STAFF MEMO

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Abstract

This paper presents a framework for quantifying uncertainty around point forecasts for GDP, inflation and house prices in Norway. The framework combines quantile regressions using a broad set of uncertainty indicators with a skewed t-distribution, allowing for time-variation and asymmetry in the uncertainty forecasts. This approach helps provide deeper insights into the macroeconomic uncertainty surrounding forecasts than more traditional time-series models, where uncertainty is usually symmetric and with limited time-variation. Formal tests, such as the log score and the Continuous Ranked Probability Score (CRPS), show that using informative indicators tend to improve density forecasts, particularity in the medium run.

Keywords: GDP, house prices, inflation, forecasting, quantile regressions, Growth-at-risk, House-prices-at-risk, Inflation-at-risk, density forecast, fan charts

JEL classification: C53, E23, E27, E3, E44

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1 Introduction

Projections about future macroeconomic developments are associated with a substantial degree of uncertainty. This uncertainty will likely vary over time. For example, it is natural to assume that forecasts made during episodes of high volatility, such as the Great Financial Crisis (GFC) or the Covid pandemic, are more uncertain than forecasts made in more normal times. In addition, uncertainty is not necessarily symmetric. For instance, the uncertainty of GDP forecasts could be skewed to the downside in periods of tight financial conditions, or the uncertainty of house price forecasts could be skewed to the upside after large interest rate cuts.

The uncertainty attached to the macroeconomic outlook has received a lot of attention among central banks, particularly after the financial crisis in 2008 (Lagarde, 2022; Yellen, 2017). In addition to providing sobriety regarding the accuracy of a central bank's point forecasts, uncertainty may have direct implications for optimal monetary policy in itself. In periods with high uncertainty it could be optimal to change policy rates less than in periods with low uncertainty (see Brainard (1967)). Furthermore, the asymmetry of uncertainty likely matters. In periods where uncertainty is largely skewed to one side, monetary policy could be more geared towards avoiding very bad outcomes, rather than only focusing on the most likely scenario (see Kamenik et al. (2015)). Despite this, forecasts are most commonly presented only as point forecasts. This likely relates to the fact that most workhorse models used by central banks and other forecasting institutions often assumes away skewness and time-variation in uncertainty.[1]

In recent years, growth-at-risk (GaR) models have become influential in monitoring risks to financial stability and many institutions use such models in their financial stability assessments.[2] GaR apply quantile regressions, following Adrian et al. (2019), to evaluate downside risk in the medium term growth outlook. Adrian et al. (2019) use quantile regressions to model the distribution of real GDP growth in the short run conditional on a financial conditions index (FCI). The GaR-literature has shown that the procedure is useful for predicting the longer-run growth outlook by conditioning on indicators of financial imbalances (see eg Arbatli-Saxegaard et al. (2020)). This is consistent with the literature on financial cycles: Drehmann et al. (2012) and Laeven et al. (2012), among others, show that credit and asset prices are key drivers of financial imbalances and Schularick and Taylor (2012) show that credit booms are leading predictors of financial crises. In addition, Forni et al. (2023) show that financial shocks are main drivers for tail risk concerning GDP growth and inflation.

Lately, the GaR-framework has been extended to applications on other variables. In the house price-at-risk literature (HaR), Deghi et al. (2020) and Alter and Mahoney (2021) find that the indicators

[1] Some central banks illustrate uncertainty around their macroeconomic forecasts by use of fan charts. Often, these fan charts display symmetric distributions around the central bank's point forecasts based on historic forecast errors (Riksbanken and Czech National Bank). Norges Bank used to illustrate (symmetric) forecast uncertainty around key policy variables (key policy rate, output gap and inflation) based on forecast errors, combined with simulations from Norges Bank's main macroeconomic model, NEMO, lastly used in Norges Bank (2019).

[2] See e.g. IMF (Prasad et al., 2019), European Central Bank (ECB, 2021) and Norges Bank (Norges Bank, 2019).

describing downside risks to GDP forecasts also help predict downside risks to house prices. The HaR framework has been adapted by the European Central Bank (Jarmulska et al., 2022), Danmarks Nationalbank (Cucic et al., 2022) and Banco de España (Ganics and Rodríguez-Moreno, 2023).

A more recent branch of the literature also examines risks to the inflation outlook. Lopez-Salido and Loria (2020) shows that there has been substantial variation in tail risk attached to US inflation, even in periods where mean inflation has been low and stable. Short run variation in inflation tail risk has also been linked to variation in financial conditions (Adams et al., 2021),[3] whereas credit conditions help explain tail risk along longer horizons (Lopez-Salido and Loria, 2020).

The methodology in this paper builds on the two-step procedure of Adrian et al. (2019), where quantile regressions are estimated and the predictive quantiles are fitted to a skewed t-distribution (Azzalini, 1985). This produces time-varying distributional forecasts. We expand on this by combining forecasts from several quantile regressions and forecast uncertainty one, four, eight and twelve quarters ahead. The aim is to use informative indicators to quantify the uncertainty around point forecasts for GDP, inflation and house prices, and provide useful input to monetary policy and financial stability considerations in Norges Bank.

This paper is organised as follows: Section 2 presents the data and Section 3 the methodology. The results and evaluation are presented in Section 4, while Section 5 concludes.

2 Data and relevant literature

This section reviews the relevant data for our framework. We review some of the findings of relevant strands of the literature, focusing on the indicators that are found to predict uncertainty well. This serves as a starting point for selecting indicators to test in our framework. We further describe the ultimate variable selection process in section 3.

2.1 GDP uncertainty

We define GDP uncertainty as the predicted distribution of four-quarter real GDP growth. When measuring Norwegian GDP, it is common to exclude value added by the petroleum sector and from international shipping activities (Fløttum et al., 2012). Consistently we focus on GDP for mainland Norway, available in the quarterly national accounts from Statistics Norway.

To forecast the predictive GDP-distribution we condition on indicators of economic and financial conditions, credit growth and property prices. We have considered a large set of uncertainty indicators for Norway and our trading partners. As quantile regressions require a larger estimation sample than normal OLS-regressions, all predictors included in our analysis have observations from 1985 and onward. Our sample thus captures four events in the upper tail, and three events in the lower tail, including the Covid-19 pandemic (Figure 1).

[3] Notably, however, the improvements for inflation are more modest than for GDP and unemployment.

The existing literature explores what indicators best describe future (downside) risks to GDP:[4] For shorter horizons, Adrian et al. (2019), show that financial conditions as measured by the NFCI from the Chicago Fed[5] is a good indicator of downside risk on US data. We consider the US NFCI as well as a Norwegian FCI (Bowe et al., 2023b). FCIs measure financing costs, but will also capture financial markets' pricing of (short-term) uncertainty, reflecting factors such as geopolitical tension, policy uncertainty and uncertainties relating to other extraordinary events, like the Covid-19 pandemic. We also consider other financial market variables, including exchange rates, stock market indexes and volatility measures for Norway and main trading partners, as well as commodity prices and interest rates at different maturities.

For the medium term, the GaR literature indicates a relationship between downside risks to GDP and measures of financial imbalances. Arbatli-Saxegaard et al. (2020) look at GaR models for Norway and show that credit indicators and asset prices, notably property prices, are good predictors of downside events to GDP. We considered the same indicators used by Arbatli-Saxegaard et al. (2020). Additionally, we test the indicators from Norges Bank's heatmap for monitoring systemic risk (Arbatli and Melle, 2017). These indicators not only provide a useful starting point for projecting GDP uncertainty in the medium run, but also ensure consistency between our framework and Norges Bank's assessment of cyclical risks to the financial system.

Furthermore, we test other economic indicators commonly used in forecasting GDP, as well as some other common uncertainty measures text-based indicators. For a full overview of indicators considered, see Appendix A.

2.2 House price uncertainty

To forecast house price uncertainty, we consider the four-quarter change in Norwegian house prices. We focus on nominal house price inflation, measured by a hedonic price index.[6] The Norwegian house price index has been published by Real Estate Norway in cooperation with Eiendomsverdi and Finn.no[7] since 2003. Prior to 2003, the index was calculated by the Norwegian Association of Real Estate Agents (NEF) and Real Estate Norway (EFF) in cooperation with Finn.no and Econ/Pöyry. The quarterly index starts in 1990, but we estimate quarterly variation based on the annual observations from 1973, following the methodology outlined in appendix B in Bowe et al. (2023a).[8]

[4]Predictors of risks to upside growth has gained less attention in the literature. We tested for a wide set of indicators that have been found to predict downside risk, and also include other variables, notably asset prices and indicators of economic activity.

[5]Specifically Federal Reserve Bank of Chicago, Chicago Fed National Financial Conditions Index (NFCI), retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/NFCI, 2 May, 2023.

[6]Hedonic house price indices aim to measure the price growth of similar residences, controlling for specific attributes that influence their prices, such as type of dwelling, size, floor, plot size, year of construction, ownership of plot and dwelling, location and number and types of buildings.

[7]Finn.no is the main online platform to list houses for sale in Norway, and covers 98 percent of the market.

[8]The quarterly variation is based on the estimated quarterly house price indices of Eitrheim (1993) from 1983 and Eitrheim and Erlandsen (2005) from 1973. In addition the estimation uses household consumption expenditures

To forecast the predictive house price distribution, we condition on uncertainty indicators broadly falling into five categories: financial conditions, income, credit, interest rates and house price misalignment. All predictors considered are observed at least from 1985. This allows us to start estimation prior to the Norwegian banking crisis from 1988 to 1993, during which there was a sharp fall in house prices (Figure 1).

The HaR literature suggests several variables that perform well in describing future (downside) risks to house prices. For shorter horizons, the International Monetary Fund (IMF) and other complementing studies emphasizes the importance of financial conditions (Deghi et al., 2020; Alter and Mahoney, 2021).[9] Over longer horizons, they find that the impact diminishes. We use these findings as a starting point for selection of financial condition variables to capture house price uncertainty in Norway.

For the medium term, the same literature indicates a relationship between downside risks to house prices and measures of house price misalignment and household credit growth. Cucic et al. (2022) and Ganics and Rodríguez-Moreno (2023) also include household dispoable income, debt service ratio and mortgage lending rates in their HaR framework for the Danish and Spanish housing markets, respectively. For house price risk assessments up to five years ahead, the ECB also includes indicators of systemic risk, consumer confidence and financial market conditions (Jarmulska et al., 2022). Lastly, the IMF uses real GDP growth as a proxy for changes in household real income (Deghi et al., 2020). We consider similar indicators in our analysis, including the ratio of house prices to income and house prices to fundamentals (misalignment), as well as housing credit growth. We also test mortgage lending rates and debt service ratios.

In addition to the indicators for house price risks suggested by the HaR-litterature, we have also tested other economic indicators commonly used when analysing house prices. Details are in Appendix A.

2.3 Inflation uncertainty

To forecast inflation uncertainty, we consider four-quarter growth in the consumer price index adjusted for tax changes and excluding energy products (CPI-ATE), published by Statistics Norway. This measure of core inflation reduces much of the volatility driven primarily by the price of energy products. To avoid issues attached to a trend shift in inflation following the 1980s, the inflation sample starts in 1990 (Figure 1). The CPI-ATE from Statistics Norway is only available from December 2002. A series calculated by Norges Bank is used for the prior periods.

To forecast the predictive inflation-distribution we condition on indicators of uncertainty falling into four categories: cost indicators, money and credit, financial markets and real economic indicators.

for housing rentals and housing services, housing capital stock and housing investment from the quarterly national accounts, as well as the registered unemployment rate to inform the estimates of the quarterly variation.

[9] Deghi et al. (2020) includes data for 32 advanced and emerging economies while Alter and Mahoney (2021) looks at evidence from USA and Canada.

We consider Norwegian, as well as foreign indicators. Including indicators on prices and economic conditions among trading partners is important given the high import content of Norwegian consumer goods (Scheistrøen, 2015).

Several strands of the literature find that inflation itself holds important informational content on its future tail risk (eg Giordani and Söderlind (2003) and Fountas and Karanasos (2007)). Some also show that higher moments, such as past inflation volatility, are important determinants of inflation uncertainty Giordani and Söderlind (2003). Hence, it is crucial that we not only include lagged inflation in our analysis, but also higher moments and sub-indexes of measured consumer prices.

Further, the existing inflation-at-risk literature highlight the value of surveys and financial conditions in forecasting inflation uncertainty. Andrade et al. (2012) show that subjective distributions measured by surveys, such as the Survey of Professional Forecasters, provide valuable information about the tail risk of inflation. As for GDP and house price risks, it is shown that financial indicators are instrumental when forecasting inflation uncertainty (Adams et al., 2021). Lopez-Salido and Loria (2020) finds that credit conditions are especially important to modelling the tail risk of US inflation. Motivated by these findings, we test the use of financial conditions and credit variables on the forecast density of inflation.

Most papers focus on risks to US inflation. There are reasons to believe that determinants of inflation tail risk in the US would differ from those in a small open economy. Banerjee et al. (2020) consider a panel of advanced and emerging economies, extending the methodology of Adrian et al. (2019). They find that current inflation, output and financial conditions are important for the predicted inflation distribution. We include indicators along all three of these dimensions in our framework. Furthermore, Banerjee et al. (2020) finds that exchange rates are especially important to emerging economies. Motivated in part by this, and the high import-content in Norwegian consumer goods, we also consider various measures of exchange rates and import costs.

Figure 1: GDP mainland Norway, Norwegian house price index and Norwegian CPI-ATE. Four-quarter change. $5th$, $25th$, $75th$ and $95th$ percentiles.

3 Method

Our framework builds on the the two-step procedure suggested by Adrian et al. (2019), and uses bivariate quantile regressions[10], following Koenker and Bassett (1978):

$$\Delta y_{t+h,q} = \beta_{0,h,q} + \beta_{1,h,q}\Delta y_t + \beta_{2,h,q} I_t + \epsilon_{t,h,q},$$

The quantiles, q, for the variable of interest, Δy, are predicted h steps ahead, conditional on some indicator of uncertainty, I.[11] The regressions are estimated on four-quarter growth rates and include lagged values of the variable of interest.

We estimate the regression for the median and the $5th$, $25th$, $75th$ and $95th$ percentiles. We estimate a number of models for each quantile at horizon $t+1$, $t+4$, $t+8$ and $t+12$, each with a different indicator of uncertainty I. At every quantile and horizon, each corresponding model is combined to one forecast using an unweighted average.

A different set of indicators is used at each quantile for every horizon. This allows us to take advantage of the fact that some indicators contain more information about the uncertainty at certain

[10]Quantile regressions differs from an ordinary least squares (OLS) regression in two ways: First, the quantile regression minimises the sum of absolute errors, rather than the sum of squared errors. Second, it puts differential weights on the errors depending on whether an error term is above or below the quantile (Adrian et al., 2019).

[11]Note that forecasts for $t+h$ are made around the middle of period $t+1$ in line with the calendar for Norges Bank's Monetary Policy Reports. At this point, quarterly data on the variable of interest and the indicators are available until period t. The exception to this is financial market variables, where data is published at a higher frequency. For these variables, we lead the average of available data for period $t+1$ as the indicator I_t.

horizons or parts of the distribution. For example, financial variables tend to contain more information about the short run, whereas other indicators are better at projecting longer-run vulnerabilities.

Norges Bank has a rich model framework for projecting point forecasts for GDP, inflation and house prices. In our framework, we therefore combine our density forecasts and forecasts from Norges Bank's system of empirical models, SMART (Bowe et al., 2023a), by centring the predictive density forecasts *around* the SMART projections. For the sake of simplicity, we assume that Norges Bank's SMART projections represent the median forecast, and simply add the distance between the quantiles and the median projection at every point of our distribution.[12] SMART forecasts start in 2001 for GDP and 2003 for CPI-ATE, and are not (yet) available for house prices. For GDP and CPI-ATE we use an AR forecast as the median projection in the period prior to SMART availability. For house prices we use Norges Bank quarterly monetary policy projections from 2014 as the median projection. Prior to their availability, we use an AR forecast as the median projection in the house price distribution.[13]

The quantile regressions provide point-forecasts for each quantiles at each horizon. By keeping the problem linear, we can subtract the quantile projections from the median projection of each regression and, by linearly interpolating between the quantile projections at each horizon, translate our outcomes into traditional fan charts.

After combining and rescaling all quantiles, we continue the two-step procedure of Adrian et al. (2019) and fit the quantile projections at each horizon to a skewed t-distribution, applying the Azzilini algorithm (Azzalini, 1985). To ensure stable results, we add the following steps to the algorithm:

1. Estimate normal distribution.
2. Match a skewed t-distribution to the estimated normal distribution.
3. Use the parameter from the matched skewed t-distribution as the initial value for estimating the skewed t-distribution on the original quantiles.

As a result, we produce full predictive distributions, conditional on indicators of uncertainty, and for all relevant forecasting horizons.

The regressions are estimated in pseudo real-time. The recursive forecast period starts in 2000Q1 for all three variables. To select what indicators to include when forecasting macroeconomic uncertainty, we developed a three-step procedure:

1. We consider the economic **meaningfulness of the signs** of the coefficients for the different

[12] Adams et al. (2021) suggests a framework to combine quantile projections to point forecasts from the Survey of Professional Forecasters (SPF), by estimating the quantile regressions on their median forecasting error. The predicted value from the quantile regression are simply added to the point forecast, assuming that that the level of the point forecast provides no information about uncertainty beyond the conditioning variable. However, the quarterly forecasting history in Norges Bank is not sufficiently long to adapt this method.

[13] In future, we aim to use SMART (Bowe et al., 2023a), as the median forecast for all components.

percentiles.

2. We consider the **significance of the coefficients** for the percentiles. Both in absolute terms (normal t-test) and relative to the median coefficient (Wald-test).

3. We run a horse-race of combinations of the qualifying indicators from step 1 and 2, aiming to **minimise the out-of-sample forecasting errors** of their distributional forecasts.

The first two steps evaluate the information content of the linear coefficients for each indicator at every quantile and horizon. The economic significance of the coefficients indicates whether an estimation returns a meaningful result. The t-test ensures that the quantile-coefficients are significantly different from zero. We follow Koenker and Bassett (1982), and use the Wald test to check for significant skewness in the regressors, more precisely that the slope of the quantile estimates are significantly different than that of the median coefficients.

$$Wald\ statistic = \frac{(\beta_{2,j,q} - \beta_{2,j,0.5})^2}{\hat{\sigma}^2_{(\beta_{2,j,q} - \beta_{2,j,0.5})}}$$

$\beta_{2,j,q}$ is the quantile coefficient and $\hat{\sigma}^2_{(\beta_{2,j,q} - \beta_{2,j,0.5})}$ is the estimated variance of the difference between the two coefficients.

Finally, we run a horse-race of different combinations of regressors for the up- and downside of the predictive distribution. The different combinations of indicators were evaluated at their pseudo out-of-sample forecasting performance. To evaluate the out-of-sample density prediction, we have considered three measures of forecasting performance: the average logarithmic predictive scores (log score), the Continuous Ranked Probability Score (CRPS) and the probability integral transformation (PIT), with focus on the two first. Log scores are commonly used in density forecast evaluation (see eg Adrian et al. (2019)), but have been criticised for heavily penalising forecasts that assign close to zero probability to an observed outcome (Gneiting and Raftery, 2007; Boero et al., 2011; Mitchell et al., 2022). We therefore also consider the forecast accuracy of the uncertainty distribution by the use of CRPS, which is considered more robust to outliers.

The log score is based on the logarithm of the predictive density, p. Higher numbers indicate a better forecasting performance. Following Gneiting and Raftery (2007), we define the logarithmic score, $LogS$, as:

$$LogS(p, y) = logp(y)$$

where p is the predictive density, or density forecast, and y the outcome variable. Also following Gneiting and Raftery (2007), the CRPS is defined as:

$$CRPS(F, y) = -\int_{-\infty}^{\infty} (F(x) - \mathbb{1}\{x \geq y\})^2 dx$$

where F represents the CDF of the distributions in question. Similar to mean absolute error (MAE), a lower CRPS indicates better forecasting performance.[14]

Finally, we add some judgement to the indicator selection, where the aim has been to maintain consistency with other analytical frameworks used by Norges Bank (like the GaR). For the sake of simplicity and for communication purposes, we also restrict that the models used for the 25th and the 75th percentiles are the same as 5th and 95th percentiles.

4 Results

Using the procedure outlined in Section 3, we select 10 indicators for GDP, 10 for inflation and 11 for house prices. For GDP, two to six bivariate models are combined for each quantile at each horizon, four to five models for the inflation system and three to five for the house price forecasts. For an overview of the selected variables and the applied transformations, see Appendix B.

For all three main variables, we find that high frequency variables that respond quickly to changes in the outlook, such as financial market variables, are generally good predictors of the short term outcome, consistent with findings in the literature (Adrian et al., 2019; Adams et al., 2021; Deghi et al., 2020). In the inflation forecasts, various price and cost indicators are also included for the short horizons, like the import deflator. For upside risks to GDP growth, we find that the Oslo Børs Technology Index is a reliable indicator, possibly capturing the growth outlook. For house prices, household real disposable income appears to be a reliable indicator of upside risks, while for inflation, cost indicators appear throughout to be a good indicators for the upside.

For longer horizons, the indicators selected for GDP and house prices reflect financial instabilities to a larger degree: credit growth and asset inflation. The house price system also include the debt service ratio, household real disposable income and house price misalignment. For inflation, indicators for the real economy are selected, together with credit growth.

Using quantile projections, we can illustrate how uncertainty has evolved over time. Below, we compute the **magnitude** and **asymmetry** of the predicted uncertainty (Figures 2, 3 and 4). The magnitude of uncertainty is defined as the spread between the 95th and 5th quantile, at every horizon. The figures below illustrate spread against its historical average. Higher (lower) values indicate higher (smaller) uncertainty. A value above zero indicates higher-than-normal uncertainty.

Furthermore, we illustrate the asymmetry/skewness of the forecasts using the difference between the estimated mean forecast[15] at every horizon and the corresponding median.[16] If uncertainty is tilted to the downside (upside), the mean is lower (higher) than the median. The interpretation is therefore as follows: higher values indicate relatively more upside risk than downside risk.

To better understand what drives the changes in uncertainty, we decompose the evolution in spread

[14] As a cross-check, we also considered the PIT-scores of our distributional forecasts.

[15] The mean is calculated as the average across directly estimated 5th, 25th, 50th, 75th and 95th percentiles.

[16] Skewness quantifies the asymmetry in a probability distribution and can be calculated using various methods. It is important to note that different approaches may yield slightly different results.

and skewness into contributions from each of the included indicators. We group indicators with similar features, following the overview in Appendix B. The autoregressive component of each regression is grouped together to show the effect of the variable on its own density forecast.[17] The historical decompositions are calculated using the the latest coefficient estimates.

4.1 GDP

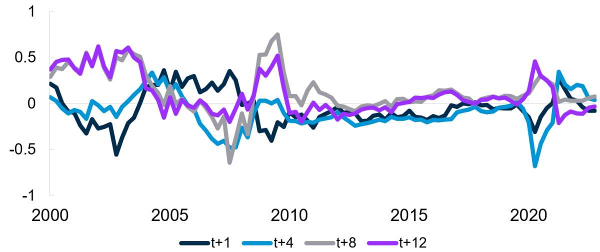
Mainland GDP growth has varied substantially during our sample period, but it has been largely stationary around 2.5 percent (Figure 1). The sample from 2000 is characterised by two events of negative growth: the GFC of 2007/2008 and the Covid-19 pandemic in 2020. Particularly high growth rates were observed leading up to the GFC and during the pandemic recovery in 2021. The results of our quantile regressions show that except in the run-up to these events, tail risks have been relatively balanced in terms of both skewness and magnitude (Figure 2).

Decomposing the spread and the skewness of the uncertainty to the GDP forecasts shows that volatility in uncertainty is largely driven by past realisations of GDP. This reflects persistence in the effect of economic shocks to GDP. For shorter horizons, financial market variables, predominantly variations to FCIs, also meaningfully contribute to variation in the sign and magnitude of uncertainty (Figures 6a and 7a). Along longer horizons, credit growth and property prices make important contributions, primarily to the skewness. Both show rapid increases from the early 2000s, and have since contributed to downside risk (Figures 6c and 6d). On the other hand, at these horizons, the Oslo Børs Technology Index contributed to upside uncertainty throughout, while its effect on spread is minimal.

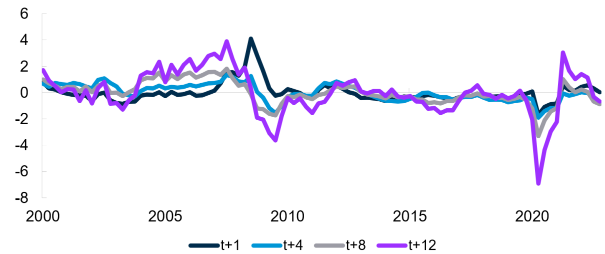
Using data through 2022Q4, the predicted GDP distribution is narrower than its historical average, meaning the spread is below zero in figure 2b. Illustrated by uncertainty one year ahead, this seems to be largely driven by slower household credit growth. The growth outlook one year ahead has been tilted to the upside on the back of high GDP growth during the post-Covid recovery. However, upside risks have recently decreased, in response to increasing financial market turmoil.

The decompositions further illustrate how, leading up to and during the GFC, the forecasted GDP distribution widened markedly and was clearly skewed to the downside at all horizons (Figures 2d and 2c). In the short run, the increased downside risk was driven by heightened financial market uncertainty, while in the longer run, high credit growth over time was especially important for increasing uncertainty. Since the GFC, the main spike in GDP growth was the Covid-pandemic. In the wake of the pandemic the spread for the medium-term growth outlook increased, mainly driven by past realisations of GDP.

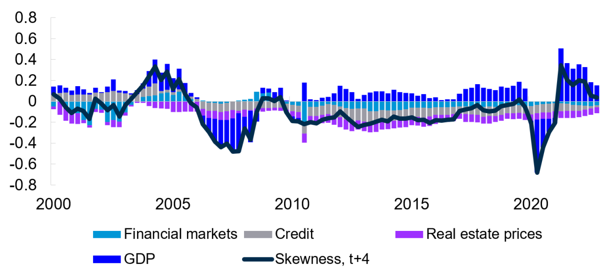
[17] A full overview of the decomposed skewness and spread for all variables at all horizons is found in Appendix C. Spread and skewness for all variables calculated recursively are found in Appendix D.



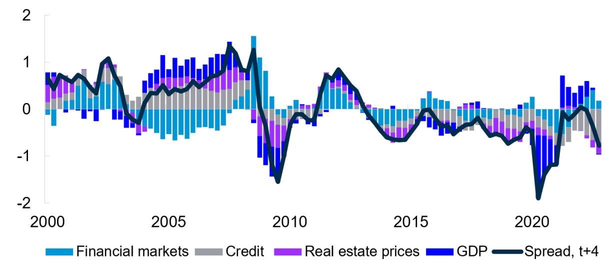
(a) Skewness



(b) Spread



(c) Decomposed skewness, t+4



(d) Decomposed spread, t+4

Figure 2: Skewness and spread for GDP uncertainty. Percent. 2000Q1 - 2022Q4.

4.2 House prices

House price growth in Norway has been relatively volatile over time, see figure 1. During the 1980s and 1990s especially, the growth of house prices exhibited wide fluctuations, with some years experiencing an increase of up to 30 percent, while others saw a decrease of approximately 10 percent. House price growth has recently been more stable with a tendency towards positive growth. However, figure 3 shows that there has been variation in the tail risk of house prices also during this period.

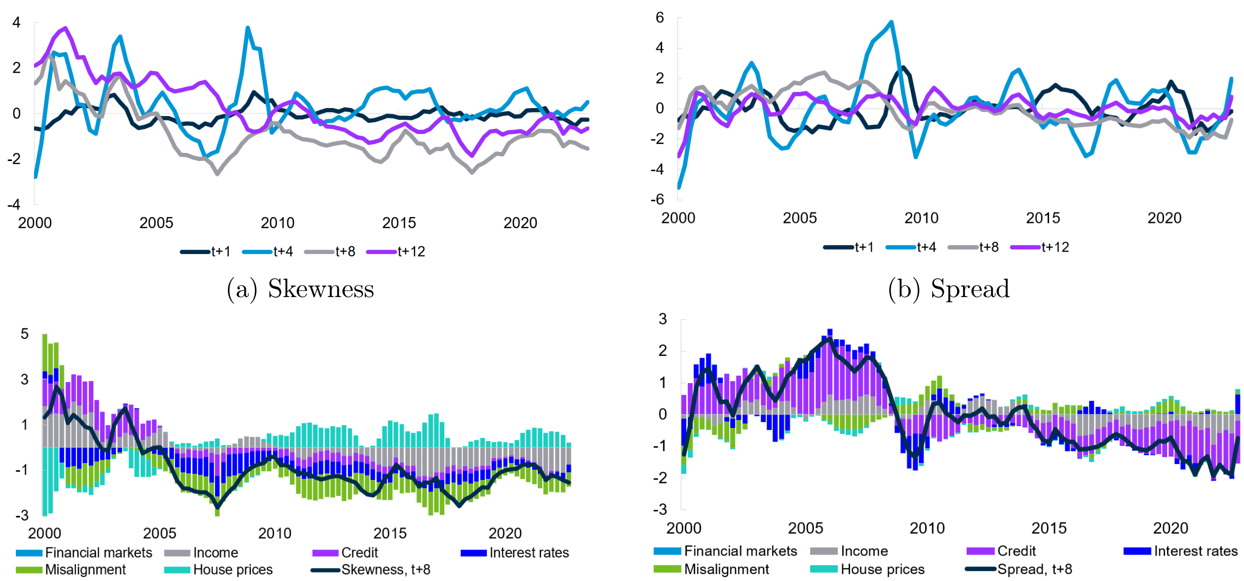
The decomposition of skewness and spread for the predicted house price density over time shows that financial market variables have been important drivers of the asymmetry and size of projected uncertainty in the short term, see figure 8 and 9 in Appendix C. While in the longer run, changes in income, house price misalignment, credit and interest rates are important drivers for the uncertainty. These findings are consistent with the literature (Section 2.2). The decomposition also shows that past realizations of house prices have been an important driver of the asymmetry and size of projected uncertainty in the long run.

Focusing on the movement of skewness and spread eight quarters ahead, it becomes evident that house price uncertainty has long been tilted to the downside (figure 3c and 3d). This movement can to a large extent be explained by misalignment measures, interest rates and household real disposable income.[18] However, past realizations of house prices have tended to tilt the risks to the

[18]The fact that household income is tilting the risks to the downside may be the opposite dynamic of what our intuition would suggest. This is caused by the constant term in the quantile regressions, which is negative. Partly, this may reflect that the constant term captures something in addition to the development in income. However, the coefficient of income in the quantile regressions is positive, indicating that an increase in income alone will contribute

upside and are thus moderating the lower tail risk. By the end of 2022 the uncertainty was tilted to the downside, but somewhat more than the average downside tilt. The increase in downside tilt is largely due to credit and real disposable income, raising upside risk less than they have previously. Furthermore, the forecasted spread eight quarters ahead was somewhat below the average spread between 2000 and 2022. These movements indicate a slight increase in downside risks to house prices and partly reflect the recent increase in interest rates in Norway. Household income has contributed in the other direction. The recent increase in interest rates is also contributing to an increase in the spread eight quarters ahead, although the spread remains below the average level.

The decompositions also illustrate how the forecasted house price distribution widened markedly and was clearly skewed to the downside during and leading up to GFC. These movements are present for both shorter and longer horizons, see figure 8 and 9 in the appendix. In the short run, the increased downside risk was driven by heightened financial market uncertainty. While in the longer run, higher interest rates combined with high credit growth over time was especially important for the rise in uncertainty. In addition, house prices rose substantially more than income in the years leading up to the GFC, also contributing to the rise in uncertainty and the risk being skewed to the downside.



(a) Skewness

(b) Spread

(c) Decomposed skewness, t+8

(d) Decomposed spread, t+8

Figure 3: Skewness and spread for house price uncertainty. Percent. 2000Q1 - 2022Q4.

4.3 Inflation

Compared to GDP and house price growth, the volatility of core inflation in Norway has been limited until recently (see figure 1). However, despite relatively stable inflation over the sample period, figure 4 shows that there has been considerable variation in the tail risk of inflation over the

to an increase in the upper tail risk.

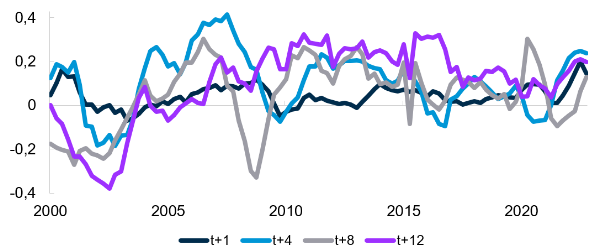
past 20 years. For example, following the GFC, the magnitude of medium-term inflation uncertainty rose. Meanwhile, both the 2015 decline in oil prices and the Covid pandemic were accompanied by marked shifts in the skewness of inflation uncertainty.

Decomposing the movement of skewness and spread of predicted inflation density shows that inflation itself has been an important driver of the asymmetry and size of projected uncertainty, in line with Fountas and Karanasos (2007) and Giordani and Söderlind (2003). Generally, our results suggest that the importance of inflation at time t for the inflation uncertainty distribution h periods ahead declines with the size of h.

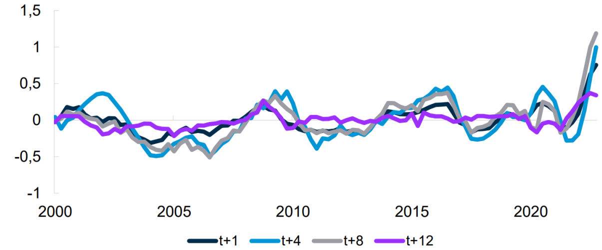
In the short term, money and credit conditions have generally contributed to risks tilting to the downside, except for the period around the GFC. The magnitude of uncertainty in the medium term has tended to be somewhat pro-cyclical, whereby improved real economic variables tend to raise the probability of higher inflation and its upper tail risk, see figure 11 in Appendix C. Meanwhile, higher cost indicators have tended to skew the forecasted distribution to the upside, and are found to be important along most horizons for changes in both the magnitude and skewness of projected uncertainty.

In 2022 core inflation rose markedly. Figures 4a and 4b show that both skewness and spread of inflation uncertainty picked up in mid-2021. Figures 4c and 4d decompose the drivers of this increase for our one-quarter-ahead density forecasts. Money and credit conditions' contributions to the downside considerably declined during and after the pandemic, remaining at a lower level until the end of 2022. Meanwhile, cost indicators contributed to suppressing the upside tilt of inflation risks until mid-2021, when their contribution began rising rapidly. Starting in 2021Q3, costs contributed to the steep increase in forecasted inflation risks.

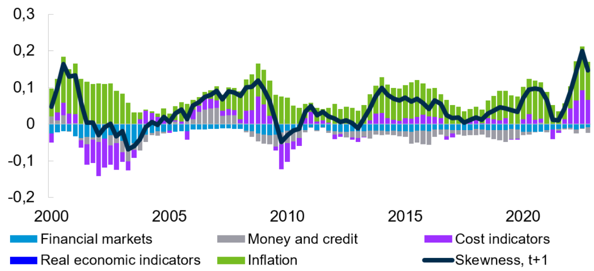
By the first quarter of 2022 the forecasted one-quarter-ahead skewness was well over double the average skewness between 2000 and 2020. CPI-ATE did not reach a quarterly average above the inflation target until 2022Q2. This was in line with the forecasted short-term upside risk rising in early 2022. From mid-2022 inflation dynamics became increasingly important in determining both the size and skewness of projected uncertainty.



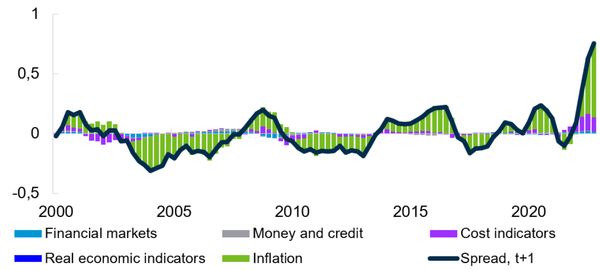
(a) Skewness



(b) Spread



(c) Decomposed skewness, t+1



(d) Decomposed spread, t+1

Figure 4: Skewness and spread for inflation uncertainty. Percent. 2000Q1 - 2022Q4.

4.4 Evaluation

Following our methodological approach, we evaluate our preferred predictive distribution using CRPS and log scores. The evaluation sample is set to the period 2000Q1 - 2019Q4 and everything is estimated in pseudo real time. All the forecasted distributions are compared with a benchmark distribution. Similar to Adrian et al. (2019), our benchmark is an estimated quantile distribution with only the variable of interest as an explanatory variable. In Table 1 we report the log score and CRPS of our forecasted GDP, inflation and house price uncertainty distributions relative to the benchmark. If the score is reported as higher than one, our preferred distribution performs better than the benchmark. Correspondingly, a score between 0 and 1 indicates that the benchmark performs better in our evaluation period. The results include results from a one-sided Diebold-Mariano (DM) test, testing if the preferred distribution performs significantly better (worse) than the benchmark.[19] Finally, we also consider the PIT empirical cumulative distribution functions of the preferred distributions and their benchmark. These are shown in Appendix E. An empirical CDF closer to the 45 degrees line indicates that the given model is better calibrated. Using this criteria, we can compare the PITs of our benchmark and the preferred model.

Using this approach, we find that including explanatory variables in addition to the past realisations of our dependent variables generally improves the performance density forecasting. There are some exceptions at individual horizons for some of our considered variables. Nonetheless, our results illustrate how economic and financial indicators can improve our understanding and prediction of macroeconomic uncertainty.

[19] (*) Significant at 1 percent level, (**) significant at 5 percent level, (***) significant at 10 percent level.

At most horizons, the predictive uncertainty distribution for GDP outperforms a simple benchmark model which only includes past realizations of GDP. The log score for the preferred GDP distribution including explanatory variables is higher than the benchmark at all horizons, but the difference is only significant at $t + 8$. CRPS results are more mixed, with the preferred GDP distrbution only significantly outperforming the benchmark at $t + 4$, whereas the benchmark is performing slightly better than the preferred GDP distribution at the longer horizons. However, the benchmark is not significantly better at these horizons. Furthermore, PIT CDFs, as seen in Appendix E, indicates that the preferred GDP distribution performs better or equally as well as the benchmark model. Consequently, the log score, CRPS and PIT suggests, all in all, that the inclusion of economic and financial indicators help us capture outlier events in the GDP-growth distribution, such as the GFC, and improve our forecast of GDP growth uncertainty.

The predictive uncertainty distribution for house prices indicates in general great uncertainty. It might, therefore, not be surprising that our preferred quantile distribution with indicators of uncertainty outperforms a simple model which only includes past realizations of house prices. Both the log score and the CRPS for our preferred model outperforms the benchmark model at most horizons, with only CRPS at $t + 1$ being the exception. The results are varying in significance but either log score or CRPS are significant for each of the forecasted horizons, also highlighting that the below-benchmark-score at $t + 1$ is not significant. These results suggest that including indicators of uncertainty when forecasting future house prices will give better predictability than only the simple benchmark model. PIT, illustrated in Figure 14 in Appendix E, also supports this statement.

During our evaluation period, there has been little variation in inflation as measured by the CPI-ATE. Consequently, a simple model that includes the past realizations of inflation would have been fairly accurate in forecasting future inflation during the sample period. Maybe unsurprisingly, therefore, the results in Table 1 indicate that there are few significant differences between the quantile distribution with or without explanatory variables. Nevertheless, our preferred distribution has a higher log score for all but $t + 8$, and which the preferred $t + 4$ performs significantly better than the benchmark. CRPS results are more mixed, indicating only better performance at $t + 1$ and $t + 12$. However, at both of these horizons the preferred inflation distribution is significantly better, whereas it does not perform significantly worse at $t + 4$ and $t + 8$. Finally, PIT CDFs indicate that the preferred distribution performs better or equally well compared to the benchmark, see Appendix E. It indicates that the preferred distribution performs especially well at $t + 4$.

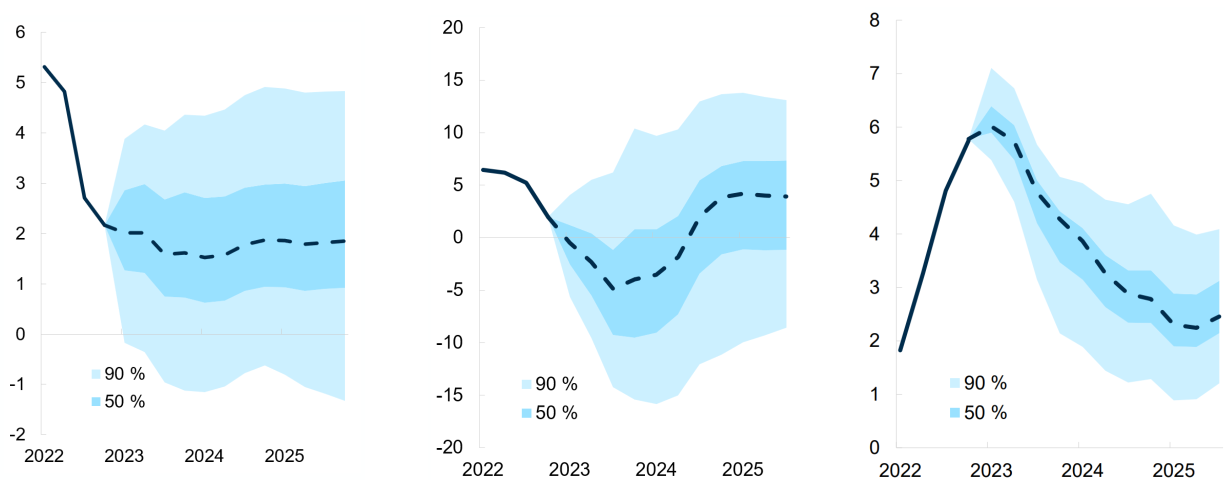
There are some individual horizons and variables where there does not appear to be a clear advantage to our asymmetric approach with more explanatory variables. Nonetheless, we believe that as long as asymmetric distributions based on a broader set of variables do not perform significantly worse than simpler benchmarks, there are still important advantages of utilising a richer set of information.

Method	H1		H4		H8		H12	
	LS	CRPS	LS	CRPS	LS	CRPS	LS	CRPS
GDP	1.06	1.01	1.03	1.03**	1.11*	0.95	1.09	0.96
Inflation	1.06	1.03***	1.07**	0.98	0.95	0.95	1.01	1.05*
House prices	1.04*	0.99	1.02***	1.03**	1.03	1.01**	1.03**	1.15*

Table 1: Relative log score (LS) and CRPS. A score higher than one indicates that the preferred distribution performs better than the benchmark. The difference is tested by Diabold Modigliani at *10 percent significance, ** 5 percent and *** 1 percent.

5 Summary and further development

This paper builds on a growing literature that uses quantile regressions on indicators to give time-varying forecast for uncertainty. Overall, it seems to work well on Norwegian data, both in terms of detecting uncertainty before episodes such as the Great Financial Crisis and the recent inflation surge, and in more formal tests of density forecasting accuracy. This could be a useful tool in the surveillance of the economic outlook. It also provides a quantitative indicator of the uncertainty surrounding macroeconomic projections. The framework could be used to construct illustrative fans around the variables of interest, as illustrated in figure 5, where they are based on data through 2022Q4. This paper documents a first version of our uncertainty framework. Going forward we would like to explore implementing smooth quantile regressions using the approach in Fernandes et al. (2021). We will continue to work on improving the system, both in terms of investigating different indicators and new empirical methods.



(a) GDP (b) House prices (c) Inflation

Figure 5: Fan charts for uncertainty. 2022Q1 - 2022Q4. Projections from SMART 2023Q1 - 2026Q4.

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A Overview of the data set

This table summarises indicators of uncertainty that have been tested for the constructing conditional predictive distributions.

Categories of indicators of macroeconomic uncertainty				
Data	Source	GDP	Inflation	House prices
National accounts	SSB	X	X	X
CPI and sub-indices	SSB	X	X	X
Credit indicators	SSB	X	X	X
Registred labour market data	NAV	X	X	X
Employments and earnings	SSB	X	X	
Exchange rates	NB, Datastream	X	X	X
Norges Bank's output gap	NB	X	X	X
House prices	Eiendomsverdi, Finn.no, Real Estate Norway	X	X	X
Housing construction	SSB			X
Commercial property prices	CBRE, DN, JLL, OPAK, SSB, Norges Bank	X		X
Tax rate income	Ministry of Finance			X
Interest rates	NB, SSB, Datastream	X	X	X
Stock market indexes	Datastream	X		X
FCIs	NB, Chicago Fed	X	X	X
Inflation expectations (US)	Cleveland Fed		X	
Producer price index	SSB, OECD		X	
KANTAR consumer confidence	KANTAR/Finans Norge	X		X
Business tendency survey	SSB	X		
Industrial production	SSB	X		
CPI various trading partner	Datastream	X	X	X
Norges Bank's output gap	NB	X	X	X
Norges Bank's Regional network	NB	X		
Norges Bank's Expectations Survey	NB	X	X	
TBU's inflation expectations	TBU		X	
Construction cost index	SSB		X	X
Monetary aggregates	SSB		X	
Commodity prices	IMF, Datastream, NB, SSB	X	X	
Volatility index (VIX)	Datastream	X		

Sources: *NB: Norges Bank. SSB: Statistics Norway. NAV: Norwegian Labour and Welfare Administration. NIMA: Norwegian Association of Purchasing and Logistics. Datastream: Refinitiv Datastream.*

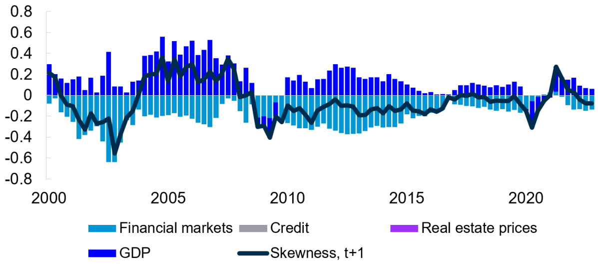
B Variable selection

This table summarises indicators of uncertainty used for the conditional predictive distributions.

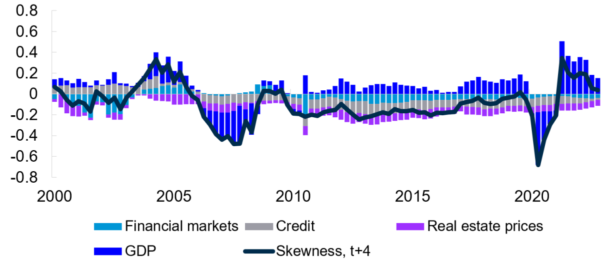
Indicators	Transf.	H1		H4		H8		H12	
		0.05	0.95	0.05	0.95	0.05	0.95	0.05	0.95
GDP									
Finance markets									
FCI NOR	level	X	X	X					
NFCI US	level	X							
Tech index OSEBX	level		X		X		X		X
Credit									
Real household credit (C2)	4Q change			X	X	X	X	X	X
Real NFC credit (C2)**	12Q change					X	X	X	X
Real estate prices									
Real house prices	4Q change			X	X				
House price to income	hp-gap*					X	X		
House price to income	20Q growth							X	X
Real CRE prices	12Q growth					X	X	X	X
House prices									
Finance markets									
Exchange rate (I44)	12Q growth	X		X	X				
Stock prices (OSEBX)	4Q growth	X							
Real stock prices***	4Q growth		X						
Oil prices	4Q growth		X						
Income									
Household real disposable income	4Q growth			X	X	X	X	X	X
Credit									
Household credit (C2)	8Q growth			X					
Household credit (C2)	4Q growth				X	X	X		
Household credit (C2)	16Q growth							X	X
Interest rates									
Mortgage lending rate	1Q change	X	X						
Lending rate adjusted for tax	8Q change			X					
Lending rate adjusted for tax	4Q change				X				
Debt service ratio	4Q change					X		X	
Debt service ratio	8Q change					X			X
House price misalignment									
House price to income	12Q growth			X	X	X	X		
House price to fundamentals****	Gap							X	X
Inflation									
Money and credit									
Money supply (M3)	4Q change	X	X						
NFC credit (C2)	4Q growth					X	X		
Household credit (K2)	4Q growth							X	X
Financial markets									
3M NIBOR	4Q change	X	X	X	X	X	X		
10Y, gov. bonds rates	4Q change							X	X
FCI NOR	level							X	X
Cost and price indicators									
Import deflator	4Q growth	X	X	X	X		X		X
CPI (3m average)	4Q change	X	X	X	X				
PPI consumption goods	4Q growth				X				
Real economic indicators									
Production gap	4Q change			X	X				
Registered unemployment	4Q change					X	X		X
Wage income	4Q growth					X	X	X	

** **HP-gap:** one-sided HP filter with Lambda 400.000. One year extrapolation by averaging the last four observations.*
** Discounted by nominal GDP.
*** OSEAX deflated by CPI.
**** Fundamentals measured by equilibrium levels of interest rates, unemployment and income.

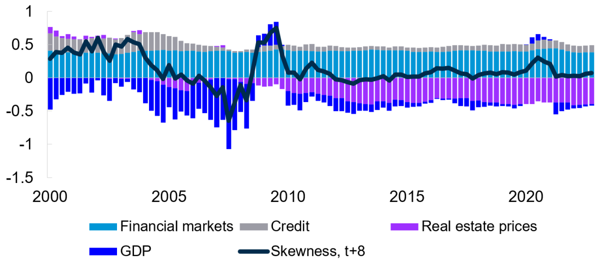
C Skewness and spread



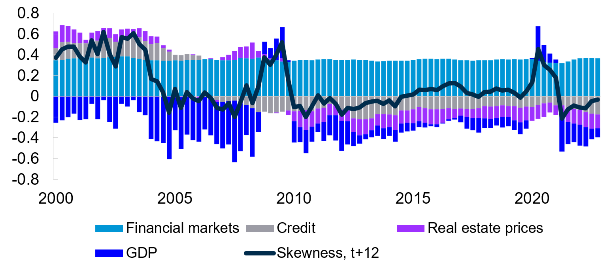
(a) Skewness, t+1



(b) Skewness, t+4

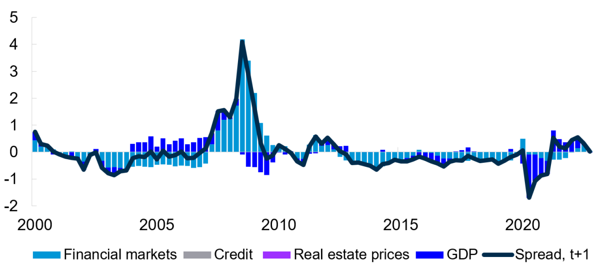


(c) Skewness, t+8

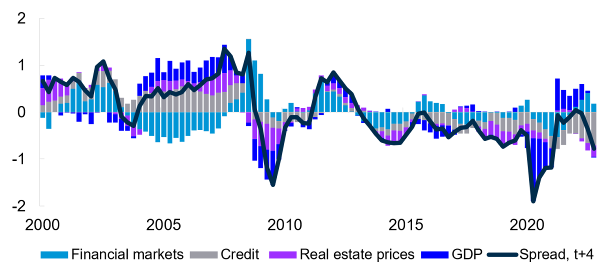


(d) Skewness, t+12

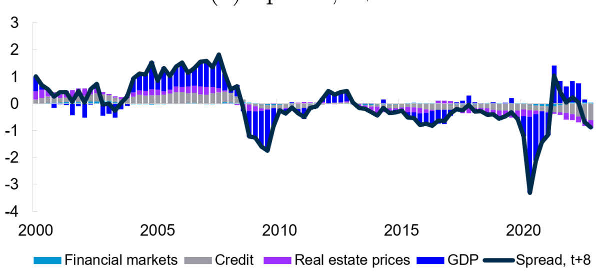
Figure 6: Skewness for **GDP uncertainty**. Percent. 2000Q1-2022Q4.



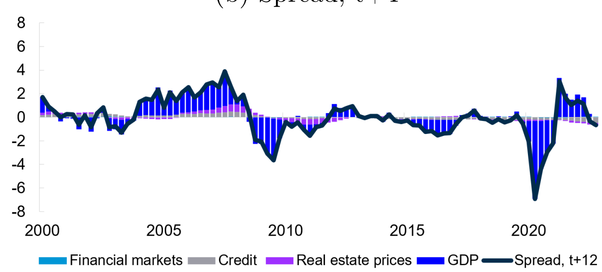
(a) Spread, t+1



(b) Spread, t+4

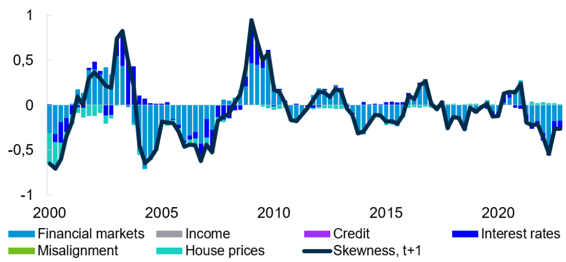


(c) Spread, t+8

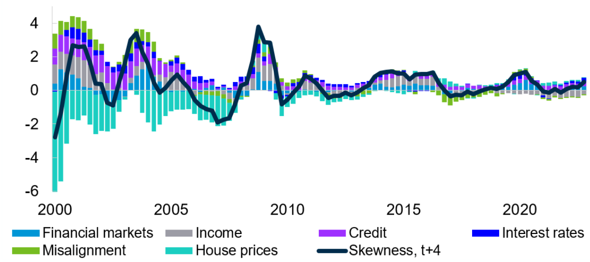


(d) Spread, t+12

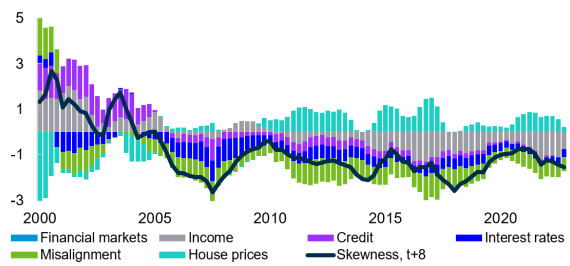
Figure 7: Spread for **GDP uncertainty**. Percent. 2000Q1 - 2022Q4.



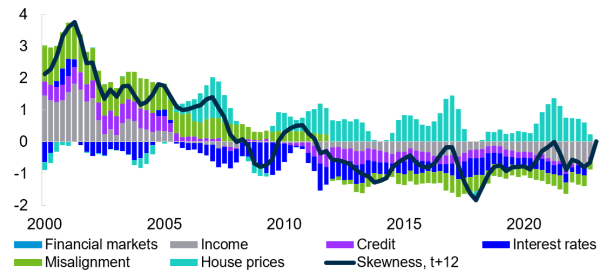
(a) Skewness, t+1



(b) Skewness, t+4

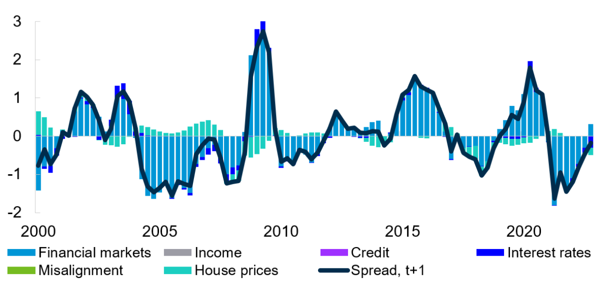


(c) Skewness, t+8

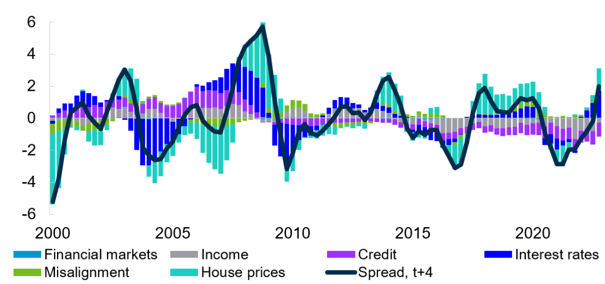


(d) Skewness, t+12

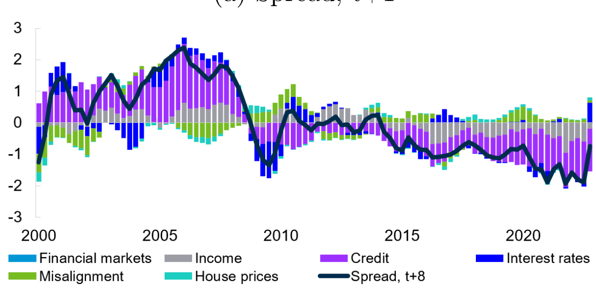
Figure 8: Skewness for **house price uncertainty**. Percent. 2000Q1 - 2022Q4.



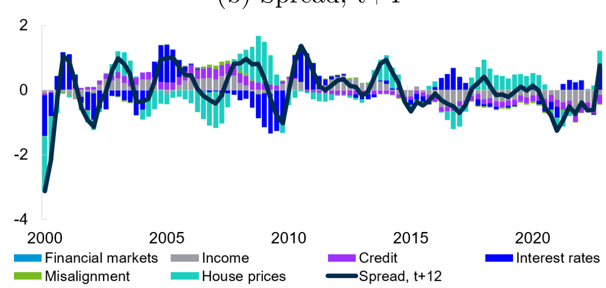
(a) Spread, t+1



(b) Spread, t+4

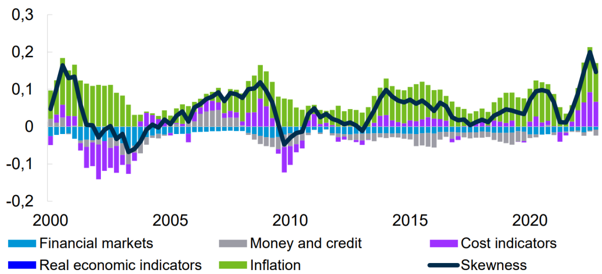


(c) Spread, t+8

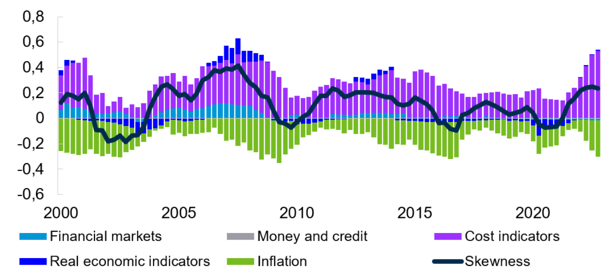


(d) Spread, t+12

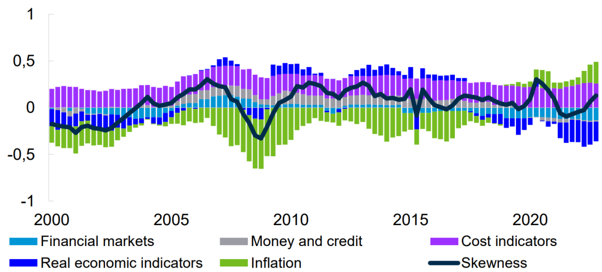
Figure 9: Spread for **house price uncertainty**. Percent. 2000Q1 - 2022Q4.



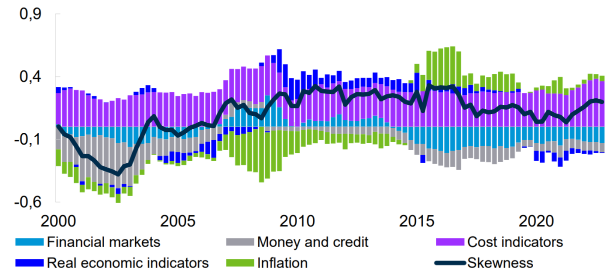
(a) Skewness, t+1



(b) Skewness, t+4

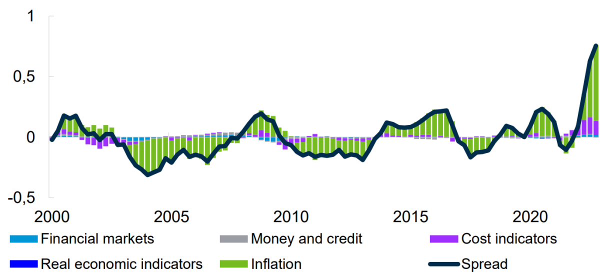


(c) Skewness, t+8

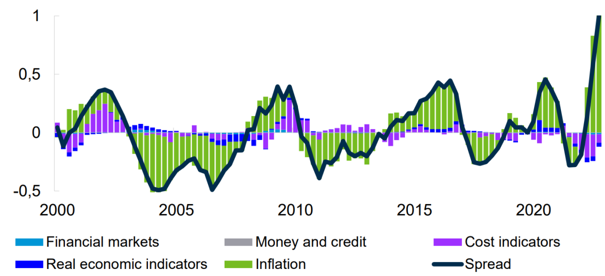


(d) Skewness, t+12

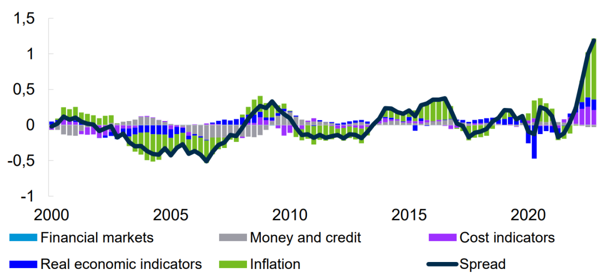
Figure 10: Skewness for **inflation uncertainty**. Percent. 2000Q1 - 2022Q4.



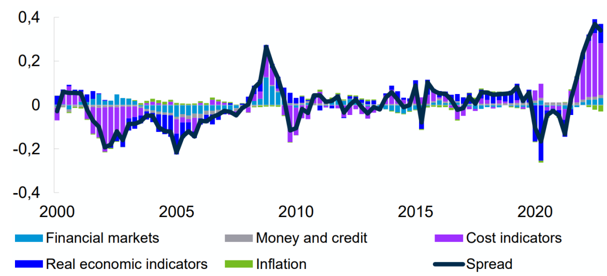
(a) Spread, t+1



(b) Spread, t+4



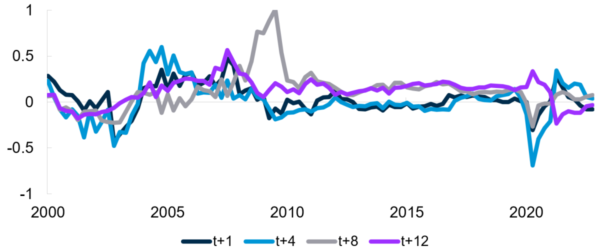
(c) Spread, t+8



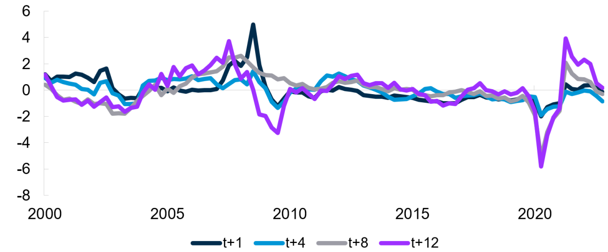
(d) Spread, t+12

Figure 11: Spread for **inflation uncertainty**. Percent. 2000Q1 - 2022Q4.

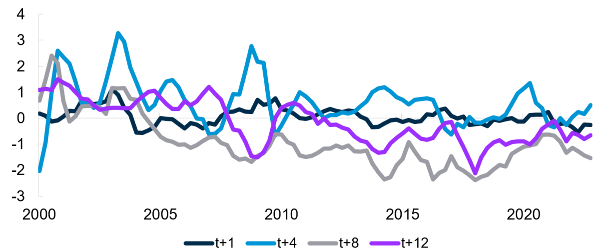
D Recursive skewness and spread



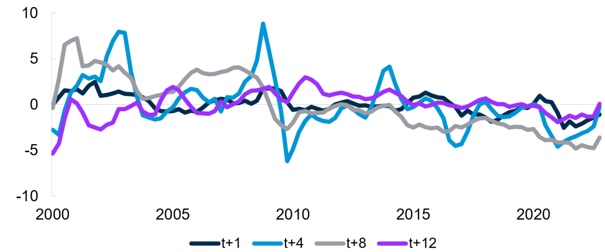
(a) **GDP**: Recursive skewness



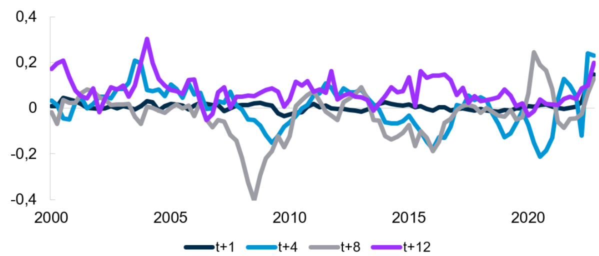
(b) **GDP**: Recursive spread



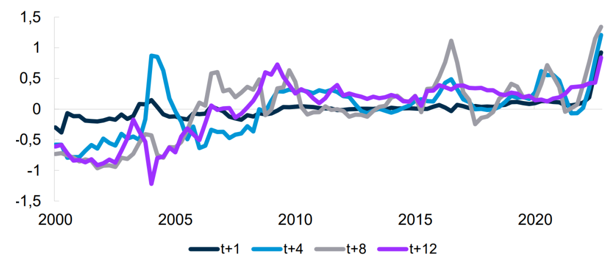
(c) **House prices**: Recursive skewness



(d) **House prices**: Recursive spread



(e) **Inflation**: Recursive skewness



(f) **Inflation**: Recursive spread

Figure 12: Recursive skewness and spread. Percent. 2000Q1 - 2022Q4.

E PIT empirical cumulative distributions

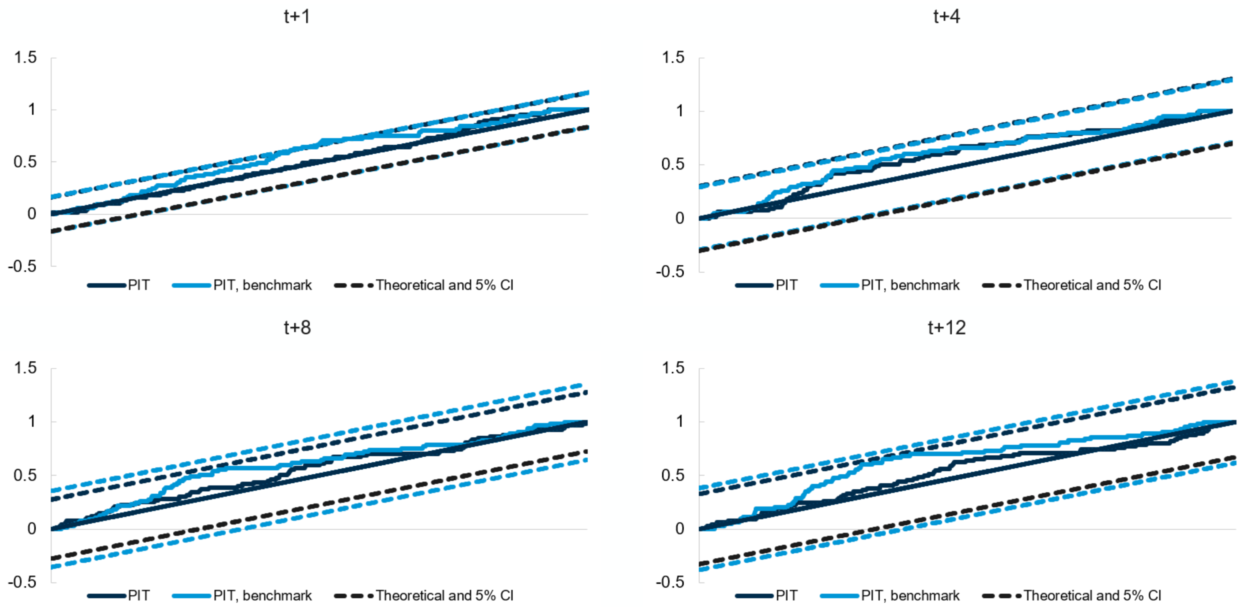


Figure 13: GDP PITs

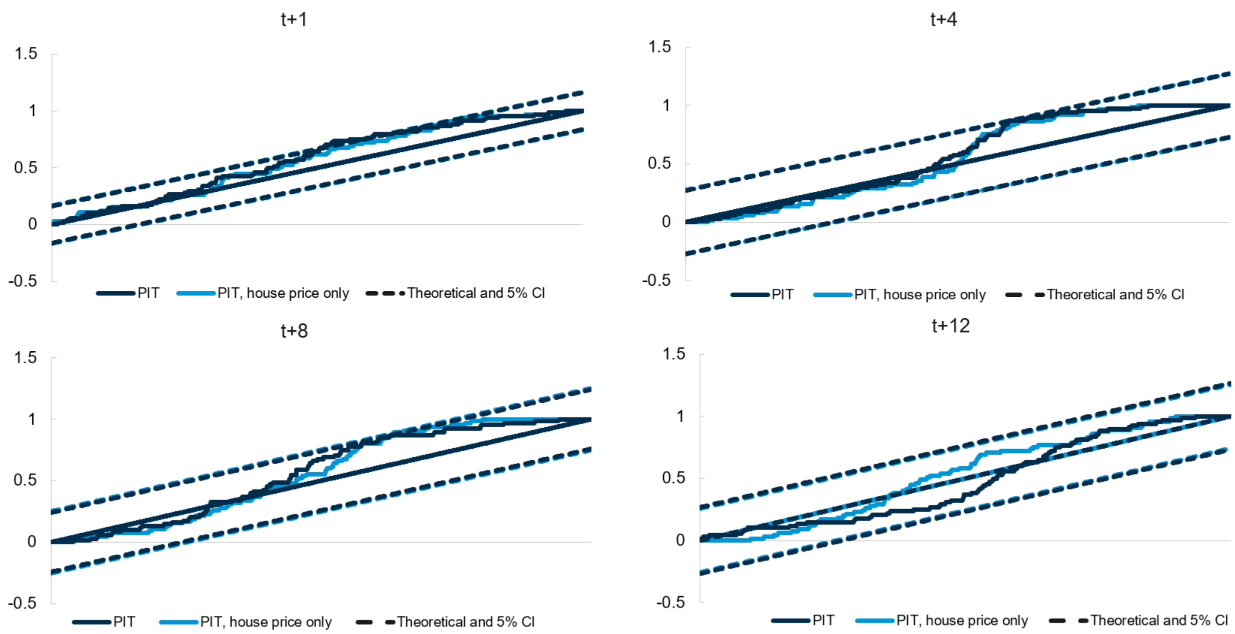


Figure 14: House price PITs

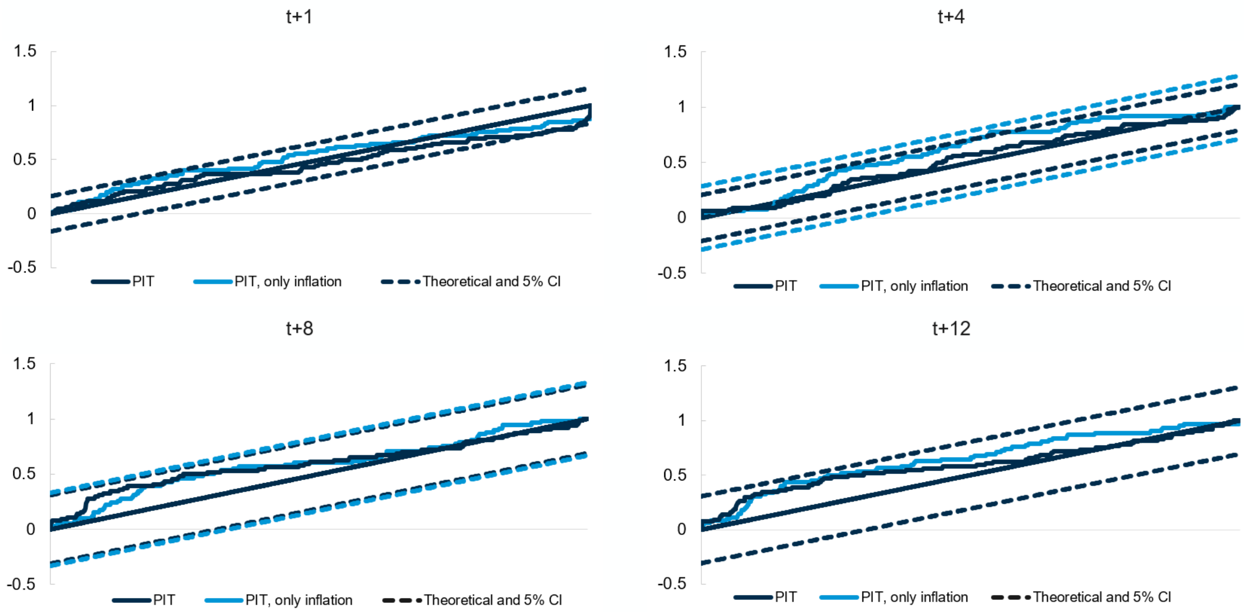


Figure 15: Inflation PITs