Analysis

The impact of uncertainty on tail risk in the Dutch economy

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May 2025

DeNederlandscheBank
EUROSYSTEEM

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Summary and policy implications

Measures of uncertainty have surged recently, especially following the announcements of trade tariffs by the US administration. This reflects not only uncertainty about the implementation of the tariffs, but also about the economic and financial impact of a trade war. Rather than being an isolated event, the recent surge in uncertainty adds to a broader pattern observed over the past decade. A series of shocks to the global economy and financial system have repeatedly led to spikes in financial, geopolitical, and economic policy uncertainty. These dimensions of uncertainty have increasingly moved together, rather than peaking in isolation as in the past.

Based on a Growth-at-Risk (GaR) model we show that elevated uncertainty is associated with heightened tail risks for the Dutch economy and financial system. We identify and quantitatively analyse the channels through which uncertainty in general affects the economy and the financial system. In addition, we examine the role of bank capitalization in mitigating these downside risks to economic growth.

High uncertainty affects the economy through real and financial channels. On the real side, uncertainty discourages consumption, investment and trade, dampening aggregate demand. On the financial side, heightened uncertainty increases investors' risk aversion and the risk of disorderly market price corrections, widening credit spreads, and driving up funding costs for banks, households and firms. These channels affect both the real economy and financial stability.

Our analysis indicates that elevated uncertainty in the current environment heightens the risk of adverse outcomes for GDP growth and inflation. While uncertainty is expected to increase the range of possible outcomes, we find that an increase of uncertainty in general foremost negatively affects the lower tail outcome of GDP growth and raises the upper tail of inflation in the Netherlands. These combined tail effects on GDP and inflation imply that an increase of uncertainty has effects similar to a negative supply shock, at least in the short run. For the euro area, uncertainty increases the dispersion of inflation outcomes, making both extremely high and low inflation scenarios more likely. This increased inflation volatility complicates monetary policy decision-making.

In addition to raising tail risks to GDP growth, elevated uncertainty also implies higher financial stability risks due to a greater probability of significant asset price drops. Via the financial channel, high uncertainty is associated with a higher risk of sharp declines in asset prices and higher funding costs for banks, households and firms. Using the Growth-at-Risk framework, our analysis finds that elevated uncertainty significantly increases the size of corrections in equity prices, corporate bonds and bank bonds. While uncertainty negatively affects both the typical outcome and tail risks, the effect on the latter is considerably larger and more persistent.

A well-capitalized banking sector helps to dampen the adverse financial stability effects of heightened uncertainty, while it is not necessarily associated with lower median economic growth. Examining data from the Netherlands and eight other advanced economies, we find that sufficiently high bank capital ratios are associated with reduced tail risks to GDP growth in our sample. Moreover, adequate bank capital also directly reduces the impact of uncertainty on tail risks to the economy. Both findings reflect that a sufficiently well-capitalized banking sector reduces the risk of amplification effects following a negative shock, such as a rise in geopolitical or economic uncertainty. At the same time, we find no evidence that higher bank capital is associated with lower median economic growth, suggesting that a well-capitalized banking sector need not come at the expense of the typical pace of economic growth.

Our analysis underscores the importance of maintaining current levels of capital to ensure a resilient financial sector capable of withstanding shocks. Banks with solid capital buffers help reduce the negative impact of shocks such as those stemming from elevated uncertainty, by keeping credit available to the economy. Efforts to simplify regulation should therefore not come at the expense of robust capital standards, as this would materially increase the risk of severe economic downturns.

In today's environment of heightened uncertainty - driven largely by global factors - multilateral frameworks and institutions are essential for preserving financial stability. Rising uncertainty, fuelled by shifting trade policies and geopolitical tensions, underscores the need for coordinated strategies to mitigate risks and enhance resilience. Given the deep interconnectedness of economies and financial systems, unilateral strategies to contain risk are often insufficient. Therefore, policymakers should continue to safeguard international cooperation to reduce uncertainty and to increase economic and financial sector resilience if adverse shocks materialize.

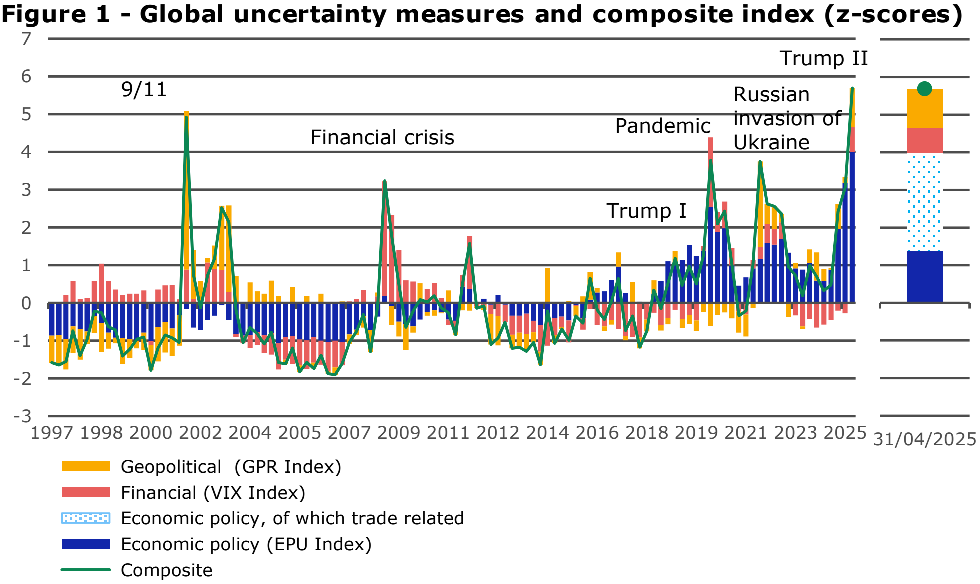
1. An uncertain environment

1.1 Measuring uncertainty

Uncertainty has spiked frequently in recent years, reflecting a series of shocks that have hit the global economy. This environment of heightened uncertainty has multiple dimensions, as illustrated by different proxies of uncertainty. Uncertainty in financial markets can, for example, be measured by the VIX index, reflecting the implied volatility of stock prices. Other well-known metrics aim to reflect uncertainty about geopolitics (geopolitical risk index, GPR), uncertainty about economic policies in general (EPU) or uncertainty about specific policy areas such as trade (TPU).[1] The latter three metrics are based on the frequency of newspaper articles that cover these dimensions of uncertainty.

In recent years the dimensions of uncertainty have often risen in tandem, rather than peaking in isolation. Before 2015, the uncertainty metrics tended to peak in a single dimension. Geopolitical uncertainty jumped after the 9/11 attacks and the start of the Iraq war, while financial uncertainty spiked during the global financial crisis in 2008. More recently, the various measures of uncertainty have increasingly risen simultaneously, leading to clusters of heightened uncertainty (Figure 1). Economic policy uncertainty increased under the first Trump administration, largely driven by trade policies, and later increased in tandem with financial uncertainty at the onset of the COVID-19 pandemic. All three dimensions of uncertainty – geopolitical, economic and financial – spiked in unison following Russia's invasion of Ukraine in February 2022. The most recent spike in uncertainty is driven by economic policy uncertainty, particularly related to trade, which has also spilled over into a significant increase in financial uncertainty (Figure 1, rhs). The different dimensions of uncertainty are sometimes interrelated and can overlap, as Hodula et al. (2024) show. We therefore construct a composite index based on principal component analysis to measure the overall level of uncertainty throughout this analysis.

Figure 1 - Global uncertainty measures and composite index (z-scores)



Source: DNB calculations. Note: Figure shows the first principal component the standardized EPU, VIX and GPR Index, see Baker et al. (2016) and Caldara, Dario and Matteo Iacoviello (2019). The individual contributions at a given time are determined by multiplying the value of each index by its loading in the first principal component (PC1). The value for February, March and April includes an ARIMA (2,1,2) estimate for the global EPU index based on the US version.

[1] See for an overview and detailed definitions: https://www.policyuncertainty.com/gpr.html.

The economic impact of uncertainty is hard to estimate using standard modelling approaches. This is due to fundamental uncertainty, in the sense that the distribution of shocks, their transmission mechanism and outcomes are unknown.[2] Under such conditions, structural economic models are less useful, as they typically rely on past regularities and known probability distributions. This makes the identification of shocks – for example whether they more closely resemble a supply or demand-shock – problematic and complicates designing an optimal policy response. In this analysis we use a Growth-at-Risk (GaR) model to assess the impact and nature of uncertainty shocks. This is an appropriate model to analyse the impact of high uncertainty, as we will explain in Section 1.3.

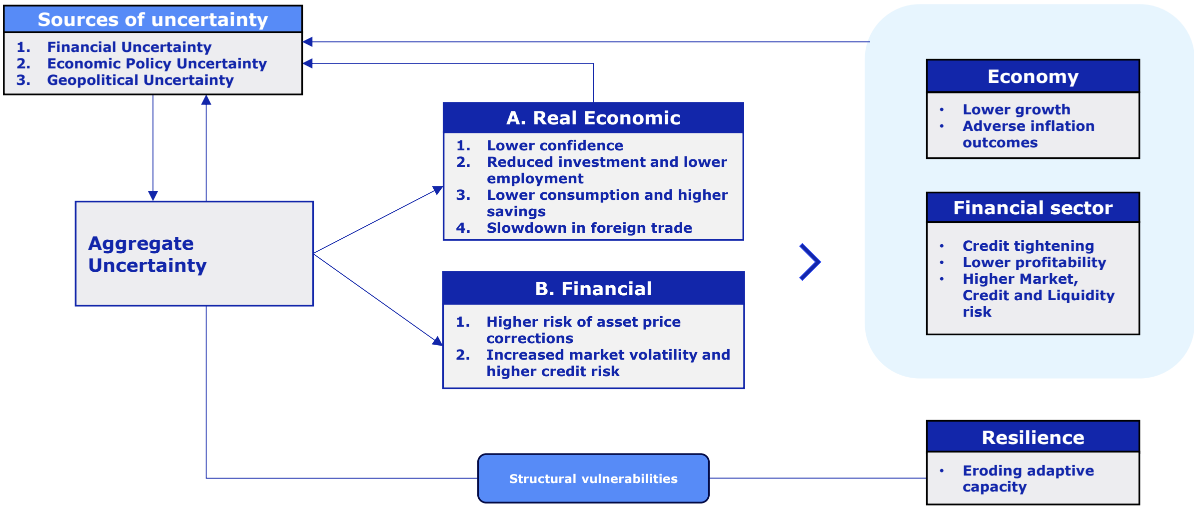
1.2 Real and financial transmission channels

Uncertainty has wide-ranging effects which work through financial and real economic channels (see Figure 2, which is similar to the framework outlined by the IMF, 2024). Through the financial channel, an uncertainty shock can affect market liquidity, asset prices and risk spreads, thereby influencing broader financial conditions. For instance, a decline of stock prices lowers the market value of listed firms, making equity finance more expensive. Heightened risk aversion in global financial markets may spill over and reduce the supply of credit if uncertain business conditions impair borrowers' or creditors' creditworthiness, prompting lenders to tighten their credit standards. These channels can interact and mutually reinforce one another, amplifying the overall effect of macroeconomic uncertainty on financial stability (IMF, 2024). Studies show that measures of macroeconomic uncertainty are indeed associated with lower asset returns and higher volatility (e.g. Asgharian et. al. 2015, Bali et. al. 2017). Moreover, similar results are found for measures focusing on (geo-)political uncertainty (e.g. Caldara and Iacoviello 2022, DNB 2023, Pastor and Veronesi 2013). These studies, however, do not focus on the full distribution of outcomes, but only on average effects.

Through the real economic channel, increased uncertainty can depress spending and investment, leading to lower aggregate demand (Schaal, 2017). In an uncertain environment, confidence effects can render consumers more reluctant to spend and more eager to save for precautionary reasons, while firms may suspend investments as they become more pessimistic or uncertain about demand in the future. Changes in confidence can be thought of as a shift in agents' perception about the probability of a particular outcome (Nowzohour and Stracca, 2020). This differs from higher uncertainty, which is associated with an increasing range of possible outcomes and thus an increased dispersion of the probability distribution. The real economic channel can also work through international factors such as trade linkages. For example, uncertainty about trade policy or geopolitical events can affect global trade by disrupting global supply chains, increasing production costs and reducing access to foreign markets.

[2] See for instance Lempert et al.(2003) and Walker et al. (2013).

Figure 2 - Transmission channels of uncertainty



Source: DNB

1.3 Modelling the effects of uncertainty

We model the impact of uncertainty on the economy and financial sector with a Growth-at-Risk (GaR) model. This tool is commonly used by the IMF and central banks for tail risk and scenario analyses, see for instance Adrian et al. (2019), Adrian et al. (2022), Lopez-Salido and Loria (2024) and Lane (2024). GaR is a simple reduced form framework, which does not impose much structure on the data. This is an appropriate feature for states of the world in which the dynamic relations between variables are unknown ex-ante. By quantile regressions, the impact of shocks on the distribution of key variables like GDP growth is estimated. This is similar to the Value-at-Risk concept used in financial risk management to estimate the potential loss of a portfolio in a tail scenario.

Quantile regression takes into account that uncertainty shocks could propagate differently in the tails of the distribution.[3] By estimating different coefficients for each quantile of GDP growth, for example, GaR takes into account the non-linear effects of uncertainty shocks. This is an important feature, because larger shocks can have a disproportionately greater impact (Brignone et al., 2024). It also helps uncover downside risks that may be overlooked by standard regression models. For example, there are periods where financial markets are stable while uncertainty is high or increasing, referred to as a “market-macro” disconnect (see Bialkowsi et. al. 2022, IMF 2024). In standard regression models, the inclusion of these periods would lower estimates of the effect of uncertainty on GDP growth, even though these effects could be larger in the tail of the distribution. The ability to uncover such non-linear relationships makes GaR a useful tool to analyse tail events.

[3] Quantile regression is useful in the presence of heteroscedasticity or nonlinear relationships, which are common in complex systems with high uncertainty. Quantile regression is robust to outliers, does not assume a specific form of the distribution of the dependent variable and does not assume that the residuals are normally distributed.

Based on the IMF GaR model (Adrian et al., 2019) we estimate the impact of uncertainty on the Dutch economy and financial sector. We extract the common component of three uncertainty measures (EPU, GPR, VIX), which we will refer to as composite uncertainty.[4] This composite uncertainty measure is estimated as the first principal component of the three uncertainty measures, a standardized version of the principal component is shown in Figure 1. We then estimate how this composite uncertainty affects the conditional distribution of GDP and inflation (see Annex A for the model specification). Subsequently, we estimate tail risks to financial asset prices stemming from uncertainty and investigate the role of bank capital in reducing tail risks to GDP growth. Throughout this analysis we use the 10^{th} percentile of the distribution when we refer to tail risks. For example, in the case of tail risks to GDP growth we estimate how uncertainty affects the worse 10% outcomes of GDP growth, i.e. how uncertainty affects relatively low outcomes for economic growth.

[4] TPU is not included in the common component, because trade uncertainty is part of the EPU index.

2. Uncertainty and the real economy

In this chapter we analyse the effects of uncertainty on the real economy. Uncertainty affects the economy via its effect on consumer and producer confidence, spending and trade. These effects can be non-linear and can give rise to tail risks for economic growth and inflation. We first discuss the impact of uncertainty on the specific channels before outlining the overall impact on GDP- and inflation-at-risk.

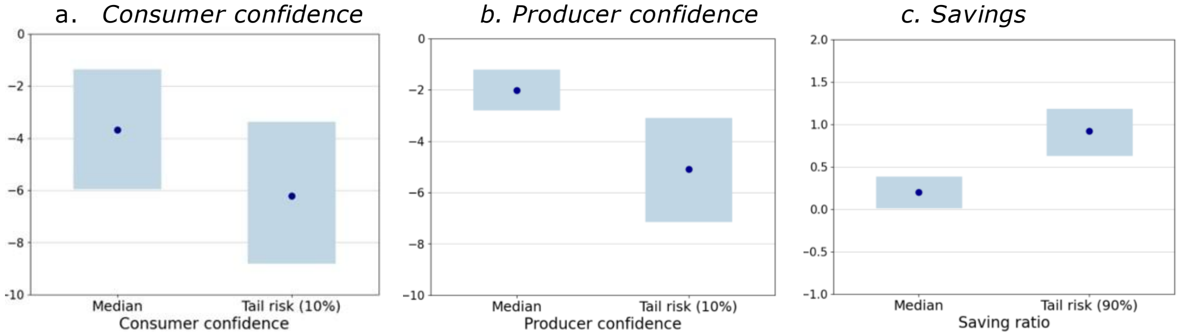
2.1 Confidence effects and the real economic channel

Through the real economic channel, uncertainty affects spending and investment. This can work through confidence effects, if uncertainty makes households and firms more cautious and reluctant to spend. We analyse this channel by estimating the effect of composite uncertainty on the tail outcomes of confidence and household savings in the Netherlands.

The results show that confidence is negatively affected by uncertainty, especially in the lower tail of the confidence distribution (Figure 3a-3b). In the lower tail, the negative effect of composite uncertainty on consumer confidence is 1.6 times stronger than typical (i.e. the median effect). This suggests that uncertainty shocks have a disproportionate effect on confidence in periods where confidence is already subdued or declining rapidly. Producer confidence is even more strongly affected by uncertainty: producer confidence drops 2.5 times more in the tail of the distribution compared to the effect at the median. The results overall show that elevated uncertainty is not only associated with lower confidence in general, but especially with sharper drops in both consumer and producer confidence.

Household savings in the Netherlands tend to increase after a rise in composite uncertainty (Figure 3c). Uncertainty has an upward effect on both the typical savings rate as well as on the upper tail of the distribution. However, the effect on the upper (90%) tail of the savings ratio is significantly larger than the median effect: a one standard deviation increase of uncertainty raises the upper tail of the savings ratio by nearly 1 pp one quarter ahead (compared to an average savings ratio in 2020-2024 of 4.6%). Elevated uncertainty is thus associated with larger-than-usual increases in household savings.

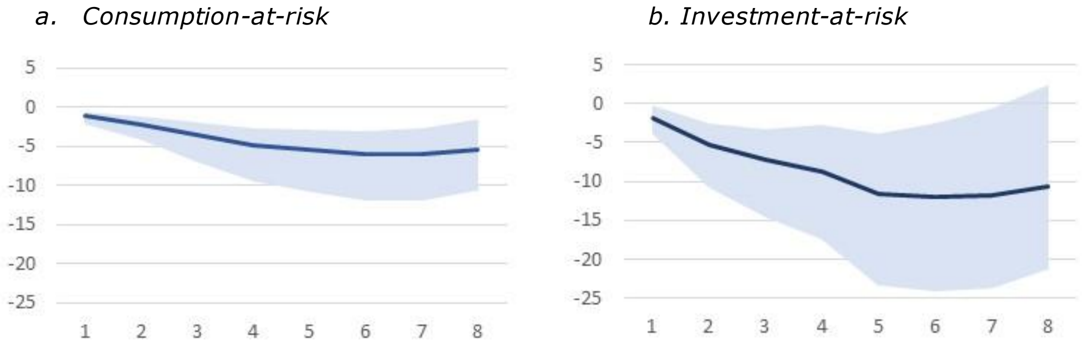
Figure 3 – Estimated impact of composite uncertainty on confidence and savings in the Netherlands



Notes: Median and tail quantile regression coefficients of one quarter lagged composite uncertainty in an equation with confidence index (included in levels) and in an equation with household savings (individual savings over income) as dependent variables. Blue dots are the estimated coefficients in percentage points. Boxes indicate 90% confidence intervals.

Uncertainty also raises the risk of very low consumption and investment growth. An increase of uncertainty has a significant downward effect on consumption and investment growth in the lower (10%) tail of the distribution (Figure 4a-4b). Elevated uncertainty is thus associated with sharp drops in consumption and investment growth. This effect materializes with a lag, with the impact of uncertainty peaking after around 1½ year. The impact on investment is clearly higher than on consumption, in line with the relatively strong tail impact of uncertainty on producer confidence. The downward tail effect of composite uncertainty on consumption matches with the upward tail effect on household savings shown in Figure 3c.[5]

Figure 4 – Estimated impact of composite uncertainty on spending growth in the Netherlands



Notes: Impact of one standard deviation increase of composite uncertainty on the 10% quantile of private consumption and corporate investment growth (y-o-y). The regression of consumption (investment) growth includes composite uncertainty as regressor, next to one lag of the confidence variable. Bold line shows the cumulative impulse response based on local projections (IRF, computed as the sum of the non-scaled coefficients) and shaded areas the 90% confidence intervals. Impact in percentage points on y-axis and time horizon in quarters on x-axis.

[5] To distinguish the effects of uncertainty and confidence on spending, we estimate an alternative model specification with composite uncertainty, (consumer or producer) confidence and their interaction as regressors. The outcomes show that uncertainty and confidence separately have a significant effect on consumption and investment (the 10% quantile coefficients being significant). Although we showed in Figure 3 that uncertainty has a significant effect on confidence, based on the alternative model we do not find that a change of uncertainty strengthens the effect of confidence on spending-at-risk: the estimated coefficient of the interaction term is not significant (for alle quantiles).

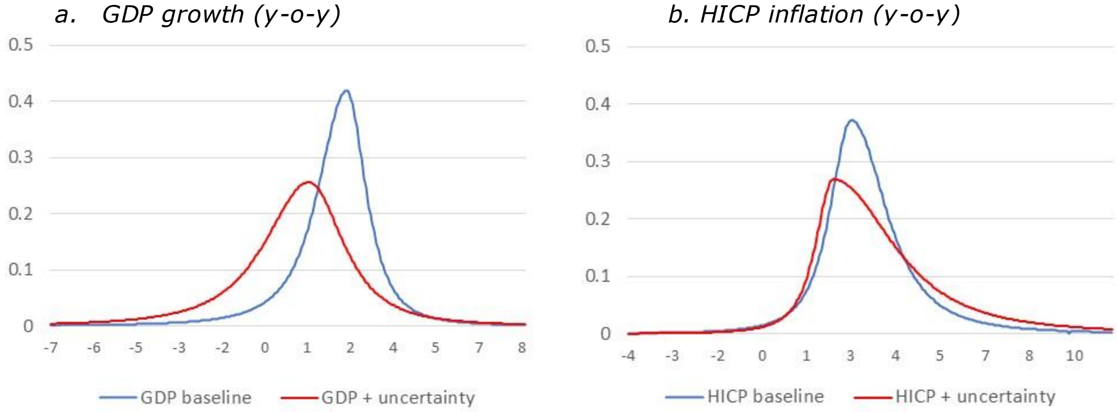
2.2 GDP and inflation-at-risk

Heightened uncertainty increases the risk of extreme adverse real economic outcomes. Such outcomes are summarised in measures for GDP-at-risk and, relatedly, inflation-at-risk. As before, we define these measures as the cutoff value for annual GDP growth and annual inflation at the 10% and 90% tails respectively. We forecast the distributions of GDP growth and inflation using the common component of uncertainty as one of the input variables. Comparing this forecasted distribution with that without using the uncertainty variable (i.e., the baseline distribution) shows the effect of uncertainty on the distribution of GDP growth and inflation.

Uncertainty affects the distribution of GDP growth in the Netherlands by increasing the probability of large negative outcomes (Figure 5a). For the one quarter ahead forecast, the 10% tail of GDP growth conditional on uncertainty is 2.3 pp lower than GDP-at-risk in the baseline. In other words, elevated uncertainty is not just associated with lower growth overall, but especially with more severe recessions. Figure 6a zooms in on the difference between the median and tail impact of uncertainty on GDP growth. It shows that the coefficient of the 10% quantile is significantly lower than the median. This means that a one standard deviation increase of uncertainty negatively affects the left tail outcome of GDP growth by 1.3 pp. This tail outcome is at the lower end of the range estimated by the IMF (2024) for a panel of advanced and emerging market economies.

Figure 5 - One quarter ahead forecast of probability distributions for the Netherlands

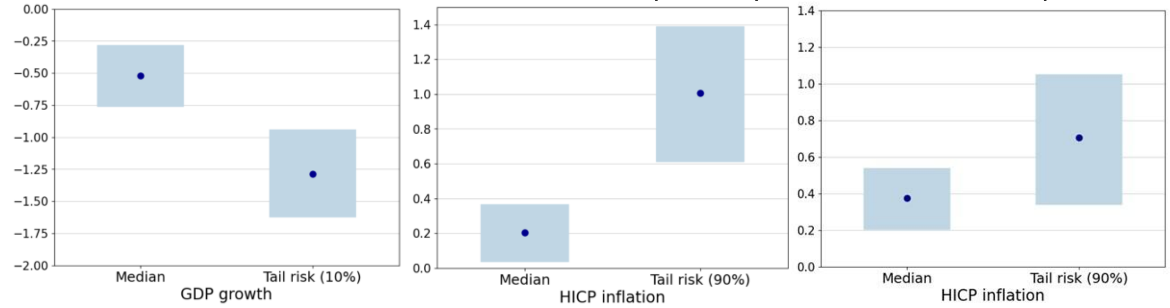
a. GDP growth (y-o-y) *b. HICP inflation (y-o-y)*



Notes: Baseline (blue distribution) is the (direct) one quarter ahead forecast of the autoregressive baseline model, based on data of 2024Q4. GDP (inflation) + uncertainty (red distribution) is the one quarter ahead forecasted distribution of GDP growth (inflation) conditional on composite uncertainty as additional regressor. Probability on y-axes. GDP growth and inflation on x-axes in percentage points.

Figure 6 – Estimated impact of composite uncertainty on Dutch GDP and inflation-at-risk

a. *GDP-at-risk* b. *Inflation-at-risk (baseline)* c. *Inflation-at-risk (alternative)*

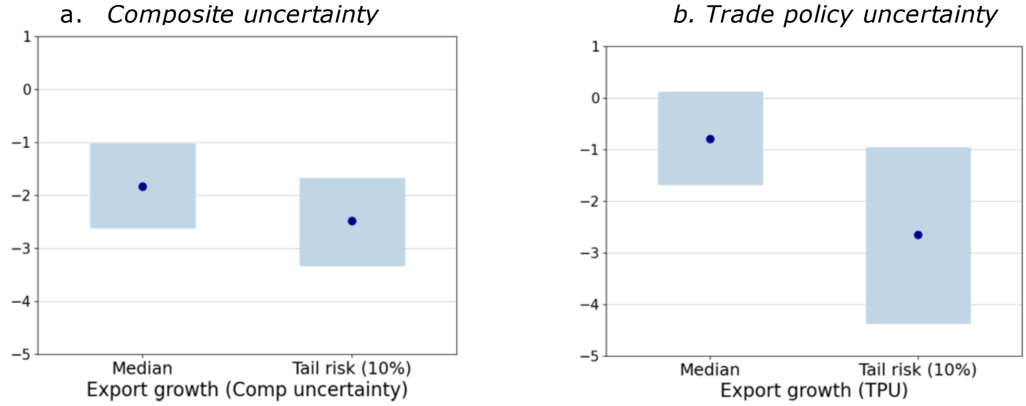


Notes: Median and tail quantile regression coefficients of one quarter ahead lagged composite uncertainty in an equation with GDP growth and in an equation with HICP inflation (middle panel based on the baseline specification with composite uncertainty and lagged inflation as regressors; right panel based on an alternative specification with composite uncertainty, lagged inflation, GDP growth and wage growth as regressors). Blue dot is the estimated (not scaled) coefficient for the median and tail quantiles. Box is the 90% confidence interval. Impact on GDP growth and inflation in percentage points on y-axis.

The downward effect on GDP-at-risk could relate to the impact of economic and trade policy uncertainty on trade flows. In response to looming import tariffs and higher trade costs, world trade growth may slow down. The downward demand effect via the trade channel is illustrated in Figure 7. It shows that – compared to the median effect - the lower left tail risk of Dutch export growth is more negatively affected by trade policy uncertainty than by general (composite) uncertainty, although the differences are generally not statistically significant.

Figure 7 – Estimated impact of uncertainty on export growth for the Netherlands, one year ahead

a. *Composite uncertainty* b. *Trade policy uncertainty*



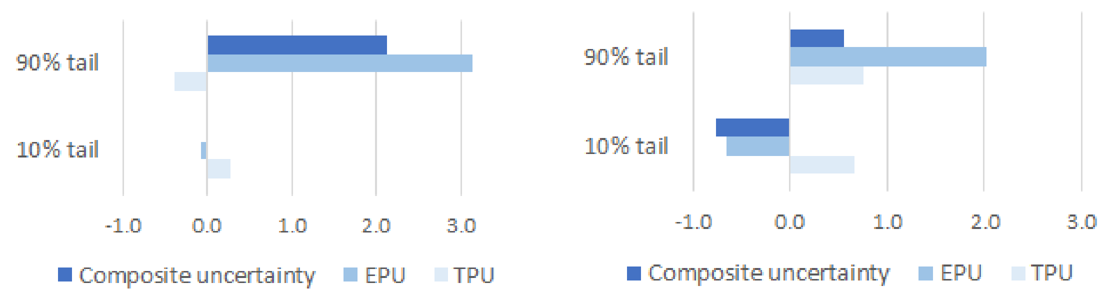
Notes: Median and tail quantile regression coefficients of 4 quarters lagged uncertainty in an equation with export growth (y-o-y, exports of goods and services). Blue dot is the estimated (not scaled) coefficient for the media and tail quantiles. Box is the 90% confidence interval. The 4-quarter lag is chosen because the effect of uncertainty peaks at that horizon. Impact on export growth in percentage points on y-axis.

Uncertainty affects the distribution of Dutch inflation by increasing the probability of large positive outcomes (Figure 5b). For the one quarter ahead forecast, the 90% (upper) tail of inflation is 2.1 pp higher than in the baseline (the impact on the median outcome of inflation is 0.2 pp and the impact on the 10% lower tail is negligible). This implies that inflation is more likely to reach unusually high levels during periods of elevated uncertainty. The sensitivity of inflation-at-risk to changes in uncertainty is further illustrated by the quantile coefficients in Figure 6. The coefficient of the 90% quantile is significantly higher than the median (Figure 6b): a one standard deviation increase of uncertainty raises the upper tail of inflation by nearly 1 pp.[6] Given the downward effect on GDP-at-risk and upward effect on inflation-at-risk, the tail effects of an increase of uncertainty resembles that of a negative supply shock, at least in the short-run.

The distribution of inflation in the euro area instead becomes more dispersed, implying that more extreme high and low outcomes are more likely. The euro area inflation distribution becomes more dispersed when conditioning on uncertainty: the upper (90%) tail shifts to the right and the lower (10%) tail to the left, see Figure 8, panel b (the coefficients of the 10^{th} and 90^{th} percentiles are both significant) and Annex B. It implies both higher upward inflation risks and larger downward inflation risks. In other words, elevated uncertainty increases the risk of both very high and low inflation outcomes in the euro area. This effect is asymmetric, with the upward inflation effect being stronger than the downward effect. In the Netherlands, higher uncertainty is more associated with upward inflation risk than with an increasing dispersion of inflation outcomes. This could be explained by the sensitivity of Dutch inflation to global shocks, which tend to cause excess inflation in the Netherlands compared to the euro area (De Grip and van den End, 2025).

Figure 8 - Dispersion of inflation outcomes due to uncertainty

a. *Netherlands* b. *Euro area*



Notes: Impact of uncertainty on the tail outcomes of HICP inflation, forecasted 1 quarter ahead. 90% is upper tail outcome; 5 and 10% are lower tail outcomes. Impact as deviation of outcome conditioned by uncertainty from outcome baseline model, in percentage points.

[6] In an alternative specification with proxy variables from the Phillips curve framework included as additional controls, uncertainty also has a significant upward effect on inflation-at-risk, although the difference between the median and 90% tail is not significant in that specification.

3. Uncertainty and financial stability

This chapter examines the impact of uncertainty on financial stability. It explores how rising uncertainty is associated with greater tail risks in European equity prices, credit spreads, and overall financial conditions. The chapter concludes by analysing how bank capital can help mitigate economic risks including those linked to elevated uncertainty.

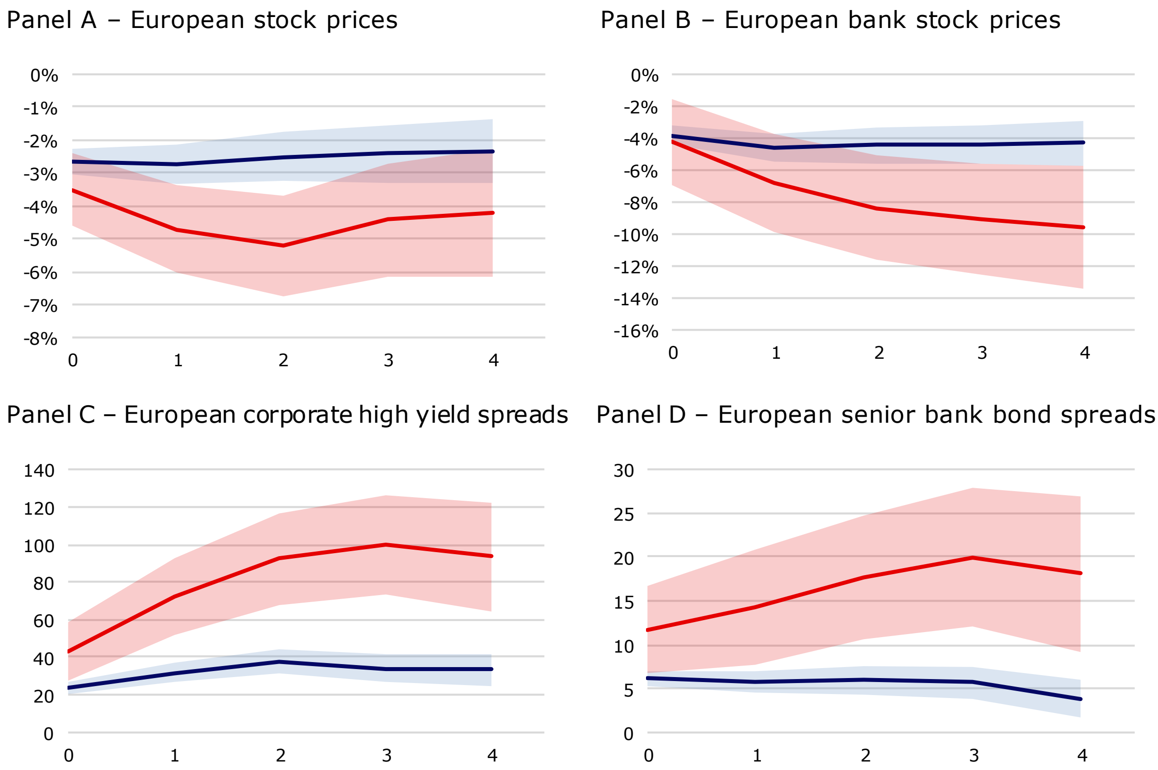
3.1 Uncertainty and financial asset prices

Uncertainty can trigger volatility in asset prices and widen risk premia, thereby affecting overall financial conditions. In periods of high or increasing uncertainty, investors may exhibit more risk-averse behaviour, resulting in declining asset prices and tighter financial conditions. We estimate the relationship between uncertainty and several European asset prices during periods of market stress, thereby providing a direct measure of how composite uncertainty is associated with sharply negative equity market returns and high credit spreads (i.e. the risk of a market correction). Specifically, we examine the relationship between composite uncertainty and the tail of European asset price returns (or spreads for bonds), defined as the 10th percentile of the distribution (the 90th percentile in the case of bond spreads).

Our analysis indicates that an increase in composite uncertainty leads to significantly higher tail risks to European equity prices and credit spreads. Figure 9 illustrates the effect of changes in composite uncertainty on financial asset prices in the euro area, showing both the median response (blue) and the tail response (10th percentile, red). For all assets, higher uncertainty is associated with more extreme outcomes, as evidenced by the difference between the blue and red lines. The fact that the tail response is at least double the median response across assets implies that higher uncertainty results in more severe market corrections. For instance, when uncertainty increases by one standard deviation, the 10th percentile of European stock market returns is projected to be 4% lower after four months. For European bank stocks we find a decline of about 10%. In both cases the estimated coefficient for the 10th percentile is about twice as large as for the median, indicating that elevated uncertainty is associated with larger market corrections. For credit spreads, the difference between the median response and the tail risk response is even larger, showing that credit spreads are particularly sensitive to higher uncertainty. The differences between the baseline and tail scenario response are statistically significant over the entire four-month horizon for spreads and for part of the horizon for stock prices.[7]

[7] For bank stocks the difference between tail and median outcomes is less pronounced, and not significantly different.

Figure 9 – Estimated impact of composite uncertainty on financial assets



Source: BofA, Bloom et. al. (2016), Bundesbank, Caldara and Iacoviello (2022), Datastream, DNB, ECB, iBoxx, Prasad et. al. (2019), DNB calculations.
Notes: Figure shows the estimated response of asset prices to a standard deviation change in composite uncertainty over the first four months, based on quantile local projections. Blue colours refer to the median effect, while red colours refer to the 10^{th} quantile for stock prices and 90% quantile for bond spreads ('tail risk'). Stock prices refer to the Euro Stoxx 50, bank stocks to the Euro Stoxx Banks index, corporate spreads to the non-financial corporate euro high yield index from Bank of America, and bank bond spreads to iBoxx eurozone senior unsecured bank bond spreads. Shaded areas represent 90% confidence intervals. The sample runs 1998M1 (1999M2 for bank bonds) until the end of 2024, using monthly data. We estimate the models in first differences (log returns for stock prices) and include a lag of the dependent variable. Impact in percentage points for stocks and basis points for bonds on the y-axis and time horizon in months on x-axis.

We do not find clear evidence that uncertainty shocks significantly affect Dutch government bond yields or the euro exchange rate in either direction.[8] This reflects that uncertainty shocks can have divergent effects on (risk-free) bond yields and the exchange rate. For instance, there can be an upward effect on risk-free bond yields if uncertainty increases (expected) inflation, while there can be a downward effect if uncertainty goes in tandem with flight to safety. In other words, the impact on government bond yields depends on the nature of the shock. As exchange rates are closely linked to changes in (relative) interest rates, the same holds for the exchange rate.

[8] The results are not shown here but are available at request from the authors. We use the on-the-run 10-year Dutch government bond and the broad euro exchange rate.

Our analysis shows stock markets and credit spreads are more vulnerable to large declines when uncertainty is elevated, increasing financial stability risks. While high uncertainty is associated with lower financial asset prices in general (as also shown in aforementioned studies), our results show that higher uncertainty has an even more substantial negative effect on tail scenarios. These findings are also confirmed in Box 1, where we use a Value-at-Risk model that is more tailored to variables that are available on a high frequency (such as asset prices). Overall, this means that surges in uncertainty can increase financial stability risks in the short run by severely tightening financial conditions and raising borrowing costs for both firms and banks. Through its impact on financial conditions, the financial market channel of uncertainty also feeds into GDP-at-risk as described above, with negative implications for financial stability in the medium-term.

Box 1. Growth-at-Risk versus Value-at-Risk for equity returns

Conceptually, Growth-at-Risk is a macro-economic application of a Value-at-Risk (VaR) framework, in that both methods focus on quantifying the potential for extreme adverse outcomes (Adrian et al. 2022). Both frameworks are designed to capture tail risks and assess the probability of extreme adverse outcomes. While VaR is used in asset management and trading to manage risks using high-frequency data, GaR focuses on the likelihood of economic downturns over longer horizons using lower-frequency variables.[9] A 5% VaR, for example, estimates the price loss that is exceeded only 5% of the time. Though GaR is useful for assessing macroeconomic risks, it may not fully capture the volatility dynamics seen in short-term equity returns under high uncertainty. For such cases, high-frequency models are generally preferred to assess downside risks in financial markets.

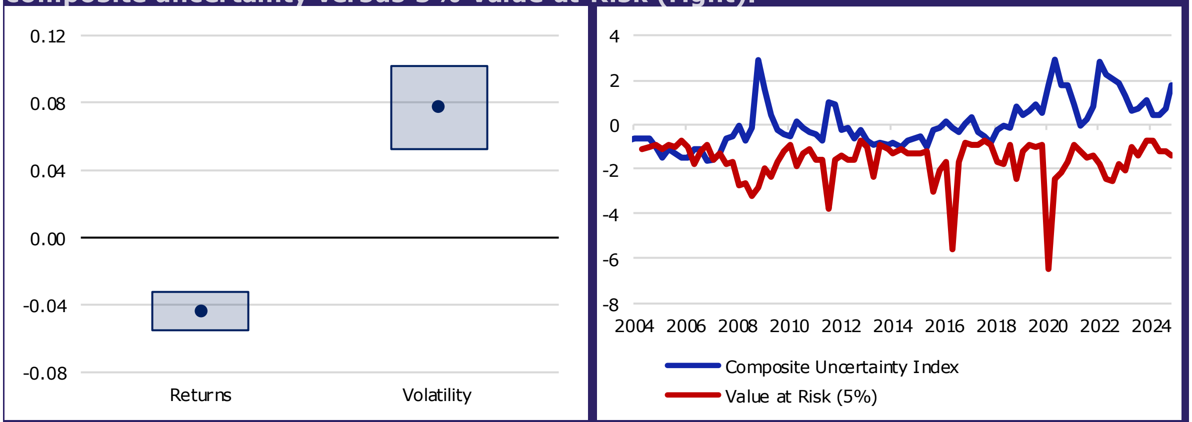
To estimate the relationship between uncertainty and near-term downside risk in the equity market we apply a VaR model on European equity returns. For the analysis we use daily equity returns in the STOXX 50 index. We model the returns using a GARCH-type model that accounts for the asymmetry in equity return volatility (GJR-GARCH). This allows us to account for the fact that negative shocks increase volatility more than positive shocks (Glosten et al. 1993). As we expect that uncertainty (Figure A) can both affect returns (negatively) and volatility (positively) we add composite uncertainty to both the mean and variance equation of the model.

The results indicate that uncertainty is negatively correlated with equity returns, and positively with volatility. The results indicate that higher uncertainty coincides with declining equity prices and increased equity market volatility (see figure A), in line with the GaR approach. For instance, a standard deviation increase in uncertainty translates into a daily decline in equity prices of around 5%, and an increase in volatility of around 8%. Figure A, panel b shows that higher composite uncertainty coincides with larger downside risks on European equity markets. Moreover, adding uncertainty to the model improves the estimates of downside risks (as measured by the VaR). Using a back-testing exercise, we find that the model that includes uncertainty was able to predict tail-risk –

[9] A potential drawback of the VaR approach compared to quantile regressions is that it does not directly estimate the relationship between uncertainty and tail returns; instead, it relies on a parametric assumption about the distribution of the error terms. In our case, a Kolmogorov-Smirnov test confirms that daily returns closely follow a skew-t distribution.

defined as the 5% lower tail of returns - in five instances, where the model excluding uncertainty did not, which suggests a minor improvement compared to the naïve model.

Figure A. Estimated impact of uncertainty on returns and return-volatility (left) and composite uncertainty versus 5% Value-at-Risk (right).



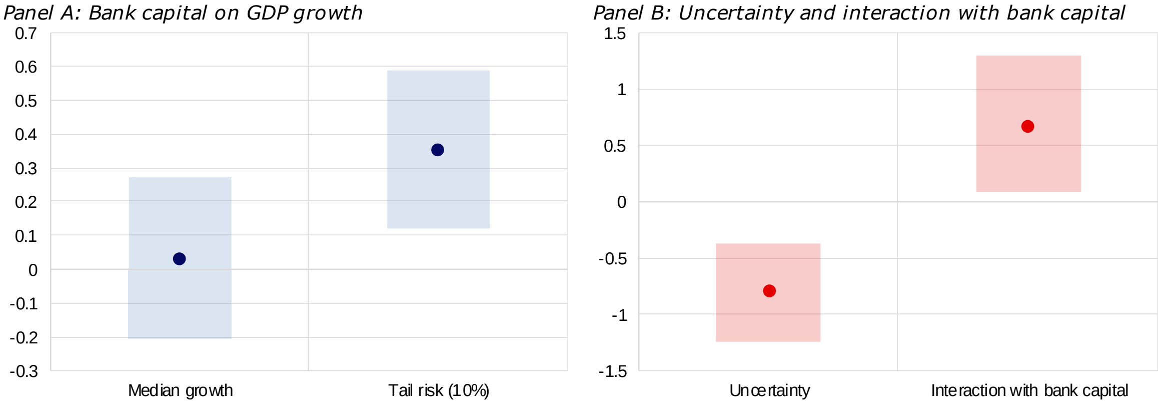
Sources: Bloomberg and DNB calculations.
Notes: Left, figure shows coefficients for the Composite Uncertainty Index in the mean (returns) and variance (volatility) equation of a GJR-GARCH (1,1) model. Returns are log-differences over the period Jan 1 2004-March 5 2025, the Composite Uncertainty Index is the first principal component of a daily-time series for the VIX, EPU and GPR indices, where the EPU reflects the US Economic Policy Uncertainty index as a proxy for the Global EPU, as a Global EPU is not available with a daily frequency (see Baker, Bloom and Davis (2016)). Right, Value-at-Risk shows tail risks for daily equity returns based on a GJR-GARCH (1,1) including the Composite Uncertainty Index as external regressor in the mean and variance equation. Log-returns are assumed to follow a skew-t distribution. For more details on the Composite Uncertainty Index, see Figure notes of Figure 1. Volatility is approximated by the impact of composite uncertainty on the coefficient for uncertainty divided by two times the conditional variance.

3.2 Uncertainty, bank capital and growth-at-risk

In this section we assess whether adequately capitalized banks can reduce tail risks to GDP growth stemming from higher uncertainty. We use data on the capitalization of the consolidated banking system for the Netherlands and, in Box 2, for eight other advanced economies. Specifically, we use the ratio of tier 1 equity over total assets, thus creating a measure akin to the leverage ratio of the domestic banking sector.[10] We re-estimate the GaR-framework described in the previous sections, but add the standardized tier 1 capital ratio as additional explanatory variable next to our composite uncertainty metric. This captures the effect of bank capital for economic tail outcomes. As before, the approach here mainly captures the forecasting ability of the explanatory variables for the distribution of GDP growth, i.e. we do not necessarily capture the causal effect of bank capital on GDP growth.

[10] Our sample spans from 1998Q1 to 2019Q4, we exclude the 2020 – 2024 period as, next to the significant swings in GDP growth over this period, bank capital ratios were also impacted by extraordinary measures taken by supervisors and central banks, including restrictions on dividends (supporting bank capital ratios) and measures that limited loan losses. We use bank capital in levels as in Aikman et. al. (2019). Our results are robust for taking moving averages to smooth out transitional swings driven by changing reporting requirements.

Figure 10 – Estimated direct and indirect effect of bank capital on tail risks after one quarter



Sources: Bloom et. al. (2016), Caldara and Iacoviello (2022), DNB, ECB, Prasad et. al. (2019), DNB calculations.
Notes: Figure shows the quantile regression coefficients and 90% confidence intervals from a quantile regression model with year-on-year GDP growth as dependent variable, including one lag of GDP growth, our composite measure of uncertainty and the tier 1 capital ratio for the consolidated domestic banking sector. The x-axis refers to the quantiles, and the y-axis to the impact on year-on-year GDP growth (in percentage points).

Our results show that a well-capitalized banking sector can reduce the severity of economic downturns. A one standard deviation increase in the bank tier 1 capital ratio – equivalent to 0.7 pp - improves GDP-at-risk by over 0.3 pp after one quarter (see Figure 10, Panel A). This means that when bank capital ratios are one standard deviation higher in our sample, we expect that the bottom 10th percentile of GDP growth is less negative by a statistically and economically significant margin. In other words, economic downturns become less severe. The positive effect of bank capital on downside risks to GDP growth increases further over time, to 1.2 pp after four quarters. A likely mechanism behind this result is that higher banking sector capitalization limits adverse macro-financial amplification mechanisms like a sharp slowdown in lending following an adverse economic shock, consistent with theoretical macrofinancial models like Brunnermeier and Sanikov (2014).

By contrast, bank capital has no significant effect on median GDP growth, with the one-quarter-ahead coefficient being statistically indistinguishable from zero (Figure 10, Panel A). The model thus expects no change in usual growth outcomes conditional on whether bank capital is high or low. These findings are consistent with the literature on the costs and benefits of bank capital (BCBS, 2019) and hold when extending the analysis to a broader panel of countries (see box 2).

We also find that bank capital can directly reduce downside risks stemming from uncertainty. While the previous paragraph showed bank capital mitigates GDP-at-risk, we also find that capital reduces the effect of uncertainty on GDP-at-risk. To estimate this, we add the interaction between composite uncertainty and bank capital as additional variable to the model. The coefficient of this interaction term is positive and statistically significant for the 10th percentile (see Figure 10, panel B). This indicates that, while higher uncertainty tends to lead to deeper recessions, better capitalized banks can soften the blow from uncertainty. This results in better growth outcomes in adverse scenarios. More specifically, the coefficients suggest that with bank capital at its sample average, downside risks to GDP increase by 0.8 pp after an increase in uncertainty of one standard deviation. When bank capital is one standard deviation above the sample average, however, the effect is only 0.2 pp.

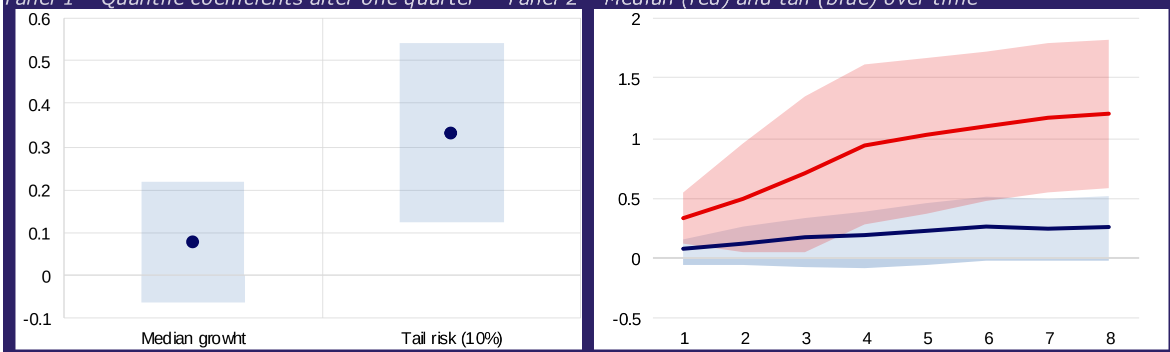
Box 2. Growth-at-Risk and Bank Capital across Advanced Economies

To make a broader assessment of the relation between bank capital and Growth-at-Risk, we extend our analysis to other advanced economies. In addition to the Netherlands-specific analysis for the relation between bank capital and Growth-at-Risk described in the main text, we use panel quantile regressions to assess whether our findings also hold in a wider set of countries. For the panel estimates we use the methodology described in Adrian et. al. (2022) and Lloyd et. al. (2024) and add quantile-country-fixed effects to the model to control for structural differences between countries that are stable over time (i.e. unobserved heterogeneity).[11] Subsequently, we analyse the impact of bank capitalization on growth at risk in Australia, Canada, Germany, France, Italy, Spain, the United Kingdom and the United States.[12]

In line with the results for the Netherlands, we find that bank capital also reduces tail risk in other advanced economies. On average, a one standard deviation increase in the bank capital ratio improves GDP-at-risk by a statistically significant margin of 0.3 pp after one quarter (Figure B, panel 1) and by 0.9 pp after four quarters (see panel 2). These estimates are similar to the Netherlands-only model, though the coefficients are not directly comparable given that the distribution of the variables is different.[13] We again find a negligible and not statistically significant impact of higher bank capital on median outcomes, confirming that a resilient banking sector mainly reduces tail risks to growth and does not necessarily comes at the expense of lower median growth. These findings are consistent with other empirical evidence for the US and other advanced economies (e.g. Aikman et. al. 2019, Boyarchenko et. al. 2024). The results are robust for restricting the sample to EU-countries only.

Figure B. Effect of bank capital ratio on GDP growth

Panel 1 – Quantile coefficients after one quarter *Panel 2 – Median (red) and tail (blue) over time*



Sources: Sources: Bloom et. al. (2016), Caldara and Iacoviello (2022), DNB, ECB, Lloyd et. al. (2024), various national sources, Prasad et. al. (2019), OECD, DNB calculations. Notes: Figure shows the quantile regression coefficients for the 68-confidence interval from a quantile regression model with year-on-year GDP growth as dependent variable, including one lag of GDP growth, our composite measure of uncertainty and the tier 1 capital ratio for the consolidated domestic banking sector. Panel specification includes quantile-country fixed effects as in Adrian et. al. (2022). The x-axis refers to the quantiles, and the y-axis to y-o-y GDP growth.

[11] This method is feasible as long as N²>T (Galvao and Montes-Rojas 2015). Standard errors are estimated using a block bootstrap with blocks of eight quarters and 5000 bootstrap samples.
[12] For the Netherlands we use internal DNB and (from 2014) ECB data. For the other EU-countries, we use ECB data from 2014 and extend this using national data where available or data reported to the IMF under the Financial Soundness program. For the non-EU countries, we rely on national sources. In several of our countries the tier 1 data does not span the full sample, in that case we backcast the tier 1 capital ratio using changes in the overall leverage ratio.
[13] As we draw from the distribution of the full set of countries, the 10th percentile of GDP growth will likely be slightly different in the panel model than in the country-specific model.

4. Conclusion and policy implications

Our analysis shows that elevated uncertainty is associated with more severe economic downturns and increasing tail risks to inflation. We find that high uncertainty negatively affects the economy through both real and financial channels, such as lowering consumption and raising risk premia on financial markets. Our analysis moreover shows that these effects are larger on the tails of the distribution of GDP growth, meaning that elevated uncertainty has a stronger effect on tail outcomes than on typical GDP growth. For the Netherlands elevated uncertainty also raises upside risks to inflation, implying that the effects of uncertainty are comparable to a negative supply shock.

Applied to the current environment, the recent surge in uncertainty thus leads to increased tail risks for the Dutch economy. Our analysis suggests that high global uncertainty could lead to a sharper economic downturn and more persistent inflation compared to a situation with less uncertainty. However, the eventual impact will also depend on factors outside the scope of our analysis, such as the response of fiscal and monetary policymakers and potential adjustments in trade flows following the increase of trade tariffs.

Persistent elevated uncertainty thereby also poses challenges to monetary policy. We find that high uncertainty in the short term raises downside risks to growth and can increase the dispersion of possible inflation outcomes in the euro area. Potentially divergent effects on growth and inflation can complicate the optimal monetary policy response, especially when it is unclear to what extent these short-term effects carry over into the medium term. This calls for a certain flexibility and state-dependent decision-making that can respond to the materialisation of different risks (Lane, 2024).

Our findings underscore the importance of maintaining current levels of bank capital to ensure a resilient financial sector capable of withstanding shocks. We find that bank capital is effective in countering tail risks to GDP growth, including downside risks to growth specifically stemming from the current environment of elevated uncertainty. This underscores the need for a financial sector that is well-equipped to withstand the economic and financial impact of high uncertainty. Recent calls for simplifying regulatory requirements should thus not result in deregulation, as weakening financial safeguards would undermine resilience precisely when it is most needed. The US banking turmoil in March 2023 provides a clear reminder of the risks associated with looser rules and regulations.

In the interconnected global economy and financial system, multilateral institutions play a vital role in reducing uncertainty and preserving financial stability, by setting clear and predictable rules and regulations. Multilateral cooperation is crucial for building resilient financial systems through transparency, cross-border coordination, and adherence to international regulations (IMF, 2024). While some degree of fragmentation can mitigate contagion risks by reducing global interconnectedness, excessive fragmentation - particularly through inconsistent enforcement and selective application of financial rules - heightens economic uncertainty and weakens the effectiveness of global coordination, especially during financial turmoil (Claessens, 2019). A rules-based order therefore provides a foundation for effective regulatory cooperation, reducing the likelihood of regulatory arbitrage and financial contagion.

Finally, high uncertainty can amplify the adverse effects of macrofinancial vulnerabilities on the real economy through market and credit channels, but also via feedback loops in consumer and business confidence. Against this backdrop, DNB conducts stress tests to assess more in-depth the vulnerabilities to cross-border spillovers, such as a severe but plausible scenario where a global trade war materializes.[14] At the European level, the EBA is also conducting a stress test with an adverse scenario that is based on a narrative of worsening geopolitical tensions, which includes persistent trade and confidence shocks (EBA, 2025).

[14] See DNB Spring 2025 Financial Stability Review, forthcoming.

Annex A. Model and data

The baseline GDP-at-risk and inflation-at-risk (annual changes) is estimated with a naive AR (1) model, as in equation (1). The effect of uncertainty is estimated by adding the uncertainty metric x as conditioning variable to the baseline model, as in equation 2.

$$y_{t+h} = \alpha_\tau + \beta_\tau y_t + \varepsilon_{\tau,t} \tag{1}$$

$$y_{t+h} = \alpha_\tau + \beta_\tau y_t + \gamma_\tau x_t + \varepsilon_{\tau,t} \tag{2}$$

Where y_{t+h} is the dependent variable (e.g. GDP growth or HICP inflation) h quarters ahead, x_t the uncertainty metric, γ_τ the coefficient of the τ quantile regression, α_τ the associated constant and $\varepsilon_{\tau,t}$ the residual. The quantile regressions are estimated at different points of the distribution of y_{t+h}, $\tau \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$. Each gamma coefficient represents the link between the uncertainty metric x_t and the dependent variable, at different points of the distribution of the dependent variable.

The conditioning variables are standardized and included in levels, except when analysing asset returns. Composite uncertainty is the first principal component of the standardized individual uncertainty metrics (VIX, GPR, EPU in levels). Most of the analysis is based on quarterly data in 1997Q1 – 2024Q4.

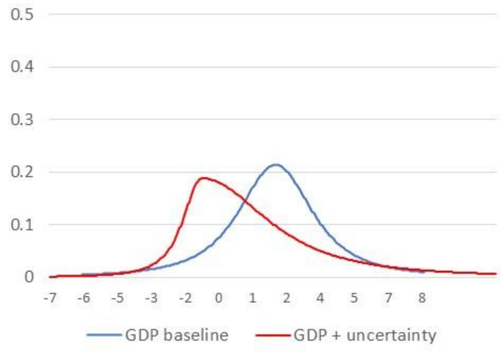
The conditional distributions of the forecasted dependent variable are derived by fitting a t-skew distribution to the predicted values of the estimated conditional quantiles, following Adrian et al. (2019). The parametric fit of the distribution mitigates issues related with extreme tail quantiles and quantile crossing. It alleviates data sparsity issues in the tails when modelling extremes (in other words, it "fills in the gaps" in the tails where data is sparse, providing smoother and more stable estimates of quantiles).

Annex B. Alternative probability distributions

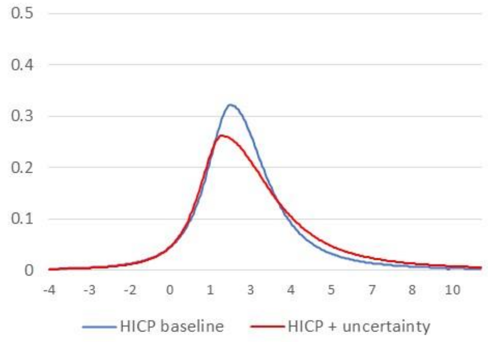
Figure B.1 shows the one and two years ahead forecasted distributions of GDP growth and inflation for the Netherlands, both the baseline and the forecast conditional on the common component of uncertainty.

Figure B.1. One and two years ahead forecast of probability distributions

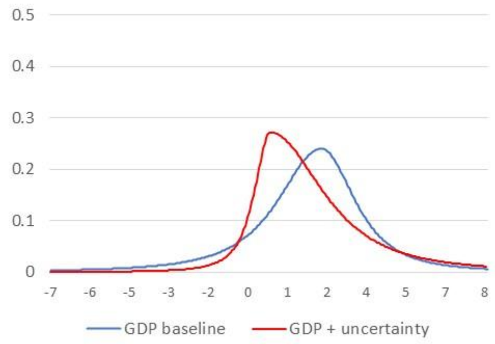
a. GDP growth (y-o-y), one year ahead



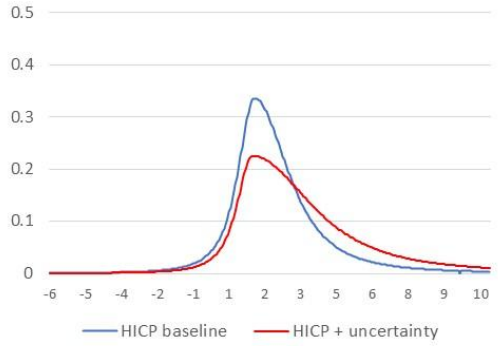
b. HICP inflation (y-o-y), one year ahead



c. GDP growth (y-o-y), two years ahead



d. HICP inflation (y-o-y), two years ahead



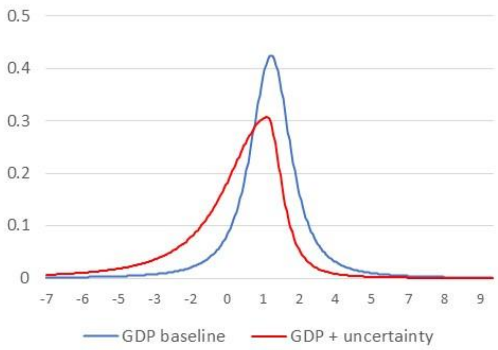
Baseline (blue line) is the (direct) forecast of the autoregressive baseline model. Uncertainty (red line) is the forecast conditional on the uncertainty metric (composite uncertainty). Probability on y-axes. GDP growth and inflation on x-axes in percentage points.

Compared to the one quarter ahead forecast in Figure 5, the one and two years ahead forecasted distributions in Figure B.1 have a lower peak and larger variance. It indicates that the baseline and conditional forecasts are associated with larger uncertainty at longer horizons.

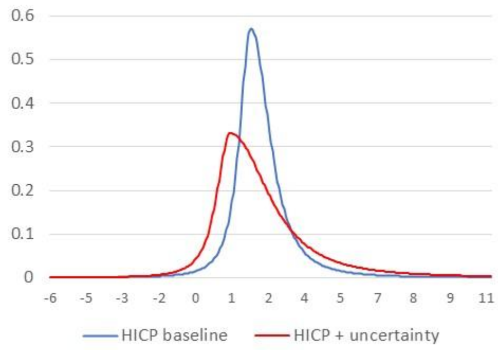
Figure B.2 shows the one quarter ahead forecasted distributions of GDP growth and inflation for the euro area.

Figure B.2. One quarter ahead forecast of probability distributions

a. GDP growth (y-o-y), one quarter ahead



b. HICP inflation (y-o-y), one quarter ahead



Baseline (blue distribution) is the (direct) forecast of the autoregressive baseline model. Uncertainty (red distribution) is the forecast conditional on composite uncertainty. Probability on y-axes. GDP growth and inflation on x-axes in percentage points.

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