987).

Figures 12 and 13 depict the estimates of β_h over h for each outcome variable that result when either the employed number of bins, $K_{i,t,h}$, or the individual ex ante variance, $\sigma^2_{i,t,h}$, are used as the dependent variable in the model from equation (23). Forecasters are classified as nonrounders based on either $D^{\text{any}}_{i,t,h}$ (first row) or $D^{\text{m5}}_{i,t,h}$ (second row).



Notes: The graphs depict the time series of the cross-sectional average over the 4-quarter-ahead variances reported in the Q1-surveys based on the individual histograms of the rounders (solid) and nonrounders (dashed) classified by $D^{\mathrm{m5}}_{i,t,h}$ for inflation (first row), output growth (second row), and unemployment (third row) in the Euro area and the U.S., that is, $\overline{\sigma^2_{t,4}}$ from equation (5). The horizontal axis depicts the year of the corresponding Q1-survey. The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 11. Average uncertainty of rounders and nonrounders for one-year-ahead predictions.



Notes: For each forecast horizon, the graphs depict the difference in the number of bins used by nonrounders and rounders. In particular, each marker denotes an estimate of the slope coefficient, β_h, based on the h-step-ahead predictions for inflation (solid), output growth (dashed), and unemployment (dotted) when $K_{i,t,h}$ is considered as the dependent variable in equation (23). The explanatory variable $D^{\mathcal{R}}_{i,t,h} \in \{D^{\text{any}}_{i,t,h}, D^{\text{m5}}_{i,t,h}\}$ denotes either the preferred decimal- (first row) or integer-based (second row) categorization from Section 4. Each regression includes time-fixed effects. Coefficients are estimated via OLS. We apply the variance-covariance estimator of Newey and West (1987). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

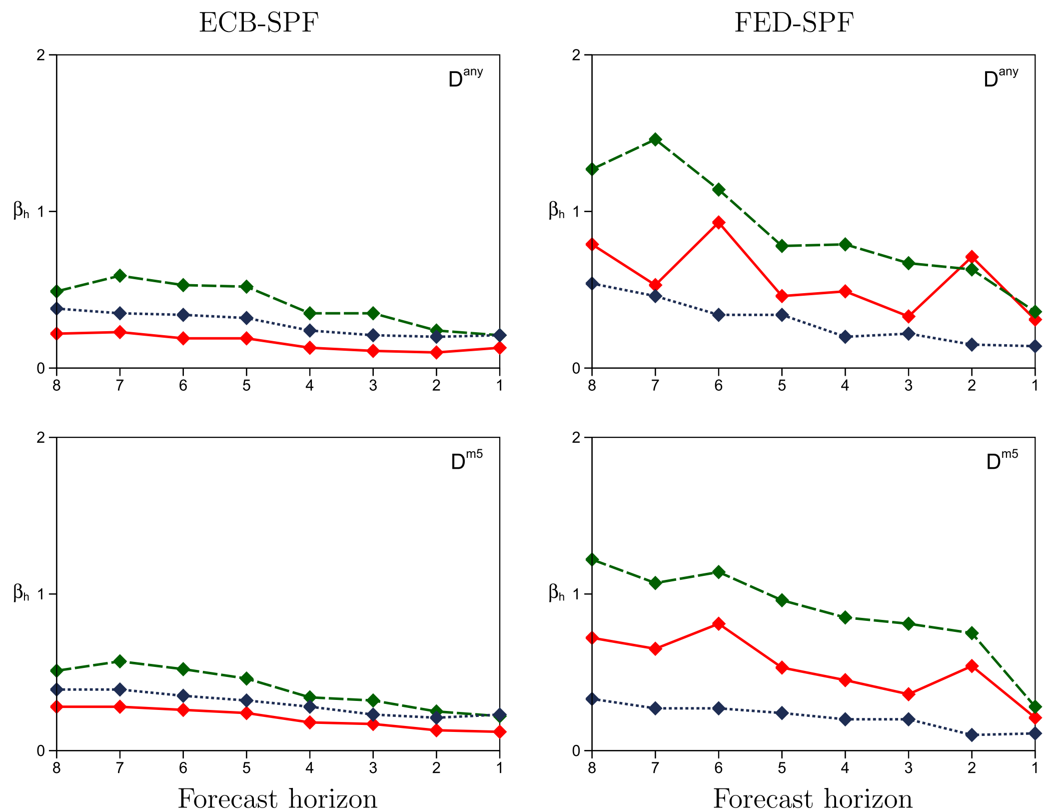
Figure 12. Average deviations in the number of bins used by nonrounders and rounders.

Generally, the results are robust to the choice of the classification scheme.[24] The estimates for the FED-SPF are more strongly affected by individual observations due to the smaller share of nonrounders in this survey (see Table 3).

The results for $K_{i,t,h}$ confirm the evidence from Figure 9 in the sense that nonrounders in both surveys use more bins than the rounders. The finding that nonrounders fill in a larger number of bins is obtained for all forecast horizons and all estimates are significantly different from zero at conventional levels.[25] On average, the

[24] Figures A.4–A.5 in the Online Supplementary Material present the results for the other categorizations.

[25] Detailed estimates of equation (23) including standard errors and goodness-of-fit statistics will be provided upon request.



Notes: For each forecast horizon, the graphs depict the difference in the ex ante variances reported by nonrounders and rounders. In particular, each marker denotes an estimate of the slope coefficient, β_h, based on the h-step-ahead predictions for inflation (solid), output growth (dashed), and unemployment (dotted) when $\sigma^2_{i,t,h}$ is considered as the dependent variable in equation (23). The explanatory variable $D^{\mathcal{R}}_{i,t,h} \in \{D^{\text{any}}_{i,t,h}, D^{\text{m5}}_{i,t,h}\}$ denotes either the preferred decimal- (first row) or integer-based (second row) categorization from Section 4. Each regression includes time-fixed effects. Coefficients are estimated via OLS. We apply the variance-covariance estimator of Newey and West (1987). The sample period is 1999Q1–2017Q4, except for the unemployment rate forecasts from the FED-SPF, which are available since 2010Q1 for our purposes.

FIGURE 13. Average deviations in the variances reported by nonrounders and rounders.

difference is approximately equal to four bins. However, in most cases the differences become less pronounced as the forecast horizon diminishes. Thus, the larger variances of the nonrounders are revised downwards more strongly as the target is approached during the forecasting process. This pattern is particularly apparent for the estimates based on the inflation and unemployment rate forecasts in the ECB-SPF.

The evidence that is obtained when $\sigma^2_{i,t,h}$ is used as the dependent variable is in line with Figure 10 in the sense that nonrounders report considerably wider histograms. This is particularly the case at forecast horizons of one year or more. These horizons correspond to those for which the difference in the variance misalignment between both groups is particularly large. The decreasing pattern of the estimated slope coefficients from Figure 12 is visible here as well. In both surveys, the difference in the average variances tends to decline in both magnitude and significance as the target approaches.[26] As with Figure 12, all estimates in Figure 13 are highly significant. Some exceptions are observed for the current-year predictions in the FED-SPF when $D^{\text{any}}_{i,t,h}$ is used as explanatory variable where some of the estimates are only weakly significant.

Overall, the patterns in Figures 12 and 13 are in line with the evolution of the average misalignment ratios from Figures 7 and 8. The values of the adjusted R^2-statistics based on the estimates of equation (23) are lower in the FED-SPF than in the ECB-SPF. It could be that differences in the survey methodology are the reason for the improved goodness of fit. In particular, the larger bin width in the FED-SPF in conjunction with the similarity in the number of employed bins across survey leads to a less pronounced gap between ex ante and ex post uncertainty in the FED-SPF as shown above.

Apart from the denominator of equation (18), the numerator can also be the reason for the variance misalignment. The size of the numerator depends on the individual forecast errors. However, when $|e_{i,t,h}|$ or $e^2_{i,t,h}$ are considered as the dependent variable in equation (23), we find no clear evidence differences in the ex post forecast performance of rounders and nonrounders in terms of absolute or squared forecast errors (see Figures A.7 and A.8 in the Online Supplementary Material). The estimates of β_h are small in magnitude, insignificant in nearly all cases and appear to fluctuate randomly across horizons with no discernible pattern. Our findings suggest that the histogram mean is relatively robust to the rounding choices of the survey participants.

In sum, our results confirm that nonrounders in the SPF use more bins and report larger variance forecasts than the rounders. In most cases, this implies that the denominator of the m_h-statistic from equation (18) is larger for the nonrounders. The differences become smaller as the target approaches, which provides a potential explanation for the similar alignment of the ex post and ex ante uncertainties reported by rounders and nonrounders at the shortest forecast horizons. In contrast, the nonrounders do not substantially differ from the rounders in terms of ex post prediction errors.

5.3.2 *Pooled regression analysis* To test whether our findings also hold for each survey as a whole, Table 4 reports the results from panel regressions for the sample of inflation forecasts in the ECB-SPF, pooled over the horizon dimension.[27] The columns correspond to the distinct dependent variables that have also been examined in the horizon-specific regression analyses. In addition, columns (5) and (6) present results for ex ante variances that are derived by means of smoothing histogram forecasts with the beta distribution, $\sigma^2_{B,i,t,h}$.

It is apparent that the effect of nonrounding is found also in the pooled specification. This is highlighted by the coefficients of the interaction terms of $D^{\text{m5}}_{i,t,h}$ with $D^{h=h'}_{i,t,h}$ for $h' = 1, \dots, 8$. In particular, our estimates indicate that forecasters use significantly more bins and report higher ex ante variances at long forecast horizons relative to the

[26] Figure A.6 in the Online Supplementary Material shows very similar patterns for the variances from the beta distributions, $\sigma^2_{B,i,t,h}$.

[27] Tables A.3–A.7 in the Online Supplementary Material present the estimates for the other variables and the FED-SPF.

TABLE 4. Pooled regressions for average deviations of inflation histogram characteristics in the ECB-SPF.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$K_{i,t,h}$		$\sigma^2_{i,t,h}$		$\sigma^2_{B,i,t,h}$		$\lvert e_{i,t,h}\rvert$		$e^2_{i,t,h}$	
$D^{\text{m5}}_{i,t,h}$	2.47	1.34	0.12	0.06	0.09	0.04	0.03	0.05	0.05	0.09
	(0.20)	(0.20)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
$D^{\text{m5}}_{i,t,h} \times D^{h=2}_{i,t,h}$	0.36	0.42	0.01	0.02	0.01	0.02	−0.05	−0.04	−0.05	−0.04
	(0.23)	(0.21)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)
$D^{\text{m5}}_{i,t,h} \times D^{h=3}_{i,t,h}$	0.69	0.77	0.05	0.05	0.04	0.05	−0.04	−0.03	−0.08	−0.07
	(0.25)	(0.22)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
$D^{\text{m5}}_{i,t,h} \times D^{h=4}_{i,t,h}$	1.05	1.32	0.06	0.08	0.06	0.07	−0.06	−0.05	−0.13	−0.13
	(0.26)	(0.23)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)
$D^{\text{m5}}_{i,t,h} \times D^{h=5}_{i,t,h}$	1.61	1.65	0.13	0.13	0.13	0.13	0.05	0.06	0.06	0.07
	(0.25)	(0.23)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)
$D^{\text{m5}}_{i,t,h} \times D^{h=6}_{i,t,h}$	1.56	1.67	0.15	0.15	0.14	0.14	0.03	0.04	0.04	0.05
	(0.26)	(0.24)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.07)	(0.07)
$D^{\text{m5}}_{i,t,h} \times D^{h=7}_{i,t,h}$	1.44	1.56	0.16	0.17	0.15	0.15	0.03	0.03	0.03	0.03
	(0.26)	(0.23)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)
$D^{\text{m5}}_{i,t,h} \times D^{h=8}_{i,t,h}$	1.40	1.64	0.17	0.18	0.15	0.17	0.03	0.04	0.07	0.06
	(0.25)	(0.23)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)
Constant	3.18	3.77	0.15	0.15	0.12	0.12	0.06	0.30	−0.01	0.09
	(0.17)	(0.38)	(0.01)	(0.04)	(0.01)	(0.04)	(0.03)	(0.04)	(0.06)	(0.09)
Observations	7498	7498	7498	7498	7498	7498	7498	7498	7498	7498
Horizon-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster-FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
$\bar{R}^2$	0.51	0.68	0.34	0.58	0.34	0.56	0.60	0.61	0.52	0.52

Note: This table presents the differences in the inflation histogram characteristics reported by nonrounders and rounders in the ECB-SPF. The explanatory variable $D^{\text{m5}}_{i,t,h}$ denotes the preferred integer-based categorization from Section 4. Each regression includes horizon- and time-fixed effects. The even-numbered columns additionally include forecaster-fixed effects. Coefficients are estimated via OLS. Newey and West (1987) standard errors are reported in parentheses. The sample period is 1999Q1–2017Q4.

one-quarter-ahead predictions. In contrast, differences in such histogram characteristics are not statistically significant from one quarter to the next in most cases. A notable exception is the difference between the five- to four-quarter-ahead forecasts for which t-statistics (not reported) diagnose significant differences. This is in line with the drop in the misalignment ratios for these particular forecast horizons (see Figures 7 and 8). Moreover, it is interesting to note the distinction between results that are based on a specification with forecaster-fixed effects in the even-numbered columns to the ones without. As the former case focuses on the average variation at the individual level over time, it becomes apparent that within-forecaster variation in the rounding incidence generates similar effects on the ex ante statistics $K_{i,t,h}$ and $\sigma^2_{i,t,h}$ as when multiple dimensions of variation are examined. The respective coefficients of $D^{\text{m5}}_{i,t,h}$ are somewhat smaller if forecaster-fixed effects are included since the estimation focuses on the variation within institutions in this case.

To summarize, rounding choices affect the denominator of the misalignment ratio in equation (18), but not the numerator. The implication of this finding is that a better calibrated quantification of ex ante uncertainty can be obtained by focusing on the nonrounders. The share of nonrounded responses has been increasing recently as seen in Figure 6. We conclude that surveys of macroeconomic expectations should be designed in such a way that its participants can submit their forecasts with as little effort as possible.

6. Discussion

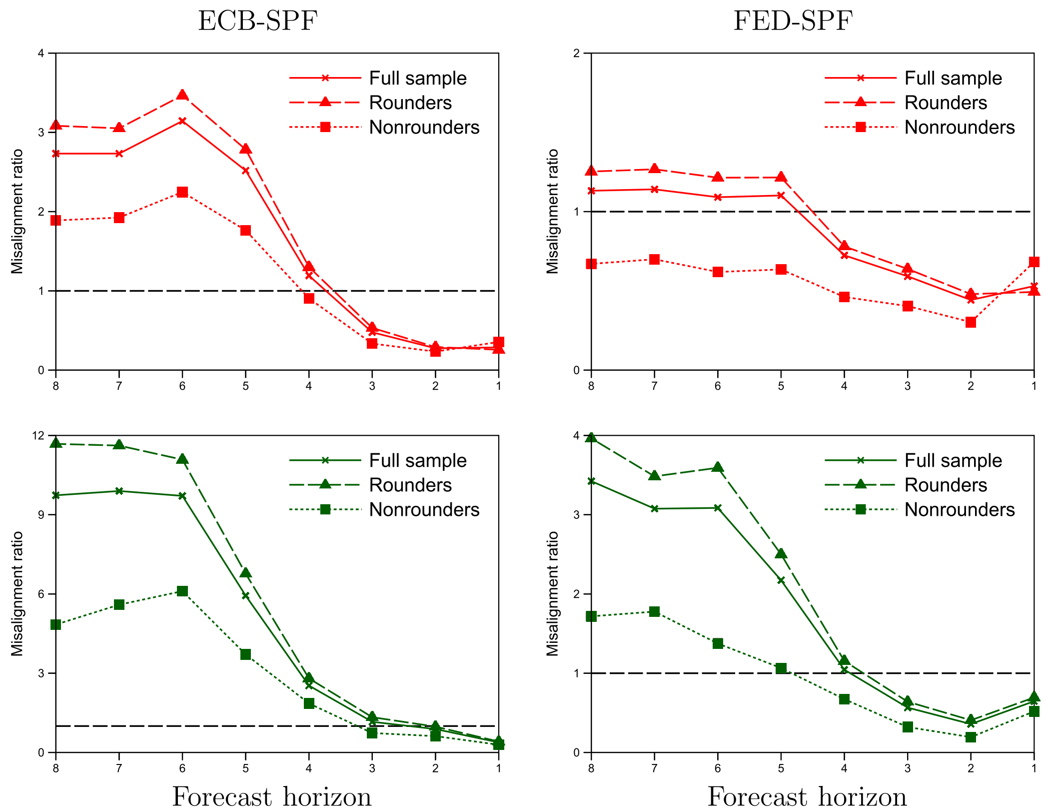
This section examines some further aspects of the measurement of ex ante uncertainty and the classification of rounders and nonrounders. First, we examine the influence of bin widths by making use of differences in their definitions across surveys and over time. Second, to relate our findings to the recent literature, we compare our classification scheme that is based on histogram probabilities to an alternative that uses the degree of rounding of the point forecast.

6.1 *Variance misalignment and the width of histogram bins*

The results from Sections 3 and 5.2 suggest that the bin width has an influence on ex-ante uncertainty, and thereby also on variance misalignment. This is important for the understanding of the previously documented findings for variance misalignment since the bin width for inflation and GDP growth forecasts differs between the FED-SPF and the ECB-SPF. Recall that the variance misalignment in Figures 7 and 8 is markedly higher for the ECB-SPF due to a larger ex ante variance. In the following, we consider two counterfactual scenarios to examine the relation between the bin width and the misalignment of variances. The first scenario enforces an alignment of the bin widths. We increase the width of the bins in the ECB-SPF and assume that the participants react to this change by filling in only half the number of bins compared to what is actually observed. In contrast, the framework of the second scenario is based on the observation that histogram forecasts in the FED-SPF do not exhibit a change in the number of bins if the bin width in the questionnaire changes. Based on this finding, we examine the effect of a bin width change under the assumption that the number of bins used by panelists remains fixed.

In scenario A, we combine adjacent bins for inflation and GDP growth in the ECB-SPF such that their boundaries align with those in the FED-SPF (for example, 1.0%–1.9%, 2.0%–2.9%,...). In general, combining the bins in this way seems to be a promising way to make histogram forecasts from distinct survey with unequal bin widths comparable. Based on the combined bin probabilities we recalculate all histogram characteristics and the misalignment ratios, along with the rounding status of panelists. The counterfactual merging of bins yields an increase in average ex ante uncertainty (numbers not reported) and, as shown in Figure 14, a drop in the misalignment ratio.[28] Consequently, the ex ante and ex post variances in the ECB-SPF and the FED-SPF become

[28]The plots for the FED-SPF in Figures 14 and 15 are identical to those in Figure 8, except for an adjusted scaling of the vertical axis in the subfigure for GDP growth in Figure 15.



Notes: Each plot depicts the adjusted misalignment ratio m_h from equation (18) for inflation (first row) and output growth (second row) in the ECB- (first column) and FED-SPF (second column) based on scenario A. In addition to the average ratio for the entire cross-section (solid line), each plot depicts separate ratios for rounders (dashed line) and nonrounders (dotted line). Nonrounders are classified by means of $D^{\mathrm{m5}}_{i,t,h}$. The sample period is 1999Q1–2017Q4.

FIGURE 14. Adjusted variance misalignment in the SPF data (scenario A).

more aligned. However, a sizeable gap remains. These findings suggest that combining bins can account for some, but not all, of the differences in the misalignment ratios between both surveys.

In scenario B, we examine the effect of a change in the bin width under the assumption that the employed number of bins remains fixed. As in scenario A, this means that the results regarding variance misalignment can be better compared across surveys. In particular, we examine how a suitable rescaling of all bins in the ECB-SPF affects misalignment ratios. Similar to the previous exercise, this analysis is to some extent counterfactual, since one might expect that adjusting the ECB-SPF questionnaire such that bin sizes are equal to the ones in the FED-SPF would lead survey participants to change the way how they fill in the questionnaires. Ceteris paribus, an increase in the width of all histogram bins should lead to a reduction in the number of bins with nonzero probability. However, comparing the number of bins with nonzero probabilities across those dimensions in our data sets where bin widths already differ shows that the number of bins that are used seems to be essentially independent of the bin width (see Figure 9). Additional evidence for a negligible effect of bin width on the number of bins used by panelists has been documented in Figure 4 for the adjustment of the inflation bins in the FED-SPF in 2014Q1.

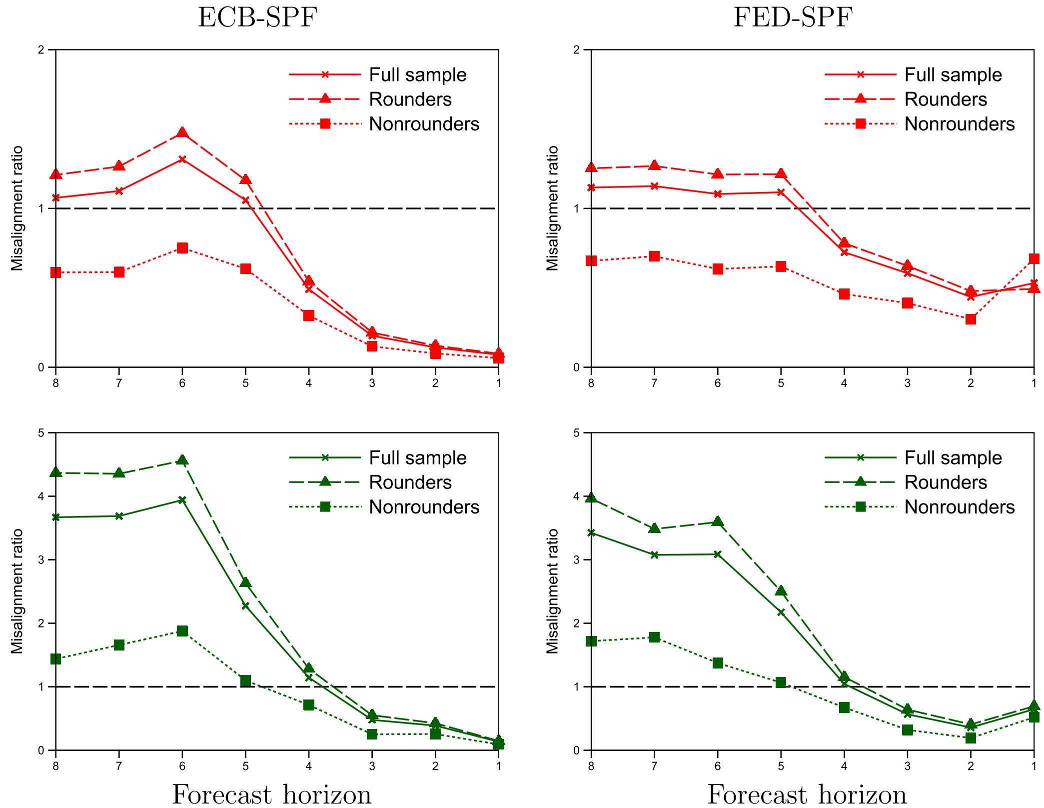
In light of these findings, we analyze the influence of bin widths by means of rescaling ex ante variances under the assumption that the number of bins with nonzero probabilities remains fixed. As noted above, the bin width in the ECB-SPF is half the size of the FED-SPF, that is, a comparable scaling is given if the bin width in the ECB-SPF is multiplied by a factor of two. Since for any random variable x and constant c, $\mathbf{Var}[cx] = c^2\,\mathbf{Var}[x]$, rescaling the forecasts in the ECB-SPF by a factor of $c = 2$ leads to a four-fold increase in the ex ante variance. Consequently, given the definition of m_h in equation (18), we divide the misalignment ratios for inflation and GDP growth in the ECB-SPF by four. Figure 15 presents the results.

Apparently, recomputing the variance misalignment statistics under the counterfactual bin width leads to a marked reduction of variance misalignment in the ECB-SPF. Notably, the magnitude of the misalignment ratios in the ECB-SPF and the FED-SPF is relatively similar after the bin size adjustment. Our findings indicate that the bin size that has been selected in the FED-SPF leads to a closer alignment between ex ante and ex post uncertainty. However, it should be noted that from the viewpoint of the designer of a questionnaire, it is a priori unclear which bin width would be most appropriate. It seems that such a potential shortcoming of a probabilistic survey can only be observed ex post, at a point where an adjustment might have the disadvantage that forecasts might be hardly comparable after the correction.

6.2 *Expert versus consumer surveys*

In a related study, Binder (2017) investigates the relationship between ex ante uncertainty and rounding in two surveys of consumer expectations. In a preliminary analysis, she finds that the average histogram width of the rounders in the Survey of Consumer Expectations (SCE) of the Federal Reserve Bank of New York is approximately twice as large as that of the nonrounders (see her Table 1). In contrast, we find that in the SPF data the histograms of the *nonrounders* exhibit higher variance. However, as will be discussed below, there are important distinctions between both analyses. Moreover, we show that our categorizations and the one used by Binder (2017) isolate distinct groups of survey participants.

First, we consider professional forecasters, whereas Binder (2017) focuses on consumers. There may be systematic differences in the way that each group computes their predictions. As discussed in Section 5.1, professional forecasters may rely on either formal models or judgment in the forecasting process. It seems likely that the relative importance of judgmental forecasting is higher for consumers than it is for experts. Second, we classify the SPF participants as rounders or nonrounders based on their histogram forecasts. Binder (2017) focuses on the point forecasts instead. For consumer surveys, this may be advantageous since consumers who are not expert forecasters may focus



Notes: Each plot depicts the adjusted misalignment ratio m_h from equation (18) for inflation (first row) and output growth (second row) in the ECB- (first column) and FED-SPF (second column) based on scenario B. In addition to the average ratio for the entire cross-section (solid line), each plot depicts separate ratios for rounders (dashed line) and nonrounders (dotted line). Nonrounders are classified by means of $D^{\text{m5}}_{i,t,h}$. The sample period is 1999Q1–2017Q4.

FIGURE 15. Adjusted variance misalignment in the SPF data (scenario B).

their attention on approximating the first moment and put less effort into a sophisticated quantification of higher moments. The categorizations employed in our study have the advantage that they are based on more than just one number due to the fact that almost all SPF participants assign nonzero probabilities to multiple bins. Thus, the two approaches can be considered as complementary to each other. However, it is possible that survey participants who report rounded point forecasts differ from respondents who round the probabilities. We show that this is the case below. Third, the employed survey data differ in other important aspects. The SCE sample used by Binder (2017) to obtain the estimates in her Table 1 covers only a short period from January 2013 to September 2015, whereas we examine the SPF data for the period 1999Q1–2017Q4. Moreover, the bins in the SCE have a width of two to four percentage points and are thus much wider than those in the SPF. As discussed in the previous subsection, this can have a marked influence on quantifications of ex ante uncertainty. Furthermore, Binder

Table 5. Correlations across categorizations in the ECB-SPF.

	Inflation	GDP Growth	Unemployment
$\widehat{\mathbf{Corr}}[D^{\text{any}}, D^{\text{m5}}]$	0.58	0.58	0.59
$\widehat{\mathbf{Corr}}[D^{\text{any}}, D^{\text{m0.5}}]$	−0.06	−0.07	−0.08
$\widehat{\mathbf{Corr}}[D^{\text{m5}}, D^{\text{m0.5}}]$	−0.05	−0.07	−0.08

Note: For each outcome variable, this table presents the bivariate correlations between distinct categorizations for nonrounders in the ECB-SPF for a pooled sample of observations across all survey participants, time instances and forecast horizons. The sample period is 1999Q1–2017Q4.

(2017) uses the interquartile range to measure the spread of the individual distributions. We follow Zarnowitz and Lambros (1987) and examine the individual variance as a measure of ex ante uncertainty. Finally, the SCE differs from the SPF in terms of the sampling scheme that is used to select surveyed individuals. In particular, the SCE constitutes a rotating panel, whereas most of the SPF forecasters have a fairly long history of survey participation. The accumulated experience of some forecasters may also be related to their rounding choice.

In order to analyze whether the distinct approaches based on point and histogram forecasts isolate the same SPF participants, we first consider the correlations between the decimal- and integer-based categorizations for the reported probabilities based on a pooled sample of observations across all forecast horizons. Here, we only consider the case of the ECB-SPF. We have documented in Section 5.1 that both approaches work well in isolating two distinct groups of forecasters who appear to rely on either judgment or models to compute their probabilities. If this is the case, the correlations between $D^{\text{any}}_{i,t,h}$ and $D^{\text{m5}}_{i,t,h}$ are expected to be positive and large.

In the second step, we follow Clements (2021) and categorize experts as rounders based on whether their point forecast, $\mu^{P}_{i,t,h}$, is a multiple of 0.5, that is,

$$\tilde{D}^{\text{m0.5}}_{i,t,h} = \begin{cases} 1 & \text{if } 0.5 \cdot \left\lfloor \dfrac{\mu^{P}_{i,t,h}}{0.5} \right\rfloor = \mu^{P}_{i,t,h} \text{ and} \\ 0 & \text{else.} \end{cases} \tag{24}$$

Note that Binder (2017) classifies consumers as rounders if the point forecast is a multiple of five, not 0.5. This is due to the fact that the range of point forecasts for inflation reported in the SCE is considerably larger than in the SPF. As in the case of the integer-based categorizations, we consider

$$D^{\text{m0.5}}_{i,t,h} = 1 - \tilde{D}^{\text{m0.5}}_{i,t,h} \tag{25}$$

in order to focus on nonrounders. If the categorizations based on point and histogram forecasts perform equally well, the correlations between $D^{\text{m0.5}}_{i,t,h}$, $D^{\text{any}}_{i,t,h}$ and $D^{\text{m5}}_{i,t,h}$ should be positive and large. Table 5 summarizes the correlations based on a pooled sample of observations across all survey participants, time instances, and forecast horizons.

The correlation statistics between $D^{\text{any}}_{i,t,h}$ and $D^{\text{m5}}_{i,t,h}$ have the expected sign and amount to 0.58, 0.58, and 0.59 for inflation, real GDP growth and unemployment, respectively. This shows again that there is a large overlap in the groups of survey participants that are classified as nonrounders by both approaches (see Section 5.1). In contrast, the correlations between $D^{\text{any}}_{i,t,h}$ and $D^{\text{m0.5}}_{i,t,h}$, that is, the categorization based on the point forecasts, are considerably smaller and close to zero. In other words, these categorizations identify separate groups of forecasters. It may be the case that the weak association is due to methodological differences between the decimal-based approach and $D^{\text{m0.5}}_{i,t,h}$. If this were the only explanation, it may be expected that the categorizations from equations (10) and (24) are more closely related, such that the association between $D^{\text{m5}}_{i,t,h}$ and $D^{\text{m0.5}}_{i,t,h}$ should be stronger. However, the corresponding correlation statistics are again close to zero, which suggests that categorizations based on point and histogram forecasts isolate distinct groups of forecasters.

7. Conclusion

We analyze the misalignment between ex ante and ex post uncertainty that is frequently observed in surveys of macroeconomic expectations. In the analysis of the Survey of Professional Forecasters for the Euro area and the U.S., we employ a variety of distinct categorizations to isolate two groups of forecasters based on their reporting behavior. We find that the variance misalignment is considerably smaller for survey participants who report nonrounded histogram forecasts. This is a consequence of the fact that this group reports significantly larger ex ante variances. In contrast, the forecast errors of rounders and nonrounders do not seem to differ in a systematic way. Thus, rounding has little impact on the first-moment dynamics but has a substantial effect on the second moment.

Our results have important implications for the evaluation of the cross-section of survey participants. In particular, measures of aggregate ex ante uncertainty that are more aligned with ex post squared forecast errors can be derived by focusing on the nonrounders and discarding the remaining responses. Due to the relatively small share of nonrounded histograms, this would result in a substantial loss of information. However, the share of nonrounders has increased substantially over time. This suggests that the quality of the SPF predictions has improved in recent years and increases the feasibility of focusing on the nonrounders. Designers of surveys of macroeconomic expectations should improve their questionnaires in such a way that reporting less strongly rounded probabilities is further encouraged. To facilitate the distinction between survey participants that provide rounded numbers and ones who do not, inquiring about participants' respective intentions in the survey questionnaire might be helpful.

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