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Heterogeneity of Beliefs and Information Rigidity in the Crude Oil Market: Evidence from Survey Data*

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Abstract

This paper assesses information contained in the micro dataset of the ECB Survey of Professional Forecasters regarding quarterly Brent crude oil price forecasts. We examine the expectations building mechanism by referring to the processing of information and confirm the presence of information rigidity within the crude oil market. However, our findings also show that simple models of imperfect information considered in the literature are insufficient to explain the behavior of professional forecasters. We provide additional stylized facts which are helpful for designing more elaborate imperfect information models.

Keywords: Crude oil, Disagreement, Expectations, Heterogeneity, Information rigidity, Survey data
JEL: D83, D84, E44

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1 Introduction

A large strand of the literature has focused on the explanation of crude oil price fluctuations, which have clearly intensified since the turn of the millennium. In this context, an important contribution has been provided by Kilian (2009), who dispensed the assumption of exogenous oil price changes due to a reverse causality from macroeconomic factors to crude oil prices. Instead he proposes an identification approach of three different types of oil price shock (i.e., supply shocks, global demand shocks and crude oil market specific demand shocks) based on a structural vector autoregression (SVAR).[1] However, large swings in crude oil prices such as the substantial drop in 2014 cannot be fully explained by these types of model as these are also driven by expectations regarding future developments in the crude oil market. This complicates the identification of structural shocks (Kilian and Murphy, 2014; Känzig, 2021). Therefore, the role of a forward-looking component in the crude oil price has been explicitly tackled by Kilian and Murphy (2014) and Kilian and Lee (2014) by including above-ground crude oil inventories into the SVAR to also model storage demand shocks while referring to speculative trading. Most recently, Känzig (2021) proposed an identification strategy for shocks to oil supply expectations exploiting variation in high-frequency oil futures prices around the Organization of the Petroleum Exporting Countries (OPEC) production announcements. The literature also emphasizes the role of informational frictions due to imperfect information and heterogeneity of beliefs when modeling fluctuations in commodity markets (Singleton, 2014; Sockin and Xiong, 2015; Gambetti and Moretti, 2017).

This highlights the relevance of imperfect information models for expectations building in the crude oil market and therefore also its importance to better understand the dynamics of the crude oil market. The lack of studies on the presence of information frictions in the crude oil market provides the motivation for the present study to examine expectations-formation and information processing relying on a micro level survey dataset. Knowledge about the way professionals process information and build their expectations is crucial for designing models to study news shocks or speculative activity. Therefore, we directly add to the literature explaining deviation from the full information rational expectations (FIRE) hypothesis in macroeconomic forecasts

[1] Several other identification approaches have been proposed in the literature in recent years (Kilian and Murphy, 2012; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Antolín-Díaz and Rubio-Ramírez, 2018; Baumeister and Hamilton, 2019; Caldara *et al.*, 2019).

by imperfect information models (see e.g., Andrade and Le Bihan, 2013; Coibion and Gorodnichenko, 2015; Bordalo *et al.*, 2020). To the best of our knowledge, this is the first study which analyzes information processing of crude oil price forecasters. The availability of information on an intraday basis that can be accessed by professional forecasters in combination with higher volatility of crude oil prices compared with macro indicators suggests that forecasters inattention might be less likely. Hence, it is interesting to examine whether information rigidity is still present in this context and if so, to also assess whether this information rigidity can be explained by the imperfect information models offered by the literature (see e.g. Mankiw and Reis, 2002; Woodford, 2003; Sims, 2003). The two most prominent models allowing for information frictions are sticky- and noisy-information models, which both result in predictability of forecast errors. For the former this is due to lags in updating the forecasters' information sets and for the latter this is due to different information sets across forecasters.

To study the presence of information rigidity and its source, we rely on data stemming from the ECB Survey of Professional Forecasters (SPF), in which participants are asked to provide Brent crude oil price predictions for the next four quarters-ahead since 2002. This dataset offers variation of crude oil price forecasts across individual institutions, over time and across four forecast horizons. Hence, we are able to compute ex post forecast errors and assess their predictability by ex ante forecast revisions relying on the regression approach proposed by Coibion and Gorodnichenko (2015), both on an aggregate level as well as on an individual level. The cross-sectional variation at each point in time also enables us to analyze whether forecasters' disagreement varies over time due to different types of shock. The sticky-information model predicts that shocks increase forecasters' disagreement because they drive a greater wedge between forecasters who update their information set and forecasters who do not. In this context, shocks are proxied by general or crude oil specific uncertainty and by OPEC announcements regarding decisions on future oil production capacity. In addition, we construct a measure of forecasters' degree of attention, which refers to the updating of the information set, and we analyze its association with forecasters' disagreement. This is also crucial as the available imperfect information models offer different implications regarding this association. While the noisy-information model predicts a positive relationship, the sticky-information model implies a negative relationship.

More generally, the present paper also relates to the modeling of oil price expectations. Market expectations for the price of crude oil may be either estimated from futures prices (Baumeister and Kilian, 2016) or proxied by a survey of professional forecasters (Reitz *et al.*, 2012; Leppin, 2016). The present study follows the second approach as we aim to examine the expectations formation and information processing of forecasters. Studies assessing survey-based crude oil price forecasts relying on different data sources include Prat and Uctum (2011), Reitz *et al.* (2012), Alquist *et al.* (2013), Leppin (2016), Kunze *et al.* (2018) and Moghaddam *et al.* (2019). Overall, these studies show that the concepts of rational expectations and unbiasedness are rejected for survey forecasts and therefore also highlight the need to study the expectations formation mechanism of professionals involved in the crude oil market.

The results of the present study show that mean forecast errors are predictable by both past forecast errors and ex ante mean forecast revisions. This provides evidence in favor of the presence of information rigidity in line with both imperfect information models and generally confirms the results of previous studies for macroeconomic forecasts (Coibion and Gorodnichenko, 2015; Bordalo *et al.*, 2020). However, the degree of information rigidity increases with the forecast horizon, which contradicts this view. This indicates that forecasters tend to pay relatively more attention to the most recent forecast horizon potentially due to higher information processing costs for longer forecast horizons. Forecasters' disagreement varies over time, increases with the horizon and depends on shocks hitting the economy. General shocks increase the disagreement in line with the sticky-information model. However, OPEC announcements regarding crude oil production expansions or cuts decrease the disagreement among forecasters. This might be explained by the fact that this information is publicly available and is neither costly to access nor difficult to interpret. The degree of forecasters' attention also varies over time, decreases with the forecast horizon but also shows periods with full attention. Contrary to the sticky-information model but in line with the noisy-information model, forecasters' disagreement increases with their attention. In addition, our findings contradict predictions of the sticky-information model as disagreement among professional forecasters does not solely stem from differences in forecasts between the groups of revisors and non-revisors but also stems from differences within these groups. Overall, we provide important empirical stylized facts for the expectation formation mechanism in the crude oil market and show that both prominent imperfect information models fail to explain the observed information rigidity adequately. This highlights the necessity to design more elaborate information models.

The remainder of this paper is organized as follows. The next section briefly reviews the theoretical foundation of the two imperfect information models, which the study builds on. Section 3 describes our dataset and Section 4 presents and discusses our empirical findings. Finally, Section 5 concludes.

2 Imperfect Information Models

The expectations building mechanism of individuals is an important building block for many economic models discussed in the existing literature. One strand of the literature is devoted to the explanation of deviations from full information rational expectations (FIRE) providing models that account for information frictions, which can be rationalized by costly access to new information and limited capacities of information processing. Two prominent examples are the sticky-information model suggested by Mankiw and Reis (2002) and the noisy-information model proposed by Woodford (2003) and Sims (2003).[2]

The sticky-information model is basically built under the premise that agents respond to new information with a time lag. More precisely, it assumes that forecasters either do not update their information set due to the associated costs, and hence do not revise their forecasts, or update their forecasts in line with FIRE. As illustrated by Coibion and Gorodnichenko (2015), this model implies predictability of ex post forecast errors by ex ante forecast revisions, which can only be observed on an aggregate level (i.e., when averaging forecasts across individuals) since on an individual level forecasters either do not revise their forecasts (inattentive agents) or update their forecasts in line with FIRE. In both cases forecast errors are uncorrelated with their ex ante forecast revisions. However, on an aggregate level forecasters update their information set and thus revise their forecasts with probability $1-\gamma$, where γ is interpreted as the degree of information rigidity. Therefore, the mean forecast in t across forecasters is a weighted average of the mean forecast in $t-1$ and current rational expectations. This results in a relationship between ex post mean forecast errors and ex ante mean forecast revisions. Therefore, the sticky-information model allows for the slow updating of information by some forecasters when $\gamma > 0$ and also includes the FIRE hypothesis as a special case for $\gamma = 0$.[3]

[2]See Appendix A.1 for technical details.

[3]Bordalo *et al.* (2020) clarifies that $\gamma > 0$ implies an under-reaction of the consensus forecast relative to FIRE, while $\gamma < 0$ would indicate an overreaction. A negative relationship between ex post forecast errors and ex ante forecast revisions might also arise from heterogeneity in the degree of loss-aversion

The second type of model considered is the noisy-information model, which basically implies that forecasters continuously update their information set, but never fully observe the true state of the variable. The latter is assumed to follow an AR(1) process while the individual forecaster i at period t solely observes a noisy signal, which consists of the true value of the variable and an individual error term. Forecasters individually use a weighted average of the current period's noisy signal and their previous period's forecast as their current forecast, where G is the weight they place on the current signal. Coibion and Gorodnichenko (2015) show that noisy information averaged across forecasters basically results in the same relationship between ex post forecast errors and ex ante forecast revisions as for sticky information. Noisy information allows for information rigidity when $G < 1$ and also has the FIRE hypothesis as a special case for $G = 1$. Therefore, $1 - G$ is now interpreted as the degree of information rigidity. The main difference between the two types of model is in the way information arrives. In the noisy-information model agents solely observe a noisy signal about the variable of interest, while in the case of the sticky-information model agents receive perfect information with probability $1 - \gamma$. In the former case forecasters gradually adjust their beliefs in reaction to new information since they do not know whether a shock reflects an innovation to the variable of interest or just noise.

Table 1 summarizes some of the main properties of the two types of imperfect information model, which will be used to check whether one of the two might be able to explain empirical patterns observed within the data. First of all, as already discussed, both models are able to explain predictability of ex post forecast errors by ex ante forecast revisions, which should not exist in the presence of FIRE. Therefore, the first step is to check whether or not a deviation from the FIRE hypothesis can be observed. If so, the next step would be to distinguish between the two types of model, which can be done by referring to the other properties. Time variation and shock dependence of the disagreement across forecasters can solely be explained by the sticky-information model, while disagreement among forecasters who update their information set can only be explained by the noisy-information model. When information is sticky, disagreement among forecasters solely arises from the fact that some forecasters update their information set but others do not. However, the updaters have the same information set, in contrast to the case of noisy information. In this case, disagreement among forecasters arises from different information sets. Finally, the association between forecasters'

(Capistrán and Timmermann, 2009; Coibion and Gorodnichenko, 2015).

disagreement and forecasters' degree of attention should be positive if information is noisy and negative if it is sticky. When information is sticky, there is no disagreement between the forecasters who update. Therefore, if the degree of attention increases, which means that more forecasters update their information set, disagreement should decrease. In contrast, the noisy-information model predicts a positive relationship between forecasters' disagreement and the degree of forecasters' attention due to the fact that disagreement arises from different information sets across forecasters due to different perceptions of reality. In the following we will go through empirical patterns observed in the data referring to all these properties. More precisely, Section 4.1 examines the first property stated in Table 1, Section 4.2 the second and Section 4.3 the remaining two.

*** Insert Table 1 about here ***

3 Data

Our empirical analysis relies on quarterly Brent crude oil price forecasts (denominated in USD per barrel) made by professional forecasters over the period from 2002Q1 to 2020Q1 for h-quarters-ahead with $h = 1, 2, 3, 4$. The data was taken from the ECB Survey of Professional Forecasters (SPF), which started in 1999 to collect forecasts for inflation rates, real GDP growth and unemployment and which was extended in 2002Q1 to also include forecasts for the Brent crude oil price as part of the assumptions made by forecasters for inflation forecasts.[4] This means that at the beginning of each quarter all participants of the survey are asked to provide their forecasts for the average Brent crude oil price for four consecutive quarters starting with the quarter when the survey is conducted.[5] The exact dates at which the survey was conducted are published by the

[4]This dataset has often been used in the literature to evaluate forecasts and/or disagreement among forecasters regarding inflation, GDP growth and unemployment (see e.g., Andrade and Le Bihan, 2013; Dovern, 2015; Abel *et al.*, 2016; Glas, 2020) and regarding the Brent crude oil price (see Reitz *et al.*, 2012; Atalla *et al.*, 2016; Leppin, 2016). The benefit of this survey dataset compared with the often considered dataset provided by Consensus Economics is that the data of the ECB SPF is freely available on the website of the ECB and therefore facilitates replication. The most popular forecast survey dataset is the one provided by the Federal Reserve Bank of Philadelphia. However, it does not include crude oil price forecasts.

[5]Between 2002Q1 and 2010Q1 in each ECB SPF round participants were asked to provide forecasts for five consecutive quarters. However, since 2010Q2 5-quarters-ahead forecasts have not been provided. Therefore, the present study focuses on forecasts with horizons up to $h = 4$.

ECB on their website. A clear benefit of this survey is that professional forecasters can be considered as informed economic agents and their expectations provide a conservative benchmark for analyzing potential deviations from FIRE (Coibion and Gorodnichenko, 2015).[6] In total, 103 different institutions, which mostly recruit from banks and research institutes across the Euro Area (see Appendix A.2 for details), revealed their Brent crude oil price forecasts within this survey over the sample period. The number of participating forecasters varies over time, as is illustrated in Figure A.1 in the Appendix and ranges between 33 and 57 within the sample period.

Figure 1 visualizes individual quarterly Brent crude oil price point forecasts (given by black points) together with the corresponding mean forecasts across all individuals (shown by the red line) for the period from 2002Q1 to 2020Q1 and for the four forecast horizons h. The points around the red line illustrate the disagreement across forecasters regarding the future development of the Brent crude oil price and show less dispersion in the early 2000s compared with the following years, which were characterized by large swings in the crude oil price. To compute ex post forecast errors, we also accessed daily spot prices for the corresponding sample period from the US Energy Information Administration (EIA) retrieved from Federal Reserve Economic Data (FRED) and constructed a quarterly series of average Brent crude oil spot prices using the simple arithmetic mean since the participants of the survey are asked to provide their forecasts for quarterly averages. See Appendix A.3 for an illustration of mean forecasts in comparison with realized values and their descriptive statistics.

*** Insert Figure 1 about here ***

4 Empirical Analysis

4.1 Information Rigidity

As a next step, we use the individual forecasts available in the survey to compute ex post forecast errors as $e_{i,t,t+h} = y_{t+h} - f_{i,t}(y_{t+h})$, where y_{t+h} denotes the quarterly average of realized Brent crude oil prices in $t+h$ and $f_{i,t}(y_{t+h})$ represents its forecast

[6] It can be argued that professional forecasters might have lower costs to access new information and higher information processing capacities compared with households. However, it has also been shown that the expectations of professional forecasters influence the beliefs and decisions of households (Carroll, 2003).

made by forecaster i at the beginning of the quarter in t. Appendix A.4 reports the descriptive statistics and diagnostic tests for Brent crude oil price ex post mean forecast errors and documents the predictability of forecast errors by their own past, which can be explained by information frictions.[7] To further explore the predictability of forecast errors with respect to the information processing of professional forecasters, we also compute ex ante forecast revisions made by forecaster i as $f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h})$. See Figure A.3 in Appendix A.5 for a detailed description.

To make inference on the information processing of professional forecasters, we rely on the expectations formation process test regressions proposed by Coibion and Gorodnichenko (2015) and therefore we regress Brent crude oil price ex post mean forecast errors across individuals on the corresponding ex ante mean forecast revisions for the forecast horizons of $h = 1, 2, 3$:

$$y_{t+h} - \overline{f}_t(y_{t+h}) = \beta_0 + \beta_1[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{t,t+h}. \tag{1}$$

$\beta_1 > 0$ indicates the presence of information rigidity. OLS estimation results are provided in Panel (a) of Table 2. The estimate for β_1 is significantly positive for each forecast horizon at the 1% level, which basically conforms with the findings presented by Coibion and Gorodnichenko (2015) for inflation forecasts.[8] Therefore, information frictions are statistically significant and the rejection of the null of FIRE goes in the direction predicted by information models with frictions. In contrast to the findings provided by Coibion and Gorodnichenko (2015), who show that the degree of information rigidity is invariant to the forecast horizon h according to both imperfect information models, β_1 estimates increase with h. This result points to a difference of information processing for different variables observed at different frequencies and can be rationalized by a tendency of agents to pay more attention to the most recent forecast horizon compared with the others since the processing of information is costly and requires capacity. While crude oil prices can be monitored at an intraday frequency before forming expectations, inflation can only be observed once per month. However, although information might be processed faster for crude oil prices compared with macroeconomic

[7]It should also be noted that the persistence in forecast errors might also arise from serial correlation in random disturbances resulting in periods of under- or over-prediction, even for rational forecasts (Kilian and Hicks, 2013). Therefore, the presence of information rigidity is also studied in the following by predictive regressions from forecast errors on forecast revisions as well as from forecast revisions on previous periods' deviations from the consensus.

[8]In their paper they also examine information rigidity for forecasts of other macroeconomic variables such as the growth of GDP or industrial production.

indicators, we still provide evidence in favor of information rigidity in line with both imperfect information models. Both models also predict $\beta_0 = 0$ and this null cannot be rejected in all cases. Regressions excluding the constant provide nearly the same estimates for β_1 but are not shown to save space.

*** Insert Table 2 about here ***

The degree of information rigidity in the context of sticky-information discussed in Section 2 is given by $\hat{\gamma} = \hat{\beta}_1/(1+\hat{\beta}_1) = 0.1335$ for $h = 1$ and is therefore lower compared with the value of 0.54 found by Coibion and Gorodnichenko (2015) for quarterly inflation forecasts with $h = 3$. This value implies that agents update their information sets much more quickly. According to our findings, agents update their information set on average every three to four months for $h = 1$ $(1/(1 - 0.1752) = 1.1541)$. For $h = 2$ and $h = 3$ the degree of information rigidity $\hat{\gamma}$ is much higher and thus indicates a substantially slower updating, which lies around the estimate of Coibion and Gorodnichenko (2015) for inflation. Noisy-information models imply that agents put a weight of $G = 1/(1+\beta_1)$ on new information and a weight of $1 - G$ on their previous forecasts. Therefore, for $h = 1$, agents put a weight of 0.8665 on new information; a large share compared with inflation forecasters. This might imply that agents see new information as more relevant for financial market forecasts compared with macroeconomic forecasts. For longer forecast horizons the weight on new information is considerably lower and clearly below 0.5.

Table 2 also reports the results for two robustness checks: Panel (b) uses the regression model shown in Eq. (1) but also accounts for the observed change in the price of Brent crude oil, since Coibion and Gorodnichenko (2015) also show that heterogeneity in signal-noise ratios across individuals results in an additional predictability stemming from lags of the variable being forecasted, and Panel (c) uses the regression model shown in Eq. (1) while replacing the quarterly averages of realized Brent crude oil prices y_{t+h} with the corresponding end-of-quarter values. When referring to the middle panel of Table 2, the predictability of ex ante forecast revisions stays significantly positive at the 5% level, or at least at the 10% level, also after controlling for the observed change in the price of Brent crude oil for $h = 1$ and $h = 2$. This also continues to hold (even more clearly) when allowing for past forecast errors instead of past actual changes (results are not shown). Finally, the bottom part of Table 2 clearly confirms the findings reported in Panel (a).

As outlined in Section 2, the sticky-information model implies predictability of ex ante forecast revisions for ex post forecast errors, but solely on an aggregate level. Therefore, according to the theory this predictability should not be observed for individual forecasts. Our micro dataset enables us to also test this theoretical implication empirically. Therefore, we go one step further and also regress individual ex post forecast errors on their individual ex ante forecast revisions in line with Bordalo *et al.* (2020)

$$y_{t+h} - f_{i,t}(y_{t+h}) = \beta_{i,0} + \beta_{i,1}[f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h})] + \nu_{i,t,t+h}. \tag{2}$$

Our dataset includes 103 individual forecasters, which is reduced to 90 forecasters for $h = 1$ (89 for $h = 2$ and 86 for $h = 3$) due to the exclusion of forecasters that rarely participated in the survey resulting in only a few time series observations. Estimating Eq. (2) with OLS for all remaining forecasters results in the rejection of the FIRE hypothesis $\beta_{i,1} = 0$ at the 5% level in 16.67% of cases for $h = 1$, 12.22% for $h = 2$ and 8.14% for $h = 3$. The low number of rejections is roughly in line with FIRE, as especially for $h = 3$ the rejection rate is only slightly above the chosen significance level. The highest share of rejections is observed for $h = 1$ and this seems to contradict the theory. The estimated coefficients are illustrated in Figure 2, which highlights rejections of the FIRE hypothesis in red and which shows that estimated coefficients are equally distributed around zero. To ensure that the forecasters for whom we observe rejections do not drive the overall result on the aggregate level, we also re-run the estimation of Eq. (1) by excluding 'irrational' forecasters.[9] The result clearly confirms the robustness of the finding reported in Table 2 and gives a β_1 coefficient of 0.1999 with a standard error of 0.0986, which implies significance at the 5% level (p-value = 0.0464). This shows that although all individual forecasters might act in line with the FIRE hypothesis, we still observe information rigidities at the aggregated level. Therefore, this finding strongly supports the argument provided by Coibion and Gorodnichenko (2015) that predictability can arise from aggregation.

[9]The term 'irrational' is set in quotation marks to make clear that it does not necessarily imply that these forecasters are actually irrational but just do not act in line with FIRE. Bordalo *et al.* (2020) also shows that individual forecasters often overreact to their noisy signals and therefore overestimate y_{t+h}, which results in a negative $\beta_{i,0}$ coefficient. We also observe significant deviation of FIRE into the negative territory in Figure 2.

*** Insert Figure 2 about here ***

A further potential explanation for the finding of this predictability on the aggregate level might be the tendency of forecasters to herd. Therefore, forecasters might revise their forecasts due to the previous period's deviations of their own forecasts from the consensus of forecasters, which can be observed by the forecasters as the data is publicly available. To test this hypothesis, we regress the individual forecast revision on the difference between the previous period's individual forecast and the previous period's mean forecast across forecasters following Fuhrer (2018). The estimation results using a pooled and a fixed effects model are reported in Table 3. These show that forecasters seem to inefficiently revise their forecasts due to the previous period's consensus forecast as the corresponding coefficient is significantly different from zero for each horizon, no matter if we rely on a pooled model or on a fixed effects model. The negative coefficient indicates some kind of correction towards the consensus forecast and is therefore in line with the herding behavior hypothesis. This can also be seen as further evidence for the presence of information rigidity as it shows that forecasters revise their forecasts due to an older information set, which was already available in $t-1$.

*** Insert Table 3 about here ***

4.2 Disagreement among Forecasters

As outlined in Section 2 both models allowing for information frictions also offer implications for the presence of disagreement among forecasters. The sticky-information model explicitly promotes disagreement among forecasters since at each point in time one part of the forecasters does not update their information set and the other part acts in line with FIRE. Therefore, when the economy is hit by a relatively large shock, we would expect the difference in expectations between forecasters to be relatively large. This implies that forecasters' disagreement should vary over time and should react to shocks to the economy. In contrast, the noisy-information model also allows for disagreement among forecasters since each forecaster has a different perception of reality but these different perceptions are randomly assigned and do not depend on shocks. Therefore, forecasters' disagreement should be constant over time (Coibion and Gorodnichenko, 2012).[10]

To examine the presence of disagreement among professional forecasters, we compute the cross-sectional standard deviation across forecasters and the corresponding inter-quartile range as two potential measures of quarterly disagreement among Brent crude oil price forecasters.[11] Both time series are plotted in Figure 3 over the sample period for all four forecast horizons together with the actual quarterly volatility of daily prices of Brent crude oil measured by the standard deviation within a quarter. The plots display that the disagreement among professional forecasters strongly varies over time and roughly shows a similar pattern as the actual volatility of daily prices. The strongest spike is observed at the end of 2008 as the Brent crude oil price was at its historical peak. The time varying pattern of forecasters' disagreement and its correlation to volatility of realized daily prices both indicate its shock dependence. This suggests that the information processing of forecasters is in line with the sticky-information model but clearly contradicts the noisy-information model. An intuitive pattern that emerges for both disagreement measures is that disagreement increases with the horizon.[12]

*** Insert Figure 3 about here ***

The fluctuations observed in Figure 3 indicate a shock dependence of forecasters' disagreement, which is examined more in-depth by regressing the disagreement measures on lags of different rough proxies of shocks hitting the economy. In doing so, we first rely on the ex post uncertainty regarding Brent crude oil price forecasts measured by absolute errors of mean forecasts across forecasters. This measure mimics shocks hitting the price of crude oil between t and $t + h$.[13] To empirically verify the shock dependence hypothesis, we regress forecasters' disagreement over each horizon h on

[10]However, time varying forecasters' disagreement can also arise from more sophisticated versions of the noisy-information model as outlined by Andrade and Le Bihan (2013).

[11]The inter-quartile range is defined as the difference between the 0.75- and the 0.25-quantile of forecasts across forecasters at each point in time t and is therefore not sensitive to outliers (i.e., extreme forecasts made by just a few forecasters).

[12]This indicates an upward sloping term structure of disagreement, which has also been observed by Lahiri and Sheng (2010) as well as Patton and Timmermann (2010) for inflation and GDP growth forecasts, by Andrade *et al.* (2016) for federal funds rate forecasts and by Ter Ellen *et al.* (2019) for exchange rate forecasts.

[13]Basically, this concept of uncertainty goes back to Jurado *et al.* (2015) and follows the idea that uncertainty regarding any economic variable is not expressed by the realized variability of this variable but the variability of its unpredictable component. However, before computing the conditional volatility of the unpredictable component across forecasters, we first of all correct the forecast errors

lagged forecast uncertainty as a measure of the amplitude of past shocks hitting the economy (Andrade and Le Bihan, 2013). In addition, we include lags of other more general uncertainty measures shown in Figure A.4, a proxy for ECB (unconventional) monetary policy suggested by Hachula *et al.* (2019)[14], the crude oil supply shock series computed by Baumeister and Hamilton (2019) and global economic activity measured by the Kilian (2009, 2019) index as controls. The corresponding findings are reported in Table 4 and clearly show that lagged uncertainty related to the crude oil price significantly increases forecasters' disagreement. This implies that shocks hitting the economy increase disagreement among forecasters in line with the sticky-information model since a large shock hitting the economy in combination with the inattention of some forecasters implied by the model produces a greater dispersion among forecasters. This finding generally confirms results provided by Andrade and Le Bihan (2013) for inflation, unemployment rate and real GDP growth forecasts but does not concur with the results found by Coibion and Gorodnichenko (2012), who are not able to find significant effects of shocks on the dispersion of inflation forecasts. Therefore, this finding strongly contradicts the noisy-information model, which predicts disagreement to be constant over time and independent of shocks.

*** Insert Table 4 about here ***

As another source of shocks, we examine how forecasters' disagreement is affected by OPEC announcements regarding future production decisions and crude oil futures price changes around OPEC announcements. The latter directly follows the idea introduced by Känzig (2021).[15] More precisely, we rely on the production quota decisions of the last OPEC meeting prior to the deadline, at which the participants had to send their forecasts to the ECB, but after the deadline of the last quarter's forecast. Information

made by professionals for potential individual forecast biases. In doing so, we rely on the structural model for forecast errors proposed by Davies and Lahiri (1995). See Appendix A.6 for details. Our measure is also closely related to the predictability measure proposed by Diebold and Kilian (2001). Figure A.4 compares our measure of Brent crude oil price ex post forecast uncertainty for $h = 1$ and $h = 4$ with other more general uncertainty proxies available in the literature.

[14] We account for monetary policy of the ECB since the forecasters participating in the survey are all from institutions within the Euro Area. For methodological details we refer to Hachula *et al.* (2019).

[15] His approach is rooted in the idea that OPEC announcements may affect crude oil price expectations and that this effect is measurable under weak assumptions such as a constant risk premium. In addition, Kilian (2008a,b) shows that the variation in production of OPEC countries during major events such as wars is one source of exogenous oil supply shocks.

on OPEC meetings was taken directly from the OPEC press releases published on their website (`https://www.opec.org/`) and was matched with the exact dates on which the ECB SPF was conducted. Similar to Spencer and Bredin (2019) OPEC decisions are classified as follows: 'agreement to decrease production' (CUT), 'agreement to increase production' (INC), 'agreement to maintain production' (ATM) and 'failure to agree production intentions' (FTA).[16] In addition, we include a proxy of oil supply surprises provided by Känzig (2021), which basically measures how daily crude oil futures prices change within a sufficiently tight window around OPEC announcements to isolate the impact of OPEC decisions. This accounts for the fact that the latter cannot be considered exogenous but also depend on the state of the global economy (Barsky and Kilian, 2004; Känzig, 2021). We use a quarterly surprise series by aggregating all daily surprises for the corresponding quarter. Then we regress both measures of forecasters' disagreement on four binary variables representing the different types of OPEC decision and the changes of crude oil futures prices around OPEC announcements.

Regression results for all four forecast horizons are reported in Table 5 and basically show that announcements of a change in the production quotas (i.e., an increase or a decrease in production) significantly decrease the disagreement among professional forecasters. More precisely, the decision to decrease production (CUT) significantly reduces disagreement, at least at the 10% level, in nearly all cases. This decision also impacts the term structure of disagreement since the reduction in disagreement becomes stronger when increasing the forecast horizon h. For example, for $h = 1$ the cross-sectional standard deviation across forecasts is reduced by 1.19 USD per barrel, while it is lowered by 2.18 USD per barrel for $h = 4$. Similarly, the announcement to increase production (INC) also significantly decreases disagreement among forecasters, at least at the 10% level (expect for $h = 2$ in case of the IQR). In contrast, the effect of the other two decisions (ATM and FTA), which do not imply any change of the production quotas are not statistically significant. The proxy of oil supply surprises

[16] This approach gives very rough proxies of oil shocks that might relate to expectations with regard to supply, demand or precautionary demand based on news on future oil production that is publicly available. This is beneficial in the context of studying information processing, although OPEC members may not always comply with the agreed quotas. It is worth noting that it is not always straightforward to extract the direction of future OPEC oil production from OPEC statements. Therefore, as a robustness check we have also used a broader but more straightforward classification by aggregating all three categories, where an agreement has been reached (i.e., CUT, INC and ATM). This robustness check verifies our result discussed below that reaching an agreement on future oil production significantly decreases disagreement among forecasters, at least at the 10% level.

provided by Känzig (2021) is also significantly negative in nearly all cases. Overall, the findings show that forecasters' disagreement significantly depends on shocks, in line with the sticky-information model. However, OPEC announcements reduce disagreement in contrast to the prediction of the sticky-information model. This might be explained by the fact that OPEC decisions are easier to foresee by professionals than shocks in general based on publicly available information, which is neither costly to access nor difficult to interpret. Therefore, in these periods relatively more forecasters tend to update their information sets according to FIRE and hence disagreement among them is reduced.[17]

*** Insert Table 5 about here ***

4.3 Forecasters' Inattentiveness

To also examine the implication of the sticky-information model that disagreement arises from the inattention of some forecasters, we also exploit the cross-sectional dimension of our dataset and compute a measure of attentiveness of professional forecasters following Andrade and Le Bihan (2013). The degree of attention of Brent crude oil price forecasters is measured as the fraction of forecasters who revise their forecasts compared with the previous quarter[18] and is therefore computed as $\lambda_{t,t+h} = \frac{1}{n_t}\sum_{i=1}^{n_t} I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$, where $I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$ is an indicator function equal to 1 if $f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h})$ and 0 otherwise. n_t represents the time varying number of forecasters participating in the survey at time t, which is visualized in Figure A.1. The time series of $\lambda_{t,t+h}$ are shown in Figure 4 for the period from 2002Q1 to 2020Q1 and for the forecast horizon of $h = 1, 2, 3$.

*** Insert Figure 4 about here ***

[17] This argument is supported by the finding of a significantly positive effect of INC on forecasters' attention (results are not reported). The attention of forecasters is introduced and examined in the next subsection.

[18] It should be noted that this measure of forecasters inattention assumes that an update of the information set is defined by a revision of the previous period's forecast. More precisely, this rules out the possible case that a forecaster has updated his information set but nonetheless sticks to his previous period's forecast. However, the volatility of the crude oil price makes it unlikely that most of the non-revisions from quarter to quarter are subject to such a situation.

It can be seen that the degree of attention varies over time and decreases with the forecast horizon as the time series mean decreases from 90% to 85%. The latter confirms the view already provided in Section 4.1 that forecasters pay more attention to the most recent forecast horizon and react less to new information for longer forecast horizons since the processing of information is costly. Therefore, the willingness of forecasters to rely on an outdated information set tends to increase with the forecasting horizon. The average degree of attention lies between 85 and 90% for the three horizons and is roughly comparable to the degree of attention found by Andrade and Le Bihan (2013) for forecasts regarding inflation, unemployment and GDP growth as well as by Dovern *et al.* (2015) for GDP growth forecasts, although the price of crude oil is generally much more volatile compared with core macroeconomic indicators.[19] This finding is evidence in favor of inattentiveness of a part of the forecasters and is basically in line with the sticky-information model. Figure 4 also illustrates that the degree of attention varies between 70% and 100% for $h = 1$. The longest period of full attention is observed between 2008 and 2009, i.e., the period characterized by the peak of the Brent crude oil price and a subsequent large drop. The finding of an increase in forecasters' attention after large shocks generally confirms the results provided by Andrade and Le Bihan (2013).

As a next step, we examine the association between the disagreement among Brent crude oil price forecasters measured either as the cross-sectional standard deviation across forecasters or as the corresponding inter-quartile range (see Section 4.2) and the degree of attention of forecasters over the sample period for the different forecast horizons. This empirical relationship lets us verify the implications of both imperfect information models within our dataset. The regression results provided in Panel (a) of Table 6 clearly report a significantly positive relationship between forecasters' attention and their disagreement at the 1% level for each forecast horizon and both disagreement measures. This result confirms the findings of Andrade and Le Bihan (2013) and is at odds with the sticky-information model since disagreement among forecasters seems not to result solely from the inattention of some forecasters but also from a disagreement

[19] In contrast, other studies examining inflation forecasts argue in favor of a substantially lower degree of attention, i.e., (clearly) below 50% (Mankiw *et al.*, 2003; Carroll, 2003; Kiley, 2007; Döpke *et al.*, 2008; Giacomini *et al.*, 2020). In addition, it is worth mentioning that an alternative explanation for the larger inattention of forecasters at longer forecast horizons is that the high volatility of crude oil prices compared with macro variables might discourage forecasters to attempt to give an accurate prediction for the long run.

among revisors pointing to different information sets. This clearly shows that the sticky-information model is not able to explain the expectations building mechanism in its basic form. The association between disagreement and attention also seems to be an increasing function of the forecast horizon. In addition, we regressed forecasters' disagreement on a full attention dummy $\text{Full}_{t,t+h}$, which is equal to 1 if $\lambda_{t,t+h} = 1$ and 0 otherwise. The corresponding results are reported in Panel (b) of Table 6 and roughly confirm the positive association of attention and disagreement, which is clearly significant for the inter-quartile range but less so for the standard deviation.

*** Insert Table 6 about here ***

Panel (a) of Table 7 also provides regression results studying the relationship between forecasters' disagreement (measured by the standard deviation) and the mean of revisions across forecasters compared with the previous quarter in absolute terms. The significantly positive relationship (at the 1% level) confirms the findings discussed above and also concurs with the implications of the sticky-information model. A visual inspection also suggests a potential nonlinearity, which is addressed by also including a quadratic term into the regression model reported in Panel (a) of Table 7 as well. Accounting for this nonlinearity, which turns out to be significant for $h = 2$ and $h = 3$, the general finding of a positive relationship between disagreement and the magnitude of revisions still holds. In addition, this potential nonlinearity also shows that the positive association might be even stronger in general but decreases with the magnitude of revisions. Finally, Figure 5 also illustrates the mean and the variation of forecasters' disagreement provided by boxplots, which distinguish between forecasters who revise their forecasts compared with the previous quarter and forecasters who do not. In line with the previous results, the mean of disagreement for non-revisors is lower compared with the mean for revisors for each forecast horizon. The difference between the two groups is statistically significant at the 5% (10%) level for $h = 2$ ($h = 3$) according to the t-test also provided in Panel (b) of Table 7. This contrasts with the findings provided by Giacomini *et al.* (2020), who observe a lower disagreement for revisors compared with non-revisors when assessing inflation forecasts from Bloomberg's survey of professional forecasters. Our findings show that disagreement does not solely stem from differences in forecasts between the groups of revisors and non-revisors consistent with the sticky-information model but also stems from differences within groups, which are more pronounced for the group of revisors. Overall, the findings contradict the prediction of the sticky-information model but are in line with the noisy-information model as forecasters who revise their forecasts use different information sets. This appears to be reasonable since the forecasters participating in the survey are forecast units from research institutes and banks across the Euro Area and may have access to different information.

*** Insert Figure 5 and Table 7 about here ***

5 Summary and Concluding Remarks

The present study examines the expectations formation mechanism in the Brent crude oil market by exploiting the variation in the cross-section and over time inherent in the ECB SPF. Our main findings are as follows. Mean forecast errors exhibit predictability, which is evidence for the presence of information rigidity in line with both imperfect information models. However, the degree of information rigidity increases with the forecast horizon, which contradicts this view. This indicates that forecasters tend to pay relatively less attention to longer forecast horizons potentially due to larger information processing costs. Forecasters' disagreement varies over time, increases with the horizon and depends on shocks hitting the economy. In general, shocks increase the disagreement in line with the sticky-information model but in contrast to the noisy-information model. However, OPEC announcements regarding future crude oil production expansions or cuts decrease the disagreement among forecasters. This is plausible since this information is publicly available and is easier to access and interpret. The degree of forecasters' attention also varies over time, decreases with the forecast horizon but also shows periods with full attention. In contrast to the sticky-information model but in line with the noisy-information model, forecasters' disagreement increases with their attention. In addition, our findings contradict predictions of the sticky-information model as disagreement among professional forecasters does not solely stem from inattention. We observe not only differences in forecasts between the groups of revisors and non-revisors but also within both groups, which are even more pronounced for the group of revisors.

Overall, we provide robust evidence for the presence of information rigidity, which meets several predictions of both imperfect information models. However, all the stylized facts derived within our study and outlined in Table 1 can neither be generated by the sticky- nor by the noisy-information model. The time varying pattern of forecasters' disagreement and especially its dependence on shocks hitting the economy clearly shows that the basic form of the noisy-information model fails to explain the expectations formation mechanism of professional forecasters in the Brent crude oil market. The same can be concluded about the sticky-information model, especially due to the finding that forecasters who update their information set also disagree on the future development of the crude oil price and do so even more strongly compared with forecasters who do not update. Hence, our findings suggest that modeling the expectations formation mechanism of professional forecasters requires at least both types of information rigidity, as forecasters on the one hand do not update their information set every period and on the other hand if they do, they have different perceptions of the true reality and thus rely on different information sets.

Therefore, Andrade and Le Bihan (2013) built an expectations model featuring the properties of both imperfect information models but were unable to replicate the patterns of forecast errors and disagreement observed in survey data. Giacomini *et al.* (2020) confirm this finding that the combination of the sticky- and noisy-information models provides a poor fit to the data. To explain expectations formation, they propose a Bayesian updating approach, which accounts for three different channels of heterogeneity: heterogeneous priors, heterogeneous models and heterogeneous inattention. They demonstrate that their model fits better to survey data compared with any alternatives available in the previous literature and therefore provides a crucial step to a better understanding of decision making. However, even this model is not able to explain the larger disagreement among updaters compared with non-updaters found in the present study. Therefore, our study provides further insights into the process of expectations formation and clearly shows that simple models of imperfect information are insufficient to explain the behavior of professional forecasters in the crude oil market. A promising avenue of future research is to design a model of information frictions, which fits the empirical patterns outlined above.

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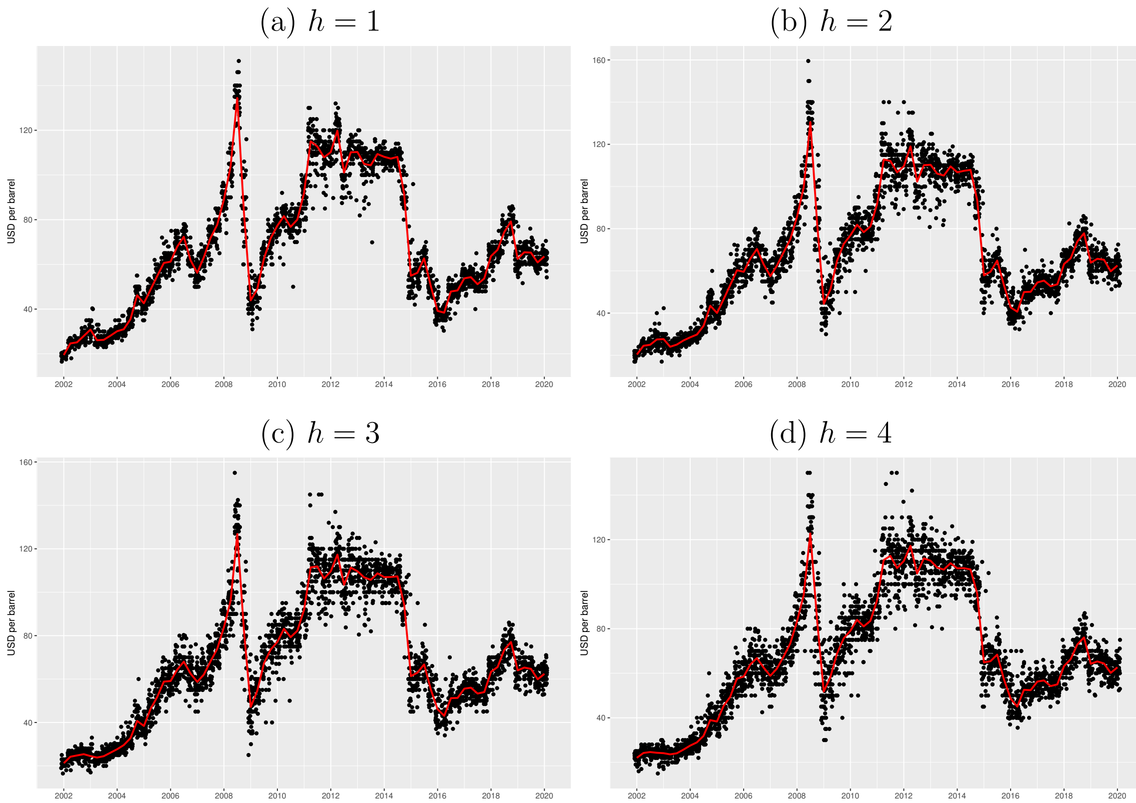
Figures

Figure 1: **Individual and mean forecasts for Brent crude oil prices**

The plots show quarterly time series of Brent crude oil price (denominated in USD per barrel) forecasts across individual forecasters (black points) together with mean forecasts across individuals (red line) for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The data was taken from the ECB Survey of Professional Forecasters (SPF).



(a) $h = 1$ (b) $h = 2$ (c) $h = 3$ (d) $h = 4$

Figure 2: **Individual information rigidity coefficients for $h = 1$**

The plot illustrates OLS estimates of information rigidity coefficients $\beta_{i,1}$ for individual forecasters and a horizon of $h = 1$ plotted against heteroskedasticity and autocorrelation consistent (HAC) standard errors following Andrews (1991) based on the following regression

$$y_{t+h} - f_{i,t}(y_{t+h}) = \beta_{i,0} + \beta_{i,1}[f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h})] + \nu_{i,t,t+h}.$$

Red dots represent coefficient estimates, which are significantly different from zero at the 5% level.

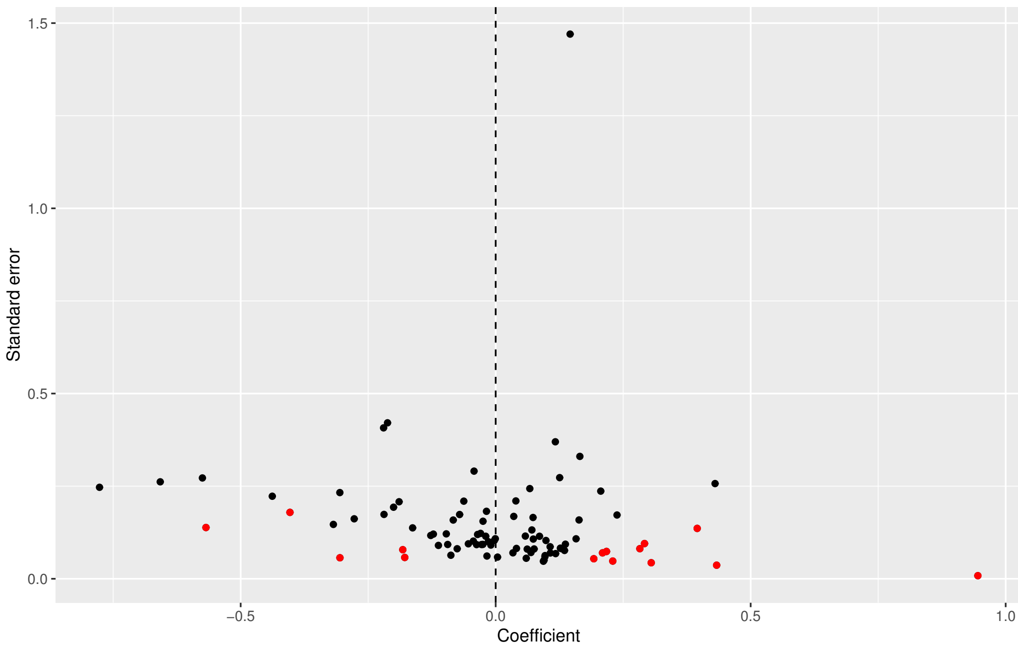


Figure 3: **Brent crude oil price forecasters disagreement**

The plot shows quarterly disagreement among Brent crude oil price forecasters measured either as the cross-sectional standard deviation across forecasters (denominated in USD per barrel) or the corresponding inter-quartile range (IQR) for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The data was taken from the ECB survey of professional forecasters (SPF). The plot also shows the quarterly volatility of daily prices of Brent crude oil measured by the standard deviation within a quarter.

(a) Cross-sectional standard deviation across forecasters

(b) Cross-sectional inter-quartile range (IQR) across forecasters

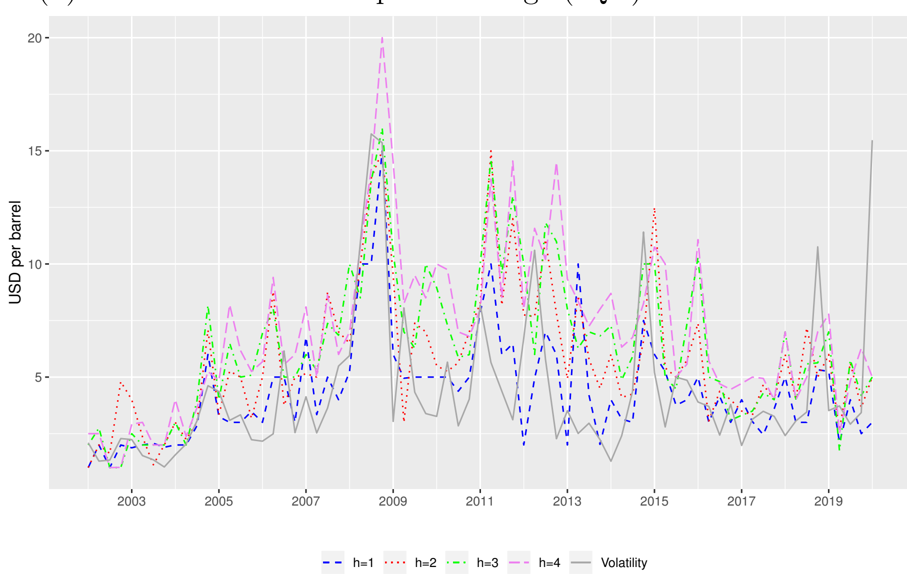


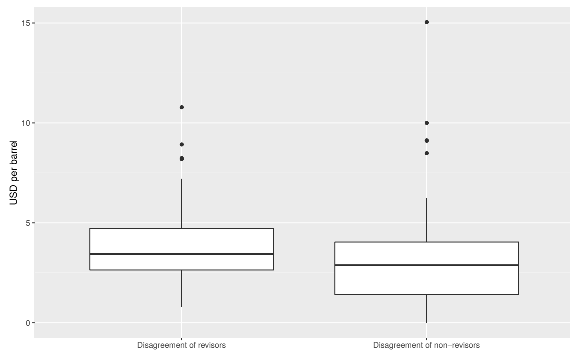
Figure 4: **Degree of attention of Brent crude oil price forecasters**

The plot shows the degree of attention of Brent crude oil price forecasters measured as the fraction of forecasters who revise their forecasts compared with the previous quarter for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The degree of attention is computed as $\lambda_{t,t+h} = \frac{1}{n_t}\sum_{i=1}^{n_t} I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$, where y_{t+h} denotes the quarterly average of realized Brent crude oil prices in $t+h$, $f_{i,t}(y_{t+h})$ represents its forecast made by forecaster i at the beginning of the quarter in t and $I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$ is an indicator function equal to 1 if $f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h})$ and 0 otherwise. The data was taken from the ECB Survey of Professional Forecasters (SPF).

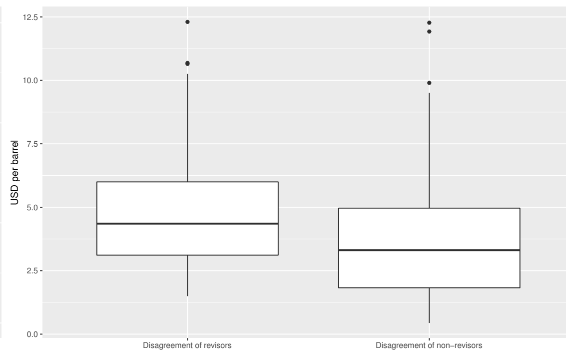
Figure 5: **Disagreement of revisors vs. non-revisors**

The boxplot diagrams illustrate the disagreement among Brent crude oil price forecasters who revise their forecasts compared with the previous quarter and forecasters who do not revise their forecasts compared with the previous quarter for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The data was taken from the ECB Survey of Professional Forecasters (SPF).

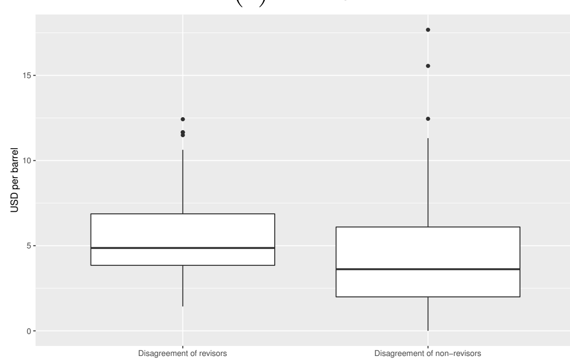
(a) $h = 1$



(b) $h = 2$



(c) $h = 3$



Tables

Table 1: **Properties of the imperfect information models**

Properties	**Sticky**	**Noisy**
Predictability of ex post forecast errors by ex ante forecast revisions	✓	✓
Time-variation and shock dependence of forecasters' disagreement	✓	x
Disagreement among forecasters who update their information set	x	✓
Association between forecasters' disagreement and forecasters' degree of attention	-	+

Table 2: **Tests of the expectation formation process for Brent crude oil price mean forecasts**

	$h = 1$	$h = 2$	$h = 3$
(a) $y_{t+h} - \overline{f}_t(y_{t+h}) = \beta_0 + \beta_1[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{t,t+h}$			
β_1	0.1541	1.2295	1.5530
se	(0.0528)	(0.0523)	(0.1716)
p-value	[0.0047]	[0.0000]	[0.0000]
β_0	0.3406	0.4885	1.5722
se	(0.7715)	(0.8252)	(1.2720)
p-value	[0.6602]	[0.5557]	[0.2207]
Adj. R^2	0.0555	0.7798	0.6837
γ	0.1335	0.5515	0.6083
G	0.8665	0.4485	0.3917
(b) $y_{t+h} - \overline{f}_t(y_{t+h}) = \beta_0 + \beta_1[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \beta_2[y_{t+h} - y_{t-1+h}] + \nu_{t,t+h}$			
β_1	0.2741	0.5311	-0.0327
se	(0.1246)	(0.2887)	(0.2133)
p-value	[0.0311]	[0.0703]	[0.8787]
β_2	-0.1428	-0.3608	-0.0677
se	(0.1507)	(0.1627)	(0.1986)
p-value	[0.3466]	[0.0300]	[0.7341]
β_0	0.2923	1.1661	1.7442
se	(0.7956)	(2.1886)	(3.7682)
p-value	[0.7144]	[0.5959]	[0.6450]
Adj. R^2	0.0533	0.0337	-0.0228
(c) $y_{t+h} - \overline{f}_t(y_{t+h}) = \beta_0 + \beta_1[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{t,t+h}$			
β_1	0.2124	1.2856	1.6114
se	(0.0946)	(0.0950)	(0.2168)
p-value	[0.0280]	[0.0000]	[0.0000]
β_0	-0.0531	0.1060	1.2083
se	(1.5584)	(1.6087)	(1.7358)
p-value	[0.9729]	[0.9477]	[0.4887]
Adj. R^2	0.0185	0.4948	0.5406
γ	0.1752	0.5625	0.6171
G	0.8248	0.4375	0.3829

Note: The table reports expectation formation process tests following Coibion and Gorodnichenko (2015) for quarterly time series of Brent crude oil price (denominated in USD per barrel) ex post mean forecast errors across individuals for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. Mean forecasts $\overline{f}_t(y_{t+h})$ are computed as cross-sectional means of $f_{i,t}(y_{t+h})$, where $f_{i,t}(y_{t+h})$ represents the forecast made by forecaster i at the beginning of the quarter in t, and y_{t+h} denotes in Panel (a) the mean of realized Brent crude oil prices across the quarter being forecasted and in Panel (c) end-of-quarter realized Brent crude oil prices. Therefore, $y_{t+h} - \overline{f}_t(y_{t+h})$ gives ex post mean forecast errors and $\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})$ represents ex ante mean forecast revisions. In this context it should be noted that $\overline{f}_t(y_{t+h})$ and $\overline{f}_{t-1}(y_{t+h})$ both forecast the value of the Brent crude oil price in the same quarter, e.g., $\overline{f}_{2019\text{Q}2}(y_{t+1})$ is the one-quarter-ahead forecast for 2019Q3 made in 2019Q2 and $\overline{f}_{2019\text{Q}1}(y_{t+2})$ is the two-quarters-ahead forecast for 2019Q3 made in 2019Q1, and therefore the forecast revision refers to the revision of the forecast for the same quarter. This results in the fact that forecast revisions are not available for $h = 4$ since the four-quarters-ahead forecast for each t refers to a quarter that has not been forecasted in the previous quarter. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets. γ denotes the degree of information rigidity and is computed as $\gamma = \beta_1/(1 + \beta_1)$. G gives the weight on new information and is calculated as $G = 1/(1 + \beta_1)$.

Table 3: **Test for efficiency of forecast revisions among Brent crude oil price forecasters**

		$h=1$	$h=2$	$h=3$
(a) $f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h}) = \beta_0 + \beta_1[f_{i,t-1}(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{i,t,t+h}$				
	β_1	-0.6810	-0.6424	-0.5289
	se	(0.0798)	(0.0695)	(0.0599)
	p-value	[0.0000]	[0.0000]	[0.0000]
Pooled	β_0	1.1018	0.9001	0.4968
	se	(0.2742)	(0.2506)	(0.2431)
	p-value	[0.0001]	[0.0003]	[0.0411]
	Adj. R^2	0.0493	0.0744	0.0698
	$n_t \times T$	2752	2727	2698
(b) $f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h}) = \beta_{i,0} + \beta_1[f_{i,t-1}(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{i,t,t+h}$				
	β_1	-0.7084	-0.6796	-0.5625
	se	(0.0959)	(0.0780)	(0.0696)
FE	p-value	[0.0000]	[0.0000]	[0.0000]
	Adj. R^2	0.0526	0.0779	0.0674
	$n_t \times T$	2752	2727	2698

Note: The table reports efficiency tests following Fuhrer (2018) for quarterly time series of Brent crude oil price (denominated in USD per barrel) forecast revisions for individual forecasters for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The test is based on regressing individual forecast revisions $f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h})$ on the previous period's difference between individual forecasts and the consensus forecast given by the mean across all forecasters $\overline{f}_{t-1}(y_{t+h})$. Therefore, this might also be interpreted as a test for the presence of herding behavior among forecasters. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets. n_t represents the time-varying number of forecasters participating in the survey at time t and T gives the number of quarters within the sample period. Therefore, $n_t \times T$ gives the total number of observations. Panel (a) provides the pooled OLS estimates and Panel (b) reports estimates for the corresponding individual fixed effects model.

Table 4: **Disagreement of Brent crude oil price forecasters and uncertainty shocks**

			Including further controls z_{t-1}								
		$U_{t,t+h}$	**US EPU**	**EA EPU**	**GEPU**	**MU**	**FU**	**RU**	**HPR**	**BHOPS**	**KI**
$s_t(y_{t+h}) = \beta_0 + \beta_1 U_{t-1,t+h} + \beta_2 z_{t-1} + \nu_{t,t+h}$											
	β_1	0.2150	0.2135	0.2156	0.2148	0.2194	0.2142	0.2024	0.2077	0.2268	0.2151
	se	(0.0497)	(0.0438)	(0.0388)	(0.0413)	(0.0560)	(0.0556)	(0.0575)	(0.0546)	(0.0458)	(0.0475)
	p-value	[0.0001]	[0.0000]	[0.0000]	[0.0000]	[0.0002]	[0.0003]	[0.0010]	[0.0003]	[0.0000]	[0.0000]
$h = 1$	β_2		0.0050	0.0026	0.0008	-0.4986	0.0798	0.0297	-9.0028	-0.0729	-0.0001
	se		(0.0057)	(0.0041)	(0.0038)	(1.8654)	(1.5231)	(0.2773)	(3.3113)	(0.1131)	(0.0035)
	p-value		[0.3905]	[0.5320]	[0.8293]	[0.7900]	[0.9584]	[0.9153]	[0.0087]	[0.5210]	[0.9684]
	Adj. R^2	0.3192	0.3207	0.3164	0.3099	0.3099	0.3094	0.2883	0.3422	0.3165	0.3094
	β_1	0.0803	0.0792	0.0814	0.0803			0.0581	0.0799	0.0843	0.0812
	se	(0.0284)	(0.0254)	(0.0254)	(0.0242)			(0.0509)	(0.0312)	(0.0272)	(0.0233)
	p-value	[0.0061]	[0.0027]	[0.0021]	[0.0015]			[0.2596]	[0.0132]	[0.0028]	[0.0009]
$h = 2$	β_2		0.0046	0.0022	-0.0001			0.5779	-10.0966	-0.0709	0.0023
	se		(0.0079)	(0.0063)	(0.0060)			(0.7648)	(5.7155)	(0.1346)	(0.0059)
	p-value		[0.5683]	[0.7331]	[0.9860]			[0.4538]	[0.0828]	[0.6001]	[0.6923]
	Adj. R^2	0.1639	0.1585	0.1551	0.1516			0.1566	0.1825	0.1565	0.1575
	β_1	0.0834	0.0832	0.0840	0.0830			0.0746	0.0799	0.0829	0.0836
	se	(0.0321)	(0.0231)	(0.0225)	(0.0228)			(0.0572)	(0.0332)	(0.0330)	(0.0243)
	p-value	[0.0115]	[0.0006]	[0.0004]	[0.0005]			[0.1992]	[0.0195]	[0.0145]	[0.0010]
$h = 3$	β_2		0.0019	0.0011	-0.0014			0.4002	-12.8488	0.0305	0.0019
	se		(0.0098)	(0.0077)	(0.0073)			(0.7707)	(5.1935)	(0.1308)	(0.0063)
	p-value		[0.8484]	[0.8888]	[0.8541]			[0.6062]	[0.0165]	[0.8166]	[0.7615]
	Adj. R^2	0.2121	0.2013	0.2010	0.2011			0.2148	0.2344	0.2011	0.2035
	β_1	0.0969	0.0971	0.0970	0.0966	0.0761	0.0760	0.1177	0.0900	0.0968	0.0969
	se	(0.0347)	(0.0294)	(0.0313)	(0.0308)	(0.0418)	(0.0366)	(0.0699)	(0.0367)	(0.0360)	(0.0333)
	p-value	[0.0068]	[0.0015]	[0.0029]	[0.0026]	[0.0731]	[0.0420]	[0.0995]	[0.0176]	[0.0092]	[0.0049]
$h = 4$	β_2		0.0057	0.0002	-0.0012	9.0438	14.1556	0.0772	-10.1904	0.0046	0.0014
	se		(0.0098)	(0.0087)	(0.0080)	(9.7586)	(7.9830)	(0.9619)	(7.7628)	(0.1450)	(0.0071)
	p-value		[0.5643]	[0.9839]	[0.8835]	[0.3574]	[0.0808]	[0.9364]	[0.1948]	[0.9748]	[0.8454]
	Adj. R^2	0.2628	0.2590	0.2516	0.2521	0.2715	0.3016	0.3177	0.2523	0.2516	0.2530

Note: The table reports OLS estimation results for a predictive regression of quarterly time series of disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ on one-quarter lagged forecast uncertainty $U_{t-1,t+h}$ and further uncertainty measures as potential controls for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. Disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ is measured as the cross-sectional standard deviation across individual forecasts (denominated in USD per barrel). Other uncertainty measures include the US newspaper-based economic policy uncertainty (US EPU) index suggested by Baker *et al.* (2016) as quarterly means, the corresponding European EPU (EA EPU) and the global EPU (GEPU) index, the macroeconomic uncertainty (MU) measure provided by Jurado *et al.* (2015) as quarterly means for the 3-month and the 12-month horizon, the corresponding financial uncertainty index (FU) and the uncertainty measure proposed by Rossi *et al.* (2020) (RU). In addition, HPR represents the measure suggested by Hachula *et al.* (2019) to account for ECB (unconventional) monetary policy and BHOPS denotes oil price shocks computed according to Baumeister and Hamilton (2019). As a control for the state of the global business cycle, we also include the global economic activity measured by the Kilian (2009, 2019) index (KI) constructed from ocean bulk dry cargo freight rates. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets. Estimates for β_0 are not provided to save space but these are significantly positive in all cases.

Table 5: **Disagreement of Brent crude oil price forecasters and OPEC announcements**

	Standard deviation				Interquartile range			
	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
$s_t(y_{t+h}) = \beta_0 + \beta_1\text{CUT}_t + \beta_2\text{INC}_t + \beta_3\text{ATM}_t + \beta_4\text{FTA}_t + \beta_5\text{Kaenzig}_t + \nu_{t+h}$								
β_1	-1.1943	-1.6144	-2.1259	-2.1757	-1.3184	-2.0950	-2.2592	-2.4897
se	(0.6619)	(0.8106)	(0.9228)	(1.0488)	(0.8853)	(1.1242)	(1.1914)	(1.4697)
p-value	[0.0757]	[0.0505]	[0.0243]	[0.0419]	[0.1411]	[0.0668]	[0.0622]	[0.0949]
β_2	-1.0913	-1.3464	-1.9661	-2.2711	-1.7195	-1.1103	-1.5467	-2.9873
se	(0.5377)	(0.6259)	(0.6705)	(0.7818)	(0.6631)	(0.9724)	(0.9284)	(1.1082)
p-value	[0.0464]	[0.0351]	[0.0046]	[0.0050]	[0.0117]	[0.2576]	[0.1004]	[0.0089]
β_3	-0.1900	-0.1155	-0.4244	-0.4420	-0.5294	-0.3577	-0.1953	-1.1761
se	(0.5069)	(0.6630)	(0.7643)	(0.8042)	(0.7020)	(0.8794)	(0.9170)	(0.9661)
p-value	[0.7090]	[0.8622]	[0.5806]	[0.5844]	[0.4534]	[0.6855]	[0.8320]	[0.2278]
β_4	0.5747	0.5675	0.3899	0.5622	0.1560	-0.2462	0.8716	-0.2103
se	(0.7335)	(0.8219)	(0.8804)	(0.9669)	(0.9856)	(1.0728)	(1.0382)	(1.3438)
p-value	[0.4361]	[0.4923]	[0.6593]	[0.5629]	[0.8747]	[0.8192]	[0.4042]	[0.8761]
β_5	-0.2025	-0.1930	-0.1990	-0.1775	-0.2787	-0.2908	-0.3588	-0.2574
se	(0.1038)	(0.1100)	(0.1103)	(0.1255)	(0.1447)	(0.1455)	(0.1311)	(0.1858)
p-value	[0.0552]	[0.0840]	[0.0756]	[0.1619]	[0.0584]	[0.0497]	[0.0080]	[0.1704]
β_0	4.3067	5.3111	6.1798	6.6945	4.9206	6.4158	6.8135	8.1263
se	(0.4147)	(0.5349)	(0.6039)	(0.6714)	(0.5754)	(0.7886)	(0.7788)	(0.8441)
p-value	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Adj. R^2	0.1094	0.0881	0.0995	0.0852	0.1036	0.0654	0.1287	0.0662

Note: The table reports OLS estimation results for a regression of quarterly time series of disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ on binary variables describing OPEC decisions for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. Disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ is measured either as the cross-sectional standard deviation (SD) across individual forecasts (denominated in USD per barrel) or as the cross-sectional inter-quartile range (IQR) across individual forecasts. OPEC decisions are classified similar to Spencer and Bredin (2019) as follows: 'agreement to decrease production' (CUT), 'agreement to increase production' (INC), 'agreement to maintain production' (ATM) and 'failure to agree production intentions' (FTA). The binary variables $x = \text{CUT}, \text{INC}, \text{ATM}, \text{FTA}$ take a value of 1 if the OPEC held a meeting in the previous quarter (i.e., in-between the date of the last forecast in $t-1$ and the date of the current forecast in t) and made decision x and 0 otherwise. Information on OPEC meetings was taken directly from the OPEC press releases published on their website (`https://www.opec.org/`). In addition, we include a proxy of oil supply surprises provided by Känzig (2021) (Kaenzig_t), which basically measures how daily crude oil futures prices change around OPEC announcements. We use a quarterly surprise series by aggregating all daily surprises for the corresponding quarter. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets.

Table 6: **Disagreement and attention of Brent crude oil price forecasters**

		$h=1$	$h=2$	$h=3$	$h=1$	$h=2$	$h=3$
	(a) $s_t(y_{t+h}) = \beta_0 + \beta_1 \lambda_{t,t+h} + \nu_{t,t+h}$				**(b)** $s_t(y_{t+h}) = \beta_0 + \beta_1 \text{Full}_{t,t+h} + \nu_{t,t+h}$		
	β_1	6.7910	9.7192	10.3344	1.1976	1.7526	1.0381
	se	(2.4584)	(2.8685)	(3.1396)	(0.6948)	(1.1018)	(0.8213)
	p-value	[0.0073]	[0.0012]	[0.0016]	[0.0892]	[0.1162]	[0.2104]
SD	β_0	-2.0581	-3.5196	-3.1505	3.8079	4.7454	5.5912
	se	(2.0870)	(2.3969)	(2.6290)	(0.3075)	(0.4744)	(0.3253)
	p-value	[0.3275]	[0.1465]	[0.2348]	[0.0000]	[0.0000]	[0.0000]
	Adj. R^2	0.0818	0.1377	0.1585	0.0568	0.0681	-0.0058
	β_1	9.9553	15.0554	15.1355	2.3814	2.8243	3.2062
	se	(3.6780)	(4.2791)	(3.8418)	(1.0066)	(1.1203)	(1.0585)
	p-value	[0.0085]	[0.0008]	[0.0002]	[0.0208]	[0.0140]	[0.0034]
IQR	β_0	-4.5605	-7.3580	-6.4327	3.8910	5.2303	5.6977
	se	(3.0399)	(3.5140)	(3.2123)	(0.2811)	(0.4146)	(0.5192)
	p-value	[0.1381]	[0.0399]	[0.0491]	[0.0000]	[0.0000]	[0.0000]
	Adj. R^2	0.1180	0.2028	0.2317	0.1658	0.1511	0.1696

Note: The table reports OLS estimation results for a regression of quarterly time series of disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ either on the degree of attention $\lambda_{t,t+h}$ or a full attention dummy $\text{Full}_{t,t+h}$ for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. Disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ is measured either as the cross-sectional standard deviation (SD) across individual forecasts (denominated in USD per barrel) or as the cross-sectional inter-quartile range (IQR) across individual forecasts. The degree of attention is computed as $\lambda_{t,t+h} = \frac{1}{n_t} \sum_{i=1}^{n_t} I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$, where y_{t+h} denotes the quarterly average of realized Brent crude oil prices in $t+h$, $f_{i,t}(y_{t+h})$ represents its forecast made by forecaster i at the beginning of the quarter in t and $I(f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h}))$ is an indicator function equal to 1 if $f_{i,t}(y_{t+h}) \neq f_{i,t-1}(y_{t+h})$ and 0 otherwise. Full attention is measured by the binary variable $\text{Full}_{t,t+h}$ equal to 1 if $\lambda_{t,t+h} = 1$ and 0 otherwise. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets.

Table 7: **Disagreement and revision of Brent crude oil price forecasters**

		$h=1$	$h=2$	$h=3$	$h=1$	$h=2$	$h=3$
	(a) $s_t(y_{t+h}) = \beta_0 + \beta_1\lvert\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})\rvert + \nu_{t,t+h}$				$+\beta_2\lvert\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})\rvert^2$		
	β_1	0.1668	0.2158	0.2594	0.2257	0.3668	0.5247
	se	(0.0194)	(0.0259)	(0.0362)	(0.0745)	(0.0859)	(0.0957)
	p-value	[0.0000]	[0.0000]	[0.0000]	[0.0034]	[0.0001]	[0.0000]
	β_2				-0.0014	-0.0039	-0.0074
SD	se				(0.0015)	(0.0020)	(0.0025)
	p-value				[0.3519]	[0.0578]	[0.0038]
	β_0	2.6109	3.2931	3.7002	2.3085	2.5846	2.5410
	se	(0.2665)	(0.3647)	(0.4780)	(0.4500)	(0.4689)	(0.4968)
	p-value	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
	Adj. R^2	0.5581	0.5718	0.5524	0.5592	0.5928	0.6037
	β_1	0.2037	0.2821	0.3005	0.3132	0.5445	0.7455
	se	(0.0328)	(0.0340)	(0.0469)	(0.0964)	(0.1103)	(0.1265)
	p-value	[0.0000]	[0.0000]	[0.0000]	[0.0018]	[0.0000]	[0.0000]
	β_2				-0.0027	-0.0068	-0.0124
IQR	se				(0.0026)	(0.0025)	(0.0036)
	p-value				[0.3003]	[0.0084]	[0.0009]
	β_0	2.6459	3.6171	4.1971	2.0839	2.3858	2.2529
	se	(0.2961)	(0.3959)	(0.4939)	(0.4939)	(0.5216)	(0.6347)
	p-value	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0000]	[0.0007]
	Adj. R^2	0.5328	0.5819	0.4906	0.5428	0.6246	0.5910
	(b) Welch's t-test testing the null of equal means						
	Revisors	3.8902	4.9463	5.5505			
SD	Non-Revisors	3.4091	3.9293	4.5927			
	t-Stat	0.9752	2.0972	1.7535			
	p-value	[0.3330]	[0.0385]	[0.0823]			

Note: Panel (a) reports OLS estimation results for a regression of quarterly time series of disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ on ex ante mean forecast revision in absolute terms for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The right-hand side of the table also includes a quadratic term of ex ante mean forecast revision. Disagreement among Brent crude oil price forecasters $s_t(y_{t+h})$ is measured either as the cross-sectional standard deviation (SD) across individual forecasts (denominated in USD per barrel) or as the cross-sectional inter-quartile range (IQR) across individual forecasts. $\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})$ represents ex ante mean forecast revision, where $\overline{f}_t(y_{t+h})$ denotes the mean forecast computed as cross-sectional means of $f_{i,t}(y_{t+h})$, where $f_{i,t}(y_{t+h})$ represents the forecast made by forecaster i at the beginning of the quarter in t, and y_{t+h} denotes the quarterly average of realized Brent crude oil prices in $t+h$. In this context it should be noted that $\overline{f}_t(y_{t+h})$ and $\overline{f}_{t-1}(y_{t+h})$ both forecast the value of the Brent crude oil price in the same quarter, e.g., $\overline{f}_{2019\text{Q}2}(y_{t+1})$ is the one-quarter-ahead forecast for 2019Q3 made in 2019Q2 and $\overline{f}_{2019\text{Q}1}(y_{t+2})$ is the two-quarters-ahead forecast for 2019Q3 made in 2019Q1, and therefore the forecast revision refers to the revision of the forecast for the same quarter. This results in the fact that forecast revisions are not available for $h=4$ since the four-quarters-ahead forecast for each t refers to a quarter that has not been forecasted in the previous quarter. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets. Panel (b) reports group means across t for the disagreement among forecasters measured as the cross-sectional standard deviation (SD) across individual forecasts for the groups of revisors (i.e., forecasters who revise their forecasts compared with the previous quarter) and non-revisors together with the t-statistic and p-value for Welch's t-test testing the null of equal means.

A Appendix

A.1 Imperfect Information Models

The sticky-information model implies that the mean forecast in t across forecasters $\overline{f}_t(y_{t+h})$ is a weighted average of the mean forecast in $t-1$ and current rational expectations $E_t(y_{t+h})$ regarding the variable of interest over a horizon of h:

$$\overline{f}_t(y_{t+h}) = (1-\gamma)E_t(y_{t+h}) + \gamma\overline{f}_{t-1}(y_{t+h}) \quad \text{with} \quad E_t(y_{t+h}) = y_{t+h} - \nu_{t,t+h}, \tag{A.1}$$

where γ is interpreted as the degree of information rigidity, y_{t+h} denotes the realized value in $t+h$ (in the context of the present study the realized value of the Brent crude oil price) and $\overline{f}_t(y_{t+h})$ represents the corresponding cross-sectional mean forecast made in t. ν_{t+h} is a rational expectations error term, which is independent of the information set from t and the past. This results in the relationship between ex post mean forecast errors $y_{t+h} - \overline{f}_t(y_{t+h})$ and ex ante mean forecast revisions $\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})$

$$y_{t+h} - \overline{f}_t(y_{t+h}) = \frac{\gamma}{1-\gamma}[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{t,t+h}. \tag{A.2}$$

The noisy-information model implies that forecasters continuously update their information set, but never fully observe the true state of the variable y_t. The latter is assumed to follow an AR(1) process while the individual forecaster i at period t solely observes a noisy signal of it $z_{i,t}$, which consists of the true value of the variable and an individual error term $\omega_{i,t}$

$$y_t = \rho y_{t-1} + \nu_t \quad \text{and} \quad z_{i,t} = y_t + \omega_{i,t}, \tag{A.3}$$

where ρ is the persistence of y_t and ν_t its i.i.d. normally distributed innovation. Forecasters individually use a weighted average of the current period's noisy signal $z_{i,t}$ and their previous period's forecast $f_{i,t-1}(y_t)$ as their current forecast, where G is the weight they place on the current signal:

$$f_{i,t}(y_t) = Gz_{i,t} + (1-G)f_{i,t-1}(y_t) \quad \text{and} \quad f_{i,t}(y_{t+h}) = \rho^h f_{i,t}(y_t). \tag{A.4}$$

Coibion and Gorodnichenko (2015) show that noisy information averaged across forecasters basically results in the same relationship already shown in Eq. (A.2)

$$y_{t+h} - \overline{f}_t(y_{t+h}) = \frac{1-G}{G}[\overline{f}_t(y_{t+h}) - \overline{f}_{t-1}(y_{t+h})] + \nu_{t,t+h}, \quad \nu_{t,t+h} = \sum_{j=1}^{h} \rho^{h-j}\nu_{t+j}. \tag{A.5}$$

The OLS method provides unbiased estimates for $\gamma/(1-\gamma)$ and $(1-G)/G$, respectively, when $\nu_{t,t+h}$ is uncorrelated with the information set from t and therefore allows an empirical test for the presence of information rigidity.

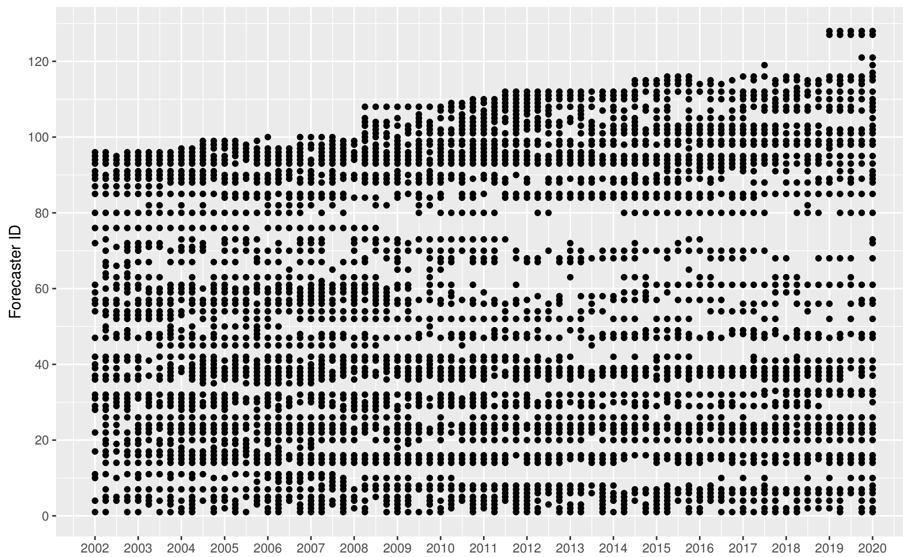
A.2 ECB Survey of Professional Forecasters

The participating institutions of the ECB SPF include: ABN AMRO Bank N.V., AIB Global Treasury, Allianz SE, Alpha Bank, Analistas Financieros Internacionales (AFI), Banco Bilbao Vizcaya Argentania (BBVA), Banco Santander, Banco Santander Totta, Bank Austria, Bank Julius Bär, Bankia, Bank of America Merrill Lynch, Bank of Ireland Global Markets, Belgian Federal Planning Bureau, Bloomberg Intelligence, BNP Paribas, Bundesverband deutscher Banken (Association of German Banks), Berlin, la Caixa, Centro Europa Ricerche (CER), ODDO BHF Aktiengesellschaft, Capital Economics, Coe-Rexecode, Commerzbank AG, Confederation of Danish Industry (DI), Confederation of Swedish Enterprise (CSE), Confindustria, CPB Netherlands Bureau for Economic Policy Analysis, CPR Asset Management, Crédit Agricole SA, Credit Suisse Group, Davy Economic Research, Deutsche Bank Research, Deutscher Industrie- und Handelskammertag e.V. (DIHK), Deutsches Institut für Wirtschaftsforschung e.V. (DIW Berlin), Belfius Bank, EFG Eurobank Ergasias S.A., EIPF, Ekonomski inštitut, European Forecasting Network (EFN), Goldman Sachs Economic Research, Goldman, Sachs & Co. OHG, Hamburg Institute of International Economics (HWWI), HSBC Bank plc, KBC Asset Management, KBC Bank Ireland, The Kiel Institute for the World Economy (IfW), Ifo Institute for Economic Research, IHS markit, ING Belgium SA/NV, Institut für Höhere Studien (IHS), Instituto Flores de Lemus, Intermoney Valores, Intesa Sanpaolo, Istat, JP Morgan, Labour Institute for Economic Research, Landesbank Baden-Wuerttemberg, Lombard Street Research Ltd, Millennium Investment Banking Financial Markets Research, Mirabaud Asset Management (Suisse) SA, National Bank of Greece, National Institute of Economic and Social Research, National Institute of Economic Research (NIER), Natixis, NCB Stockbrokers, Nordea Markets, Economic Research, Observatoire Français des Conjonctures économiques (OFCE), OP- Pohjola Group, Österreichisches Institut für Wirtschaftsforschung (WIFO), Prometeia, Rabobank Nederland, The Research Institute of the Finnish Economy (ETLA), Royal Bank of Scotland, Rheinisch-Westfälisches Institut für Wirtschaftsforschung e.V. (RWI), Danske Bank, SEB AG, Société Générale, STATEC, Swedbank's Economic Research Department, Thierry Apoteker Consulting (TAC), UBS AG, UniCredit Group, Université catholique de Louvain Institut de Recherches Economiques et Sociales (UCL-IRES), Zentralverband des Deutschen Handwerks (German Confederation of Skilled Crafts), ZDH, Zentrum für Europäische Wirtschaftsforschung GmbH (Centre for European Economic Research), and ZEW. Other participants remain anonymous. See the website for details.

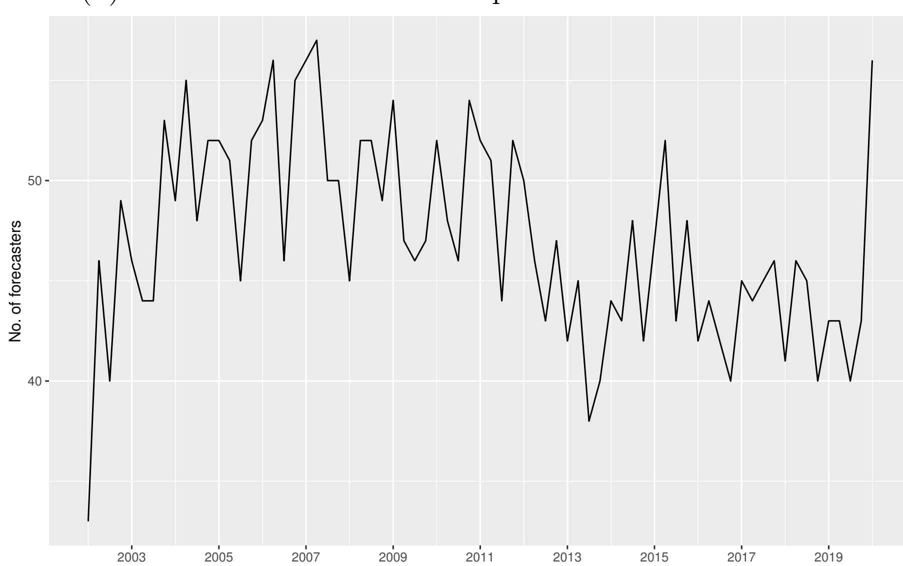
Figure A.1: **Number of Brent crude oil price forecasters**

The plots show which forecaster has participated in the ECB Survey of Professional Forecasters (SPF) at each point in time (Panel (a)) and the quarterly time series of the number of forecasters participating in the ECB SPF in the given quarter (Panel (b)).

(a) Participation of Brent crude oil price forecasters



(b) Number of Brent crude oil price forecasters over time



A.3 ECB SPF Brent Crude Oil Price Forecasts

To compare the forecasts of the ECB SPF with actual realizations of the Brent crude oil price, we also accessed daily spot prices for the corresponding sample period from the US Energy Information Administration (EIA) retrieved from Federal Reserve Economic Data (FRED). Using this data we have, first of all, constructed a quarterly time series of the actual Brent crude oil price on the date t the forecast was made by matching the daily data with the exact deadline dates, at which the forecasts had to be submitted to the ECB by the participating institutions. The corresponding time series is displayed in Panel (a) of Figure A.2 (by the solid black line) together with mean forecasts across individual forecasters for each horizon and shows that mean forecasts are closely attached to the current spot price, but also illustrates forecasters' expectations about the change in the price of crude oil. For instance, the first period up to 2008 was characterized by a steadily rising oil price and forecasters most of the time believed that Brent crude oil was overvalued and therefore expected an upcoming decline. This is shown by the fact that mean forecasts are mostly below the actual spot price at the day of the forecast. Analogously in periods of a downward trending oil price, professionals expected crude oil to be undervalued and thus expected an increase in the future.

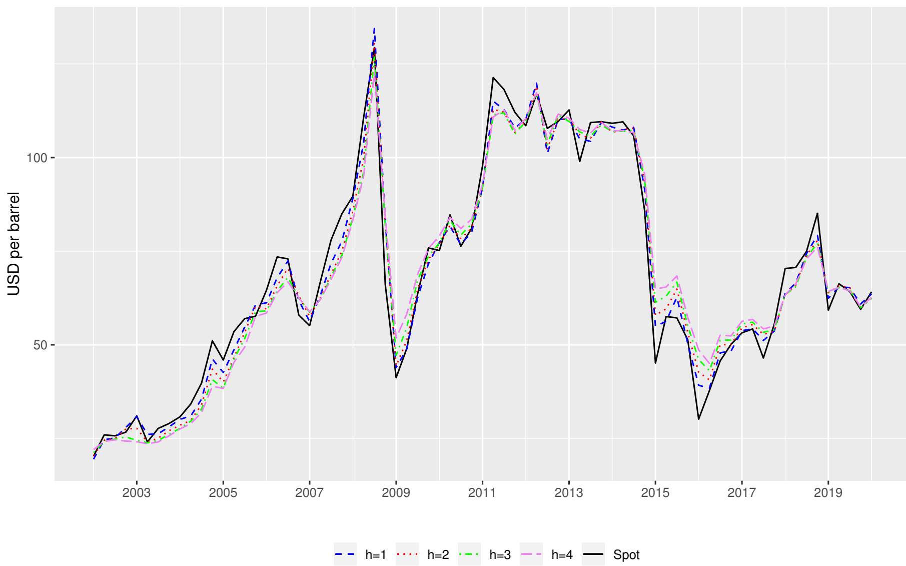
Furthermore, to also enable the computation of ex post forecast errors, we constructed a quarterly series of average Brent crude oil spot prices using the simple arithmetic mean since the participants of the survey are asked to provide their forecasts for quarterly averages. The corresponding time series is shown in Panel (b) of Figure A.2 again together with mean forecasts for each horizon. Therefore, the difference between the spot price and the mean forecast gives the ex post mean forecast error. This figure shows that periods of substantial under- or overestimation were very persistent and this points in favor of the predictability of forecast errors.

Table A.1 reports descriptive statistics for the mean forecasts across individuals, their actual realizations and the number of forecasters. A pattern observed for mean forecasts is that their skewness and kurtosis (provided as excess kurtosis compared to the Gaussian) both decrease with the forecast horizon. This finding basically implies that forecasts for longer horizons are less extreme and therefore tend to converge to the unconditional mean in the long run.

Figure A.2: **Mean forecasts and actuals for Brent crude oil prices**

The plots show quarterly mean forecasts for Brent crude oil prices and their actual realizations (denominated in USD per barrel) for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. The data was taken from the ECB Survey of Professional Forecasters (SPF).

(a) Mean forecasts and actual realizations at the time forecasts are made t



(b) Mean forecasts and actual realizations for the time being forecast $t + h$

Table A.1: **Descriptive statistics for Brent crude oil price forecasts**

	$h = 1$	$h = 2$	$h = 3$	$h = 4$	Spot in t	Spot end	Spot mean	No. Forecasters
Mean	68.0649	67.8809	67.8483	68.2518	68.6153	68.2575	68.5428	47.0685
SD	28.2681	28.0450	27.8809	27.9060	28.8392	28.9542	28.2465	4.9731
Median	63.1568	63.8876	64.0185	64.4040	64.2300	66.0600	63.0973	46.0000
Min	19.4606	20.3818	21.2500	22.0197	20.2600	14.8500	21.1160	33.0000
Max	134.4474	130.5734	126.8278	122.8154	129.3400	138.4000	121.2044	57.0000
Skewness	0.3067	0.2545	0.1981	0.1481	0.2915	0.2966	0.3076	-0.0201
Kurtosis	-0.8627	-0.8823	-0.8968	-0.9249	-0.9749	-0.8608	-1.0292	-0.4333

Note: The table reports descriptive statistics for quarterly time series of Brent crude oil price (denominated in USD per barrel) mean forecasts across individuals, their actual realizations (Spot in t, Spot end and Spot mean give the spot price at the time forecasts are made, at the end of the quarter and its mean across the quarter being forecast, respectively) and the number of forecasters (No. Forecasters) for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. SD denotes standard deviation and Kurtosis gives excess Kurtosis compared with the Gaussian (= Kurtosis - 3).

A.4 Brent Crude Oil Price Forecast Errors

Table A.2 reports descriptive statistics and diagnostic tests for Brent crude oil price ex post mean forecast errors across individuals. The means of ex post forecast errors across time t and individuals i differ from zero in the positive direction, which indicates an underestimation of the Brent crude oil price on average, but the difference from zero is not statistically significant due to relatively large standard errors.[20] This is shown by a simple unbiasedness test, for which we regress ex post mean forecast errors taken over i on a constant term. For all four horizons the null that the mean of the forecast errors is zero cannot be rejected, although the means of ex post forecast errors increase with the forecast horizon. This result would imply that mean forecasts appear to be unbiased. However, although the bias is not statistically significant in all cases due to large standard errors, the predictability of forecast errors by their own past is often documented in the literature for survey-based forecasts (see e.g., Mankiw *et al.*, 2003) and points in favor of imperfect information models explaining the expectation formation mechanism.

Therefore, as a next step we also regress ex post mean forecast errors on their first lag. Except for horizon $h = 1$, the link to past forecast errors found within this efficiency test is highly significant (at the 1% level). Therefore, errors are predictable and the persistence in forecast errors implies a systematic bias, which can be explained by information frictions. Solely for $h = 1$ mean forecasts across professional forecasters appear to be unbiased. Moreover, the variation of mean forecast errors reported by their standard deviation and the root mean squared error also increases with the forecast horizon h. The skewness of forecast errors is negative, which implies an overestimation of the actual value. We also report the root mean squared error (RMSE) relative to the no-change forecast and the Diebold and Mariano (1995) test statistic together with its p-value. These metrics show that the mean forecast across forecasters is slightly worse compared with the no-change forecast but the difference between both is not statistically significant at the 5% significance level and reverses at the highest horizon.

[20] In this context, it should be noted that we use heteroskedasticity and autocorrelation consistent (HAC) standard errors following Andrews (1991).

Table A.2: **Descriptive statistics and tests for Brent crude oil price ex post mean forecast errors**

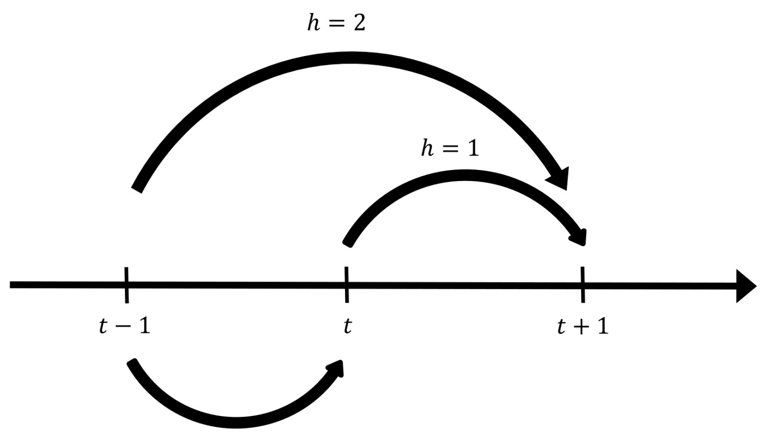
(a)	$h=1$	$h=2$	$h=3$	$h=4$
Mean	0.4779	1.2467	1.7856	1.9339
SD	7.1195	15.6909	19.7234	21.9080
Median	0.9504	3.7055	3.3752	3.6416
Min	-28.0850	-75.5450	-82.3057	-63.9379
Max	17.3843	35.4673	47.2805	53.7487
Skewness	-1.2076	-1.9563	-1.3603	-0.7565
Kurtosis	3.1839	7.1324	4.0417	0.9883
RMSE	7.0867	15.6314	19.6653	21.8367
Rel. RMSE	1.2976	1.0954	1.0206	0.9887
DM	1.9169	1.8259	0.5817	-0.2076
p-value	[0.0592]	[0.0720]	[0.5626]	[0.8361]
(b) Unbiasedness test: $e_{t,t+h} = \beta_0 + \nu_{t,t+h}$				
β_0	0.4779	1.2467	1.7856	1.9339
se	(0.8928)	(2.1468)	(3.4530)	(4.9124)
p-value	[0.5941]	[0.5633]	[0.6067]	[0.6950]
(c) Efficiency test: $e_{t,t+h} = \beta_0 + \beta_1 e_{t-1,t+h} + \nu_{t,t+h}$				
β_1	0.1538	0.4008	0.6303	0.7722
se	(0.0978)	(0.0935)	(0.0975)	(0.1190)
p-value	[0.1205]	[0.0001]	[0.0000]	[0.0000]
β_0	0.3586	0.6370	0.4591	0.2102
se	(0.8374)	(1.7618)	(2.2122)	(2.0609)
p-value	[0.6697]	[0.7188]	[0.8362]	[0.9191]
Adj. R^2	0.0084	0.1475	0.3846	0.5851

Note: The table reports descriptive statistics and diagnostic tests for quarterly time series of Brent crude oil price (denominated in USD per barrel) ex post mean forecast errors across individuals for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. SD denotes standard deviation, Kurtosis gives excess Kurtosis compared with the Gaussian (= Kurtosis - 3), RMSE represents root mean squared error, Rel. RMSE provides the ratio of RMSEs between mean survey forecasts and no-change forecasts and DM denotes the modified Diebold and Mariano (1995) test statistic proposed by Harvey *et al.* (1997). Ex post mean forecast errors are computed as cross-sectional means of $e_{i,t,t+h} = y_{t+h} - f_{i,t}(y_{t+h})$, where y_{t+h} denotes the mean of realized Brent crude oil prices across the quarter being forecast and $f_{i,t}(y_{t+h})$ represents its forecast made by forecaster i at the beginning of the quarter in t. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (se) following Andrews (1991) are provided in parentheses and p-values are given in square brackets.

A.5 Brent Crude Oil Price Forecast Revisions

Figure A.3: **Ex ante forecast revision**

The graph illustrates ex ante forecast revision made by forecaster i $f_{i,t}(y_{t+h}) - f_{i,t-1}(y_{t+h})$, where y_{t+h} denotes the quarterly average of realized Brent crude oil prices in $t+h$ and $f_{i,t}(y_{t+h})$ represents its forecast made by forecaster i at the beginning of the quarter in t. The upper arrows in the graph refer to forecasts for the same quarter, which are made in different quarters ($t-1$ and t) and therefore refer to different forecast horizons h ($h=2$ and $h=1$). For example, $f_{i,2019\text{Q}2}(y_{t+1})$ is the one-quarter-ahead forecast for 2019Q3 made in 2019Q2 and $f_{i,2019\text{Q}1}(y_{t+2})$ is the two-quarters-ahead forecast for 2019Q3 made in 2019Q1, and therefore the forecast revision refers to the revision of the forecast for the same quarter. The difference between these two forecasts gives the ex ante forecast revision for $h=1$ displayed by the bottom arrow. The same principle is applied to compute forecast revisions for $h=2$ and $h=3$. However, forecast revisions are not available for $h=4$ since the four-quarters-ahead forecast for each t refers to a quarter that has not been forecasted in the previous quarter (i.e., it is a completely new forecast).



A.6 Ex Post Brent Crude Oil Price Forecast Uncertainty

The concept of uncertainty applied in the present study goes back to Jurado *et al.* (2015) and follows the idea that uncertainty regarding any economic variable is not expressed by the realized variability of this variable but the variability of its unpredictable component. Jurado *et al.* (2015) compute the conditional volatility of the purely unforecastable component and aggregate it across all variables to obtain a general measure of macroeconomic uncertainty.[21] We instead rely on the cross-sectional mean of forecasts made by professional forecasters by using information available at time t, which mimics the approach by Jurado *et al.* (2015) as outlined by Ter Ellen *et al.* (2019). However, before computing this conditional volatility of the unpredictable component across forecasters, we first of all correct the forecast errors made by professionals for potential individual forecast biases. In doing so, we rely on the structural model for forecast errors proposed by Davies and Lahiri (1995). According to them, forecast errors can be decomposed into an individual bias $\phi_{i,h}$, a common factor $\theta_{t,h}$, which mimics the dynamics of macroeconomic shocks, and a forecaster-specific error $\varepsilon_{i,t,h}$

$$y_{t+h} - f_{i,t}(y_{t+h}) = \phi_{i,h} + \theta_{t,h} + \varepsilon_{i,t,h}. \tag{A.6}$$

We are especially interested in the common factor $\theta_{t,h}$, which is computed separately for each horizon h. Therefore, first of all, we estimate the individual bias by taking the time series mean of forecast errors for each forecaster. Second, we subtract the individual forecast errors by the estimated individual biases $\hat{\phi}_{i,h}$ and take cross-sectional means across the forecasters participating in the survey at the corresponding period of time:

$$\hat{\phi}_{i,h} = \frac{1}{T}\sum_{t=1}^{T}\left[y_{t+h} - f_{i,t}(y_{t+h})\right] \quad \text{and} \quad \hat{\theta}_{t,h} = \frac{1}{n_t}\sum_{i=1}^{n_t}\left[y_{t+h} - f_{i,t}(y_{t+h}) - \hat{\phi}_{i,h}\right]. \tag{A.7}$$

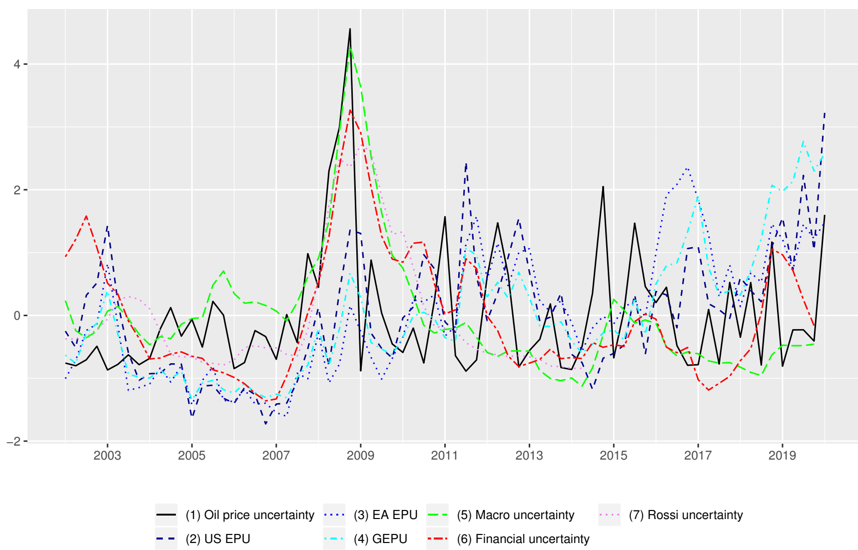
Finally, $\hat{\theta}_{t,h}$ gives a time series of macro shocks for each horizon h and the absolute value of this series is used as the uncertainty measure $U_{t,t+h} = \sqrt{\left[\hat{\theta}_{t,h}\right]^2}$ following the concept of Jurado *et al.* (2015). Figure A.4 compares our measure of Brent crude oil price ex post forecast uncertainty for $h = 1$ and $h = 4$ with other more general uncertainty proxies available in the literature. The plots show that although our forecast uncertainty measure shares some general patterns with alternative measures, especially for the period around the global financial crisis, it also exhibits unique dynamics that are specific to the crude oil market such as, for instance, the spike around 2014/15. In this period a tremendous drop in the price of oil was observed.

[21] They also apply the same approach to construct an index of financial uncertainty (Ludvigson *et al.*, 2021). Monthly time series of both measures are provided by the authors on their website (`https://www.sydneyludvigson.com/`) for $h = 1, 3, 12$ months-ahead.

Figure A.4: **Uncertainty measures**

The plots compare quarterly ex post uncertainty regarding Brent crude oil price forecasts measured as absolute mean forecast errors across forecasters (corrected for individual biases) to other uncertainty measures for the period from 2002Q1 to 2020Q1 and for the forecast horizon of h-quarters-ahead. Other uncertainty measures include the US newspaper-based economic policy uncertainty (EPU) index suggested by Baker *et al.* (2016) as quarterly means, the corresponding European EPU (EA EPU) and the global EPU (GEPU) index, the macroeconomic uncertainty measure provided by Jurado *et al.* (2015) as quarterly means for the 3-month and the 12-month horizon, the corresponding financial uncertainty index and the uncertainty measure proposed by Rossi *et al.* (2020). All time series have been scaled to a zero mean and a variance of unity.

(a) $h = 1$



(b) $h = 4$