Conditional Macroeconomic Survey Forecasts: Disagreement, Revisions and Errors

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Abstract

Using data from the European Central Bank's Survey of Professional Forecasters, we analyze the role of ex-ante conditioning variables for macroeconomic forecasts. In particular, we test to which extent the heterogeneity, updating and ex-post performance of predictions for inflation, real GDP growth and unemployment in the euro area are related to beliefs about future oil prices, exchange rates, interest rates and wage growth. While oil price and exchange rate predictions are updated more frequently than the macroeconomic forecasts, the opposite is true for interest rate and wage growth expectations. Our findings indicate that beliefs about future inflation are closely associated with oil price expectations, whereas expected interest rates are used primarily to predict output growth and unemployment. Exchange rate and wage growth predictions also matter for macroeconomic forecasts, albeit less so than oil prices and interest rates.

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1 Introduction

Policy makers have to rely on accurate macroeconomic forecasts to implement adequate policy measures. Surveys among professional forecasters provide a popular source of such information. However, these predictions come along with considerable uncertainty and non-negligible errors (e.g., Dovern, 2013). Moreover, several studies document non-zero and time-varying disagreement in expert's predictions (Andrade *et al.*, 2016; Abel *et al.*, 2016; Glas and Hartmann, 2016; Glas, 2020).

Various theoretical models attempt to rationalize the existence of disagreement and heterogeneous forecast errors. Promising candidates are models of information rigidities such as noisy information (Woodford, 2002; Sims, 2003; Mackowiak and Wiederholt, 2009) or sticky information models (Mankiw and Reis, 2002). In the former, forecasters continuously update their information sets. However, since the signals they receive are polluted with idiosyncratic noise, new information is only partly incorporated into expectations. In sticky information models agents update their information sets infrequently, either because it is costly to do so or due to limited processing capacities (rational inattention). Consistent with sticky information, survey forecasts are often not fully revised from one period to the next and exhibit time-varying disagreement (Coibion and Gorodnichenko, 2015; Baker *et al.*, 2020). However, such models cannot fully explain the disagreement and errors commonly observed in surveys, which raises the question of further explanatory approaches. In particular, one may be interested in the role of key conditioning variables that are included in experts' information sets and that are used as inputs in the forecasting process. For example, Baumann *et al.* (2021) show that oil prices are a key driver of short-term inflation expectations in the euro area.[1] In addition to realizations of such variables, the information sets likely also include expectations about their future path (e.g., oil price expectations).

In this paper, we analyze the explanatory power of several forward-looking variables for the heterogeneity, updating and performance of survey-based macroeconomic expectations. Our research connects to the ideas of conditional forecasting where variables of interest

[1] Based on a panel of experts from 34 OECD economies including the euro area, Moessner (2021) finds that exchange rate depreciations and rising oil prices increase short-term inflation expectations.

(in our case, macroeconomic forecasts) are related to future paths of other variables and examines changes in conditional (mean) forecasts in response to adjustments in the conditioning set. As a framework to explore such issues, the European Central Bank's Survey of Professional Forecasters (SPF) collects point forecasts for inflation, real GDP growth and unemployment in the euro area provided by experts employed by financial and research institutions. In addition to their macroeconomic predictions, panelists provide information on their expectations about future conditions on financial markets as well as other economic factors such as commodity prices. This includes beliefs about future oil prices, the EUR/USD exchange rate, the ECB's main refinancing operations and wage growth. The role of these variables for macroeconomic forecasting is not fully understood so far.

Our paper relates to the literature that tests whether survey expectations are consistent with inattention models. Andrade and Le Bihan (2013) find that the upating frequency of macroeconomic expectations in the SPF is well below 100% (in line with sticky information) and that forecasters who update their predictions disagree about macroeconomic outcomes (in line with noisy information). In contrast, Czudaj (2022) finds that the oil price expectations in the SPF are revised more often with particularly frequent updating at short horizons. Our analysis builds upon such findings and provides a comprehensive analysis of macroeconomic forecasts and ex-ante conditions including variables that have been hardly noticed so far (exchange rates, interest rates and wage growth). In line with sticky information, we find evidence of time-varying disagreement in all variables and infrequent revisions of macroeconomic forecasts. However, the updating frequencies for predictions of external conditions differ substantially. While oil price and exchange rate expectations are revised almost continuously, updating frequencies for interest rates and wage growth are below those of the macroeconomic forecasts.

We also contribute to the literature that analyzes the connection between macroeconomic expectations and ex-ante conditions. Some papers explore the immediate relationship between errors in expectations about macroeconomic variables and external conditions. Engelke *et al.* (2019) find a positive effect of squared errors for the interest rate and world trade on squared errors for German GDP growth. Fortin *et al.* (2020) show that misconceptions about euro area GDP growth translate into higher forecast errors of Austrian GDP growth, whereas inaccurate predictions of the Austrian inflation rate are more closely related to oil price errors. Interestingly, Fortin *et al.* (2020) find that the strength of the linkage between macroeconomic predictions and beliefs about external conditions increases with the forecast horizon. Similarly, Fioramanti *et al.* (2016) study the European Commission's GDP forecasts for several European countries and the euro area and find that the impact of conditioning variables on forecast errors tends to be smaller for current year predictions. In contrast, a large share of the forecast error for the next calendar year is explained by unexpected changes in the expectations about the future state of the world. The structure of the SPF data allows us to evaluate macroeconomic forecasts and conditioning variables at distinct forecast horizons and to control for any differences via horizon-fixed effects.

We extend these studies in several ways. First, the samples used in these papers are fairly small. While the estimates in Fortin *et al.* (2020) are based on 20 observations on average, the sample in Engelke *et al.* (2019) includes approximately 600 observations. In contrast, the rich SPF dataset provides several thousand forecasts per variable. Second, previous studies mostly focus on the role of conditioning variables for GDP growth, although Fortin *et al.* (2020) also consider the inflation rate. We expand upon their analysis by analyzing predictions of GDP growth, inflation and the unemployment rate. Third, both studies focus exclusively on prediction errors. While this is clearly important, the connection between macroeconomic forecasts and expected future conditions at other stages of the forecasting process may also provide important insights. For example, Czudaj (2021) shows that the heterogeneity of GDP growth expectations in the SPF is related to disagreement about future interest rates. To account for such channels, we explore (i) whether disagreement among forecasters can be explained by the heterogeneity in conditioning variables, (ii) if the updating of macroeconomic forecasts is in accordance with revisions of expectations about external conditions and (iii) to what extent prediction errors of macroeconomic variables are related to misconceptions about the future state of the world.

We find strong evidence for the existence of a link between disagreement about future conditions and disagreement about macroeconomic outcomes. However, the importance of the covariates varies across outcome variables. While oil price disagreement matters in particular for the variability of predictions for the inflation rate, interest rate disagreement is more relevant for the dispersion of GDP growth and unemployment rate forecasts. In line with these findings, revisions of oil price expectations co-move closely with revisions of inflation forecasts, whereas revisions of interest rate predictions correlate with revisions of GDP growth forecasts. Building upon these findings, we analyze the connection between forecast errors for macroeconomic and conditioning variables and document similar relationships. Around 30–50% of the variation in forecast errors for macroeconomic variables can be explained by the variation in prediction errors for external conditions. When controlling for institutional-, time- and horizon-fixed effects, the explanatory power rises to 60–80%. We conclude that predictions of future conditions explain a substantial part of the forecast performance of SPF participants. In particular, our findings indicate that panelists could have nearly doubled forecast accuracy if they had correctly anticipated future external conditions.

The paper is structured as follows: Section 2 describes the data and provides descriptive evidence. Sections 3–5 present our empirical findings for disagreement, revisions and errors, respectively. Section 6 summarizes and concludes.

2 Data

This section provides an overview of the SPF by focusing on the key features of the survey and its associated dataset. The SPF is a quarterly survey of macroeconomic expectations and has been carried out since 1999Q1. In the first month of each quarter, the questionnaire is sent to various experts employed by financial and research institutions.[2] Participants provide predictions for key macroeconomic indicators such as HICP inflation (*inf*), real GDP growth (*gdp*) and the unemployment rate (*une*) in the euro area for several forecast horizons.[3] We use the fixed-event forecasts, which are characterized by a fixed target year $t = 1, \dots, T$ and a rolling quarterly anticipation horizon $h = 1, \dots, H$. The employed data comprise forecasts for the current calendar year ($h \in \{1, \dots, 4\}$) and the next calendar year ($h \in \{5, \dots, 8\}$).[4]

[2] Data for the previous quarter is not available to the forecasters at the time the survey is conducted.
[3] Since 2016Q4, the SPF covers core inflation forecasts, which we do not use due to the short time series.
[4] In some cases, the SPF provides forecasts for the calendar year after next ($h \in \{9, \dots, 12\}$), which we do not use in our analysis because they are available only for selected survey rounds and variables.

After combining these forecasts, we obtain a sequence of individual h-step-ahead predictions for target year t with forecast horizons $h \in \{1, \ldots, 8\}$.

Our sample includes 72 surveys waves conducted between 2002Q1 and 2019Q4 and focuses on predictions for the years 2002–2019 ($T = 18$).[5] In total, 101 forecasters participated in the SPF during this period. Although a forecast panel is provided in each survey round, it is rather unbalanced, reflecting the non-responses by some institutions, the introduction of new panelists or the dropping out of former participants. To mitigate the influence of outliers that may arise from a lack of familiarity with the survey design, we consider only institutions that have at least three years worth of survey experience, i.e., participants that have been included in twelve or more (potentially non-consecutive) survey rounds. This leaves 89 forecasters in the reduced sample. On average, 45–50 institutions provide their assessment of the economic outlook per survey round.

In addition to the macroeconomic expectations, respondents are asked about their beliefs about future economic and financial conditions including the Brent crude oil price in US-Dollars per barrel (*oil*), the Euro/US-Dollar exchange rate (*usd*; defined such that higher values indicate that the euro appreciates versus the US-Dollar), the ECB's interest rate (*ir*; main refinancing operations) and annual growth in compensation per employee (*lab*; henceforth: wage growth).[6] These variables are referred to as 'assumptions' in the SPF dataset and in related ECB releases. In the following, we adopt the term 'assumptions' without necessarily suggesting a causal relationship between macroeconomic forecasts and these variables. For example, if some forecasters rely on a Taylor rule, predictions of future interest rates may depend on expectations of inflation and GDP.[7] Due to a lack of instrumental variables to account for such potential endogeneity issues, the estimates from the regressions should best be interpreted as correlations. Nonetheless, the survey questionnaire clarifies that panelists are asked to "[...] *report selected information underlying* [*their*] *forecasts*

5 Since data on the conditioning variables is available only since 2002Q1, we have to discard the macroeconomic forecasts from the 1999Q1-2001Q4 surveys. Moreover, we omit the next calendar year forecasts reported in the 2019Q1–2019Q4 surveys to exclude potential outliers due to the COVID-19 outbreak.

6 A big asset of the survey is that point forecasts for macroeconomic outcomes are amended by probability distributions, which provide insights into the institutions' assessment of uncertainty (see Manzan, 2021). Unfortunately, the SPF does not elicit histograms for the variables relating to external conditions.

7 Czudaj (2021) finds evidence that SPF participants form their expectations in line with a Taylor rule, although he shows that the evidence has become weaker since interest rates hit the zero lower bound.

[. . .]". The questions regarding these assumptions are posed to the SPF participants on the same spreadsheet as the inflation expectations. This may suggest to panelists that there is a particularly close connection between the inflation rate and assumptions. As discussed in several special surveys, the assumptions primarily consist of 'in-house' forecasts, which are frequently complemented by market data such as futures prices or averages of recent spot rates (ECB, 2009, 2014, 2019). This is particularly the case for the oil price assumptions. Exchange rate predictions are often based on the average of recent values. Expectations for the ECB's main refinancing rate tend to be based more on judgment. In the following, we consider only the responses of participants who provide predictions for at least one of the macroeconomic variables and one of the assumptions in a given quarter.

While macroeconomic forecasts for both the current and the next year are available for the entire sample period, corresponding wage growth assumptions have been elicited only since 2004Q3. Assumptions on oil prices, exchange rates and interest rates in the next calendar year are available from 2010Q2 onwards. Unfortunately, the SPF data does not provide current-year assumptions for these variables. Since 2002Q1, however, the survey elicits forecasts with fixed horizons ranging from one and four quarters ahead. Depending on the forecast horizon, we combine the fixed-horizon assumptions with realizations to calculate oil price, exchange rate and interest rate assumptions for the current year: For the surveys conducted in Q1, current year assumptions for *oil*, *usd* and *ir* are calculated as the average over the respondents' four consecutive quarters starting with the quarter when the survey is conducted. For the Q2-surveys, we proceed in the same way but replace the Q1 value with the actual realization, i.e., the quarterly average over the corresponding series. For the Q3-surveys, we take the average over the Q1 and Q2 realizations and the assumptions for the two consecutive quarters. For the Q4-surveys, we compute the average over the Q1–Q3 realizations and the assumption for the current quarter.

The limited availability of the assumptions restricts our analysis in several ways: First, when focusing on wage growth assumptions, we cannot use the macroeconomic forecasts from the 2002Q1–2004Q2 period. Second, since these early survey rounds do not include next-year predictions for any of the other assumptions, we discard the corresponding next-year macroeconomic forecasts from the sample altogether. In contrast, current-year oil price, exchange rate and interest rate assumptions are available since 2002Q1, such that we can keep the current-year macroeconomic forecasts. Third, the sample for the next-year oil price, exchange rate and interest rate assumptions is further restricted to the 2010Q2–2018Q4 period. Thus, the sample size varies considerably depending on the assumptions included in the analysis. Consecutive predictions for all forecast horizons $h \in \{1, \ldots, 8\}$ are available for the target years 2006–2019 in case of the macroeconomic forecasts and wage growth. For the other assumptions, complete forecast data is provided for the years 2012–2019. To make sure that our findings are not driven by the overrepresentation of current-year predictions, we re-estimate all regression models on a subsample of observations that includes only the target years 2012–2019 for which we observe expectations of all variables at each forecast horizon. Table 1 summarizes the sample size for each variable.

Table 1: Number of fixed-event forecasts provided by SPF participants

	Forecast horizon h										
Variable	8	7	6	5	4	3	2	1	$\sum_h$	FP	PR (%)
Inflation rate	597	603	613	656	928	913	860	941	6111	6691	91.33
GDP growth	598	604	616	660	929	917	864	945	6133	6691	91.66
Unemployment rate	580	584	596	639	900	883	832	905	5919	6691	88.46
Oil price	339	395	380	404	827	843	784	846	4818	5438	88.60
Exchange rate	347	394	382	414	833	833	802	871	4876	5438	89.67
Interest rate	384	421	417	455	915	896	849	926	5263	5438	96.78
Wage growth	449	434	456	464	476	455	475	481	3690	6228	59.25

Notes: For each variable, this table reports the number of predictions per forecast horizon and the total number of observations across all horizons. The sample period is 2002Q1–2019Q4. Predictions for the next calendar year are included from 2004Q3 onwards based on the availability of wage growth assumptions. For the other assumptions, next year predictions have been elicited since 2010Q2. The column 'FP' shows the number of observations that could have been elicited under full participation, i.e., if in each survey wave all active participants would have reported predictions for all variables and horizons. The column 'PR' presents the corresponding participation rate.

Our sample includes approximately 6,000 forecasts for each macroeconomic variable. For the oil price, exchange rate and interest rate assumptions, around 5,000 predictions are provided, although we observe some instances where participants provide assumptions for the interest rate, but not for the oil price and/or the exchange rate. The sample size for wage growth is noticeably smaller. To disentangle the effect of distinct response patterns from the availability of assumptions, we calculate the number of forecasts that would have been observed if in each survey wave all active participants had reported predictions for all variables and horizons (i.e., full participation; column 'FP'). We compute the participation rate

('PR') by comparing this number to the actual number of predictions. While participation rates for most variables are around 90%, it is below 60% for wage growth. In particular, we observe that nine institutions in our sample have never reported wage growth assumptions despite participating in the SPF at times when these predictions have been elicited. It may be that wage growth assumptions are not part of the primary work at these institutions. In contrast, all 89 panelists regularly contribute predictions for the macroeconomic variables and the other assumptions during their time as active SPF participants.

In line with the nature of the SPF, we use real-time data for the realizations of the macroeconomic variables, which tend to be revised over time. We employ the Real Time Database provided by the ECB's Statistical Data Warehouse.[8] Based on real-time figures for the Harmonized Index of Consumer Prices (monthly) and real GDP (quarterly), annual growth rates are calculated as the percentage change of the annual average for the current year relative to the annual average for the previous year. For unemployment, we take the average over the monthly unemployment rates for the current year. Since the data for the assumptions are not revised, we calculate annual averages based on the released figures.

Let $\hat{y}_{i,t,h}$ and $\hat{x}_{i,t,h}$ denote the h-step-ahead prediction of macroeconomic variable $y \in \{inf, gdp, une\}$ respectively assumption $x \in \{oil, usd, ir, lab\}$ in target year $t = 1, \ldots, T$ issued by forecaster $i = 1, \ldots, N$. The average (or 'consensus') forecast based on the N predictions for $z \in \{x, y\}$ is given by

$$\bar{\hat{z}}_{t,h} = \frac{1}{N} \sum_{i=1}^{N} \hat{z}_{i,t,h}. \tag{1}$$

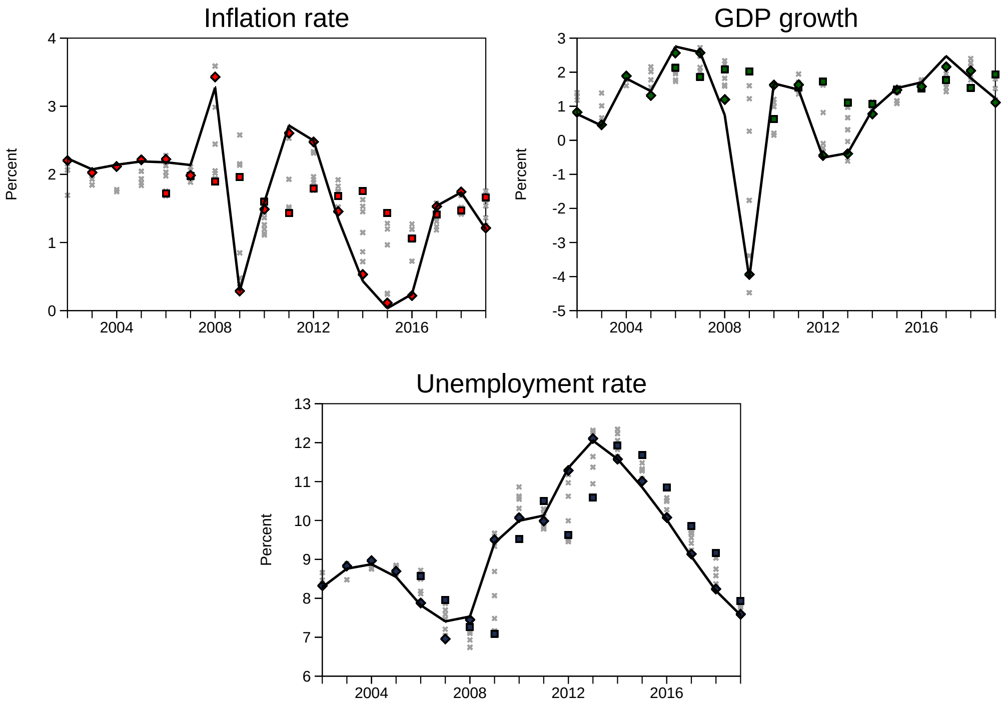
Figure 1 shows the realizations along with $\bar{\hat{z}}_{t,h}$ for $h \in \{1, \ldots, 8\}$ over the distinct target years. The 8- and 1-step-ahead forecasts are highlighted differently from the other horizons.[9] While we defer a discussion of forecast performance to Section 5, it is clear that the consensus forecasts are mostly well-aligned with the realizations for $h = 1$, i.e., the current quarter.

[8] The Real Time Database is an experimental dataset consisting of vintages ('snapshots') of time series of several variables, based on series reported in the ECB's Economic Bulletin and previously in the ECB's Monthly Bulletin. The dataset is updated semi-annually, at the beginning of January and July.

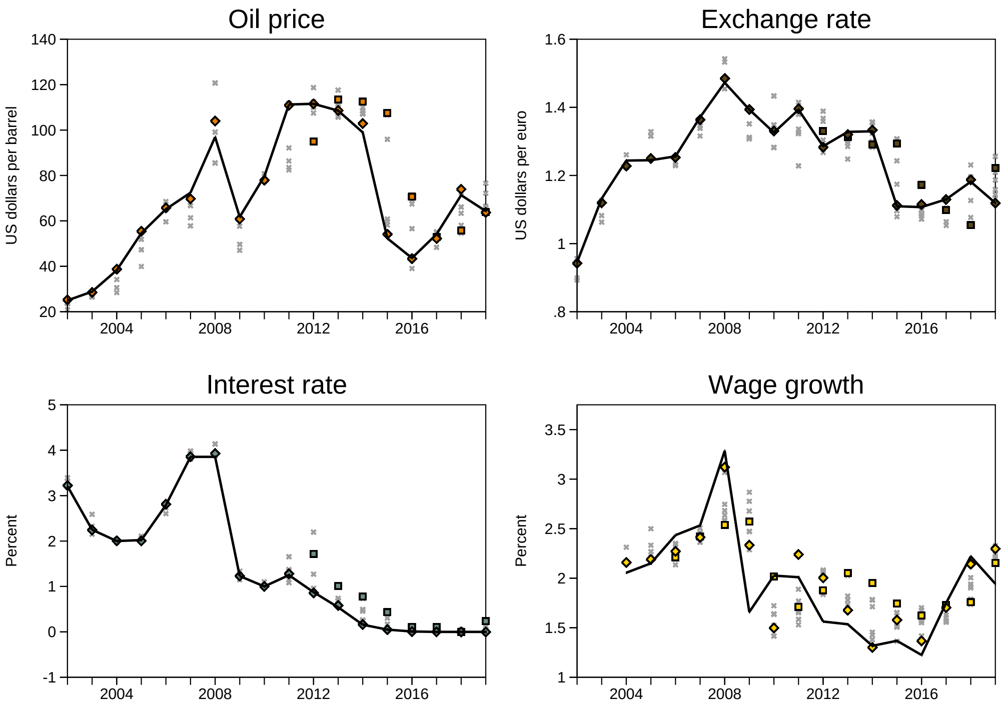
[9] Since next-year assumptions for oil prices, exchange rates and interest rates are available only since 2010Q2, the data for these variables does not include 8-step ahead predictions for 2011.

Figure 1: Realizations and consensus forecasts

(a) Macroeconomic variables



(b) External conditions



Notes: Solid black lines depict the real-time realizations of the respective variable. Squares (□) represent the average across the 8-step-ahead predictions, while diamonds ($\diamond$) indicate the average over the 1-step-ahead predictions. Crosses ($\times$) depict h-step-ahead consensus predictions for intermediate forecast horizons. The horizontal axis depicts the target period, i.e., the year that is being forecasted. The sample period is 2002Q1–2019Q4.

3 Forecast disagreement

A natural question is to ask whether there is evidence of heterogeneity ('disagreement') in the SPF predictions. If this is the case, it seems advisable to proceed with an analysis at the individual level. If not, it may be sufficient to focus on aggregate measures. In light of these considerations, we calculate disagreement as the standard deviation of the point forecasts:

$$s_{z,t,h} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\hat{z}_{i,t,h} - \bar{\hat{z}}_{t,h})^2} \tag{2}$$

Disagreement is a commonly used indicator of forecast heterogeneity and captures the extent to which individual predictions are spread around the consensus forecast.[10] Figure 2 shows the evolution of disagreement for all variables over the target years. To improve readability, solid lines indicate disagreement averaged across the current year series, while dashed lines represent average disagreement for the next year.

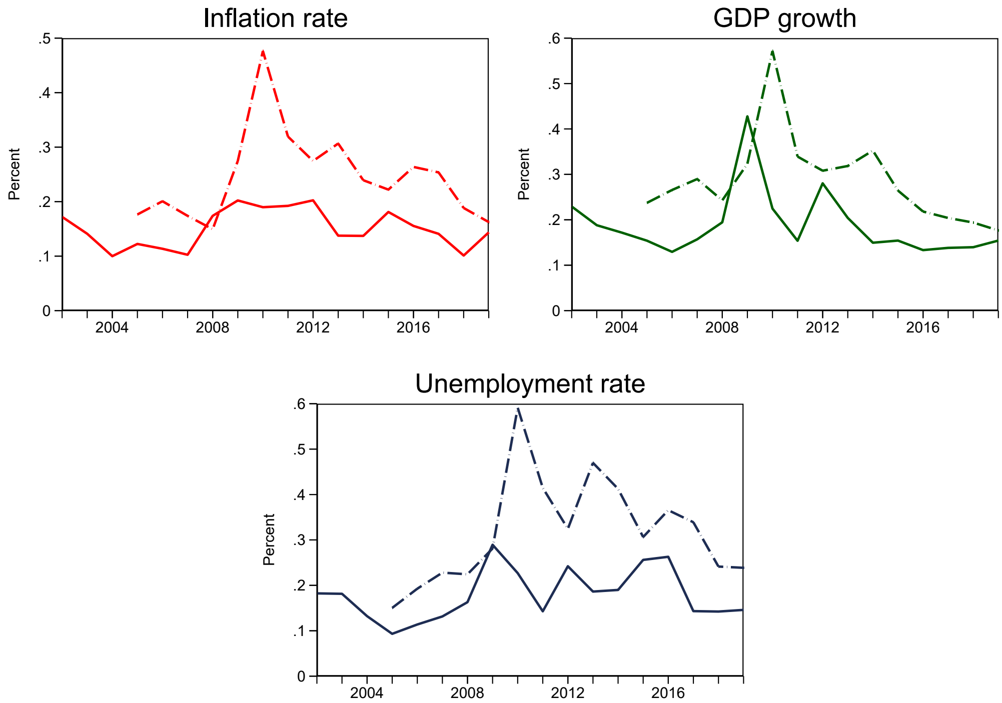
We observe several notable patterns. For example, disagreement about the current year is generally lower than disagreement about the next year. This likely reflects the increasing amount of information about the outcome as the target period approaches. The series for wage growth is a notable exception, which could be related to the fact that wages are affected by union wage-setting. The series for the macroeconomic variables are broadly in line with those for the assumptions in the sense that we document considerable time-variation. In particular, Figure 2 shows notable spikes in disagreement about macroeconomic outcomes during the financial crisis.[11] Time-varying disagreement is in line with sticky information models because forecasters who update their predictions in response to a large shock can produce markedly different forecasts than those who do not update. Since these differences are less pronounced in calm periods, disagreement can vary over time. However, the evolution of current-year disagreement is usually more stable than that of next-year disagreement.

[10] Disagreement is sometimes used as a proxy for uncertainty, although the validity of this approach has been questioned frequently (e.g., Abel *et al.*, 2016; Glas and Hartmann, 2016; Glas, 2020). See Clements (2022) for a multivariate measure of disagreement.

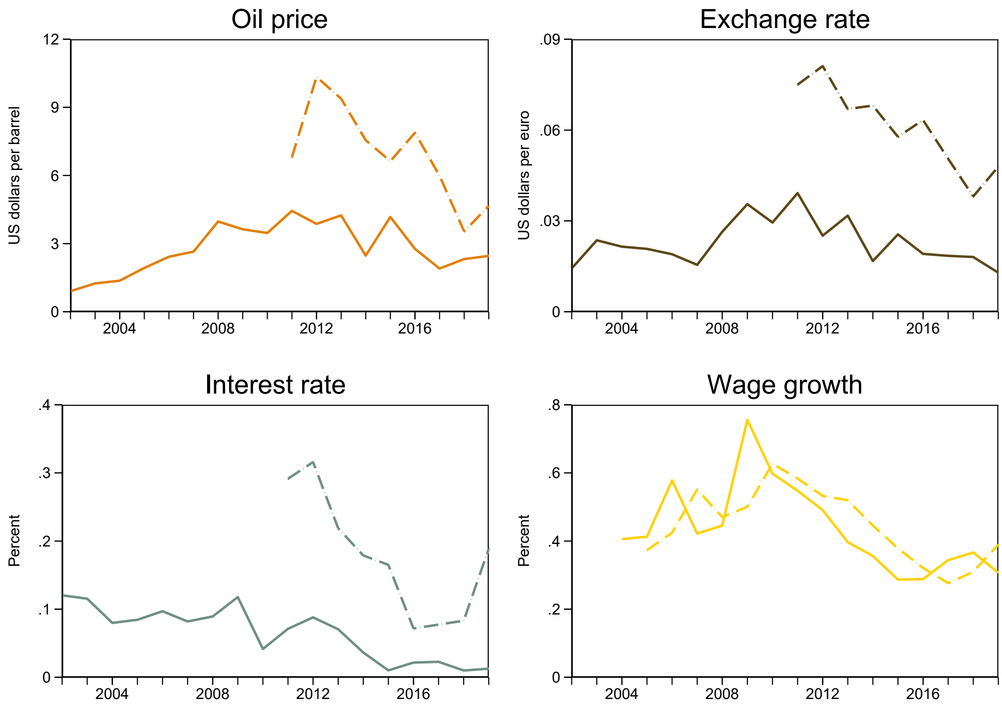
[11] Bürgi and Sinclair (2021) show that increases in disagreement help to predict recessions. Similarly, Dovern *et al.* (2012) find that disagreement about GDP growth rises during recessions, whereas disagreement about inflation and interest rates is related to the credibility of the central bank.

Figure 2: Forecast disagreement

(a) Macroeconomic variables



(b) External conditions



Notes: Solid lines depict disagreement among SPF participants averaged across the disagreement series for the current year, whereas dashed lines represent average disagreement based on predictions for the next year. The horizontal axis depicts target years 2002–2019. The sample period is 2002Q1-2019Q4.

Atalla *et al.* (2016) find that oil price disagreement in the SPF is related to the volatility of actual oil prices. Therefore, the relatively stable evolution of current-year oil price disagreement may simply reflect stable oil prices in our sample. An interesting pattern emerges for current-year interest rate disagreement, which declines over time and approaches zero in recent years. This decline coincides with interest rates hitting the zero lower bound. Thus, if disagreement is relatively high for one variable, the same may not necessarily be the case for other variables at the same time. Although the disagreement series tend to co-move across variables, their relationship may vary for distinct years and forecast horizons.

To investigate whether the heterogeneity in the forecasts for macroeconomic outcomes is related to heterogeneity in the assumptions, we regress the h-step-ahead disagreement for macroeconomic variable y on the corresponding h-step-ahead assumption disagreement series based on a pooled sample of observations that includes all forecast horizons:

$$s_{y,t,h} = \alpha + \sum_{x} \beta_x s_{x,t,h} + \lambda_t + \lambda_h + \nu_{y,t,h} \tag{3}$$

In Eqn. (3), $(\beta_{oil}, \beta_{usd}, \beta_{ir}, \beta_{lab})'$ is the vector of unknown parameters of interest, λ_t and λ_h represent target-year- and horizon-fixed effects, respectively, and $\nu_{y,t,h}$ is the error term.

Table 2 presents the estimates of Eqn. (3). In columns (1)–(3), we introduce oil price, exchange rate and interest rate disagreement as covariates one at a time. Column (4) presents the estimates when all three disagreement series are included simultaneously and column (5) additionally includes both sets of fixed effects. In columns (6)–(8), we include wage growth disagreement in the estimation. We opt for a separate analysis of wage growth assumptions because, as discussed in Section 2, data for the other assumptions are available for different survey rounds (see Figure 1) and nine institutions in our sample have never reported wage growth assumptions. The parameters of Eqn. (3) are estimated by ordinary least squares (OLS). We apply the variance-covariance estimator of Newey and West (1987) to account for arbitrary levels of heteroscedasticity and autocorrelation in the data.

Columns (1)–(3) of Table 2 show that the relationship between inflation and assumption disagreement is positive and statistically significant. Thus, forecasters disagree more about future inflation at times when they also have diverging expectations for external conditions.

Table 2: The relationship between forecast and assumption disagreement

	Dependent variable: $s_{y,t,h}$ for $y \in \{inf, gdp, une\}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation rate				
$s_{oil,t,h}$	0.021***			0.015***	0.011***		0.017***	0.012***
	(0.002)			(0.002)	(0.002)		(0.002)	(0.003)
$s_{usd,t,h}$		2.363***		0.732*	-0.365		0.783**	-0.368
		(0.263)		(0.415)	(0.397)		(0.335)	(0.459)
$s_{ir,t,h}$			0.488***	0.051	-0.088		-0.043	-0.112
			(0.067)	(0.112)	(0.119)		(0.088)	(0.116)
$s_{lab,t,h}$						0.170**	0.014	-0.054
						(0.084)	(0.023)	(0.035)
Constant	0.093***	0.098***	0.132***	0.089***	0.198***	0.122***	0.078***	0.214***
	(0.010)	(0.012)	(0.015)	(0.011)	(0.030)	(0.030)	(0.012)	(0.028)
No. of obs.	107	107	107	107	107	120	97	97
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.667	0.608	0.365	0.679	0.796	0.071	0.713	0.799
				Real GDP growth				
$s_{oil,t,h}$	0.019***			0.007	0.006		0.008	0.006
	(0.003)			(0.006)	(0.004)		(0.007)	(0.005)
$s_{usd,t,h}$		2.318***		0.313	-0.161		0.491	-0.167
		(0.318)		(0.755)	(0.731)		(0.830)	(0.769)
$s_{ir,t,h}$			0.673***	0.465***	0.397***		0.329***	0.414***
			(0.091)	(0.091)	(0.103)		(0.100)	(0.098)
$s_{lab,t,h}$						0.358***	0.168*	-0.017
						(0.118)	(0.093)	(0.074)
Constant	0.132***	0.130***	0.144***	0.124***	0.111**	0.076*	0.052*	0.115***
	(0.016)	(0.015)	(0.012)	(0.015)	(0.042)	(0.043)	(0.031)	(0.041)
No. of obs.	107	107	107	107	107	120	97	97
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.321	0.338	0.401	0.428	0.664	0.198	0.476	0.659
				Unemployment rate				
$s_{oil,t,h}$	0.029***			0.010**	-0.002		0.011*	-0.002
	(0.004)			(0.004)	(0.004)		(0.006)	(0.005)
$s_{usd,t,h}$		3.520***		2.266***	1.212		2.284***	1.221
		(0.408)		(0.836)	(0.926)		(0.859)	(0.989)
$s_{ir,t,h}$			0.719***	0.075	0.226*		0.056	0.234*
			(0.141)	(0.121)	(0.118)		(0.128)	(0.134)
$s_{lab,t,h}$						0.188	-0.035	0.031
						(0.121)	(0.078)	(0.079)
Constant	0.113***	0.108***	0.159***	0.102***	0.231***	0.166***	0.113**	0.218***
	(0.021)	(0.018)	(0.027)	(0.019)	(0.059)	(0.050)	(0.046)	(0.066)
No. of obs.	107	107	107	107	107	120	97	97
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.556	0.609	0.358	0.618	0.756	0.044	0.608	0.745

Notes: This table displays the estimates of Eq. (3). The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated by OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroscedasticity and autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

However, the economic significance varies across assumptions. In particular, oil price and exchange rate disagreement explain a much higher share of the variation in $s_{inf,t,h}$ than interest rate disagreement. The simultaneous inclusion of the covariates in column (4) renders the coefficient on $s_{ir,t,h}$ insignificant. When taking into account time- and horizon-fixed effects in column (5), the estimate of β_{usd} becomes insignificant as well. Although the coefficient on $s_{lab,t,h}$ is significantly positive in column (6), it becomes insignificant in columns (7) and (8). In contrast, the estimate of β_{oil} remains positive and statistically significant throughout. We conclude that oil price disagreement is the most important driver of inflation disagreement. This finding is in line with the evidence in Czudaj (2021). Given that energy prices are a component of HICP headline inflation, it seems intuitive that higher disagreement on future oil prices increases the heterogeneity of inflation expectations.

For real GDP growth, we also obtain significantly positive coefficients and relatively high goodness of fit statistics for all assumptions. However, when including all covariates and fixed effects, only the coefficient on $s_{ir,t,h}$ remains statistically significant. Results for unemployment rate disagreement are broadly in line with those for real GDP growth in the sense that interest rate disagreement remains the only (weakly) significant predictor when simultaneously including all assumptions and fixed effects. Although exchange rate disagreement explains most of the variation ($R^2 = 0.61$), the effect becomes insignificant once we include the fixed effects in columns (5) and (8). However, the broad picture for unemployment disagreement is not as clear as that for inflation and output growth.

We conduct several robustness checks (not shown but available upon request). First, to assess whether the findings are affected by the overrepresentation of current-year predictions, we re-estimate Eqn. (3) on the 2012–2019 subsample for which we observe all variables at all horizons. Second, to make sure that our results are robust to changes in the forecasting environment we include a recession indicator as a covariate in the full-sample regressions.[12] Third, we include a measure of realized stock market volatility as an alternative to the recession indicator.[13] Broadly speaking, the estimates are very similar to our main findings.

[12] Survey periods are classified as a recession by the Euro Area Business Cycle Network. Our data includes two recession periods: 2008Q2–2009Q2 and 2011Q4–2013Q1.

[13] Based on daily data for the Euro Stoxx 50 price index (taken from Datastream), we compute daily log returns and calculate volatility as the square root of the sum of squared returns within each quarter.

Taken together, we find that heterogeneity in the macroeconomic forecasts is related to the disagreement about external conditions. However, the importance of the distinct assumptions varies across macroeconomic outcomes. In particular, we find that oil price assumptions are most influential in the formation of inflation forecasts, while predictions of real GDP growth and the unemployment rate are closely related to interest rate assumptions. We generally observe a considerable increase in the coefficient of determination due to the inclusion of time-fixed effects in columns (5) and (8). There may be concerns that the estimates are driven by a mechanical correlation in the disagreement series. However, the results from the following sections suggest that this is not the case.

4 Forecast revisions

In this section, we examine the updating behavior of SPF participants based on the individual-level panel data. This analysis provides evidence on whether forecasters update their predictions in line with models of information rigidities, i.e., whether and how quickly they react to new information. While some forecasters may choose not to revise their predictions despite of having updated information sets, Andrade and Le Bihan (2013) argue that this is unlikely given the vast amount of information available to professional forecasters. According to ECB (2019), the majority of SPF participants indeed conduct a full update of their macroeconomic forecasts each quarter with more frequent updating for inflation and unemployment. Usually, revisions are conducted according to institutions' own internal timetables, although data releases might determine the updating frequency. Formally, revisions are defined as the difference between two successive forecasts for the same target year,

$$\Delta \hat{z}_{i,t,h} = \hat{z}_{i,t,h} - \hat{z}_{i,t,h+1}. \tag{4}$$

For example, in the last quarter of a year t forecaster i's one-quarter-ahead revision for the inflation rate in year t is defined as the difference between her current inflation forecast for that year ($h = 1$) and her previous prediction for the same year ($h = 2$), where the latter has been submitted in the previous survey wave. Hence, using data provided in eight consecutive forecast rounds for a specific target year, we are able to assess seven forecast revisions.

4.1 Assessing the attentiveness of SPF participants

If the SPF participants regularly incorporate new information into their predictions, one would expect to observe very few cases of zero revisions. Andrade and Le Bihan (2013) refer to the frequency of updating as the 'attention degree', which is a key parameter in a sticky information model. We follow Andrade and Le Bihan (2013) and Baker *et al.* (2020) and estimate the attention degree $\lambda_{z,h}$ as the share of h-step-ahead predictions that are different from the ones reported in the previous quarter, i.e.,

$$\hat{\lambda}_{z,h} = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbb{1}(\Delta \hat{z}_{i,t,h} \neq 0). \tag{5}$$

Table 3 presents the results. In the last row, we report the overall attention degree based on a sample that includes all horizons.

Table 3: Share of attentive forecasters

	Macroeconomic variables			External conditions			
h	Inflation rate	GDP growth	Unemployment rate	Oil price	Exchange rate	Interest rate	Wage growth
1	69.9%	84.2%	68.2%	100.0%	100.0%	45.0%	59.1%
2	82.2%	79.3%	71.0%	100.0%	100.0%	60.0%	59.3%
3	83.9%	83.7%	77.0%	100.0%	100.0%	64.2%	60.1%
4	84.8%	85.4%	78.9%	97.3%	94.8%	48.5%	65.1%
5	74.5%	80.8%	75.8%	83.7%	79.7%	48.7%	61.2%
6	68.1%	71.7%	74.6%	83.2%	77.9%	60.3%	56.0%
7	72.1%	71.7%	76.7%	80.2%	78.6%	58.8%	58.4%
All	77.1%	80.2%	74.3%	94.8%	93.5%	55.5%	60.0%

Notes: For each variable, this table reports the share of attentive SPF participants for the h-step-ahead predictions, i.e., the fraction of cases with $\Delta \hat{z}_{i,t,h} \neq 0$. In the last row, we report the corresponding statistics based on a pooled sample that includes all horizons. The sample period is 2002Q1–2019Q4.

Table 3 shows that the SPF participants frequently update their macroeconomic forecasts. More than two thirds of all point forecasts are updated regardless of the forecast horizon. This is in line with the evidence from the special SPF surveys (ECB, 2009, 2014, 2019). However, updating is far from complete, i.e., well below 100%. This can be interpreted as evidence of inattention in the SPF data.[14] As discussed in Andrade and Le Bihan (2013),

[14] Hur and Kim (2016) find similar evidence for the US-SPF.

our finding of incomplete updating of forecasts is in line with the predictions of a sticky information model.[15] Notably, the figures for the overall attention degree reported are nearly identical to those documented in Andrade and Le Bihan (2013) for the 1999Q1–2012Q4 surveys. Their overall degree of attention across all variables of 75% compares to 77% for our larger sample.[16] We conclude that the attentiveness of SPF participants has not changed in a meaningful way since Andrade and Le Bihan (2013) conducted their study.[17]

We next examine the horizon-specific estimates. Broadly speaking, updating of macroeconomic forecasts tends to increase as more information becomes available, i.e., as h declines. Andrade and Le Bihan (2013) argue that mean reversion may induce long-run forecasts to remain close to the unconditional mean of the process and that forecasters may pay more attention to revising predictions close to the target. While Table 3 shows that most forecasts are indeed strongly revised at short horizons (especially for GDP growth), we also find that updating frequencies for inflation and unemployment decline noticeably for $h = 1$.

Next, we consider revisions in assumptions. Compared to the macroeconomic variables, oil price and exchange rate assumptions are updated more regularly. As discussed in ECB (2019), these forecasts are often based on futures prices or the average of recent prices (random walk forecast), which are available at high frequencies. Notably, *all* oil price and exchange rate assumptions are revised at short horizons. The frequent updating of those variables serves as evidence against sticky information models and casts doubt on the argument that infrequent updating is the result of limited processing capabilities. In contrast, we document relatively low updating frequencies for the interest rate and wage growth assumptions. For the former, this likely reflects the ECB's infrequent interest rate adjustments in

15 See Jain (2019) for a discussion of persistence in survey-based inflation forecasts.

16 We document $\hat{\lambda}_z$-values of 77%, 80% and 74% for inflation, real GDP growth and unemployment, respectively. The corresponding figures from Table 3 in Andrade and Le Bihan (2013) are 72%, 80% and 75%. However, their sample ends in 2012. When we re-calculate the attention degree parameters for the years 2002–2012, we obtain values of 77%, 83% and 76%. The inclusion of 8- and 9-step-ahead revisions as in Andrade and Le Bihan (2013) would likely result in lower figures.

17 Using the Consensus Economics dataset, Baker *et al.* (2020) classify attentive forecasts as those who provide predictions in more than 95% of the monthly survey rounds that they are present in the sample. However, it is not clear whether a panelist who participates in 100% of the survey rounds but reports identical point forecasts each time can really be considered more attentive than a forecaster who participates only in 80% of the surveys but regularly updates her predictions. Thus, we employ the measure of Andrade and Le Bihan (2013), which Baker *et al.* (2020) also use in a robustness check.

recent years, particularly since interest rates hit the zero lower bound (see Figure 1).[18] Wage growth assumptions are primarily informed by wage negotiations within euro area member countries. The frequency of such meetings differs across countries and depends on the structure of the respective labor market. Moreover, the importance of individual member states for the euro area economy depends on the size of their economy. Thus, it is not surprising that wage growth assumptions are not updated continuously.

We conclude that while the overall degree of attentiveness in the SPF data is relatively high, notable differences exist across variables. While the results for the macroeconomic variables square with the evidence in Andrade and Le Bihan (2013), we show that assumptions are revised at distinct frequencies. Importantly, the frequent updating of oil price and exchange rate assumptions casts doubt on the interpretation that the incomplete updating of other variables is merely the result of rational inattention. While Czudaj (2022) finds similar evidence for the oil price assumptions, the results for the other assumptions are new.

4.2 Qualitative forecast and assumptions revisions

It is tempting to examine whether forecast revisions of macroeconomic variables are related to assumption revisions. As reflected in the responses to hypothetical questions in ECB (2019), the majority of SPF participants would react to a permanent 10% increase in oil prices by adjusting their inflation expectations upwards. Similarly, a permanent 10% increase in the EUR/USD exchange rate would lead to a persistent downward adjustment of the average forecasts for inflation and real GDP growth.[19] Although the results of this special survey are based on a small number of responses, they nonetheless serve as an indication that SPF participants believe in a close connection between macroeconomic aggregates and conditioning assumptions and that these relations differ across variables. We contribute to these findings by providing a more rigorous analysis below. Table 4 indicates the direction of revisions for the macroeconomic variables conditional on directional updating of assumptions, i.e., for each macroeconomic variable the figures in a row add up to 100%.

[18] We find that $\hat{\lambda}_{ir}$ increases from 55.4% to 71.7% if the years 2015–2019 are excluded.

[19] For US forecasters, Berge *et al.* (2019) find that forecasts of macroeconomic variables and interest rate projections are revised together.

Table 4: Revisions in macroeconomic forecasts conditional on assumption revisions

		$\Delta\widehat{inf}$			$\Delta\widehat{gdp}$			$\Delta\widehat{une}$		
		down	same	up	down	same	up	down	same	up
$\Delta\widehat{oil}$	down	57.4%	20.0%	22.6%	52.2%	17.8%	30.0%	41.8%	24.8%	33.4%
	same	38.7%	40.5%	20.8%	32.1%	36.3%	31.6%	46.6%	28.8%	24.5%
	up	24.8%	23.1%	52.1%	42.8%	19.6%	37.6%	42.9%	29.2%	27.9%
$\Delta\widehat{usd}$	down	38.6%	20.3%	41.1%	57.5%	16.4%	26.1%	39.0%	27.4%	33.6%
	same	41.4%	36.5%	22.1%	42.6%	36.8%	20.6%	40.8%	28.4%	30.9%
	up	36.8%	22.6%	40.6%	35.4%	21.3%	43.3%	48.0%	25.8%	26.2%
$\Delta\widehat{ir}$	down	49.5%	21.1%	29.4%	65.9%	17.1%	17.1%	35.4%	26.4%	38.3%
	same	36.3%	25.0%	38.7%	34.5%	21.9%	43.6%	48.5%	29.4%	22.1%
	up	21.7%	17.1%	61.2%	34.1%	20.9%	45.0%	47.1%	23.2%	29.7%
$\Delta\widehat{lab}$	down	51.8%	17.4%	30.8%	52.7%	16.8%	30.5%	41.1%	20.2%	38.8%
	same	32.6%	31.7%	35.6%	40.8%	25.4%	33.8%	43.0%	29.6%	27.4%
	up	32.0%	20.0%	48.0%	42.0%	16.8%	41.2%	45.6%	21.1%	33.3%

Notes: This table reports the relative frequencies of qualitative revisions in macroeconomic forecasts conditional on qualitative revisions of assumptions. For each macroeconomic variable, the numbers in a row add up to 100%. The sample period is 2002Q1–2019Q4.

Table 4 documents a positive relationship between revisions of oil prices and inflation forecasts. Inflation forecasts are revised downwards in 57% of all cases where the oil price assumption has been revised downwards. Similarly, 52% of participants revise their inflation forecasts upwards when increasing their assumption about the future oil price. This is in line with the responses to the hypothetical oil price increase described in ECB (2019). In fact, the share of panelists expecting rising inflation increases to 65% when focusing on the participants who revise their oil price assumptions upwards by 10% or more (not shown). For these forecasters, the average (median) revision of inflation forecasts equals 0.2 (0.1) percentage point, which is nearly identical to the numbers reported in ECB (2019).

We observe that more panelists tend to revise their inflation and GDP growth forecasts upwards — rather than downwards — in response to an upward adjustment in the exchange rate, which is somewhat at odds with those in ECB (2019). This pattern holds if we focus on participants with an upward revision of their exchange rate assumptions by at least 10%. The average and median revisions of both inflation and output growth forecasts are close to zero for these individuals. However, we observe only about 50 cases where SPF participants update their exchange rate assumptions this strongly.

For the interest rate, Table 4 clearly shows a positive co-movement with revisions of inflation and GDP growth forecasts as well as a negative relationship with predictions of the unemployment rate.

Although approximately 85% of SPF participants state that their point forecasts for unemployment and wage growth are jointly determined and more than half of the panelists indicate that updates of these predictions are dependent on each other (ECB, 2019), we do not find clear evidence of a relationship between these variables.

Overall, our results indicate that SPF participants frequently update their macroeconomic forecasts when updating their assumptions. Our findings are mostly in line with the evidence from thought experiments conducted in the special SPF surveys.

4.3 Quantitative forecast and assumptions revisions

To investigate the magnitude of the connection between revisions of macroeconomic forecasts and assumptions, Figure 3 depicts $\Delta\hat{y}_{i,t,h}$ (vertical axis) against $\Delta\hat{x}_{i,t,h}$ (horizontal axis) and documents considerable heterogeneity in the revisions of all variables. The fitted regression lines indicate a positive correlation between forecast revisions of both GDP and inflation and all assumption revisions. The relationship between revisions of unemployment rate expectations and assumptions tends to be negative.

To formally assess the statistical significance of these relationships, we regress the individual h-step-ahead revisions of macroeconomic forecasts on the corresponding h-step-ahead assumption revisions for the same target year t, i.e.,

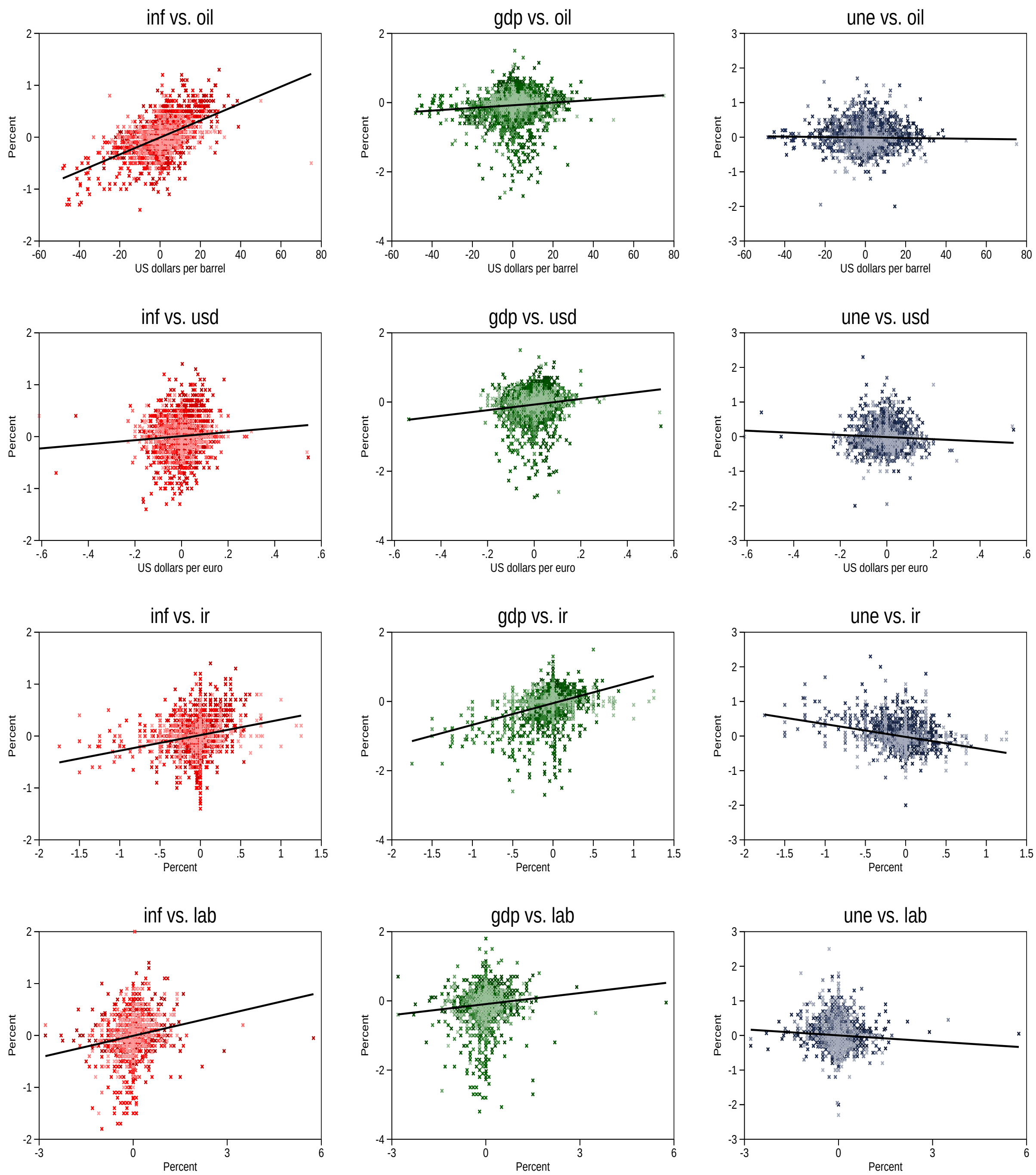
$$\Delta\hat{y}_{i,t,h} = \alpha + \sum_x \beta_x \Delta\hat{x}_{i,t,h} + \lambda_i + \lambda_t + \lambda_h + \nu_{y,i,t,h}. \tag{6}$$

We check for non-biasedness in revisions by including institutional-fixed effects λ_i in addition to target-year- and horizon-fixed effects. Table 5 presents the estimates of Eqn. (6).[20]

The relationship between revisions of inflation forecasts and assumptions is positive and statistically significant in columns (1)–(3) and (6). However, the explanatory power varies

[20] The estimates in columns (1)–(3) and (6) correspond to the black lines in Figure 3.

Figure 3: Bilateral forecast and assumption revisions



Notes: Forecast revisions $\Delta\hat{y}_{i,t,h} = \hat{y}_{i,t,h} - \hat{y}_{i,t,h+1}$ for inflation (first column), GDP growth (second column) and unemployment (third column) on the vertical axis. Assumptions revisions $\Delta\hat{x}_{i,t,h} = \hat{x}_{i,t,h} - \hat{x}_{i,t,h+1}$ for oil price (first row), exchange rate (second row), interest rate (third row) and wage growth (fourth row) on the horizontal axis. A higher marker intensity indicates forecasts close to the target, i.e., small h. Solid black lines represent the least squares regression lines estimated across all h. The sample period is 2002Q1–2019Q4.

considerably across assumptions. In line with our findings for disagreement, we find that oil price revisions explain a much higher share of the variation in the revisions of inflation forecasts ($R^2 = 0.27$) than revisions of other assumptions. The magnitude of this effect is modest. According to our estimates, a forecaster with an oil price revision of -2.19 US-Dollar (the lower quartile) is predicted to adjust her inflation forecast downwards by 0.04 percentage point. An oil price revision of 4.89 US-Dollar (the upper quartile) is associated with a predicted upwards adjustment of the inflation forecast by 0.08 percentage point. Thus, the predicted effect size based on the interquartile range (IQR) is 0.12 percentage point. Our finding of a positive relationship between inflation rate and oil price revisions is in line with the evidence for a forward-looking Phillips Curve in López-Pérez (2017). The inclusion of all assumption revisions in column (3) changes the sign of the coefficient on $\Delta\widehat{usd}_{i,t,h}$ and reduces its statistical significance. This can be interpreted as evidence that inflation forecasts and the distinct assumptions are jointly determined. The inclusion of fixed effects further reduces the significance of the coefficient on $\Delta\widehat{usd}_{i,t,h}$. The coefficients on the other assumptions remain significantly positive throughout all specifications. Based on the gains in the goodness of fit, we conclude that oil price revisions are the most important predictor of inflation revisions.

Revisions of interest rate forecasts explain in particular the movement of real GDP growth revisions, although the coefficients on the other assumptions are positive and significant as well. Based on the results in column (3), an interest rate revision equivalent to the IQR ($0 - (-0.0625) = 0.0625$ base points) is predicted to increase $\Delta\widehat{gdp}_{i,t,h}$ by approximately 0.04 percentage point. This effect is economically significant given that annual interest rates in the sample range from 0 base points in 2017–2019 to 3.85 base points in 2007–2008. The coefficient on $\Delta\widehat{lab}_{i,t,h}$ becomes insignificant once we include all assumptions and fixed effects in columns (7) and (8). Exchange rate revisions are statistically positive throughout, although the R^2 in column (2) is relatively small.

Consistent with Okun's Law, the estimated coefficients for the unemployment rate generally have the opposite sign as those for output growth. In particular, we find that revisions of interest rate assumptions are the most important predictor of unemployment rate revisions ($R^2 = 0.07$). Using again the IQR of the revisions of interest rate assumptions to evaluate the effect size, we find that a $\Delta\widehat{ir}_{i,t,h}$ of 0.0625 base points is predicted to decrease $\Delta\widehat{une}_{i,t,h}$ by 0.02 percentage point. In contrast to output growth revisions, the other assumptions do not appear to play a role once we include $\Delta\widehat{ir}_{i,t,h}$ as a predictor variable.

In summary, we find that revisions of macroeconomic forecasts are related to assumption revisions. Our results suggest that oil price revisions are most important for inflation revisions, while interest rate revisions matter for revisions of real GDP growth and unemployment rate expectations. The estimated relationships are economically meaningful and hold after carrying out the same robustness checks as in Section 3, i.e., subsample analysis and the inclusion of a recession indicator or realized stock market volatility. We find no evidence for systematic biases in revisions across institutions but observe an increase in the goodness of fit due to the inclusion of time-fixed effects. We conclude that SPF participants update their macroeconomic forecasts in response to new information for selected assumptions.

5 Forecast errors

In the previous section we have shown that the updating of macroeconomic forecasts is closely related to revisions of assumptions. It is not clear whether and how this relationship contributes to the ex-post forecast performance of SPF participants. In this section, we analyze the size of and connection between forecast and assumption errors. In a fixed-event setting, the information set of a forecaster increases as the target period approaches. Thus, one would generally expect predictions and realizations to become better aligned as the forecast horizon diminishes.

Figure 1 gives a first impression of forecast performance by comparing actuals to consensus forecasts. In recent years, the euro area economy has been affected by a number of considerable shocks and it is important to assess the extent to which SPF participants have been able to predict accurately how such shocks are transmitted to the economy. Not surprisingly, Figure 1 depicts particularly large and persistent average forecast errors for all macroeconomic variables in 2009. During the years following the Great Recession, SPF participants underpredicted inflation at long horizons, whereas they overpredicted inflation after the ECB implemented its low interest rate policy.

Table 5: The relationship between forecast and assumption revisions

	Dependent variable: $\Delta\hat{y}_{i,t,h}$ for $y \in \{inf, gdp, une\}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation rate				
$\Delta\widehat{oil}_{i,t,h}$	0.016***			0.016***	0.013***		0.016***	0.014***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.392***		-0.219**	-0.170*		-0.216**	-0.117
		(0.116)		(0.098)	(0.097)		(0.109)	(0.104)
$\Delta\widehat{ir}_{i,t,h}$			0.301***	0.151***	0.177***		0.108***	0.136***
			(0.026)	(0.028)	(0.029)		(0.034)	(0.037)
$\Delta\widehat{lab}_{i,t,h}$						0.140***	0.063***	0.045**
						(0.024)	(0.021)	(0.019)
Constant	-0.005	0.009*	0.018***	0.002	-0.209***	-0.007	-0.007	-0.061***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.081)	(0.007)	(0.006)	(0.022)
No. of obs.	3,213	3,207	3,569	2,894	2,894	2,554	1,674	1,674
N	87	86	88	84	84	67	65	65
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.271	0.006	0.048	0.277	0.390	0.030	0.306	0.420
				Real GDP growth				
$\Delta\widehat{oil}_{i,t,h}$	0.004***			-0.000	0.004***		0.000	0.004***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.812***		0.436***	0.658***		0.420**	0.500***
		(0.149)		(0.145)	(0.146)		(0.185)	(0.182)
$\Delta\widehat{ir}_{i,t,h}$			0.627***	0.594***	0.451***		0.547***	0.438***
			(0.035)	(0.045)	(0.040)		(0.056)	(0.051)
$\Delta\widehat{lab}_{i,t,h}$						0.107***	0.009	-0.010
						(0.030)	(0.036)	(0.040)
Constant	-0.077***	-0.074***	-0.051***	-0.053***	-0.589***	-0.094***	-0.043***	-0.191*
	(0.007)	(0.007)	(0.006)	(0.007)	(0.104)	(0.012)	(0.009)	(0.108)
No. of obs.	3,222	3,219	3,590	2,903	2,903	2,563	1,679	1,679
N	87	86	88	84	84	67	65	65
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.008	0.015	0.121	0.112	0.365	0.009	0.110	0.362
				Unemployment rate				
$\Delta\widehat{oil}_{i,t,h}$	-0.001			0.002**	-0.000		0.001	-0.001
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		-0.306***		-0.156	-0.241**		-0.167	-0.231*
		(0.109)		(0.112)	(0.105)		(0.134)	(0.121)
$\Delta\widehat{ir}_{i,t,h}$			-0.370***	-0.389***	-0.288***		-0.404***	-0.312***
			(0.032)	(0.038)	(0.034)		(0.048)	(0.043)
$\Delta\widehat{lab}_{i,t,h}$						-0.058***	0.012	0.020
						(0.020)	(0.020)	(0.020)
Constant	-0.010	-0.013**	-0.025***	-0.025***	-0.166	0.002	-0.034***	0.014
	(0.006)	(0.006)	(0.006)	(0.006)	(0.138)	(0.008)	(0.008)	(0.057)
No. of obs.	3,091	3,075	3,439	2,789	2,789	2,528	1,663	1,663
N	84	83	86	83	83	66	64	64
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.000	0.004	0.069	0.075	0.284	0.005	0.090	0.300

Notes: This table displays the estimates of Eq. (6). The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated by OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroscedasticity and autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

With respect to the assumptions, we document large positive oil price errors for the next-year predictions in 2015 and 2016 and persistent overprediction of interest rates at long horizons during the European sovereign debt crisis. Notably, phases of persistent over- or underprediction appear to occur more frequently for large anticipation horizons. As discussed in Andrade and Le Bihan (2013), periods of persistent under-/overestimation indicate predictable average forecast errors, a characteristic of both sticky and noisy information models.

5.1 Aggregate forecast performance

In order to assess more formally whether SPF participants over- or underpredict macroeconomic outcomes at distinct horizons, we define the h-step-ahead forecast error as

$$e_{z,i,t,h} = \hat{z}_{i,t,h} - z_t \tag{7}$$

for $z \in \{x, y\}$, $y \in \{inf, gdp, une\}$ and $x \in \{oil, usd, ir, lab\}$. Note that prediction errors are defined such that positive values indicate overprediction, while negative values represent cases of underprediction. Table 6 shows the mean error (ME) for each h, calculated as the average over all periods and panelists: $\bar{e}_{z,h} = (1/(NT)) \sum_i \sum_t e_{z,i,t,h}$. In addition, the last row shows the ME-statistics for a pooled sample of observations across all horizons, i.e., $\bar{e}_z = (1/(NTH)) \sum_i \sum_t \sum_h e_{z,i,t,h}$.

Table 6: Mean and root mean squared forecast and assumption errors

	Macroeconomic variables						External conditions							
	inf		*gdp*		*une*		*oil*		*usd*		*ir*		*lab*	
h	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE	ME	RMSE
1	-0.002	0.123	-0.001	0.203	0.011	0.195	0.447	2.541	-0.001	0.011	0.008	0.037	0.063	0.547
2	0.019	0.200	-0.003	0.422	0.035	0.263	1.258	7.639	-0.003	0.033	0.035	0.099	0.013	0.538
3	-0.066	0.287	0.064	0.518	0.048	0.327	-1.643	6.831	-0.007	0.053	0.037	0.115	0.001	0.634
4	-0.107	0.518	0.197	0.822	0.056	0.467	-5.451	10.881	-0.010	0.072	0.033	0.188	0.020	0.602
5	0.059	0.861	0.331	1.226	0.008	0.718	2.419	20.455	0.012	0.080	0.105	0.245	0.077	0.645
6	0.144	0.980	0.477	1.605	0.001	0.931	5.712	24.884	0.003	0.122	0.244	0.480	0.075	0.694
7	0.141	0.951	0.560	1.715	-0.028	1.046	6.365	23.787	0.016	0.117	0.379	0.591	0.097	0.686
8	0.156	0.947	0.575	1.768	-0.048	1.128	7.605	24.858	0.022	0.116	0.348	0.505	0.094	0.651
All	0.026	0.643	0.234	1.090	0.016	0.663	0.770	14.591	0.001	0.073	0.103	0.283	0.055	0.625

Notes: For each macroeconomic variable/assumption, this table reports the mean error (ME) and the root mean squared error (RMSE) for the h-step-ahead predictions. In the last row, we report the corresponding statistics based on a pooled sample that includes all horizons. The sample period is 2002Q1–2019Q4.

The results for the pooled sample indicate that forecasters generally overpredict macroeconomic outcomes and assumptions. In particular, panelists are too optimistic with respect to GDP growth and too pessimistic when predicting inflation or the unemployment rate.

With respect to the horizon, we find that the ME series tend to decline as the target year approaches. Interestingly, the average forecaster overpredicts inflation and exchange rates in the next year but underpredicts those variables in the current year. However, forecast errors are relatively small on average. This is particularly true for the exchange rate.

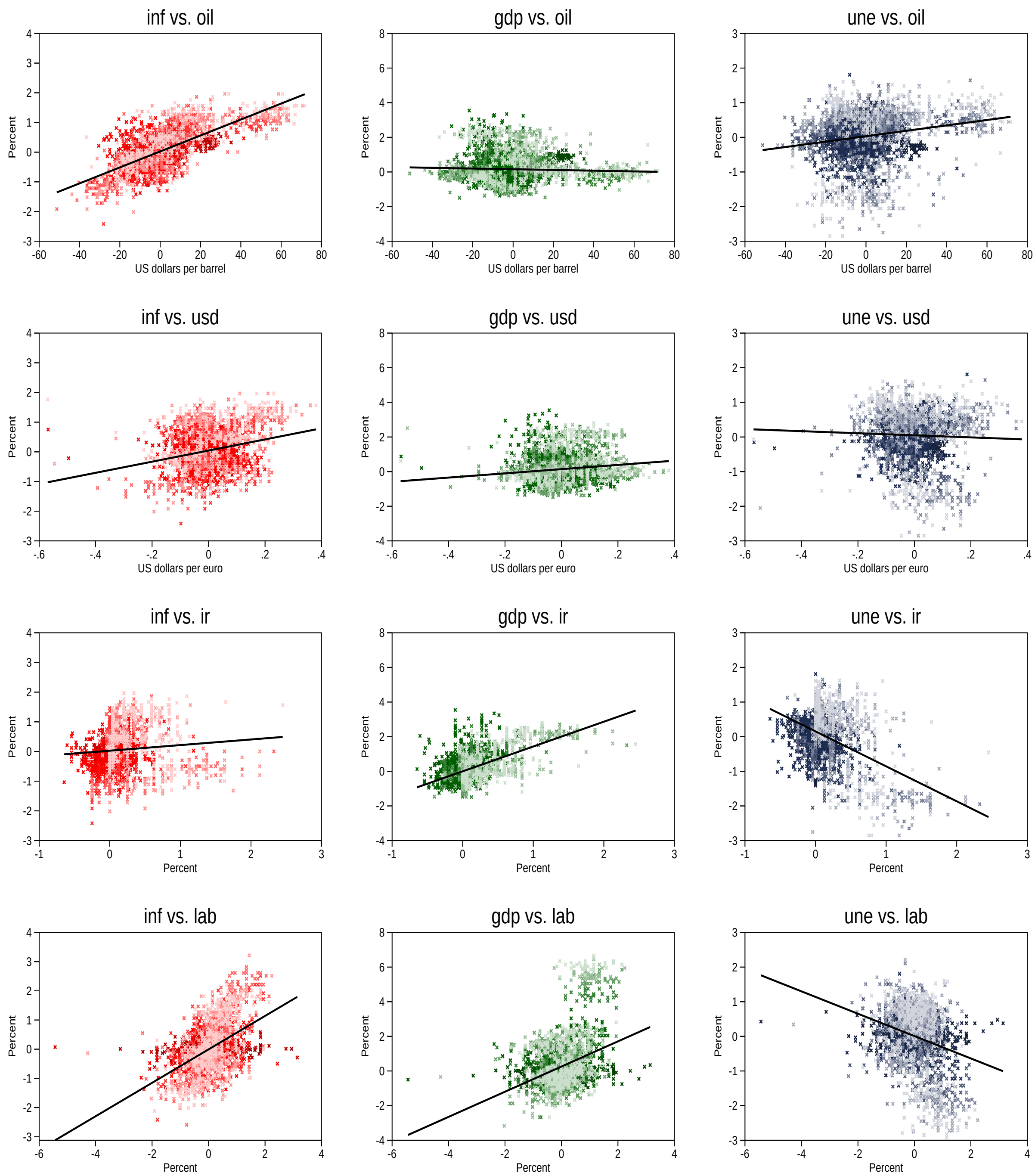
Our findings for the ME series indicate a good forecast performance of SPF participants. A drawback from analyzing average errors is that positive and negative errors can offset each other and distort the size of the error. Thus, Table 6 also reports horizon-specific and pooled root mean squared errors (RMSE), i.e., $\text{RMSE}_{z,h} = \sqrt{(1/(NT)) \sum_i \sum_t e^2_{z,i,t,h}}$ and $\text{RMSE}_z = \sqrt{(1/(NTH)) \sum_i \sum_t \sum_h e^2_{z,i,t,h}}$. We find that the RMSE series decrease for all macroeconomic variables and assumptions with decreasing forecasting horizon. To our knowledge, we are the first to document this feature of the SPF assumptions.

So far, the analysis in the section has focused on the aggregate level. However, it is likely that forecast performance varies across panelists. Meyler (2020) finds no evidence of statistically significant differences in the accuracy of individual SPF participants and shows that the average SPF forecast outperforms most of the individual predictions. However, his findings are challenged in a recent paper by Rich and Tracy (2021), who find significant differences in the accuracy of individual SPF forecasters. Moreover, Rich and Tracy (2021) show that differences in forecast performance depend on the forecast environment. Based on these findings, we next turn to an analysis on the individual level.

5.2 Individual forecast performance

In a recent study, Lambrias and Page (2019) analyze the decomposition of ECB's GDP and inflation forecast errors into errors in technical assumptions, international projections and other factors. They find that in particular assumption errors for the oil price and the exchange rate explain a considerable proportion of inflation errors. Kontogeorgos and Lambrias (2019) use Basic Model Elasticities to assess the impact of changes in assumptions on a given projection and find that adjusting errors in assumptions improves forecasting accuracy but does not necessarily translate to 'less bias'. Thus, the relationship between assumption and forecast errors may differ across macroeconomic outcomes.

Figure 4: Bilateral forecast and assumption errors



Notes: Forecast errors $e_{y,i,t,h}$ for inflation (first column), GDP growth (second column) and unemployment (third column) on the vertical axis. Assumption errors $e_{x,i,t,h}$ for oil price (first row), exchange rate (second row), interest rate (third row) and wage growth (fourth row) on the horizontal axis. A higher marker intensity indicates forecasts close to the target, i.e., small h. Solid black lines represent the least squares regression lines estimated across all h. The sample period is 2002Q1–2019Q4.

Figure 4 shows scatterplots of forecast errors for macroeconomic variables (vertical axis) against assumption errors (horizontal axis). We observe a positive co-movement between inflation errors and all assumption errors. The correlations between GDP growth errors and errors in exchange rates, interest rates and wage growth are also positive. There is a notable cluster of excessive GDP growth errors that exceed three percentage points in the subfigure for wage growth, which correspond to the next year forecasts for GDP growth in 2009. These observations are absent from the remaining plots in the second column due to the lack of next-year forecasts for the other assumptions in all surveys before 2010Q2. In line with Okun's Law, we document negative correlations between unemployment rate errors and errors for exchange rates, interest rates and wage growth.

A natural next step is to investigate whether misconceptions about assumptions can systematically explain differences in the forecast performance of individual survey participants. In order to assess the statistical significance of the relationships depicted in Figure 4, we regress for each macroeconomic variable the h-step-ahead forecast error of SPF participant i on the corresponding h-step-ahead assumption errors for the same target year t:

$$e_{y,i,t,h} = \alpha + \sum_{x} \beta_x e_{x,i,t,h} + \lambda_i + \lambda_t + \lambda_h + \nu_{y,i,t,h}, \tag{8}$$

This specification allows for a direct assessment of the link between forecast and assumption errors. Table 7 presents the estimates of Eqn. (8).

When evaluated individually, the relationship between inflation and assumption errors is positive and statistically significant in all cases. Consistent with our previous results, we find that oil price errors explain a much higher share of the variation in inflation errors ($R^2 = 0.52$) than the other assumptions, although wage growth also has considerable predictive power ($R^2 = 0.25$). Based on the estimated slope coefficient, an oil price error equivalent to the IQR ($4.24 - (-5.44) = 9.69$ US-Dollar) is predicted to increase $e_{inf,i,t,h}$ by approximately 0.26 percentage point.[21] The coefficients on $e_{usd,i,t,h}$ and $e_{ir,i,t,h}$ become negative when we simultaneously include all assumptions in columns (4) and (7). This suggests

[21] The relative importance of oil price errors for inflation errors is in line with the results of Fortin *et al.* (2020) for the Austrian economy.

that misconceptions in assumptions interact with each other when determining the accuracy of inflation forecasts, although the coefficient on $e_{ir,i,t,h}$ becomes insignificant once we include the various fixed effects in columns (5) and (8). This finding squares with the evidence in Knüppel and Schultefrankenfeld (2017), who show that the performance of central banks' inflation rate forecasts does not differ significantly for distinct underlying interest rate paths. The coefficients on $e_{oil,i,t,h}$, $e_{usd,i,t,h}$ and $e_{lab,i,t,h}$ remain statistically significant throughout. We conclude that oil price errors are the most important assumption in terms of explaining inflation errors, followed by wage growth errors.

For real GDP growth, it is particularly interest rate errors that explain the movement in forecast errors (see column (3), $R^2 = 0.32$), although the coefficients on the other assumptions are significant as well. This finding is in line with the evidence for GDP growth revisions from Table 5. The effect size, as evaluated by the IQR of $0.125 - 0 = 0.125$ base points, is positive and equals 0.18 percentage point. The inclusion of the fixed effects merely changes the numerical estimates, while leaving the relationships qualitatively unaffected. An exception is $e_{lab,i,t,h}$, which becomes insignificant in the full specification in column (8). Note that the excessive output errors documented in Figure 4 enter the estimation sample in column (6) but not in (7) or (8).

In line with the estimates for GDP growth, we find that interest rate errors are the most important predictor of misconceptions about future unemployment rates ($R^2 = 0.21$). The effect size based on the IQR is negative with a numerical value of -0.13 percentage point. Oil price and wage growth errors are also correlated with unemployment errors, although the goodness of fit is relatively small. The coefficient on $e_{usd,i,t,h}$ is insignificant in column (2) but becomes significant once we include all covariates simultaneously in column (4). Overall, the estimates are consistent with those for GDP growth. In line with our previous findings, we find only modest evidence for a relationship between unemployment and wage growth errors. This is surprising given that the majority of SPF participants state that they jointly form their expectations for unemployment rates and wage growth (ECB, 2019).

To illustrate the economic importance of correctly predicting assumptions when forecasting macroeconomic outcomes, we conduct a counterfactual exercise: In a first step, we compute the predicted forecast errors, $\hat{e}_{y,i,t,h}$, based on the estimates in column (8) when all

Table 7: The relationship between forecast and assumption errors

	Dependent variable: $e_{y,i,t,h}$ for $y \in \{inf, gdp, une\}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation rate				
$e_{oil,i,t,h}$	0.027***			0.030***	0.023***		0.028***	0.023***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.875***		-1.123***	-0.490***		-0.979***	-0.460***
		(0.221)		(0.162)	(0.099)		(0.198)	(0.123)
$e_{ir,i,t,h}$			0.189***	0.020	0.043		-0.144***	-0.018
			(0.062)	(0.043)	(0.028)		(0.046)	(0.034)
$e_{lab,i,t,h}$						0.573***	0.219***	0.115***
						(0.035)	(0.021)	(0.018)
Constant	0.023***	0.043***	0.027**	0.017**	0.317***	-0.007	0.028***	-0.156***
	(0.009)	(0.012)	(0.012)	(0.008)	(0.033)	(0.017)	(0.010)	(0.029)
No. of obs.	4,797	4,848	5,228	4,472	4,472	3,670	2,571	2,571
N	89	89	89	89	89	80	80	80
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.521	0.065	0.008	0.543	0.765	0.246	0.587	0.773
				Real GDP growth				
$e_{oil,i,t,h}$	-0.002***			-0.008***	-0.003***		-0.009***	-0.003***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.221***		0.952***	0.726***		1.065***	0.686***
		(0.229)		(0.200)	(0.137)		(0.237)	(0.162)
$e_{ir,i,t,h}$			1.433***	1.444***	1.030***		1.323***	0.983***
			(0.049)	(0.052)	(0.047)		(0.062)	(0.058)
$e_{lab,i,t,h}$						0.727***	0.201***	0.034
						(0.074)	(0.030)	(0.023)
Constant	0.156***	0.144***	-0.001	0.008	0.317***	0.256***	-0.012	0.583***
	(0.016)	(0.015)	(0.012)	(0.012)	(0.059)	(0.032)	(0.017)	(0.078)
No. of obs.	4,805	4,861	5,248	4,478	4,478	3,679	2,576	2,576
N	89	89	89	89	89	80	80	80
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.002	0.018	0.319	0.349	0.663	0.126	0.383	0.676
				Unemployment rate				
$e_{oil,i,t,h}$	0.008***			0.012***	0.006***		0.013***	0.006***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		-0.300		-0.797***	-0.670***		-0.718***	-0.533***
		(0.223)		(0.201)	(0.145)		(0.236)	(0.167)
$e_{ir,i,t,h}$			-1.009***	-1.070***	-0.847***		-1.072***	-0.898***
			(0.059)	(0.055)	(0.046)		(0.062)	(0.059)
$e_{lab,i,t,h}$						-0.323***	-0.097***	-0.020
						(0.036)	(0.025)	(0.021)
Constant	0.032**	0.049***	0.152***	0.141***	0.433***	0.008	0.159***	0.169***
	(0.014)	(0.014)	(0.010)	(0.010)	(0.059)	(0.019)	(0.013)	(0.050)
No. of obs.	4,630	4,678	5,058	4,324	4,324	3,632	2,547	2,547
N	89	89	89	89	89	79	79	79
Institutional FE	no	no	no	no	yes	no	no	yes
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.039	0.001	0.213	0.306	0.608	0.075	0.345	0.633

Notes: This table displays the estimates of Eq. (8). The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated by OLS. Newey-West (1987) standard errors accounting for arbitrary levels of heteroscedasticity and autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% critical level, respectively.

assumption errors are set to zero. Based on these predictions, we re-calculate the RMSE for each macroeconomic variable and compare it to the unconditional RMSE.[22] We find that the RMSE could be reduced by approximately 50% for inflation and 40% for GDP growth and unemployment if all SPF participants were to make zero assumption errors. These findings corroborate the high R^2-statistics in Table 7.

We conduct the same robustness checks as before. Considering the 2012–2019 subsample has the advantage that the financial crisis, for which Figure 1 shows large forecast errors, is excluded. Controlling for recessions or stock market volatility indicates that SPF participants produce higher forecast errors for inflation and GDP growth during recessions and at times of heightened stock market volatility. Otherwise, the results are similar to those in Table 7.

In a final robustness check, we replace forecast and assumption errors with their squared or absolute counterparts, mimicking a forecaster trying to minimize a squared/absolute loss function. Using squared errors allows us to compare our estimates to those in Engelke *et al.* (2019) for German GDP growth. Absolute errors are less severely affected by extreme observations. In both cases, inflation errors are most closely related to oil price errors, whereas interest rate errors strongly co-move with output growth and unemployment errors. The finding that squared interest rate errors best capture the movement of squared forecast errors for GDP growth squares with the evidence in Engelke *et al.* (2019), as does the observation that the coefficient on squared exchange rate errors becomes insignificant once horizon-fixed effects are included in the model. In line with the evidence from Table 7, squared and absolute wage growth errors mostly appear to matter for inflation.

Taken together, we find that forecast errors for macroeconomic outcomes are strongly related to assumption errors, although the importance of the distinct assumptions varies across macroeconomic variables. In line with the evidence for disagreement and revisions, our estimates suggest that oil price errors are most important for inflation, while interest rates matter for real GDP growth and the unemployment rate. Exchange rate errors are significant predictors in most cases but yield only small improvements in the goodness of fit. In contrast, wage growth errors appear to matter primarily for inflation errors. In

[22] The unconditional RMSEs used here deviates from those reported in the last row of Table 6 because the former are calculated for the estimation samples, while the latter are based on all available observations.

most cases, we observe the highest goodness of fit for inflation, which suggests that there is a particularly close connection between inflation and assumptions errors. This finding may partially reflect the design of the SPF questionnaire, which asks for the inflation rate predictions and assumptions on the same spreadsheet. The inclusion of the fixed effects generally has little impact on our findings, except for an increase in the goodness of fit due to the time-fixed effects. Our findings may explain why Rich and Tracy (2021) find only a weak association between the accuracy of point forecasts for distinct macroeconomic outcomes (relative to density forecasts). We show that the performance of these predictions is related to the accuracy of distinct assumptions. The forecastability of these assumptions is possibly quite heterogeneous and likely related to the forecasting environment.

6 Conclusion

We analyze the role of external assumptions in explaining the heterogeneity, updating and ex-post performance of macroeconomic forecasts from the European Central Bank's Survey of Professional Forecasters. While oil price and exchange rate predictions are revised more frequently than macroeconomic variables, updating frequencies for interest rate and wage growth expectations are lower. We show that these variables contain valuable information that can help understand how experts predict macroeconomic outcomes. Throughout our analysis, we consistently find that oil price assumptions are closely related to inflation rate expectations, whereas interest rate assumptions play an important role in the assessment of future real GDP growth and unemployment. The role of exchange rate and wage growth assumptions is relatively subdued, although they turn out as significant predictors in several regressions. These findings hold if we account for unobserved sources of heterogeneity via institutional-, time- and horizon-fixed effects and pass various robustness checks.

Our results have implications for both survey operators and survey participants. First, assumptions should be elicited along with forecasts so that the way expectations are formed is better understood. So far, the SPF is an exception in that it provides assumptions along with macroeconomic forecasts. Second, our estimates of the updating frequencies for oil prices and exchange rates cast some doubt on previous evidence in favor of inattention models based on survey forecasts. Such models have to be extended to account for differences in the attention degree across variables. Third, survey participants can considerably improve forecast accuracy by reducing assumption errors. In light of this finding, it seems tempting to explore how the oil price shock during the COVID-19 pandemic affects forecast performance in the SPF. Fourth, our results could be used to derive measures of conditional forecast accuracy that allow a better comparison across macroeconomic outcomes. We leave these questions to future research.

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