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Conditional Macroeconomic Forecasts: Disagreement, Revisions and Forecast Errors

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Abstract

Using data from the European Central Bank‘s Survey of Professional Forecasters, we analyse 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 the unemployment rate are related to assumptions about future oil prices, exchange rates, interest rates and wage growth. Our findings indicate that inflation forecasts are closely associated with oil price expectations, whereas expected interest rates are used primarily to predict output growth and unemployment. Expectations about exchange rates and wage growth also matter for macroeconomic forecasts, albeit less so than oil prices and interest rates. We show that survey participants can considerably improve forecast accuracy for macroeconomic outcomes by reducing prediction errors for external conditions. Our results contribute to a better understanding of the expectation formation process of experts.

Keywords: assumptions, disagreement, forecast accuracy, forecast revisions, survey forecasts

JEL classification: C53, D84, E02, E32

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). These findings put the reliability of macroeconomic forecasts into question.

Various theoretical models attempt to rationalize the existence of disagreement and heterogeneous forecast errors. Among the more promising candidates are models of information rigidities such as noisy information (Woodford, 2002) or sticky information models (Mankiw and Reis, 2002). In the former, forecasters continuously update their information but have imperfect access to it in each period. Since the signals that forecasters receive are polluted with idiosyncratic noise, they are only partly incorporated into predictions. In sticky information models agents update their expectations infrequently in response to the arrival of new information, either because it is costly to do so or because they have limited processing capacities. Consistent with sticky information models, several studies find that macroeconomic predictions of professional forecasters are not fully revised from one period to the next (Andrade and Le Bihan, 2013; Coibion and Gorodnichenko, 2015; Baker *et al.*, 2020). However, there is evidence that models of information rigidities cannot fully account for forecasters disagreement and forecast errors commonly observed in survey data which raises the question of further explanatory approaches. For example, the updating of predictions may be related to conditioning variables that are used as inputs in the forecasting process for macroeconomic outcomes. In particular, experts' information sets include their expectations about the future state of the world such as expected oil prices or interest rates.

In this paper, we analyze the explanatory power of several forward-looking variables for the heterogeneity and performance of professional forecasters' macroeconomic expectations. Our research connects to the literature on conditional forecasting, which relates variables of interest (in our case, macroeconomic forecasts) 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 assess 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 forecasts of the oil price, the EUR/USD exchange rate, the ECB's main refinancing operations and wage growth.

The role of these variables for macroeconomic forecasting is not well understood so far. Recent papers focus on the linkage between prediction errors for macroeconomic variables and expectations about future conditions. The papers most closely connected to our analysis are Engelke *et al.* (2019) and Fortin *et al.* (2020). Based on forecasts for German GDP growth from several institutions, Engelke *et al.* (2019) find a positive effect of squared errors for the interest rate and world trade on squared errors for output growth. Fortin *et al.* (2020) analyze the predictions from two major Austrian research institutions and find that misconceptions about EU 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. Thus, a common finding from both papers is that forecast accuracy of national output growth is conditional on a correct assessment of the supranational macroeconomic environment. This motivates our approach of analyzing macroeconomic predictions from the euro area perspective.

The findings of Fortin *et al.* (2020) suggest that the strength of the linkage between macroeconomic predictions and forecasts of external conditions tends to increase with the forecast horizon. This observations squares with the evidence from an earlier study by Fioramanti *et al.* (2016). Based on the European Commission's GDP forecasts for several European countries and the euro area, Fioramanti *et al.* (2016) find that the impact of conditioning variables on forecast errors tends to be small 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.

The papers discussed above suffer from a number of shortcomings. First, the sample size is relatively small. For example, 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, which is only about twice as much as the number of parameters in their full specification. Thus, the reliability and precision of the estimates may be affected by the small number of observations relative to the number of covariates. In contrast, the rich SPF dataset provides several thousand forecasts per variable. Second, these studies mostly focus on real GDP growth. The analysis of Fortin *et al.* (2020) is an exception since they also consider the inflation rate and find that the role of expected external conditions differs across outcome variables. We further explore this possibility by analyzing the role of distinct conditioning variables for predictions of real GDP growth, inflation and the unemployment rate. Third, all studies focus exclusively on prediction errors. While this is an important aspect of the forecasting process, the connection between macroeconomic forecasts and expected future conditions at other stages may also provide important insights into the expectation formation of experts. Thus, 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. To our knowledge, this paper provides the most extensive analysis of the linkage between macroeconomic forecasts and conditioning variables so far.

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 distinct covariates varies across outcome variables. According to our estimates, oil price disagreement matters in particular for the variability of predictions for the inflation rate, while 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 investigate 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 the panelists could have nearly doubled forecast accuracy if they had correctly anticipated future external conditions.

The paper is structured as follows: Section 2 discusses theoretical relationships between macroeconomic variables and ex-ante conditions. Section 3 describes the data. Section 4 provides descriptive evidence. Sections 5–7 present our empirical findings for disagreement, forecast revisions and prediction errors, respectively. Section 8 presents several robustness checks. Section 9 summarizes and concludes.

2 Theory-consistency of macroeconomic forecasts and external conditions

Several studies explore the possibility that experts' macroeconomic expectations are jointly determined (e.g., Sinclair *et al.*, 2012; Dovern, 2015; Rich and Tracy, 2021). In contrast, evidence on the connection between macroeconomic forecasts and external conditions is relatively scarce. This is surprising since there is ample reason to believe that (predictions of) macroeconomic outcomes are related to the (expected) state of the economy. For example, misconceptions about the future stance of monetary policy may lead to a diminished ability to predict future inflation rates and increase the disagreement among economic agents. Since this reduces the probability of achieving anchored inflation expectations, such information is relevant for central bankers. In this section, we describe several well-known theoretical relationships which experts may use to jointly form their expectations and report empirical evidence for their validity in surveys such as the SPF.

Phillips Curve. The original version of the Phillips Curve asserts a negative correlation between the unemployment rate and wage growth. In empirical applications, wage growth is often replaced with the inflation rate based on the assumption that prices grow along with wages. Using this definition, Dräger *et al.* (2016) find that approximately half of the forecasts in the Federal Reserve's SPF are consistent with the Phillips Curve. For the ECB-SPF, Frenkel *et al.* (2011) document similar evidence.[1] Several special SPF surveys provide additional insight into the expectation formation process of the panelists (ECB, 2009, 2014, 2019), e.g., that the majority of SPF participants form their expectations in line with a Phillips Curve relationship. López-Pérez (2017) shows that inflation, unemployment and oil price forecasts are consistent with panelists believing in a forward-looking (New Keynesian) Phillips Curve for the euro area. In particular, he finds consistent evidence for a positive relationship between inflation and oil price forecasts. Focusing on several surveys, Casey (2020) shows that experts use the original price Phillips curve for short-term forecasts and rely more on the expectations-augmented variant for longer horizons.

Okun's Law. Okun's Law postulates a negative link between economic growth and the unemployment rate. Evidence in favor of the validity of Okun's Law for the SPF expectations is documented in Frenkel *et al.* (2011) and ECB (2014). Recently, Casey (2020) finds that 89% of the SPF predictions are consistent with Okun's Law, although this linkage is less apparent for longer horizons. In light of these findings, one might expect to also find a positive relationship between expectations of output and wage growth. More generally, Okun's Law suggests that a relationship between GDP growth forecasts and external conditions implies an inverse relationship between those variables and unemployment rate expectations. However, the validity of Okun's Law likely differs across countries (see, e.g., Pierdzioch *et al.*, 2011; Ball *et al.*, 2015) and, hence, the importance of conditioning variables for the expected European unemployment rate may not necessarily be the same as that for GDP forecast errors.

Taylor Rule. This rule is frequently used to characterize monetary policy and describes a relationship between central banks' operating target, the inflation rate and GDP growth. Dräger *et al.* (2016) consider forecasts in the US-SPF to be in line with a Taylor rule if

[1] In the following, 'SPF' always refers to the ECB's version of the SPF.

rising interest rate expectations coincide with higher expected inflation and lower expected unemployment and find evidence in favor of such relationships for half of the survey participants.[2] For the euro area, Frenkel *et al.* (2011) provides evidence that the SPF forecasts are consistent with the Taylor rule.

The empirical evidence discussed above indicates that professional forecasters jointly form their expectations about macroeconomic outcomes and external conditions. However, SPF participants may believe in relationships between such variables beyond those described above. For example, in ECB (2019), panelists react to a hypothetical oil price shock by adjusting their inflation expectations upwards. For this reason we do not focus primarily on estimating such theoretical relationships, although they lend credibility to our research agenda.

3 Data

This section provides an overview of the SPF by focusing on the key features of the survey and its associated dataset.[3] The survey is conducted quarterly since 1999Q1 among experts employed by financial or non-financial institutions such as economic research institutions. Participants provide predictions for key macroeconomic indicators such as inflation (*infl*), real GDP growth (*gdp*) and the unemployment rate (*une*) in the euro area for several forecast horizons.[4] We use the fixed-event forecasts, which are characterized by a fixed target year $t = 1, \ldots, T$ and a rolling quarterly anticipation horizon $h = 1, \ldots, H$. The employed data comprise forecasts for the current calendar year ($h \in \{1, \ldots, 4\}$) and the next calendar year ($h \in \{5, \ldots, 8\}$).[5] After combining these forecasts, we obtain a sequence of individual h-step-ahead predictions for target year t with forecast horizons $h \in \{1, \ldots, 8\}$.

[2] Forecasts are still considered as consistent with the Taylor rule if only one of the macroeconomic predictions moves in the expected directions, while the other remains constant or if the predicted direction for all three variables is reversed. Moreover, the expectation of a constant interest rate must go along with constant inflation and unemployment expectations or else forecasts are considered to be at odds with the Taylor rule.

[3] http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html

[4] Since 2016Q4, the SPF elicits core inflation forecasts, which we do not use due to the short time series.

[5] In some cases, the SPF provides forecasts for the calendar year after next ($h \in \{9, \ldots, 12\}$), which we do not use in our analysis because they are available only for selected survey rounds and variables.

Our sample includes 72 surveys waves conducted between 2002Q1 and 2019Q4 and focuses on predictions for the years 2002–2019 ($T = 18$).[6] In total, 101 forecasters participated in the SPF during this period. Although a forecast panel is provided in each forecasting 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 only consider institutions that have at least three years worth of survey experience, i.e., participants that have been included in at least twelve (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, the SPF elicits forecasts of future economic and financial conditions including the Brent crude oil price in US-Dollars per barrel (*oil*), the Euro/US-Dollar exchange rate (*usd*), the ECBs main refinancing rate (*ir*) and annual growth in compensation per employee (*lab*; henceforth: wage growth).[7] These variables are refered 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. Nonetheless, the questionnaire asks panelists to "[...] *report selected information underlying* [*their*] *forecasts* [...]". It should also be noted that 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 the 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 judgement.

6 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.

7 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. Unfortunately, the SPF does not elicit histograms for the variables relating to external conditions.

While the macroeconomic forecasts are available for the entire sample period, wage growth assumptions for the current and the next year have been elicited 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 predictions with fixed forecast horizons between one and four quarters ahead. For our analysis, we combine the fixed-horizon assumptions with realizations to calculate oil price, exchange rate and interest rate assumptions for the current year. Depending on the forecast horizon, this entails a combination of first-release data for the realizations and actual predictions.[8] In the following, we only consider the responses of participants who provide predictions for at least one of the macroeconomic variables and one of the assumptions in a given 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 $h \in \{1, \dots, 8\}$ 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.[9] Table 1 provides a detailed summary of the sample size for each variable.

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[8] For the surveys conducted in Q1, current year assumptions for the oil price, exchange rate and interest rate are calculated as the average over the respondent's 1- to 4-quarter-ahead assumptions. For the Q2-surveys, we proceed in the same way but replace the 4-quarter-ahead assumption with the Q1 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 2- and 1-quarter-ahead assumptions. For the Q4-surveys, we compute the average over the Q1–Q3 realizations and the 1-quarter-ahead assumption.

[9] In a robustness check, we confirm that our results are not affected by the overrepresentation of current year predictions by focusing on the 2012–2019 period.

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

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

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.

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 due to the fact 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 have contributed predictions for the macroeconomic variables and the other assumptions at some time.

In line with the real-time 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.[10] Based on the monthly (inflation, unemployment) or quarterly (real GDP) real-time data for a macroeconomic variable, we calculate average real-time values at an annual frequency.[11] Since the data for the assumptions are not revised, we calculate annual averages based on the released figures.

[10] The Euro Area Real-Time Database is an experimental dataset that consists of vintages, or snapshots, of time series of several variables, based on series reported in the ECBs Economic Bulletin, and previously in the ECBs Monthly Bulletin. The dataset is updated semi-annually, at the beginning of January and July. See: https://sdw.ecb.europa.eu/.

[11] We use first releases for inflation and second estimates of real seasonally and calendar-adjusted GDP.

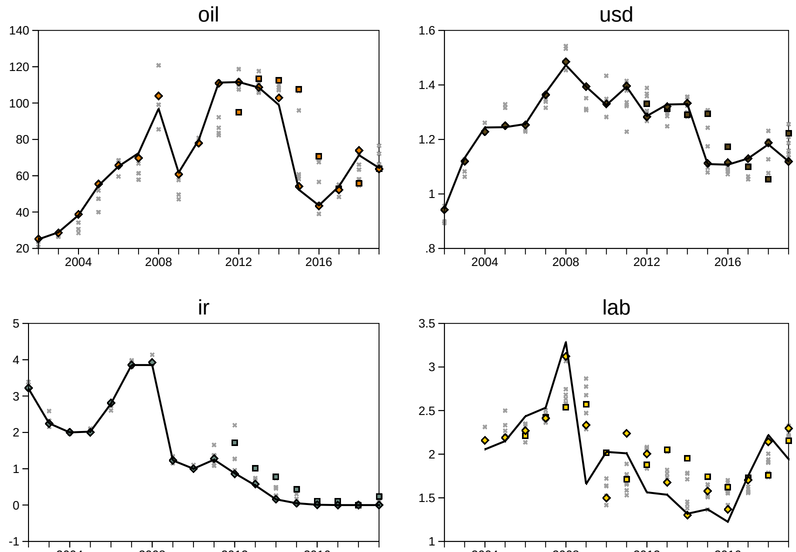
4 SPF consensus forecasts

In this section, we analyze the performance of the average predictions for macroeconomic variables and assumptions reported by SPF participants. We are particularly interested in the role of the forecast horizon. 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: Realizations and consensus forecasts

(a) Macroeconomic forecasts

(b) Assumptions



Notes: Solid black lines depict the real-time realizations of the respective variable. Squares (□) represent the average across the 8-step-ahead forecasts/assumptions, while diamonds (◇) indicate the average over the 1-step-ahead forecasts/assumptions. Crosses (×) depict h-step-ahead consensus forecasts/assumptions 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.

Let $\hat{y}_{i,t,h}$ and $\hat{x}_{i,t,h}$ denote the h-step-ahead prediction of macroeconomic variable $y \in \{\mathit{infl}, \mathit{gdp}, \mathit{une}\}$ respectively assumption $x \in \{\mathit{oil}, \mathit{ir}, \mathit{usd}, \mathit{lab}\}$ in target year $t = 1, \ldots, T$ issued by forecaster $i = 1, \ldots, N$.[12] As discussed above, y_t represents the realization of a macroeconomic variable based on first-release data. The average (or 'consensus') prediction based on the N forecasts 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 depicts $\bar{\hat{y}}_{t,h}$ and $\bar{\hat{x}}_{t,h}$ for forecast horizons $h \in \{1, \ldots, 8\}$ over the distinct target years along with the corresponding realizations in real time (black lines). Note that the 8- and 1-step-ahead predictions are highlighted differently from the other forecast horizons.

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 after the outbreak of the Great Recession. During the following years, the SPF participants underpredicted inflation at long horizons, whereas they overpredicted inflation after the ECB implemented its low interest rate policy following Mario Draghi's 'whatever it takes' speech in July 2012. The observed pattern suggests that inflation expectations for large h are at least partially anchored around the ECB's inflation target. With respect to the assumptions, we document large positive errors for the next calendar year predictions of the oil price in 2015 and 2016 and persistent overprediction of interest rates at long horizons during the European sovereign debt crisis. As discussed in Andrade and Le Bihan (2013), periods of persistent under-/overestimation are indicative of predictable average forecast errors, a characteristic of both sticky and noisy information models. A detailed analysis of forecast and assumption errors is provided in Section 7.

A natural question is to ask whether there is evidence of heterogeneity in the forecast accuracy of individual panelists. If this is the case, it seems advisable to proceed with an

[12] Due to the unbalanced nature of the panel, N differs across t and h. For notational convenience, we prefer to use N over $N_{t,h}$ to indicate the size of the cross-section.

analysis at the individual level. If not, it may be sufficient to focus on aggregate performance. Meyler (2020) finds no evidence of statistically significant differences in the forecast performance of individual SPF participants. In addition, his results indicate 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 distinct forecasters. Moreover, Rich and Tracy (2021) show that differences in individual forecast performance depend on the forecast environment. In light of these findings, it seems recommendable to investigate in a first step whether SPF participants disagree about future outcomes and if disagreement about macroeconomic outcomes depends on heterogeneity regarding ex-ante conditions.

5 Forecast disagreement

To investigate whether heterogeneity in the assumptions is informative for heterogeneity in the macroeconomic forecasts and whether these relations differ across variables, we focus on the dispersion around the respective consensus forecast. Forecast disagreement is a commonly used indicator of forecast heterogeneity and is measured as the standard deviation of the point predictions, i.e.,

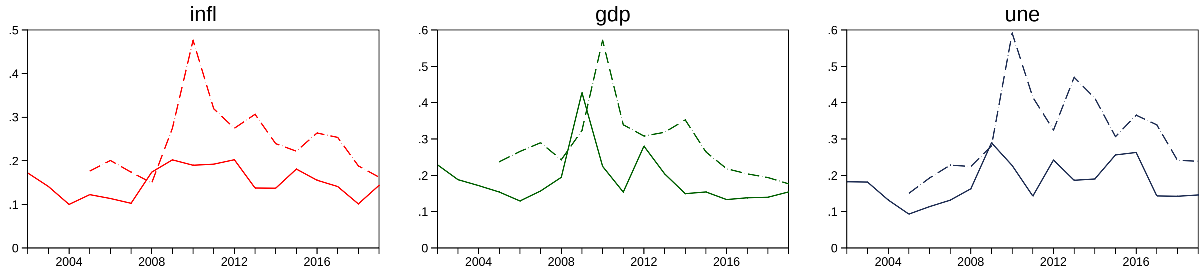
$$s_{z,t,h} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(\hat{z}_{i,t,h} - \bar{\hat{z}}_{t,h})^2}. \tag{2}$$

Disagreement captures the extent to which individual predictions are spread around the consensus forecast. It 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). Figure 2 shows the evolution of disagreement for the distinct variables over the target years. Solid lines indicate disagreement averaged across the current year series, while dashed lines represent average disagreement for the next year.

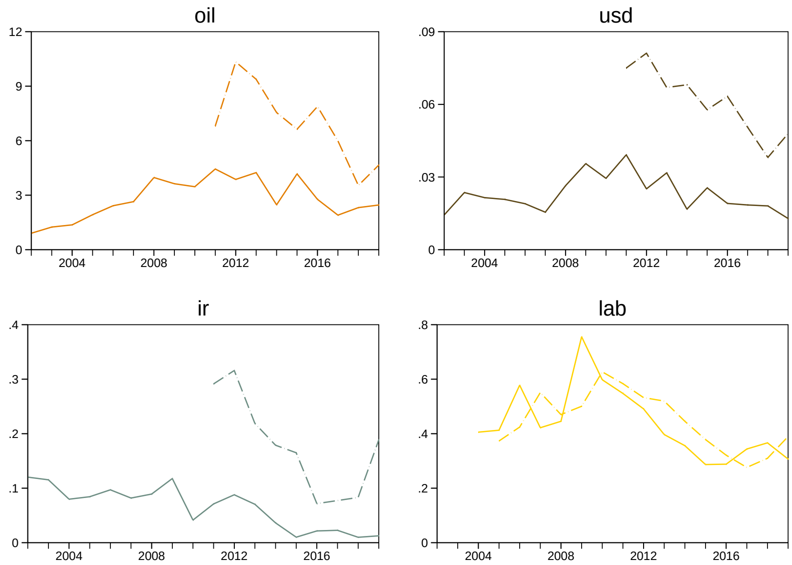
We observe several interesting disagreement patterns for the distinct series. For example, disagreement about the current year is generally lower than disagreement about the next year. This likely reflects the increasing amount of information about the outcome as the

Figure 2: Forecast disagreement

(a) Macroeconomic forecasts



(b) Assumptions



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.

target period approaches. The series for wage growth are a notable exception. Broadly speaking, the time series for the macroeconomic outcomes are broadly in line with those for the assumptions in the sense that we document considerable variation in the disagreement series across time. In particular, Figure 2 shows notable spikes in disagreement about macroeconomic outcomes during the financial crisis.[13] Time-varying disagreement is in line with sticky information models because forecasters who update their predictions in response

[13] Bürgi and Sinclair (2021) show that increases in disagreement help to predict recessions.

to a large shock will produce markedly different forecasts than those who do not update. Since these differences are less pronounced in calm periods, disagreement can vary over time. In contrast to GDP growth and unemployment, the evolution of current-year disagreement is relatively more stable for inflation and the assumptions. 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 constant oil prices in our sample. An interesting pattern emerges for the 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 for assumptions and macroeconomic variables tend to co-move, the relationship may vary across distinct target 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 each macroeconomic variable on the corresponding h-step-ahead assumption disagreement:

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

where $(\beta_{oil}, \beta_{usd}, \beta_{ir}, \beta_{lab})'$ 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 to the estimation. We opt for a separate analysis of wage growth assumptions because, as discussed in Section 3, (i) data for the other assumptions are available for different survey rounds (see Figure 1) and (ii) nine institutions in our sample have never reported wage growth assumptions. In each case, the parameters are estimated via 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.

Table 2: The relationship between forecast and assumption disagreement

	Dependent variable: $s_{y,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$s_{oil,t,h}$	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 via 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.

Columns (1)–(3) of Table 2 show that the relationship between inflation and assumption disagreement is positive and statistically significant. Thus, forecasters disagree more on future inflation at times when they also have diverging expectations for external conditions. However, the economic significance varies across assumptions. In particular, oil price and exchange rate disagreement explain a much larger share of the variation in $s_{infl,t,h}$ 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 on β_{oil} remains positive and statistically significant throughout. We conclude that oil price disagreement is the most important driver of inflation disagreement.

For real GDP growth, we also obtain significantly positive coefficients and relatively similar goodness of fit statistics for all assumptions. However, when includings all covariates and fixed effects, only the coefficient on $s_{ir,t,h}$ remains statistically significant. Interestingly, we observe a considerable increase in the coefficient of determination once due to the inclusion of time-fixed effects in columns (5) and (8).

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 significant predictor when simultaneously including all assumption series 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.

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. 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.

6 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 t,

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

6.1 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 one reported in the previous quarter, i.e.,

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

Using data provided in eight consecutive forecast rounds for a specific target year, we are able to assess seven forecast revisions. 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			Assumption variables			
h	Inflation	GDP growth	Unemployment	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 macroeconomic variable/assumption, 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), our finding of incomplete updating of forecasts is in line with the predictions of a sticky information model. 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.[15] We conclude that the attentiveness of SPF participants has not changed in a meaningful way since Andrade and Le Bihan (2013) conducted their study.[16]

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

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

[15] 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.

[16] 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 someone who participates only in 80% of the surveys but regularly updates his/her predictions. Thus, we employ the measure of Andrade and Le Bihan (2013), which Baker *et al.* (2020) also use in a robustness check.

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. For GDP growth, most forecasts are still revised at the shortest horizon, whereas, for inflation and unemployment the updating frequency noticeably declines for $h = 1$.

In contrast to other studies, we also consider revisions in assumption variables. 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. This can be interpreted 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. In case of the former, this likely reflects the ECB's infrequent interest rate adjustments during recent years, particularly since interest rates hit the zero lower bound (see Figure 1).[17] 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 on a regular basis.

We conclude that while the overall degree of attentiveness in the SPF data is relatively high, notable differences exist across variables. While our results for the macroeconomic variables square with the evidence by Andrade and Le Bihan (2013), the finding that assumptions are revised at distinct frequencies is new. 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 information rigidities.

[17] The estimate $\hat{\lambda}_{ir}$ increases from 55.4% to 71.7% if we exclude the years 2015–2019.

6.2 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. 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.

Table 4: Revisions in macroeconomic forecasts conditional on assumption revisions

		$\Delta\widehat{infl}$			$\Delta\widehat{gdp}$			$\Delta\widehat{une}$		
		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. The sample period is 2002Q1–2019Q4.

Table 4 documents a positive relationship between revisions of inflation forecasts and oil prices. 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). 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. The average (median) revision of their inflation forecasts equals 0.2 (0.1) percentage points, which is nearly identical to the numbers reported in ECB (2019).

We observe that panelists tend to revise their inflation and GDP growth forecasts upwards — rather than downwards — in response to an upward adjustment in the exchange rate. 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. These findings are somewhat at odds with those from ECB (2019). However, we observe only about 50 cases where SPF participants update their exchange rate assumptions this strongly.

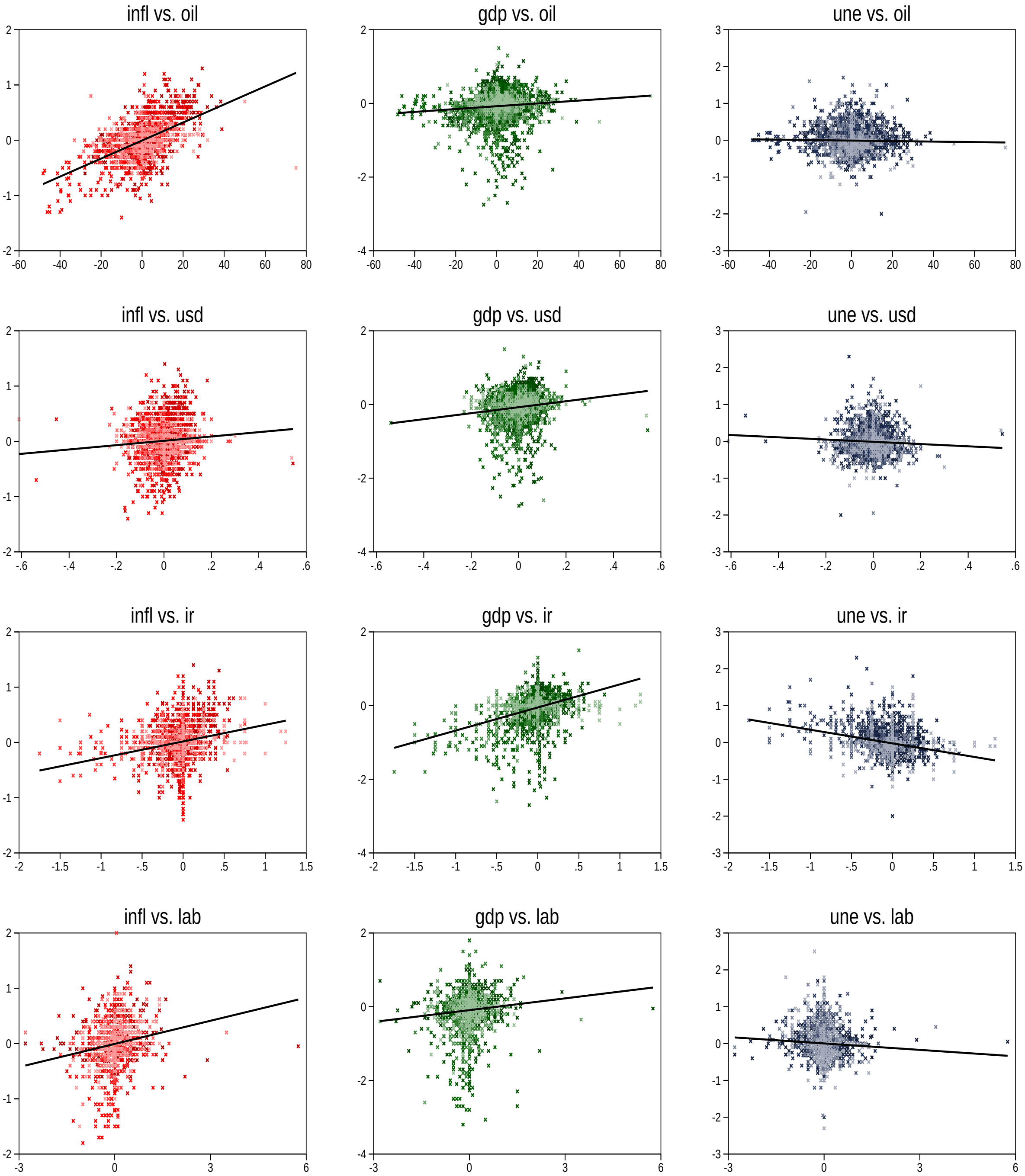
Although approximately 85% of SPF participants state that their point forecasts for unemployment and wage growth are jointly determined and more than half of the panelists indicate that updates of these predictions are dependent on each other (ECB, 2019), we do not find clear evidence of a relationship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

6.3 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 slopes of the least squares regression lines in Figure 3 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.

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.

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.,

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

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).[18]

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 considerably across assumptions. In line with our findings for disagreement, we find that oil price revisions explain a much larger share of the variation in the revisions of inflation forecasts ($R^2 = 0.27$) than revisions of the other assumptions. The magnitude of this effect is modest. According to our estimates, a forecaster with an oil price revision of -2.19 USD (the lower quartile) is predicted to adjust her inflation forecast downwards by 0.04 percentage points. An oil price revision of 4.89 (the upper quartile) is associated with a predicted upwards adjustment of the inflation forecast by 0.08 percentage points. Thus, the predicted effect size based on the interquartile range (IQR) is 0.12 percentage points. 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 assumptions are jointly determined. The inclusion of fixed effects further reduces the significance of the coefficient on $\Delta\widehat{usd}_{i,t,h}$. 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. 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.

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

Table 5: The relationship between forecast and assumption revisions

	Dependent variable: $\Delta\hat{y}_{i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$\Delta\widehat{oil}_{i,t,h}$	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 via 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.

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), a revision of $\widehat{ir}_{i,t,h}$ 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 points. 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 points. 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 sum, we find that revisions of macroeconomic forecasts are related to assumption revisions. The estimated relationships are economically meaningful. In line with the evidence from Section 5, 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. We conclude that SPF participants update their macroeconomic forecasts in response to new information for selected assumptions.

7 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 the SPF data.

The h-step-ahead prediction error is defined as

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

for $z \in \{x, y\}$, $y \in \{infl, gdp, une\}$ and $x \in \{oil, ir, usd, lab\}$. As discussed in Section 3, y_t is the first release of the respective macroeconomic variable. Note that prediction errors are defined such that positive values indicate overprediction, while negative values represent cases of underprediction.

7.1 Aggregate forecast performance

Figure 1 documents several distinct phases of persistent over- or underprediction for the macroeconomic forecasts and the assumptions. Notably, such cases appear to occur more frequently for large anticipation horizons. In order to assess more formally whether the SPF participants over- or underpredict macroeconomic outcomes at distinct forecast horizons, 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 errors						Assumption errors							
	Inflation		GDP growth		Unemployment		Oil price		Exchange rate		Interest rate		Wage growth	
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 anticipation 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 them for the current year. However, forecast errors are relatively small on average. This is particularly true for the exchange rate.

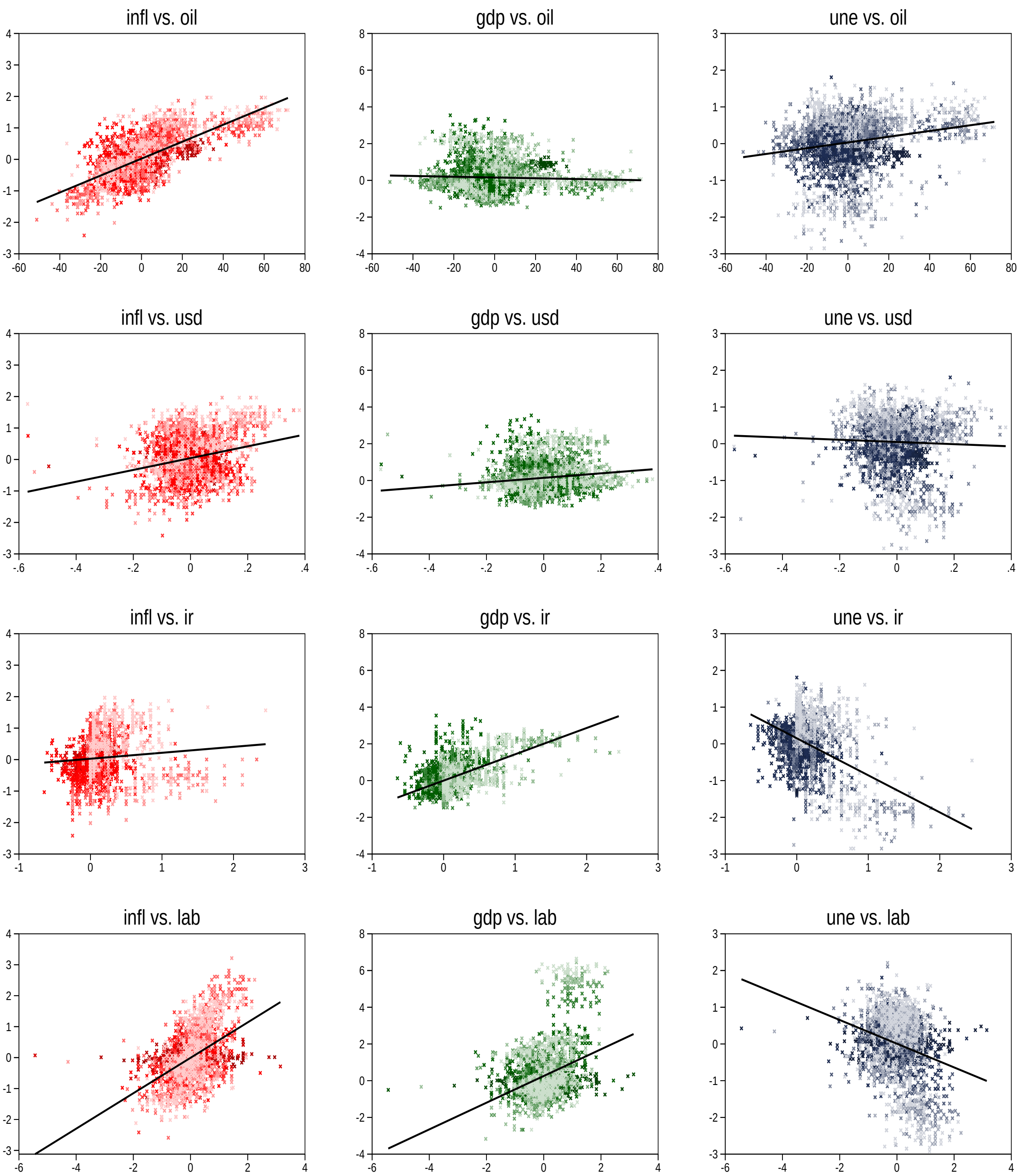
Our findings for the ME series appear to indicate a good forecast performance of SPF participants. A drawback from analyzing average errors is that positive and negative errors can offset each other and distort the size of the error. Thus, Table 6 also reports horizon-specific and pooled root mean squared 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.

7.2 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. Thus, the relationship between assumption and forecast errors may differ across macroeconomic outcomes.

Figure 4 shows scatterplots of forecast errors for macroeconomic variables (vertical axis) and 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 correlation patterns between unemployment rate errors and errors for exchange rates, interest rates and wage growth. Overall, there appears to be a close association between forecast and assumption errors.

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.

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. In line with our earlier results, we find that oil price errors explain a much larger share of the variation in inflation errors ($R^2 = 0.52$) than the other assumptions, although wage growth also has considerable predictive power ($R^2 = 0.25$). 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. Based on the estimate of the slope coefficient, an oil price error equivalent to the IQR ($e^{0.75}_{oil,i,t,h} - e^{0.25}_{oil,i,t,h} = 4.24 - (-5.44) = 9.69$ USD) is predicted to increase $e_{infl,i,t,h}$ by approximately 0.26 percentage points. 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 that misconceptions on assumptions interact with each other when determining the accuracy of inflation forecasts. In general, the findings hold when we include the various fixed effects in columns (5) and (8), although the coefficient on $e_{ir,i,t,h}$ becomes insignificant. This finding squares with the evidence in Knüppel and Schultefrankenfeld (2017), who show that the performance of central banks' inflation rate forecasts do 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.

Table 7: The relationship between forecast and assumption errors

	Dependent variable: $e_{y,i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation								
$e_{oil,i,t,h}$	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 via 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.

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. The relative importance of the interest rate errors for GDP growth errors is at odds with the results of Knüppel and Schultefrankenfeld (2017), although it should be mentioned that they focus on the predictions by central banks, whereas our cross-section is much more heterogeneous. Moreover, this finding is in line with the evidence for GDP growth revisions from Table 5. The effect size, as evaluated by the IQR of $e^{0.75}_{ir,i,t,h} - e^{0.25}_{ir,i,t,h} = 0.125 - 0 = 0.125$ base points, is positive and equals 0.18 percentage points. 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 ($R^2 = 0.21$). In this case, the effect size based on the IQR is negative with a numerical value of -0.13 percentage points. 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. Interestingly, 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).

In order to illustrate the economic importance of correctly predicting assumptions when forecasting macroeconomic outcomes, we compute the predicted forecast errors, $\hat{e}_{y,i,t,h}$, based on the estimates in column (8) when all 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.[19] We find that the RMSE could be reduced by approximately 50%

[19] The unconditional RMSEs somewhat deviates from the ones reported in the last row of Table 6 because the former is calculated for the estimation sample, whereas the latter is based on all available observations.

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.

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 yields only small improvements in the goodness of fit. In contrast, wage growth errors appear to matter primarily for inflation errors. In 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 reflect the design of the SPF questionnaire, which asks for the inflation rate predictions and assumption 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 partially 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 forecast environment. We control for the state of the business cycle in a robustness check below.

8 Extensions and Robustness

In this section, we assess the robustness of our findings in several ways: First, we check whether our results hold when controlling for recessions or stock market volatility in the euro area. Second, we check if the full sample estimates are affected by the overrepresentation of current-year forecasts by re-estimating all models for the subsample 2012–2019. Third, we analyze whether our findings from Table 7 hold if we replace forecast errors with absolute or squared errors. All estimates from this section are available in the Appendix.

8.1 Recessions and stock market volatility in the euro area

The predictability of macroeconomic outcomes is time-varying and particularly diminished in turbulent periods and times of heightened uncertainty such as the Great Recession (Rich and Tracy, 2021). While we partially control for such circumstances via the inclusion of time-fixed effects, we cannot rule out that this does not affect our estimates in other ways. To analyze the implications for the connection between macroeconomic forecasts and assumptions, we control for recession periods and stock market volatility in the euro area.

First, we re-estimate the models for disagreement, revisions and forecast errors and include the recession indicator D^{rec}_{t-h} as an additional control variable. The index $t-h$ indicates that the survey round h quarters prior to the target period t is classified as a recession period by the Euro Area Business Cycle Network.[20] Our data includes two recession periods: 2008Q2–2009Q2 and 2011Q4–2013Q1. Tables A.1–A.3 present the findings. Although the coefficient on the recession indicator is statistically different from zero and has the epxected sign in most cases, the estimates for the assumptions are very similar to our main findings.

Second, we include a measure of stock market volatility as a covariate. We use daily data for the Euro Stoxx 50 price index, compute daily log returns and calculate quarterly volatility, RV_{t-h}, as the square root of the sum of squared returns within each quarter.[21] Tables A.4–A.6 show the estimates. Again, the evidence shows that our main findings are fairly robust to controlling for changes in the macroeconomic environment.[22]

8.2 Subsample analysis

One concern may be that our findings are affected by the overrepresentation of predictions for the current year in our sample. Therefore, we re-estimate Eqn. (3), (6) and (8) on a smaller sample of observations that only includes the target years 2012–2019 for which we have forecasts and assumptions for all eight forecast horizons.[23] An additional advantage

[20] Link: `https://eabcn.org/dc/recession-indicators`

[21] Data for the Euro Stoxx 50 index is taken from Datastream.

[22] Interestingly, Tables A.3 and A.6 show that SPF participants make *smaller* forecast errors for unemployment during recession periods and at times of heightened stock market volatility.

[23] 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.

of this approach is that the estimation sample no longer includes the financial crisis, for which Figure 1 documents large forecast revisions and prediction errors. The estimates are summarized in Tables A.7–A.9.

Overall, the estimates are similar to our main findings. As before, 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. A notable exception is that interest rate disagreement no longer yields the highest R^2 in the regressions for unemployment in Table A.7 and that the effect becomes insignificant once all assumptions are included simultaneously. We conclude that our results are not severely affected by the underrepresentation of next-year assumptions in the full sample.

8.3 Squared and absolute forecast and assumption errors

In a final robustness check, we replace forecast and assumption errors in Eqn. (8) with their squared counterparts. This specification mimics a forecaster trying to minimize a squared loss function. This approach allows us to compare our estimates to those of Engelke *et al.* (2019) for the German economy, i.e., the largest economy in the euro area. Instead of minimizing a squared loss function, forecasters may alternatively minimize the mean absolute error. We account for differences across loss functions by replacing squared errors with absolute errors, which are less severely affected by extreme individual observations. The estimates are summarized in Tables A.10 and A.11.

Broadly speaking, both robustness checks confirm the importance of assumption errors in explaining forecast errors. In each case, 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 output growth squares with the evidence documented by Engelke *et al.* (2019) for predictions of German output growth, 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.

9 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. We find that assumptions 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 predictions of the inflation rate, whereas interest rate assumptions play an important role in forecaster's assessment of future real GDP growth and unemployment. The role of exchange rate and wage growth assumptions is relatively subdued, even though they turn out as significant predictors in many cases. Broadly speaking, our results hold once we account for unobserved sources of heterogeneity via institutional-, time- and horizon-fixed effects and pass various robustness checks. We conclude that ex-ante conditioning assumptions are relevant inputs in the expectation formation process of professional forecasters.

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 evidence on the updating frequencies for oil prices and exchange rates suggests that the evidence of information rigidities in macroeconomic survey forecasts documented in several studies cannot be traced back to similar rigidities in the underlying assumptions. 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 adjusted measures of forecast accuracy that allow a better comparison across macroeconomic outcomes. We leave these questions to future research.

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Appendix

Table A.1: The relationship between forecast and assumption disagreement (controlling for recessions)

	Dependent variable: $s_{y,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$s_{oil,t,h}$	0.020***			0.014***	0.010***		0.016***	0.012***
	(0.002)			(0.003)	(0.002)		(0.002)	(0.003)
$s_{usd,t,h}$		2.253***		0.795*	-0.559***		0.839**	-0.564**
		(0.296)		(0.402)	(0.161)		(0.366)	(0.215)
$s_{ir,t,h}$			0.450***	0.038	-0.087		-0.056	-0.110
			(0.052)	(0.118)	(0.112)		(0.100)	(0.104)
$s_{lab,t,h}$						0.122	0.000	-0.053**
						(0.085)	(0.027)	(0.023)
D^{rec}_{t-h}	0.021***	0.033**	0.040***	0.022**	0.049***	0.076***	0.025*	0.049***
	(0.007)	(0.014)	(0.015)	(0.010)	(0.007)	(0.021)	(0.013)	(0.009)
Constant	0.093***	0.096***	0.129***	0.089***	0.207***	0.129***	0.082***	0.223***
	(0.010)	(0.011)	(0.016)	(0.010)	(0.018)	(0.030)	(0.013)	(0.027)
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	0.677	0.632	0.400	0.687	0.830	0.165	0.725	0.835
				Real GDP growth				
$s_{oil,t,h}$	0.016***			0.003	0.005		0.006	0.005
	(0.003)			(0.005)	(0.004)		(0.006)	(0.004)
$s_{usd,t,h}$		1.982***		0.568	-0.570		0.676	-0.583
		(0.261)		(0.691)	(0.376)		(0.742)	(0.397)
$s_{ir,t,h}$			0.582***	0.412***	0.398***		0.285***	0.418***
			(0.070)	(0.081)	(0.078)		(0.085)	(0.081)
$s_{lab,t,h}$						0.286***	0.124	-0.014
						(0.104)	(0.096)	(0.027)
D^{rec}_{t-h}	0.096***	0.101***	0.096***	0.090***	0.104***	0.115***	0.083***	0.103***
	(0.028)	(0.026)	(0.021)	(0.026)	(0.018)	(0.028)	(0.024)	(0.017)
Constant	0.131***	0.126***	0.138***	0.122***	0.130***	0.087**	0.066*	0.134***
	(0.015)	(0.011)	(0.009)	(0.011)	(0.020)	(0.040)	(0.035)	(0.022)
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	0.434	0.469	0.517	0.525	0.754	0.336	0.557	0.753
				Unemployment rate				
$s_{oil,t,h}$	0.027***			0.008***	-0.002		0.010**	-0.003
	(0.003)			(0.003)	(0.004)		(0.005)	(0.005)
$s_{usd,t,h}$		3.355***		2.385***	0.857**		2.393***	0.858*
		(0.374)		(0.685)	(0.405)		(0.672)	(0.431)
$s_{ir,t,h}$			0.662***	0.049	0.227***		0.030	0.238**
			(0.104)	(0.127)	(0.086)		(0.130)	(0.102)
$s_{lab,t,h}$						0.121	-0.060	0.033
						(0.124)	(0.094)	(0.061)
D^{rec}_{t-h}	0.039	0.050*	0.060	0.042*	0.090**	0.106***	0.049*	0.090**
	(0.026)	(0.028)	(0.041)	(0.025)	(0.038)	(0.038)	(0.029)	(0.036)
Constant	0.112***	0.106***	0.156***	0.101***	0.248***	0.176***	0.121**	0.234***
	(0.020)	(0.017)	(0.030)	(0.018)	(0.036)	(0.055)	(0.050)	(0.040)
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	0.570	0.633	0.394	0.632	0.809	0.138	0.627	0.800

Notes: This table displays the estimates of Eq. (3) when including euro area recessions as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.2: The relationship between forecast and assumption revisions (controlling for recessions)

	Dependent variable: $\Delta\hat{y}_{i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation								
$\Delta\widehat{oil}_{i,t,h}$	0.016***			0.015***	0.013***		0.015***	0.014***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.433***		-0.186*	-0.139		-0.162	-0.082
		(0.119)		(0.099)	(0.098)		(0.110)	(0.104)
$\Delta\widehat{ir}_{i,t,h}$			0.354***	0.188***	0.196***		0.151***	0.155***
			(0.027)	(0.029)	(0.029)		(0.034)	(0.036)
$\Delta\widehat{lab}_{i,t,h}$						0.139***	0.059***	0.042**
						(0.024)	(0.021)	(0.019)
D^{rec}_{t-h}	0.081***	0.103***	0.141***	0.099***	0.076***	-0.012	0.112***	0.072***
	(0.012)	(0.015)	(0.014)	(0.013)	(0.021)	(0.024)	(0.016)	(0.024)
Constant	-0.018***	-0.007	-0.003	-0.012***	0.181**	-0.004	-0.026***	0.022
	(0.004)	(0.006)	(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	0.282	0.024	0.081	0.293	0.393	0.030	0.328	0.424
Real GDP growth								
$\Delta\widehat{oil}_{i,t,h}$	0.004***			0.001	0.003***		0.002*	0.003***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.642***		0.313**	0.501***		0.213	0.294
		(0.142)		(0.141)	(0.146)		(0.178)	(0.180)
$\Delta\widehat{ir}_{i,t,h}$			0.498***	0.464***	0.374***		0.400***	0.352***
			(0.034)	(0.042)	(0.042)		(0.052)	(0.054)
$\Delta\widehat{lab}_{i,t,h}$						0.094***	0.024	0.004
						(0.028)	(0.033)	(0.036)
D^{rec}_{t-h}	-0.413***	-0.389***	-0.340***	-0.349***	-0.322***	-0.563***	-0.385***	-0.340***
	(0.023)	(0.022)	(0.020)	(0.022)	(0.036)	(0.035)	(0.027)	(0.044)
Constant	-0.011**	-0.012**	-0.000	-0.002	0.243***	0.019***	0.022***	0.012
	(0.006)	(0.006)	(0.005)	(0.006)	(0.081)	(0.007)	(0.007)	(0.088)
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	0.171	0.161	0.230	0.226	0.401	0.253	0.252	0.406
Unemployment rate								
$\Delta\widehat{oil}_{i,t,h}$	-0.001*			0.000	-0.000		0.000	-0.000
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		-0.153		-0.040	-0.097		0.001	-0.071
		(0.095)		(0.101)	(0.096)		(0.122)	(0.109)
$\Delta\widehat{ir}_{i,t,h}$			-0.232***	-0.251***	-0.199***		-0.261***	-0.225***
			(0.029)	(0.034)	(0.035)		(0.043)	(0.043)
$\Delta\widehat{lab}_{i,t,h}$						-0.048**	-0.001	0.009
						(0.020)	(0.019)	(0.017)
D^{rec}_{t-h}	0.389***	0.383***	0.365***	0.359***	0.352***	0.457***	0.365***	0.329***
	(0.014)	(0.015)	(0.014)	(0.015)	(0.022)	(0.018)	(0.018)	(0.026)
Constant	-0.073***	-0.075***	-0.080***	-0.078***	-0.154	-0.088***	-0.095***	-0.153***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.135)	(0.005)	(0.006)	(0.056)
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	0.253	0.248	0.276	0.286	0.359	0.295	0.315	0.372

Notes: This table displays the estimates of Eq. (6) when including euro area recessions as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.3: The relationship between forecast and assumption errors (controlling for recessions)

	Dependent variable: $e_{y,i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation								
$e_{oil,i,t,h}$	0.027***			0.029***	0.021***		0.028***	0.021***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.909***		-1.086***	-0.288***		-0.973***	-0.291***
		(0.220)		(0.162)	(0.092)		(0.200)	(0.112)
$e_{ir,i,t,h}$			0.175***	0.009	0.134***		-0.145***	0.079**
			(0.060)	(0.041)	(0.026)		(0.045)	(0.032)
$e_{lab,i,t,h}$						0.534***	0.217***	0.084***
						(0.033)	(0.021)	(0.018)
D^{rec}_{t-h}	0.087***	0.130***	0.092***	0.069***	0.321***	0.225***	0.013	0.302***
	(0.025)	(0.029)	(0.025)	(0.024)	(0.016)	(0.037)	(0.027)	(0.020)
Constant	0.009	0.022*	0.014	0.007	0.306***	-0.050***	0.026**	-0.466***
	(0.008)	(0.013)	(0.013)	(0.007)	(0.035)	(0.018)	(0.010)	(0.053)
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	0.524	0.072	0.012	0.545	0.787	0.260	0.587	0.792
Real GDP growth								
$e_{oil,i,t,h}$	-0.003***			-0.009***	-0.004***		-0.009***	-0.004***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.412***		1.299***	0.891***		1.367***	0.841***
		(0.203)		(0.177)	(0.136)		(0.216)	(0.166)
$e_{ir,i,t,h}$			1.338***	1.340***	1.103***		1.283***	1.071***
			(0.050)	(0.051)	(0.051)		(0.062)	(0.062)
$e_{lab,i,t,h}$						0.576***	0.104***	0.006
						(0.066)	(0.023)	(0.023)
D^{rec}_{t-h}	0.743***	0.740***	0.617***	0.655***	0.264***	0.878***	0.691***	0.278***
	(0.030)	(0.031)	(0.027)	(0.028)	(0.041)	(0.076)	(0.034)	(0.050)
Constant	0.035**	0.025*	-0.094***	-0.087***	0.394***	0.087***	-0.129***	0.297***
	(0.015)	(0.014)	(0.011)	(0.012)	(0.128)	(0.027)	(0.015)	(0.074)
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	0.168	0.183	0.435	0.477	0.672	0.196	0.520	0.686
Unemployment rate								
$e_{oil,i,t,h}$	0.008***			0.013***	0.008***		0.013***	0.007***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		-0.457**		-1.089***	-0.782***		-0.968***	-0.633***
		(0.205)		(0.183)	(0.147)		(0.218)	(0.172)
$e_{ir,i,t,h}$			-0.926***	-0.983***	-0.896***		-1.037***	-0.953***
			(0.063)	(0.058)	(0.048)		(0.065)	(0.062)
$e_{lab,i,t,h}$						-0.208***	-0.020	-0.002
						(0.032)	(0.020)	(0.021)
D^{rec}_{t-h}	-0.627***	-0.600***	-0.548***	-0.553***	-0.177***	-0.671***	-0.554***	-0.177***
	(0.024)	(0.023)	(0.022)	(0.022)	(0.035)	(0.034)	(0.026)	(0.044)
Constant	0.136***	0.146***	0.235***	0.223***	0.428***	0.137***	0.252***	0.181***
	(0.013)	(0.013)	(0.009)	(0.009)	(0.028)	(0.018)	(0.012)	(0.049)
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	0.201	0.151	0.335	0.430	0.613	0.200	0.465	0.639

Notes: This table displays the estimates of Eq. (8) when including euro area recessions as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.4: The relationship between forecast and assumption disagreement (controlling for realized stock market volatility)

	Dependent variable: $s_{y,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inflation							
$s_{oil,t,h}$	0.021***			0.014***	0.011***		0.016***	0.012***
	(0.002)			(0.002)	(0.002)		(0.002)	(0.003)
$s_{usd,t,h}$		2.341***		0.856**	-0.421		0.879**	-0.376
		(0.244)		(0.403)	(0.444)		(0.390)	(0.484)
$s_{ir,t,h}$			0.476***	0.031	-0.083		-0.045	-0.111
			(0.071)	(0.103)	(0.128)		(0.096)	(0.114)
$s_{lab,t,h}$						0.129	0.006	-0.054
						(0.080)	(0.026)	(0.037)
RV_{t-h}	0.001*	0.002***	0.001	0.001**	-0.001	0.005***	0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Constant	0.083***	0.076***	0.120***	0.076***	0.201***	0.092***	0.071***	0.215***
	(0.010)	(0.011)	(0.018)	(0.012)	(0.030)	(0.023)	(0.010)	(0.029)
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	0.672	0.628	0.371	0.684	0.795	0.133	0.714	0.796
	Real GDP growth							
$s_{oil,t,h}$	0.018***			0.005	0.004		0.006	0.004
	(0.003)			(0.006)	(0.004)		(0.008)	(0.005)
$s_{usd,t,h}$		2.271***		0.618	0.001		0.690	-0.007
		(0.321)		(0.799)	(0.629)		(0.897)	(0.658)
$s_{ir,t,h}$			0.644***	0.417***	0.383***		0.324***	0.402***
			(0.096)	(0.099)	(0.097)		(0.099)	(0.091)
$s_{lab,t,h}$						0.312***	0.151*	-0.012
						(0.109)	(0.089)	(0.066)
RV_{t-h}	0.004***	0.005***	0.003***	0.004***	0.002**	0.006***	0.003	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Constant	0.095***	0.082***	0.113***	0.091***	0.103**	0.042	0.038	0.106***
	(0.012)	(0.013)	(0.016)	(0.017)	(0.041)	(0.044)	(0.038)	(0.039)
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	0.358	0.394	0.427	0.450	0.666	0.247	0.481	0.659
	Unemployment rate							
$s_{oil,t,h}$	0.028***			0.010**	-0.003		0.010	-0.003
	(0.004)			(0.004)	(0.004)		(0.007)	(0.005)
$s_{usd,t,h}$		3.503***		2.353**	1.265		2.378**	1.315
		(0.406)		(0.907)	(0.934)		(0.934)	(0.993)
$s_{ir,t,h}$			0.717***	0.061	0.221*		0.054	0.227*
			(0.149)	(0.132)	(0.116)		(0.127)	(0.131)
$s_{lab,t,h}$						0.141	-0.043	0.033
						(0.122)	(0.084)	(0.076)
RV_{t-h}	0.000	0.002	0.000	0.001	0.001	0.006	0.001	0.001
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)	(0.002)
Constant	0.110***	0.091***	0.157***	0.092***	0.228***	0.131***	0.106**	0.212***
	(0.028)	(0.028)	(0.034)	(0.030)	(0.064)	(0.043)	(0.045)	(0.072)
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	0.614	0.358	0.616	0.754	0.086	0.606	0.742

Notes: This table displays the estimates of Eq. (3) when including realized stock market volatility in the euro area as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.5: The relationship between forecast and assumption revisions (controlling for realized stock market volatility)

	Dependent variable: $\Delta\hat{y}_{i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$\Delta\widehat{oil}_{i,t,h}$	0.017***			0.016***	0.012***		0.016***	0.013***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.389***		-0.193**	-0.214**		-0.172	-0.155
		(0.118)		(0.098)	(0.097)		(0.108)	(0.107)
$\Delta\widehat{ir}_{i,t,h}$			0.304***	0.165***	0.158***		0.120***	0.125***
			(0.027)	(0.029)	(0.029)		(0.035)	(0.037)
$\Delta\widehat{lab}_{i,t,h}$						0.137***	0.059***	0.047**
						(0.024)	(0.020)	(0.018)
RV_{t-h}	0.004***	-0.000	0.001	0.005***	-0.007***	-0.009***	0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	-0.043***	0.012	0.009	-0.045***	0.275***	0.087***	-0.060***	0.257***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.090)	(0.014)	(0.012)	(0.054)
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	0.275	0.006	0.049	0.283	0.396	0.050	0.313	0.424
				Real GDP growth				
$\Delta\widehat{oil}_{i,t,h}$	0.002***			-0.001	0.002***		-0.001	0.002**
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.648***		0.352**	0.576***		0.273	0.411**
		(0.142)		(0.141)	(0.143)		(0.179)	(0.180)
$\Delta\widehat{ir}_{i,t,h}$			0.571***	0.548***	0.420***		0.511***	0.417***
			(0.035)	(0.043)	(0.040)		(0.054)	(0.051)
$\Delta\widehat{lab}_{i,t,h}$						0.097***	0.021	-0.004
						(0.030)	(0.035)	(0.040)
RV_{t-h}	-0.019***	-0.019***	-0.016***	-0.016***	-0.012***	-0.034***	-0.017***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.111***	0.108***	0.101***	0.101***	0.102	0.239***	0.124***	-0.064
	(0.012)	(0.011)	(0.010)	(0.012)	(0.093)	(0.020)	(0.017)	(0.107)
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	0.065	0.071	0.159	0.151	0.375	0.137	0.148	0.371
				Unemployment rate				
$\Delta\widehat{oil}_{i,t,h}$	0.000			0.002***	0.001		0.002**	0.000
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		-0.212**		-0.104	-0.184*		-0.070	-0.176
		(0.108)		(0.112)	(0.104)		(0.135)	(0.120)
$\Delta\widehat{ir}_{i,t,h}$			-0.339***	-0.361***	-0.263***		-0.377***	-0.295***
			(0.032)	(0.038)	(0.035)		(0.047)	(0.043)
$\Delta\widehat{lab}_{i,t,h}$						-0.051**	0.005	0.017
						(0.020)	(0.020)	(0.020)
RV_{t-h}	0.012***	0.011***	0.009***	0.009***	0.009***	0.023***	0.012***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Constant	-0.126***	-0.119***	-0.109***	-0.118***	-0.305***	-0.219***	-0.152***	0.025
	(0.010)	(0.010)	(0.009)	(0.010)	(0.058)	(0.012)	(0.013)	(0.086)
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	0.037	0.036	0.088	0.099	0.294	0.109	0.124	0.309

Notes: This table displays the estimates of Eq. (6) when including realized stock market volatility in the euro area as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.6: The relationship between forecast and assumption errors (controlling for realized stock market volatility)

	Dependent variable: $e_{y,i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$e_{oil,i,t,h}$	0.027***			0.030***	0.023***		0.028***	0.023***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.854***		-1.199***	-0.458***		-1.014***	-0.444***
		(0.219)		(0.163)	(0.099)		(0.197)	(0.122)
$e_{ir,i,t,h}$			0.220***	0.053	0.026		-0.118**	-0.025
			(0.063)	(0.044)	(0.029)		(0.046)	(0.035)
$e_{lab,i,t,h}$						0.555***	0.223***	0.110***
						(0.034)	(0.021)	(0.018)
RV_{t-h}	-0.009***	-0.006***	-0.011***	-0.010***	0.008***	0.013***	-0.012***	0.006***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Constant	0.112***	0.106***	0.128***	0.117***	0.148	-0.137***	0.138***	-0.267***
	(0.013)	(0.019)	(0.020)	(0.014)	(0.170)	(0.028)	(0.019)	(0.067)
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	0.527	0.068	0.016	0.551	0.768	0.253	0.595	0.775
				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)
$e_{usd,i,t,h}$		1.360***		1.179***	0.776***		1.161***	0.720***
		(0.215)		(0.201)	(0.136)		(0.239)	(0.161)
$e_{ir,i,t,h}$			1.345***	1.348***	1.003***		1.252***	0.969***
			(0.049)	(0.052)	(0.047)		(0.062)	(0.057)
$e_{lab,i,t,h}$						0.631***	0.189***	0.024
						(0.066)	(0.028)	(0.023)
RV_{t-h}	0.042***	0.043***	0.030***	0.031***	0.012***	0.073***	0.032***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
Constant	-0.259***	-0.275***	-0.286***	-0.286***	-0.181***	-0.454***	-0.309***	0.349***
	(0.025)	(0.023)	(0.021)	(0.021)	(0.068)	(0.046)	(0.030)	(0.092)
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	0.087	0.107	0.361	0.394	0.666	0.198	0.421	0.679
				Unemployment rate				
$e_{oil,i,t,h}$	0.008***			0.013***	0.006***		0.013***	0.006***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		-0.405*		-0.959***	-0.707***		-0.793***	-0.545***
		(0.212)		(0.202)	(0.146)		(0.233)	(0.168)
$e_{ir,i,t,h}$			-0.945***	-1.003***	-0.828***		-1.018***	-0.893***
			(0.059)	(0.056)	(0.046)		(0.062)	(0.059)
$e_{lab,i,t,h}$						-0.265***	-0.089***	-0.017
						(0.033)	(0.024)	(0.021)
RV_{t-h}	-0.030***	-0.029***	-0.022***	-0.021***	-0.008***	-0.045***	-0.024***	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.329***	0.337***	0.364***	0.345***	0.544***	0.440***	0.382***	0.197***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.064)	(0.027)	(0.023)	(0.062)
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	0.098	0.059	0.243	0.335	0.610	0.157	0.375	0.634

Notes: This table displays the estimates of Eq. (8) when including realized stock market volatility in the euro area as an additional control variable. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.7: The relationship between forecast and assumption disagreement (2012–2019 subsample)

	Dependent variable: $s_{y,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$s_{oil,t,h}$	0.021***			0.019***	0.010***		0.020***	0.011***
	(0.002)			(0.002)	(0.002)		(0.002)	(0.002)
$s_{usd,t,h}$		2.210***		0.644	-0.144		0.583	-0.157
		(0.275)		(0.491)	(0.277)		(0.424)	(0.296)
$s_{ir,t,h}$			0.455***	-0.137	-0.257***		-0.117*	-0.250***
			(0.076)	(0.090)	(0.072)		(0.067)	(0.069)
$s_{lab,t,h}$						0.302***	-0.034	-0.031
						(0.085)	(0.056)	(0.050)
Constant	0.090***	0.106***	0.150***	0.086***	0.224***	0.081**	0.097***	0.233***
	(0.010)	(0.014)	(0.015)	(0.010)	(0.024)	(0.034)	(0.012)	(0.027)
No. of obs.	64	64	64	64	64	64	64	64
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.717	0.589	0.336	0.719	0.829	0.145	0.715	0.826
				Real GDP growth				
$s_{oil,t,h}$	0.020***			0.014	0.006		0.010	0.004
	(0.004)			(0.009)	(0.005)		(0.008)	(0.005)
$s_{usd,t,h}$		2.128***		-0.441	-0.467		-0.061	-0.406
		(0.377)		(1.085)	(1.025)		(0.891)	(0.937)
$s_{ir,t,h}$			0.641***	0.411***	0.334**		0.287**	0.302*
			(0.111)	(0.129)	(0.132)		(0.134)	(0.155)
$s_{lab,t,h}$						0.553***	0.213**	0.145
						(0.087)	(0.081)	(0.094)
Constant	0.112***	0.127***	0.149***	0.121***	0.145**	0.004	0.055**	0.106*
	(0.013)	(0.017)	(0.010)	(0.017)	(0.054)	(0.030)	(0.024)	(0.056)
No. of obs.	64	64	64	64	64	64	64	64
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.456	0.378	0.462	0.507	0.538	0.337	0.530	0.540
				Unemployment rate				
$s_{oil,t,h}$	0.025***			0.005	-0.002		0.005	-0.004
	(0.005)			(0.006)	(0.005)		(0.006)	(0.005)
$s_{usd,t,h}$		3.261***		2.621***	1.892**		2.592***	1.950**
		(0.487)		(0.607)	(0.915)		(0.712)	(0.874)
$s_{ir,t,h}$			0.720***	0.045	-0.039		0.054	-0.070
			(0.167)	(0.070)	(0.145)		(0.098)	(0.182)
$s_{lab,t,h}$						0.407**	-0.016	0.137
						(0.197)	(0.173)	(0.229)
Constant	0.139***	0.136***	0.196***	0.132***	0.248***	0.114	0.137**	0.212**
	(0.031)	(0.024)	(0.028)	(0.027)	(0.077)	(0.081)	(0.068)	(0.089)
No. of obs.	64	64	64	64	64	64	64	64
Time FE	no	no	no	no	yes	no	no	yes
Horizon FE	no	no	no	no	yes	no	no	yes
R^2	0.506	0.602	0.396	0.589	0.676	0.124	0.582	0.676

Notes: This table displays the estimates of Eq. (3) based on those target years for which predictions of all variables have been elicited for all forecast horizons (2012–2019). The estimation sample covers the 2011Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.8: The relationship between forecast and assumption revisions (2012–2019 subsample)

	Dependent variable: $\Delta\hat{y}_{i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation								
$\Delta\widehat{oil}_{i,t,h}$	0.014***			0.013***	0.011***		0.013***	0.011***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.225*		-0.189	-0.288**		-0.201	-0.221
		(0.136)		(0.125)	(0.137)		(0.131)	(0.144)
$\Delta\widehat{ir}_{i,t,h}$			0.172***	0.094***	0.139***		0.066*	0.116***
			(0.025)	(0.031)	(0.033)		(0.035)	(0.038)
$\Delta\widehat{lab}_{i,t,h}$						0.142***	0.089***	0.096***
						(0.032)	(0.030)	(0.025)
Constant	-0.038***	-0.049***	-0.044***	-0.034***	-0.293***	-0.051***	-0.035***	-0.719***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.020)	(0.007)	(0.007)	(0.054)
No. of obs.	1,954	1,961	2,220	1,759	1,759	1,326	1,123	1,123
N	71	73	73	69	69	53	50	50
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	0.226	0.002	0.019	0.221	0.295	0.029	0.230	0.322
Real GDP growth								
$\Delta\widehat{oil}_{i,t,h}$	0.004***			0.001	0.004***		0.001	0.003***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		0.804***		0.420**	0.345**		0.294	0.195
		(0.194)		(0.181)	(0.170)		(0.215)	(0.196)
$\Delta\widehat{ir}_{i,t,h}$			0.587***	0.529***	0.414***		0.514***	0.404***
			(0.045)	(0.055)	(0.052)		(0.063)	(0.062)
$\Delta\widehat{lab}_{i,t,h}$						0.099***	0.047	0.032
						(0.038)	(0.044)	(0.043)
Constant	-0.070***	-0.070***	-0.048***	-0.045***	-0.309***	-0.076***	-0.044***	-0.464***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.067)	(0.010)	(0.010)	(0.083)
No. of obs.	1,963	1,974	2,238	1,768	1,768	1,328	1,125	1,125
N	71	73	73	69	69	53	50	50
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	0.013	0.021	0.159	0.146	0.322	0.010	0.155	0.320
Unemployment rate								
$\Delta\widehat{oil}_{i,t,h}$	0.000			0.002***	-0.000		0.002*	-0.001
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\Delta\widehat{usd}_{i,t,h}$		-0.479***		-0.300**	-0.265*		-0.374**	-0.283*
		(0.145)		(0.143)	(0.137)		(0.157)	(0.149)
$\Delta\widehat{ir}_{i,t,h}$			-0.424***	-0.434***	-0.323***		-0.457***	-0.349***
			(0.042)	(0.049)	(0.046)		(0.056)	(0.051)
$\Delta\widehat{lab}_{i,t,h}$						-0.047	-0.012	-0.019
						(0.030)	(0.030)	(0.031)
Constant	-0.007	-0.011	-0.027***	-0.025***	-0.108*	-0.009	-0.031***	-0.007
	(0.008)	(0.008)	(0.007)	(0.008)	(0.058)	(0.010)	(0.010)	(0.038)
No. of obs.	1,868	1,869	2,133	1,684	1,684	1,314	1,119	1,119
N	67	69	71	66	66	51	47	47
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	0.008	0.087	0.099	0.286	0.002	0.129	0.305

Notes: This table displays the estimates of Eq. (6) based on those target years for which predictions of all variables have been elicited for all forecast horizons (2012–2019). The estimation sample covers the 2011Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.9: The relationship between forecast and assumption errors (2012–2019 subsample)

	Dependent variable: $e_{y,i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inflation								
$e_{oil,i,t,h}$	0.025***			0.028***	0.020***		0.026***	0.020***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.466***		-1.249***	-0.600***		-1.157***	-0.638***
		(0.247)		(0.192)	(0.117)		(0.227)	(0.143)
$e_{ir,i,t,h}$			0.009	-0.024	-0.062*		-0.169***	-0.118***
			(0.066)	(0.049)	(0.033)		(0.051)	(0.038)
$e_{lab,i,t,h}$						0.308***	0.193***	0.144***
						(0.045)	(0.035)	(0.027)
Constant	0.103***	0.211***	0.224***	0.103***	0.509***	0.175***	0.097***	0.201***
	(0.012)	(0.016)	(0.015)	(0.011)	(0.036)	(0.020)	(0.014)	(0.055)
No. of obs.	2,739	2,787	3,047	2,548	2,548	1,792	1,590	1,590
N	77	78	78	75	75	60	58	58
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	0.490	0.044	0.000	0.519	0.771	0.065	0.536	0.770
Real GDP growth								
$e_{oil,i,t,h}$	-0.004***			-0.010***	-0.005***		-0.010***	-0.004***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		1.959***		1.795***	1.167***		1.414***	0.868***
		(0.302)		(0.258)	(0.176)		(0.286)	(0.197)
$e_{ir,i,t,h}$			1.550***	1.483***	1.034***		1.404***	1.011***
			(0.054)	(0.059)	(0.055)		(0.067)	(0.065)
$e_{lab,i,t,h}$						0.479***	0.204***	0.012
						(0.057)	(0.040)	(0.030)
Constant	0.205***	0.143***	-0.065***	-0.013	-0.209	0.108***	-0.037	0.087
	(0.025)	(0.021)	(0.016)	(0.018)	(0.183)	(0.028)	(0.024)	(0.108)
No. of obs.	2,746	2,799	3,063	2,553	2,553	1,797	1,593	1,593
N	77	78	78	75	75	60	58	58
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	0.010	0.049	0.442	0.500	0.742	0.091	0.528	0.741
Unemployment rate								
$e_{oil,i,t,h}$	0.010***			0.014***	0.008***		0.015***	0.008***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$e_{usd,i,t,h}$		-0.870***		-1.330***	-0.947***		-1.100***	-0.835***
		(0.300)		(0.265)	(0.190)		(0.285)	(0.211)
$e_{ir,i,t,h}$			-1.259***	-1.240***	-0.976***		-1.186***	-0.998***
			(0.063)	(0.059)	(0.060)		(0.064)	(0.073)
$e_{lab,i,t,h}$						-0.394***	-0.205***	-0.023
						(0.058)	(0.044)	(0.035)
Constant	0.021	0.101***	0.278***	0.208***	0.039	0.148***	0.245***	0.797***
	(0.024)	(0.020)	(0.014)	(0.016)	(0.166)	(0.024)	(0.019)	(0.086)
No. of obs.	2,626	2,669	2,936	2,448	2,448	1,777	1,579	1,579
N	77	77	78	74	74	59	56	56
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	0.051	0.010	0.300	0.402	0.662	0.066	0.455	0.671

Notes: This table displays the estimates of Eq. (8) based on those target years for which predictions of all variables have been elicited for all forecast horizons (2012–2019). The estimation sample covers the 2011Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.10: The relationship between squared forecast and assumption errors

	Dependent variable: $e^2_{y,i,t,h}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$e^2_{oil,i,t,h}$	0.001***			0.001***	0.000***		0.001***	0.000***
	(0.000)			(0.000)	(0.000)		(0.000)	(0.000)
$e^2_{usd,i,t,h}$		13.383***		2.825**	1.236		3.236**	1.781*
		(2.368)		(1.183)	(0.962)		(1.355)	(1.066)
$e^2_{ir,i,t,h}$			0.256***	0.151***	-0.061*		0.102**	-0.079**
			(0.044)	(0.045)	(0.033)		(0.045)	(0.034)
$e^2_{lab,i,t,h}$						0.256***	0.072**	0.057***
						(0.096)	(0.029)	(0.022)
Constant	0.177***	0.223***	0.276***	0.156***	0.478**	0.419***	0.150***	0.479***
	(0.008)	(0.014)	(0.010)	(0.008)	(0.230)	(0.037)	(0.013)	(0.050)
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	0.368	0.131	0.025	0.391	0.633	0.058	0.392	0.627
				Real GDP growth				
$e^2_{oil,i,t,h}$	-0.000***			-0.000***	-0.000***		-0.000***	-0.000***
	(0.000)			(0.000)	(0.000)		(0.000)	(0.000)
$e^2_{usd,i,t,h}$		8.002***		5.444***	0.682		4.009**	0.250
		(2.168)		(2.031)	(1.222)		(1.957)	(1.355)
$e^2_{ir,i,t,h}$			1.892***	1.889***	1.336***		1.741***	1.233***
			(0.183)	(0.197)	(0.181)		(0.216)	(0.199)
$e^2_{lab,i,t,h}$						1.424***	0.136***	-0.035
						(0.534)	(0.047)	(0.045)
Constant	0.493***	0.422***	0.317***	0.332***	0.361	1.161***	0.338***	-0.795***
	(0.022)	(0.021)	(0.016)	(0.019)	(0.239)	(0.201)	(0.028)	(0.139)
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	0.001	0.011	0.322	0.340	0.555	0.051	0.359	0.579
				Unemployment rate				
$e^2_{oil,i,t,h}$	0.000***			0.000	-0.000***		-0.000	-0.000***
	(0.000)			(0.000)	(0.000)		(0.000)	(0.000)
$e^2_{usd,i,t,h}$		8.082***		3.474**	0.435		2.601	-0.066
		(1.929)		(1.680)	(1.106)		(1.700)	(1.196)
$e^2_{ir,i,t,h}$			1.415***	1.374***	0.811***		1.286***	0.759***
			(0.142)	(0.150)	(0.118)		(0.166)	(0.133)
$e^2_{lab,i,t,h}$						0.222***	0.050*	0.027
						(0.084)	(0.028)	(0.025)
Constant	0.316***	0.285***	0.224***	0.202***	0.298***	0.453***	0.218***	0.431***
	(0.017)	(0.016)	(0.011)	(0.014)	(0.058)	(0.035)	(0.020)	(0.089)
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	0.005	0.025	0.371	0.388	0.604	0.033	0.400	0.617

Notes: This table displays the estimates of Eq. (8) when we replace forecast and assumption errors with squared forecast and assumption errors. The estimation sample covers the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

Table A.11: The relationship between absolute forecast and assumption errors

	Dependent variable: $\lvert e_{y,i,t,h}\rvert$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Inflation				
$\lvert e_{oil,i,t,h}\rvert$	0.022***			0.020***	0.012***		0.020***	0.012***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\lvert e_{usd,i,t,h}\rvert$		3.237***		0.485***	0.078		0.596***	0.164
		(0.162)		(0.140)	(0.115)		(0.173)	(0.144)
$\lvert e_{ir,i,t,h}\rvert$			0.545***	0.321***	-0.002		0.274***	-0.008
			(0.041)	(0.039)	(0.033)		(0.046)	(0.042)
$\lvert e_{lab,i,t,h}\rvert$						0.405***	0.090***	0.069***
						(0.043)	(0.023)	(0.018)
Constant	0.182***	0.225***	0.312***	0.137***	0.492***	0.315***	0.104***	0.373***
	(0.006)	(0.009)	(0.007)	(0.007)	(0.038)	(0.019)	(0.013)	(0.035)
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	0.437	0.210	0.124	0.492	0.701	0.108	0.497	0.702
				Real GDP growth				
$\lvert e_{oil,i,t,h}\rvert$	-0.000			-0.009***	-0.009***		-0.010***	-0.009***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\lvert e_{usd,i,t,h}\rvert$		1.924***		1.603***	0.144		1.357***	0.037
		(0.223)		(0.200)	(0.137)		(0.236)	(0.160)
$\lvert e_{ir,i,t,h}\rvert$			1.144***	1.152***	0.885***		1.109***	0.865***
			(0.047)	(0.049)	(0.047)		(0.056)	(0.054)
$\lvert e_{lab,i,t,h}\rvert$						0.840***	0.099***	-0.021
						(0.104)	(0.029)	(0.026)
Constant	0.471***	0.365***	0.307***	0.312***	0.726***	0.367***	0.308***	0.150*
	(0.011)	(0.011)	(0.008)	(0.009)	(0.113)	(0.038)	(0.017)	(0.085)
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	0.000	0.043	0.316	0.363	0.629	0.108	0.376	0.643
				Unemployment rate				
$\lvert e_{oil,i,t,h}\rvert$	0.008***			0.002**	-0.006***		0.001	-0.006***
	(0.001)			(0.001)	(0.001)		(0.001)	(0.001)
$\lvert e_{usd,i,t,h}\rvert$		2.366***		1.001***	0.008		0.946***	-0.083
		(0.191)		(0.190)	(0.144)		(0.239)	(0.178)
$\lvert e_{ir,i,t,h}\rvert$			1.008***	0.931***	0.461***		0.934***	0.481***
			(0.041)	(0.047)	(0.042)		(0.055)	(0.051)
$\lvert e_{lab,i,t,h}\rvert$						0.321***	0.035*	0.014
						(0.039)	(0.021)	(0.019)
Constant	0.325***	0.280***	0.265***	0.205***	0.510***	0.367***	0.217***	0.582***
	(0.010)	(0.010)	(0.007)	(0.008)	(0.045)	(0.017)	(0.013)	(0.057)
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	0.050	0.097	0.359	0.391	0.638	0.067	0.422	0.663

Notes: This table displays the estimates of Eq. (8) when we replace forecast and assumption errors with absolute forecast and assumption errors. The estimation sample includes the 2002Q1–2019Q4 surveys and forecast horizons $h \in \{1, 2, \ldots, 8\}$. Coefficients are estimated via 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.

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