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FINANCIAL IMBALANCES AND MEDIUM-TERM GROWTH-AT-RISK IN NORWAY

Financial imbalances and medium-term growth-at-risk in Norway *

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Abstract

We examine how measures of financial imbalances affect macroeconomic tail risks over the medium-term in Norway and in other advanced economies. We use a broad set of financial indicators to capture cyclical systemic risk in the financial system and different quantile regression models to characterise their effects on the medium-term growth distribution. We find that an increase in financial indicators is associated with both a more adverse prediction for *growth-at-risk* (5th percentile of growth distribution) and higher *downside risks* to growth (difference between the median and the 5th percentile of growth distribution). Among financial indicators, credit growth has the most significant effect on downside risks to growth. We also find that downside risks are higher under a fixed exchange rate regime. Using our estimates, we focus on two policy-relevant applications. First, we summarise how financial indicators and growth-at-risk have evolved over time in Norway and how this framework can be used to quantify and communicate risks to the economic outlook. Second, we show how this framework can be used to calibrate the severity of cyclical stress test scenarios.

JEL-codes: E44, G01, G10

Keywords: Financial stability, growth-at-risk, quantile regressions.

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1 Introduction

A fragile financial system can amplify adverse economic shocks in addition to being a source of shocks itself. Research has identified the build-up of financial imbalances as a leading predictor of financial crises. A robust result is that credit developments tend to be particularly strong prior to banking crises and increase both the probability (Schularick and Taylor (2012)) and the severity (Jordà et al. (2013)) of a crisis. Furthermore, the combination of strong credit developments and "bubbly" behaviour in real estate markets has been found to heighten the probability of a crisis further, see Anundsen et al. (2016). Based on empirical analysis of long historical data, Jordà et al. (2015) conclude that "it is not only credit growth, but the interaction of credit and asset prices that matters for financial stability risks and the economic costs of financial crises."

In this paper we examine how financial imbalances that reflect both credit and asset price developments affect macroeconomic tail risks over the medium-term, both in Norway and in other advanced economies. Following other central banks[1], we build a growth-at-risk framework that is heavily inspired by the seminal work by Adrian et al. (2019) and previous work at the International Monetary Fund (International Monetary Fund (2017)). In this framework, quantile regressions are used to estimate the relationship between financial indicators and the distribution of economic growth.[2]

We focus on medium-term tail risks and selected financial indicators to capture the risks associated with the build-up of financial imbalances. The medium-term is the relevant horizon for considering these risks given that we are interested in capturing more persistent declines in growth and filtering out shocks affecting output at shorter frequencies. Similar to Aikman et al. (2019) and Giglio et al. (2016), we employ quantile regressions and use the 5th percentile of GDP growth as our measure of growth-at-risk. By focusing on the 5th percentile, we are able to capture the more severe downturns that are typically associated with banking crises or financial stress. The 5th percentile is also used to define growth-at-risk in other studies and allows us to have a framework for analysis that is consistent with all the other studies.

Our goal is to build a bridge between assessments of financial stability risks and macroeconomic stability risks. This is important for several reasons. First, Norges Bank regularly

[1]See, for example, Duprey and Ueberfeldt (2018) and Duprey and Ueberfeldt (2020) for Bank of Canada and Aikman et al. (2019) for Bank of England.

[2]There are also studies that analyse the drivers of large downside risks to house prices (Deghi et al. (2020)) and sharp capital inflows to emerging market economies (Gelos et al. (2019)) using quantile regressions.

gives advice to the Ministry of Finance on the countercyclical capital buffer as well as other macroprudential tools. By focusing on an intuitive measure of macroeconomic tail risks associated with financial imbalances, this framework can enhance Norges Bank's assessment and communication of financial stability risks and potential policy responses to mitigate those risks. Second, Norges Bank operates under a flexible inflation targeting regime, which means that the bank targets forecasts of inflation and output. Forming a view of the risks surrounding the baseline forecasts is an important part of the forecasting process. Furthermore, this analysis can be relevant for monetary policy deliberations that take financial stability risks into account.[3]

We estimate both single-indicator models and multivariable models, and use data for Norway and a panel of 21 OECD countries. In our analysis, we distinguish between effects of financial indicators on *growth-at-risk* (5th percentile of growth distribution) and *downside risks* (difference between the median and the 5th percentile of the growth distribution). We find that an increase in financial indicators is associated with both a more adverse prediction for growth-at-risk and higher downside risks. This relationship exists both for Norway and a broader sample of advanced economies, but it appears to be stronger in the former. While several financial indicators have large and significant effects on growth-at-risk, real credit growth has the most significant effect on downside risks to growth. We also find that downside risks tend to be higher in countries with less flexible exchange rate regimes. Other macroeconomic variables, such as short-term interest rates and inflation lead to a shift in the entire growth distribution without having a material impact on downside risks.

Our paper is closely related to Aikman et al. (2019) in terms of empirical approach. Aikman et al. (2019) focus on medium-term macroeconomic tail risks originating from financial vulnerabilities and find significant effects of financial indicators on growth-at-risk. An important contribution of their paper is that they establish a link between banking system capitalisation and GDP tail risks and find that higher bank capitilisation can mitigate tail risks. We do not focus on bank capitilisation in our paper, but instead focus more closely on how financial vulnerabilities affect not only growth-at-risk but also downside risks to growth. This is also the focus in Duprey and Ueberfeldt (2020), where they differentiate between risks to the median prediction and risks specific to the tail of the GDP growth distribution (de-

[3]Norges Bank operates an inflation targeting regime which "shall be forward-looking and flexible so that it can contribute to high and stable output and employment and to counteracting the build-up of financial imbalances." For an overview over Norges Bank's conduct of monetary policy, see the speech delivered by Governor Olsen to the Norwegian Parliament on 14 May 2018. (https://www.norges-bank.no/en/news-events/news-publications/Speeches/2018/2018-05-14-hearing/).

fined also as the difference between the median and 5th percentile of future GDP growth). Similar to our findings, Duprey and Ueberfeldt (2020) find that credit growth is the key driver of downside risks to growth in the medium-term.

In this paper, we also illustrate how our framework can be used in two policy-relevant applications. In the first application we present how predictions from different models can be used together to quantify cyclical risks. Our models signal both higher risks of low growth and higher downside risks to growth in Norway in periods leading up to the banking crisis (1988-93) and the financial crisis (2008-09). The exchange rate peg plays an important role in explaining the increase in predicted downside risks leading up to the banking crisis, while high credit growth contributes more leading up to the financial crisis. Finally, we demonstrate how predicted GDP growth distributions could be used to communicate developments in tail risks and conduct scenario analysis.

In the second policy application, we focus on how this framework could be adapted to calibrate the severity of cyclical, macro-prudential stress tests by establishing a mapping between financial indicators and different measures of stress test severity. Norges Bank performs an annual macro-prudential stress test as part of the decision basis for Norges Bank's advice on the countercyclical capital buffer.[4] To work as intended, the severity of the stress test has to reflect the risk outlook of the economy.

Our paper proceeds as follows. In Section 2 we discuss how we define macroeconomic tail risks. In Section 3, we discuss our empirical strategy. Section 4 motivates the choice of different explanatory variables and Section 5 provides a description of the data and a preliminary analysis of financial indicators and GDP tail events in our sample. In Section 6, we present our quantile regression results. Policy applications are then illustrated in Section 7. Section 8 concludes.

2 Financial imbalances and macroeconomic tail risks

GDP growth may be at risk owing to a number of factors. We distinguish between factors that primarily affect the central projection of GDP growth, and thus shift the whole growth distribution, and factors that primarily affect the risks around the central projection, in our case, the downside risks to growth.

Financial imbalances, captured in our framework by a series of credit and asset price

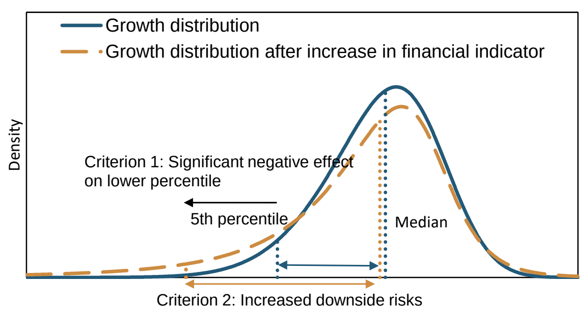
[4] A detailed description of the stress test framework is presented in Andersen et al. (2019). For more on the decision basis for Norges Bank's advice on the countercyclical capital buffer, see Norges Bank (2019a).

variables, make households, firms and financial institutions more vulnerable, amplifying the effects of adverse shocks around the baseline and leading to larger downside risks. Financial indicators can also have effects on the central or median projection. For example, a period of high credit growth can necessitate a period of slower credit growth in the future, contributing to slower growth also in the central projection.

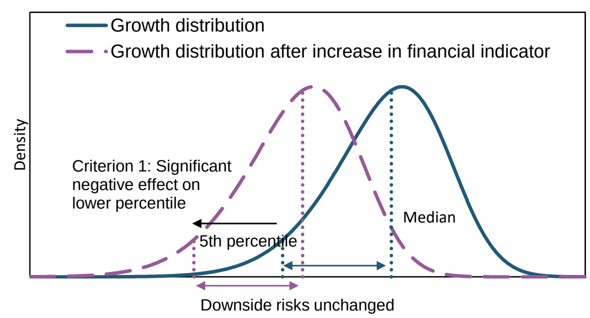
We are therefore interested in capturing the effects of financial indicators on both *growth-at-risk*, which we define as the 5th percentile of growth distribution, and *downside risks* to growth, which we define as the difference between the median and the 5th percentile. These two effects are further illustrated in Figure 1. In Figure 1a, growth-at-risk is lower due to an increase in downside risks around median growth. In figure 1b the whole distribution shifts left, resulting in lower growth predictions for both the lower percentiles and the median.

Figure 1: Illustration of growth-at-risk and downside risks to growth using distribution of GDP growth.

(a) Increase in downside risks



(b) Unchanged downside risks



Notes: The example illustrates two different distributions. In alternative (a) financial imbalances lead to an increase in downside risks, while in alternative (b) there is a shift in the whole growth distribution without a change in downside risks.

The extent to which financial imbalances increase downside risks can have an important bearing on the use of macroprudential and monetary policies. Macroprudential policy can be particularly effective in reducing downside risks to growth, by increasing buffers and dampening a further build-up of imbalances in future. Similarly, monetary policy can lean against the build-up of financial vulnerabilities to reduce downside risks. Downside risks associated with financial imbalances is therefore a critical input into the policy analysis.

We use several financial indicators to capture financial imbalances. The indicators are chosen to shed light on risks that are cyclical in nature. We have chosen indicators that are both theoretically and empirically motivated (see Section 4 for a thorough discussion). While booms and busts in credit and asset prices may be highly persistent, our empirical methodology requires that the indicators are stationary. This means that we are not capable of assessing risks that may be related to rising debt and asset price levels over time as a result of structural changes in the economy (for example lower long-term interest rates) and the financial system.

3 Empirical Methodology

In this section we first discuss the use of quantile regressions for estimating a relationship between financial indicators and growth-at-risk. We then discuss different model specifications and our strategy for model evaluation.

3.1 Quantile regressions

We use quantile regressions to estimate the effects of financial indicators on the medium-term real GDP growth distribution using both panel data and data for Norway. The panel sample requires treatment of country-specific fixed effects to avoid estimation bias. We follow Canay (2011) and Aikman et al. (2019) and assume that country fixed effects are locational shifts for the entire distribution, where the fixed effects are the same across different percentiles.

Following Aikman et al. (2019), we use a two-step procedure. In the first step, country-specific fixed effects ($\alpha_{i,h}$) are estimated using a standard within estimator. In particular, we estimate the following linear pooled panel quantile model:

$$\Delta y_{i,t+h} = \alpha_{i,h} + x_{i,t}\beta_h + \epsilon_{i,t} \tag{1}$$

where $\Delta y_{i,t+h}$ is average real GDP growth of country i, h quarters ahead, and $x_{i,t}$ a vector of explanatory variables, composed of a set of financial indicators ($fi_{i,t}$), and other macroeconomic control variables ($c_{i,t}$).

In the second step, the dependent variable is adjusted by subtracting the estimated country-specific fixed effects (i.e. $\Delta y^{new}_{i,t+h} = \Delta y_{i,t+h} - \hat{\alpha}_{i,h}$).[5]

Once we have adjusted the dependent variable, we can use standard quantile regression methods to estimate, $\beta_{h,q}$, where q denotes different percentiles of the growth distribution, by minimising the following:

[5]See Galvao (2011) for alternative methods of treating fixed effects in quantile regression settings.

$$\hat{\beta}_{h,q} = \underset{\beta}{\operatorname{argmin}} \sum_{t=1}^{T-h} \rho_q(\Delta y_{i,t+h}^{new} - x_{i,t}\beta_{h,q}) \tag{2}$$

where ρ_q is the standard quantile-weighted loss function given by:

$$\rho_q = q \cdot 1_{(\Delta y_{i,t+h}^{new} \geq x_{i,t} \cdot \beta_{h,q})} \cdot \mid \Delta y_{i,t+h}^{new} - x_{i,t} \cdot \beta_{h,q} \mid + (1-q) \cdot 1_{(\Delta y_{i,t+h}^{new} \leq x_{i,t} \cdot \beta_{h,q})} \cdot \mid \Delta y_{i,t+h}^{new} - x_{i,t} \cdot \beta_{h,q} \mid \tag{3}$$

For inference, we use block-bootstrapping methods, where blocks of four quarters of data from the temporal dimension of the dataset are resampled. In addition, in the panel model the block-bootstrapping is performed so that the cross-sectional structure of the panel is unchanged.[6] For all presented results, 10,000 bootstrap replications are used.

3.2 Model specifications and evaluation

The models we estimate differ along three dimensions:

- *Definition of left-hand side variable.* The relevant left-hand side variable to be used in our empirical model depends on the application at hand (Prasad et al. (2019)). For our baseline econometric analysis in Section 6, we employ annualised average growth in real GDP over a three-year horizon (i.e. $\frac{y_{i,t+12} - y_{i,t}}{3 \times y_{i,t}}$) to focus on persistent declines in growth. This measure is easy to communicate and explain.[7] Moreover, in the calibration of the severity of stress tests in Section 7.2, we use annual growth in GDP two years ahead and annual cumulative GDP shortfall over a three-year horizon one year ahead. We use these additional measures to align growth-at-risk predictions with two complementary measures of stress test severity. The first measure captures the largest decline in GDP over the stress test horizon, while the second measure captures the cumulative loss over the stress test horizon.

- *Financial indicators.* We estimate two types of models that differ in terms of their use of financial indicators. First, in the *single-indicator models*, we use one financial indicator at a time to predict growth-at-risk. Given their simplicity, these models allow us to estimate a relationship between financial indicators and growth-at-risk using both Norwegian and panel data. Second, in the *multivariable model*, we incorporate several financial indicators at the same time and control for several macroeconomic variables.

[6] See Kapetanios (2008) and Lahiri (2003) for more on block bootstrapping methods.

[7] This is the measure of future GDP growth used in several other studies including International Monetary Fund (2017) and Aikman et al. (2019).

The multivariable model is estimated using panel data and allows us to analyse the contribution of different financial indicators to growth-at-risk and downside risks to growth, conditional on other financial indicators. It therefore provides a richer model environment to analyse the drivers of tail risks. We discuss the set of financial indicators and control variables in more detail in Section 4 and 5.

- *Country sample.* We estimate models using data for Norway and for a panel of 21 OECD countries. The former is important to ensure that we capture relationships in the data that are specific to Norway, whereas the latter brings a much broader information set into the analysis and is important for identification and robustness (especially in the multivariable model set-up discussed above).

We evaluate the models based on several criteria. First, we examine how financial indicators affect growth-at-risk and downside risks to growth. Second, we assess models' in-sample fit and out-of-sample predictions. For the in-sample fit, we require that the model prediction for growth-at-risk and downside risks signal previous episodes of large economic downturns in Norway, i.e. the banking crisis (1988-93) and the financial crisis (2008-09). For an assessment of the out-of-sample fit, we estimate all models recursively and consider how well the models perform in predicting GDP tail events, as well as applying more formal measures of fit.

4 Explanatory variables

In this section we first discuss our choice of different financial indicators and then focus on the set of control variables that we use in our multivariable model.

4.1 Financial indicators

Our choice of financial indicators is guided to a large extent by the empirical and theoretical literature on measuring risks in the financial system. We use a broad set of indicators covering both credit and asset price developments. Empirical literature has identified credit and asset prices (especially real estate prices) as key drivers of the financial cycle (Drehmann et al. (2012b)), and credit and asset prices perform robustly well in signalling financial crises in studies using both international and Norwegian data.[8]

Several papers have focused on the co-movement of medium-term cycles in credit and property prices as the defining characteristics of the financial cycle (Claessens et al. (2011), Drehmann et al. (2012b), Aikman et al. (2015)). These papers find that cycles in financial variables tend to be distinct from business cycles, with lower frequency, and that financial cycle peaks are closely associated with financial crises, and hence low economic growth.

4.1.1 Credit

Systematic studies of financial crises that have emerged since the global financial crisis have indeed identified credit booms as the leading predictor of crises (Schularick and Taylor (2012), Dell Ariccia et al. (2012)). Jordà et al. (2013) show that financial crises preceded by credit booms are also more costly than other crises, suggesting an important link not only between credit booms and the probability of a crisis but also between credit booms and the costs associated with a crisis. Several papers by the Bank for International Settlements have also proposed an important role for credit indicators in anchoring countercyclical capital buffers (Drehmann et al. (2011), Drehmann et al. (2014)), building upon earlier studies on banking crises (Borio and Lowe (2002), Borio and Lowe (2004)). Given credit's central role in the

[8]In the case of Norway, Arbatli-Saxegaard and Johansen (2017) provide an overview over indicators found useful to construct a heatmap of risk indicators. Most of these indicators are reflected in Norges Bank's updated framework for the countercyclical capital buffer (see Norges Bank (2019a)). Furthermore, using data going back to 1819, Riiser (2005) finds that house prices and equity prices, as well as investment and credit developments are useful in predicting past banking crises in Norway. Gerdrup (2003) finds that the boom periods that preceded the three banking crises in Norway (1899-1905, 1920-28 and 1988-92) were characterised by significant bank expansion, high asset price inflation and increased indebtedness.

empirical literature on financial crises, we include real total credit and the total credit-to-GDP ratio as financial indicators.

A series of papers emphasise the rapid increase in household debt in setting the stage for the crisis in the US and the resulting debt overhang as a key mechanism for understanding the weak macroeconomic recovery since then (Eggertsson and Krugman (2012) and Mian et al. (2013)). Anundsen et al. (2016) find that booms in credit to both households and non-financial enterprises are important when evaluating the stability of the financial system. We therefore decompose the credit series into credit to non-financial enterprises (NFE) and households (HH) and include real credit by sector and the credit-to-GDP ratio by sector as additional financial indicators.

Drehmann et al. (2012a) find an important role for debt service costs as an early-warning indicator (especially in the short-run), emphasising the fact that when debt service costs are high, even small shocks to income or interest rates can lead to higher macroeconomic volatility. We therefore also include households' debt service ratio as a financial variable.[9]

4.1.2 Asset prices

Housing constitutes an important share of household wealth in many countries, and its major role as collateral makes it important in assessing vulnerabilities in the financial system. As house prices and credit are closely linked, self-reinforcing spirals can arise, where higher house prices lead to more lending, which again drives house prices up.[10] Anundsen et al. (2016) find significant effects of bubble-like behaviour in housing and credit markets, especially when they coincide with high household leverage. We therefore include house prices-to-income as one of the indicators in our analysis.

Moreover, commercial real estate loans constitute a considerable share of bank loans in Norway. Valuation pressures and excessive risk-taking in this market could therefore have important financial stability implications.[11] While disorderly adjustments in commercial real estate markets have played an important role in several international crises, international data on commercial real estate is scarce (European Systemic Risk Board (2018)). For this reason, we include only commercial real estate prices as an explanatory variable in the set of single-indicator models for Norway.

[9]For Norway, the estimated household debt service ratio is based on Drehmann et al. (2012a), but it takes into account tax deductibility for interest expenses and how this has varied over time.

[10]This financial accelerator effect may lead to both persistence and amplification of real economic shocks (see e.g. Bernanke and Gertler (1989), Bernanke et al. (1999a) and Bernanke et al. (1999b)).

[11]Kragh-Sørensen and Solheim (2014) find that the main cause of bank losses during the Norwegian banking crisis was property-related corporate lending and in particular lending to commercial real estate.

Finally, equity and bond markets are important markets for corporations to raise funding. Signs of increasing risk appetite in these markets can be captured through elevated asset valuations and low interest rate spreads. Elevated valuations in equity and bond markets can also lead to a sharp correction later on and hence constitute a source of market risk for financial institutions. We use real equity prices (given its longer time-series) to capture risk appetite and asset valuations in our analysis.

4.2 Control variables

Financial variables will typically not explain all of the variation in GDP growth. To avoid omitted variable bias, we include a set of macroeconomic control variables. In the single-indicator models, we only use current GDP growth as a control. The control variables used in the multivariable model include the 1-year change in short-term interest rate, the annual inflation rate and a variable that captures the flexibility of a country's exchange rate regime. The first two variables are important macroeconomic indicators that can account for variations in growth distributions over time and across countries.[12]

Our paper is unique in also controlling for a country's exchange rate regime in a growth-at-risk framework.[13] This is to account for country-specific room for manoeuvre in monetary policy and the stabilising effects of a flexible exchange rate, both of which can have a bearing on downside risks to growth. Exchange rate regime can also affect downside risks to growth by increasing a country's susceptibility to financial crises, for example by contributing to the build up of financial vulnerabilities.[14] In our framework, this is already captured by focusing on the role of financial imbalances on tail events.

Many countries in our sample, including Norway, have had different exchange rate regimes over the sample period. For example, Norway's exchange rate was less flexible in the 1980s and early 1990s, but has become fully flexible since then, also reflecting its transition to inflation targeting. Exchange rate flexibility has also played an important role in Norway's macroeconomic stability over time. For example, the procyclical monetary policy that resulted from Norway's fixed exchange rate against the European Currency Unit amplified the deep recession during the later stages of the Norwegian banking crisis (Eitrheim and

[12] Aikman et al. (2019) use a similar set of macroeconomic control variables in their model.

[13] Previous empirical studies have indeed found that floating exchange rate regimes are less prone to growth collapses (Ghosh et al. (2015)) and that the negative relationship between changes in household debt to GDP ratio and subsequent output growth is stronger for countries with less flexible exchange rate regimes (Mian et al. (2017)).

[14] Angkinand and Willett (2011) consider different mechanisms that contribute to a country's susceptibility to crises.

Qvigstad (2020)).[15]

Accounting for a country's exchange rate regime is also important in a panel setup. For example, Corsetti et al. (2018) argue that the exchange rate arrangement may be key in explaining the differences in the experiences of Scandinavian countries during the financial crisis. For the euro-area countries during the period following the financial crisis, one of the factors that contributed to the severity of the macroeconomic downturn was the fact that the exchange rate could not act as a stabilising factor.

Our measure of the flexibility of a country's exchange rate regime is based on the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions,[16] where each country's exchange rate is classified into seven different regimes ranging from a free float to a hard peg (no seperate legal tender/currency board). [17]

The IMF has two types of exchange rate classifications; one based on a country's declared status (de jure) and one based on the IMF's own assessment of a country's actual practice (de facto). We use the latter as it is indeed the actual practice that matters for economic outcomes.

According to the IMF's de facto exchange rate classification, Norway had a horizontal band in the 1980s and until 1992. Indeed during this period, the exchange rate was de facto less flexible, and during certain periods, the krone was formally pegged within a band, first to a basket of foreign currencies (1986-90) and later to the European Currency Unit (ECU) (1990-92). The peg was abandoned in December 1992 when international currency turbulence compelled Norway and several other countries to discontinue the fixed exchange rate system against the ECU. Norway's exchange rate regime was briefly classified as a float in 1993, and then was classified as a managed float during 1994-2001. Norway adopted inflation targeting in 2001, and since then Norway's exchange rate has been classified as a float.

For our empirical analysis, we construct an exchange rate regime variable using a linear mapping between the IMF's de facto exchange rate classification to an index that varies between 0 and 1, where a hard peg is assigned a value of 1 and a floating regime is assigned

[15]See Alstadheim (2016) for a historical review of Norway's exchange rate regimes.

[16]There are several exchange rate classifications, and they can point to different classifications. This reflects the fact that there is considerable uncertainty in classifying exchange rate regimes (especially regimes that are not hard pegs). See Rose (2010) for a detailed discussion.

[17]The seven categories of exchange rate regimes are: float, managed float, crawling peg/band, horizontal band, basket currency peg, peg to single currency and no seperate legal tender/currency board. See Karl et al. (2011) for a more detailed discussion of the exchange rate classifications and https://www.elibrary-areaer.imf.org/Pages/Home.aspx for the database.

a value of 0.

5 Data

Our measure of economic activity and dependent variable is GDP. For Norway, we use mainland GDP (i.e. gross domestic product excluding shipping and petroleum), which is a more relevant measure of economic activity for Norway than total GDP. Our panel dataset includes quarterly data for 21 OECD countries over the period 1975Q1 - 2019Q2.[18] The countries in our sample are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, the UK, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland and the US. Summary statistics for each country in our sample is provided in Appendix 9.2, and a detailed description of data sources can be found in Appendix 9.1. In this section, we first provide a brief description of the properties of financial indicators. We then study the behaviour of financial indicators around GDP tail events.

5.1 Properties of financial indicators

We use a combination of three-year and five-year average change (in percent or percentage points) for transforming the financial indicators in our sample. The choice of horizon depends on each indicator's performance in predicting medium-term risks to growth. Broadly, we find that the indicators based on house prices-to-income, total credit and household credit perform better using the five-year change, whereas real equity prices, real CRE prices and the non-financial enterprise credit indicators perform better using the three-year change.

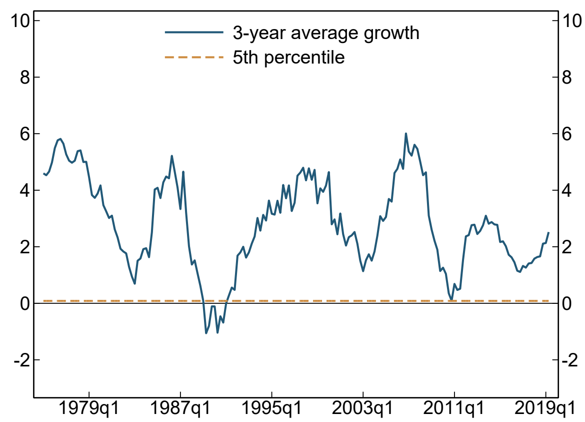
Using the five-year change typically results in somewhat longer calculated financial cycles than using the three-year change. Applying longer cycles to household-related variables is consistent with the findings in Drehmann et al. (2012b). They find that indicators based on house prices and total credit have longer cycles than indicators related to the corporate sector (such as equity prices), which have higher co-movement with the business cycle.

Figure 2 shows three-year average growth in GDP and our financial indicators for Norway. To compare the time-series across indicators and later across countries, we demean by the country-specific averages and normalise by dividing by the country-specific standard deviations.

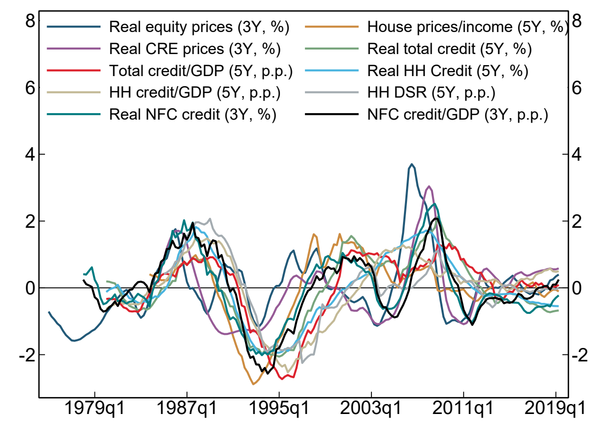
[18] If possible, we apply available data before 1975Q1 to calculate three-year and five-year average growth rates over the period 1975Q1-2019Q2.

Figure 2a shows two tail events related to the 5th percentile of three-year average growth in mainland GDP. The two events were characterised by financial distress, the Norwegian banking crisis (1988-93) and the financial crisis (2008-09), respectively. Our focus on average three-year growth in real GDP implies that we treat the banking crisis as a more severe downturn compared to the financial crisis.

Figure 2: Mainland GDP and financial indicators for Norway (1975Q1-2019Q2)



(a) Mainland GDP growth, percent



(b) Change in financial indicators, standardised

Notes: Financial indicators are standardised by subtracting the average and dividing by the standard deviation.

Furthermore, Figure 2b shows that financial indicators clearly co-move, and the majority of indicators show a pronounced rise preceding GDP tail events. The co-movement of financial indicators is further illustrated in Table 1, which reports the pairwise correlation of each financial indicator in the panel dataset. As expected, the indicators are in general highly correlated. However, Table 1 suggests that equity prices do not co-move to the same extent as the other credit and asset price variables. Developments in equity prices are based on an assessment of future economic developments and tend to be more closely related to business cycle fluctuations.[19]

Moreover, house prices-to-income and commercial real estate prices tend to co-move and are also positively correlated with the other credit indicators.[20] Different transformations of the credit variables tend to be highly correlated within the two sectors and also with broader measures based on total private credit.

[19]This is consistent with the findings in Drehmann et al. (2012b).

[20]Arbatli-Saxegaard and Johansen (2017) study the pairwise correlation between financial indicators for Norway and find that developments in asset prices tend to lead developments in credit indicators.

Table 1: Pairwise correlations between financial indicators in panel and Norwegian data (in parenthesis)

Financial indicator (3Y/5Y change)	Real equity prices	House prices /income	Real CRE prices	Real total credit	Total credit /GDP
Real equity prices	1	0.0 (0.2)	(0.7)	-0.1 (0.1)	-0.2 (0.0)
House prices/income	0.0 (0.2)	1	(0.4)	0.4 (0.7)	0.3 (0.5)
Real CRE prices	(0.7)	(0.4)	1	(0.3)	(0.1)
Real total credit	-0.1 (0.1)	0.4 (0.7)	(0.3)	1	0.8 (0.9)
Total credit/GDP	-0.2 (0.0)	0.3 (0.5)	(0.1)	0.8 (0.9)	1
Real HH credit	0.0 (0.3)	0.4 (0.6)	(0.3)	0.8 (0.9)	0.6 (0.8)
HH credit/GDP	-0.1 (0.1)	0.4 (0.3)	(0.1)	0.6 (0.6)	0.7 (0.9)
HH DRS	0.0 (0.0)	0.3 (0.3)	(0.1)	0.6 (0.6)	0.6 (0.8)
Real NFE credit	0.1 (0.4)	0.3 (0.8)	(0.7)	0.8 (0.8)	0.6 (0.6)
NFE credit/GDP	-0.1 (0.2)	0.2 (0.7)	(0.5)	0.7 (0.8)	0.8 (0.7)
Obs. panel	2625	3028		3638	3636
Obs. Norway	(178)	(143)	(140)	(158)	(158)
Financial indicator (3Y/5Y change)	**Real HH credit**	**HH credit /GDP**	**HH DSR**	**Real NFE credit**	**Total NFE /GDP**
Real equity prices	0.0 (0.3)	-0.1 (0.1)	0.0 (0.0)	0.1 (0.4)	-0.1 (0.2)
House prices/income	0.4 (0.6)	0.4 (0.3)	0.3 (0.3)	0.3 (0.8)	0.2 (0.7)
Real CRE prices	(0.3)	(0.1)	(0.1)	(0.7)	(0.5)
Real total credit	0.8 (0.9)	0.6 (0.6)	0.6 (0.6)	0.8 (0.8)	0.7 (0.8)
Total credit/GDP	0.6 (0.8)	0.7 (0.9)	0.6 (0.8)	0.6 (0.6)	0.8 (0.7)
Real HH credit	1	0.8 (0.9)	0.7 (0.8)	0.6 (0.7)	0.4 (0.7)
HH credit/GDP	0.8 (0.9)	1	0.7 (0.9)	0.4 (0.4)	0.4 (0.6)
HH DRS	0.7 (0.8)	0.7 (0.9)	1	0.5 (0.5)	0.5 (0.7)
Real NFE credit	0.6 (0.7)	0.4 (0.4)	0.5 (0.5)	1	0.8 (0.9)
NFE credit/GDP	0.4 (0.7)	0.4 (0.6)	0.5 (0.7)	0.8 (0.9)	1
Obs. panel	2858	2856	1114	2940	2938
Obs. Norway	(158)	(158)	(138)	(166)	(166)

Notes: The table reports the pairwise correlations between the standardised financial indicators based on 21 OECD countries (1975Q1-2019Q2).

5.2 Financial indicators and tail risks

In this section, we first study the behaviour of the financial indicators around GDP tail events based on our international data set. Next, we explore the conditional distribution of medium-term GDP growth when financial indicators are high.

5.2.1 Financial indicators around tail events

Similar to Aikman et al. (2019), we define the 50 weakest outcomes in the pooled panel data set as GDP tail events. To avoid clustering at the country level, we exclude all observations that are less than two years apart. The sample of 50 tail events captures the lower percentiles of the growth distribution that we are interested in studying in our panel data, constituting roughly the bottom 10 percent of observations when using one observation for each two-year window of data. Table 2 reports the tail events for the international GDP data and suggests that the international GDP tail events are to a large extent (about half) related to financial crises.[21]

Table 2: GDP tail events for 21 OECD countries in the period 1975Q1-2019Q2

Country	Year of GDP tail event	Country	Year of GDP tail event
Australia	1978, 1983, 1992*	Italy	2009*, 2014
Austria	2010*, 2015	Japan	2009, 2011
Belgium	1983, 1993, 2010*, 2014	Netherlands	1982, 2011*, 2014
Canada	1982, 1992, 2009	New Zealand	1977, 1987, 1989, 1992, 2010
Denmark	2009*	Norway	1989*, 2010 *
Finland	1993*, 2010, 2015	Portugal	2013*
France	2010*	Spain	2010*, 2013*
Germany	1982, 2004, 2009*	Sweden	1977, 1983, 1993*, 2009*
UK	1976*, 1982, 1992*, 2010*	Switzerland	1977, 1993*
Greece	2013*	US	1982, 2009*

*Notes: GDP tail events are the 50 lowest observations of three-year average GDP growth with at least two years between any two GDP tail events. * indicates that a GDP tail event is related to a financial crisis. Dating of financial crises for each country is based on Anundsen et al. (2016).*

We follow Gourinchas and Obstfeld (2012) and estimate a linear regression model given in equation (4) to determine how a financial indicator's conditional expectation depends on the temporal distance from a GDP tail event. This allows us to characterise the behaviour of financial indicators around the GDP tail events we identified earlier.

$$x_{j,i,t} = \alpha_{j,i} + \beta_{j,s}\delta_{j,i,s} + \varepsilon_{j,i,t} \tag{4}$$

In equation (4) we estimate the expected mean ($\beta_{j,s}$) of a set of variables of interest (e.g. the growth in credit, house prices etc.) as a deviation from its mean in "normal times"[22] the

[21]A GDP tail event is related to a financial crisis if it is located within the five-year window following the start date of a financial crisis.

[22]Normal times are defined as all country-quarter observations that do not fall within the event window.

four years preceding and the four years following a tail event. $x_{j,i,t} \in x_{i,t}$, denotes the variable of interest j, in country i and at time t. $\delta_{j,i,s}$ is a dummy variable taking the value one when $x_{j,i,t}$ is s quarters away from a tail event, and the value zero otherwise. The parameter $\alpha_{j,i}$ is a country fixed effect and $\varepsilon_{j,i,t}$ is an error term ($\varepsilon_{j,i,t} \sim IIN(0, \sigma^2_{x_j})$).

Figure 3 presents the behaviour of our financial indicators around the GDP tail events (i.e. estimated $\beta_{j,s}$ for different s), as well as our left-hand side measures of GDP growth and GDP shortfall (Figures 3j-3k). Close to all of the financial indicators are significantly higher than in normal times prior to GDP tail events.[23] But there are differences across indicators in terms of when they peak. Real equity price and house prices-to-income ratios tend to peak relatively early, around 12 to 16 quarters before tail events and before real GDP growth starts to decline (Figure 3a and 3b). Real equity prices decline significantly as economic conditions deteriorate, leading developments in other indicators. Indicators based on credit (Figures 3c-3f) peak somewhat later, but before GDP tail events. The corporate credit-to-GDP ratio (Figure 3i) peaks much closer to the tail events, about 4-8 quarters before. Overall, our results suggest that financial indicators have good signalling properties for GDP tail events and can potentially play an important role in explaining growth-at-risk.

5.2.2 Financial indicators and the empirical distributions

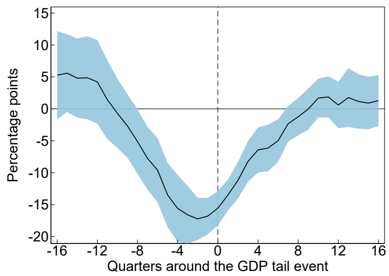
Before we proceed to the regression models, we present some stylised facts on how the empirical distribution of GDP growth depends on the financial indicators. We are particularly interested in the left tail of the distributions as our focus is on explaining growth-at-risk and downside risks to growth.

Figure 4 compares the unconditional empirical distribution of three-year average growth in GDP and the distribution conditioning on financial indicators being high three years earlier, where high is defined as above the country-specific averages.[24]

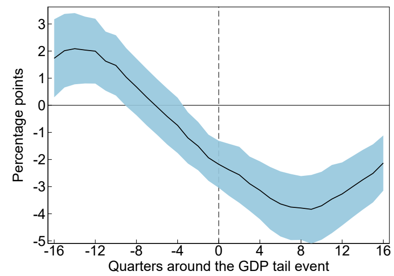
[23] Our results are broadly in line with the findings in Anundsen et al. (2016). They apply the same method to study the behaviour of financial indicators around crisis episodes.

[24] Distributions are grouped by taking the average across the conditional distributions for each asset price indicator (real equity prices, house prices-to-income and real CRE prices) and all credit indicators by sector (non-financial private sector, HH sector and NFE sector).

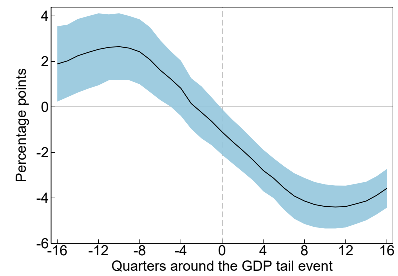
Figure 3: Behaviour of financial and economic conditions around GDP tail events



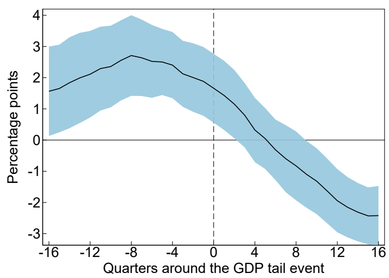
(a) Real equity prices (3Y av. growth)



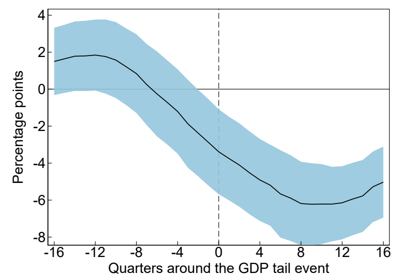
(b) House p./d.income (5Y av. change)



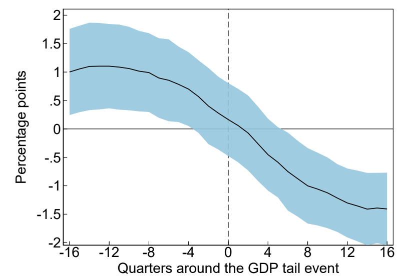
(c) Real total credit (5Y av. growth)



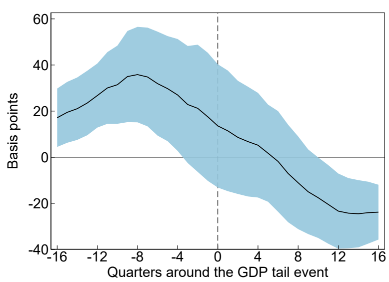
(d) Total credit/GDP (5Y av. change)



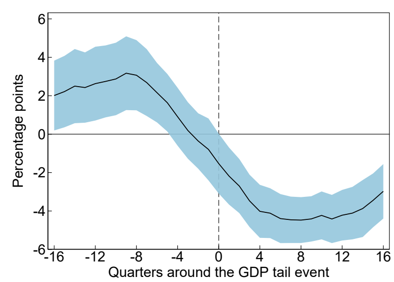
(e) Real HH credit (5Y av. growth)



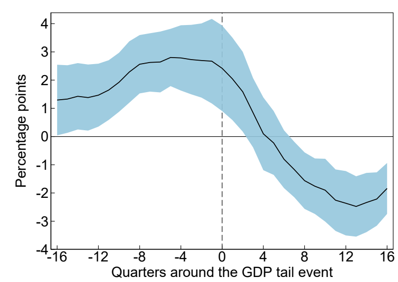
(f) HH credit/GDP (5Y av. change)



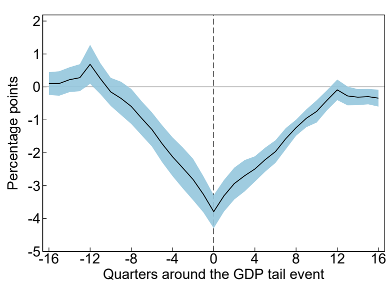
(g) HH DSR (5Y average change)



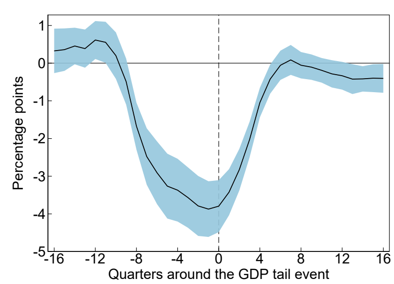
(h) Real NFE credit (3Y av. growth)



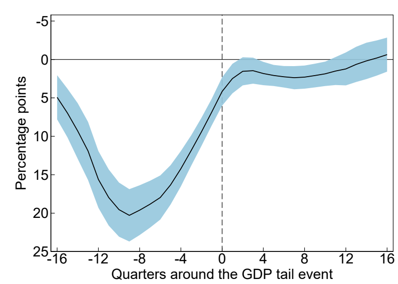
(i) NFE credit/GDP (3Y av. change)



(j) GDP (3Y average growth)



(k) Annual GDP (YoY growth)



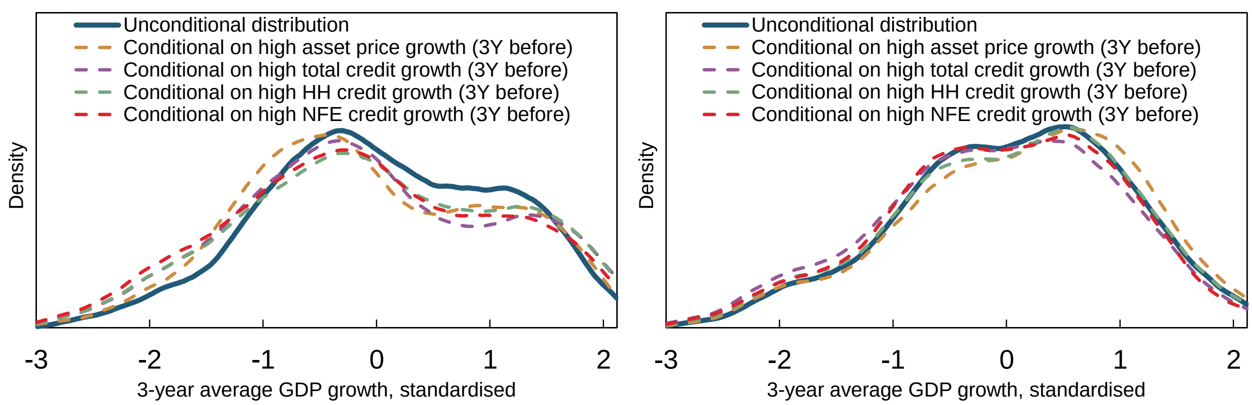
(l) Annual GDP shortfall (next 3Y)

Notes: GDP tail events are the 50 lowest observations of three-year average GDP growth with at least two years between any two GDP tail events at the country level. the lines are the conditional effects of being $s \in [-16; 16]$ *quarters away from a GDP tail event (the parameter* $\beta_{j,s}$ *in equation (4)), while the blue shaded areas show +/- two standard errors. A value different from zero means that the variable takes values that deviate from those in "normal times", defined as all country quarters outside the event window.*

The unconditional empirical distributions for both Norway and the panel reveal a fatter left and right tail than for a normal distribution. Indeed, the empirical distribution for Norway and most of the 21 OECD countries rejects the null hypothesis of normality.[25] Visual inspection of the distributions for Norway (4a) show that high values of the financial indicators are associated with a higher probability of low-growth events. Asset prices shift the mode to the left, whereas the credit indicators tend to increase the left tail, with the mode more or less unchanged. The empirical distributions based on the pooled international data indicate that only high total credit is associated with a more pronounced increase in the left tail, but the increase is more modest compared to the Norwegian data (Figure 4b).

Our preliminary look at GDP growth distributions reveals two interesting results. First, high levels of financial indicators, and in particular credit indicators, are associated with a higher probability of observing low GDP growth rates. Second, higher levels of credit indicators are not only associated with lower values of growth-at-risk but also higher downside risks.

Figure 4: Empirical distributions of three-year average growth in GDP



(a) Norwegian data

(b) Panel data

Notes: Empirical distributions of three-year average growth in GDP. Distributions are estimated using a kernel smoother. GDP growth is standardised by subtracting the country-specific averages and dividing by the country-specific standard deviations. High is defined as above country-specific averages of the financial indicators. 1975Q1-2019Q2.

[25]See Appendix 9.3.

6 Results

We present our results from the regression models using average GDP growth over a three-year horizon as our left-hand side variable to predict median growth (50th percentile) and growth-at-risk (5th percentile).[26] Results for single-indicator and multivariable models are reported separately.

6.1 Single-indicator models

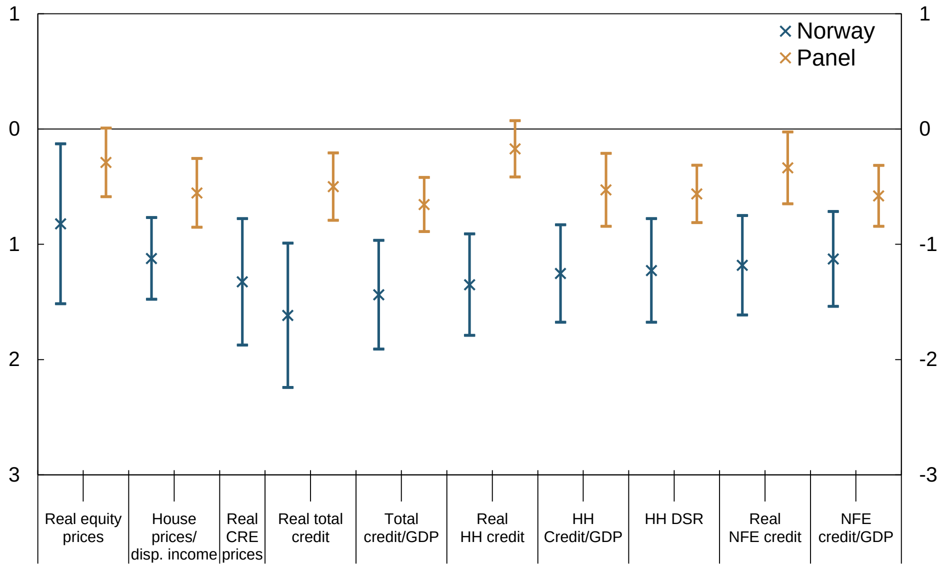
Figure 5a shows the estimated impact of a one standard deviation increase in different financial indicators on the 5th percentile of GDP growth using single-indicator models. The results are presented for two different samples: Norway and a panel of 21 OECD countries. The estimated coefficients are significantly negative for both samples but the estimated effects are larger for Norway. A one-standard deviation increase in financial indicators is estimated to reduce the 5th percentile of the growth distribution by about 0.1-0.6 percentage points based on the panel data. The estimated effects are typically higher than 1 percentage point based on Norwegian data.

Figure 5b shows the difference between the estimated coefficients for the 50th and 5th percentiles for different single-indicator models. The difference is positive for all models based on Norwegian data, suggesting that financial indicators not only have an effect on the lower percentiles of the growth distribution, but also on the size of the left tail (i.e. downside risks). In the panel data, estimates are closer to zero and in some cases negative (for example, for the change in household debt service ratio). The estimated difference is statistically significant for total credit (real and relative to GDP), real household credit and house prices-to-income for the Norwegian sample, while total credit-to-GDP is the only variable that has a statistically significant effect on downside risks in the panel data set.

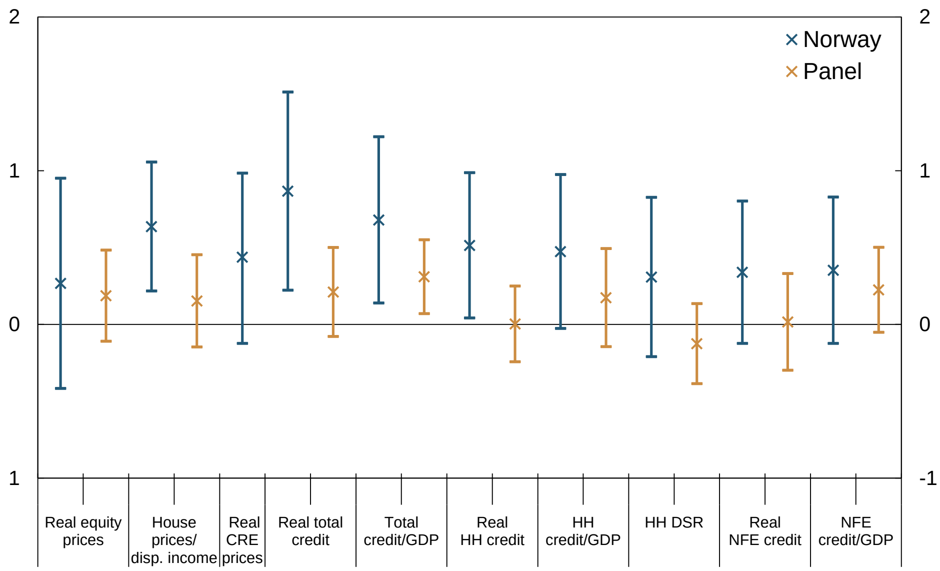
Appendix 9.4 shows the country-specific coefficient estimates for all 21 OECD countries. Close to all single-indicator models have a majority of negative country-specific coefficients for the 5th percentile and positive country-specific coefficients for the difference between the 50th and 5th percentile. The results do not indicate that Norway is an outlier in the distribution of country-specific estimates, even though Norway has a relatively low coefficient for the 5th percentile and a relatively high coefficient for the difference between the 50th and the 5th percentile.

[26]Results using the other two measures (annual growth two years ahead and average cumulative shortfall in GDP) are presented later in Section 7.2 where the calibration of stress test severity is discussed.

Figure 5: Estimated coefficients from different single-indicator models



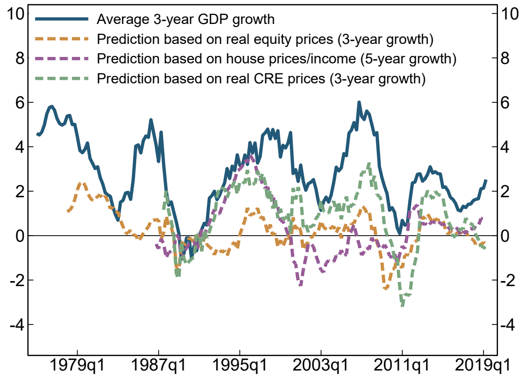
(a) 5th percentile



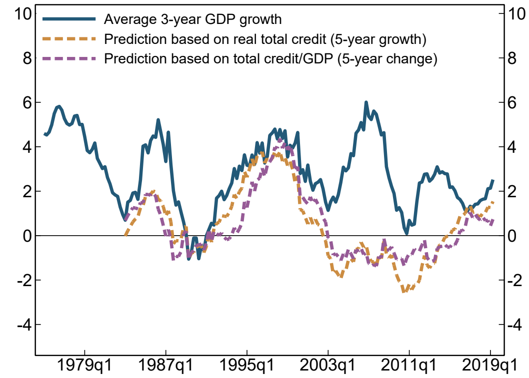
(b) Difference between the 50th and the 5th percentiles

Notes: The cross indicates the point estimate and the bars show +/- 2 standard errors obtained by bootstrapping techniques.

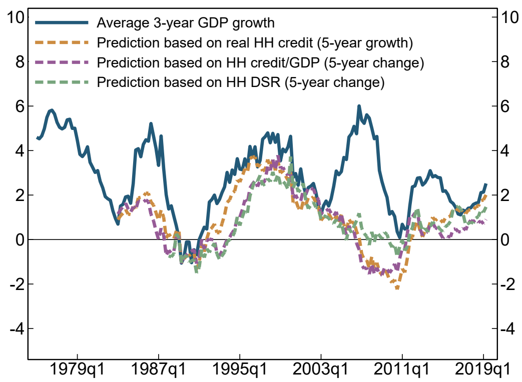
Figure 6: In-sample prediction for Norway from single-indicator models



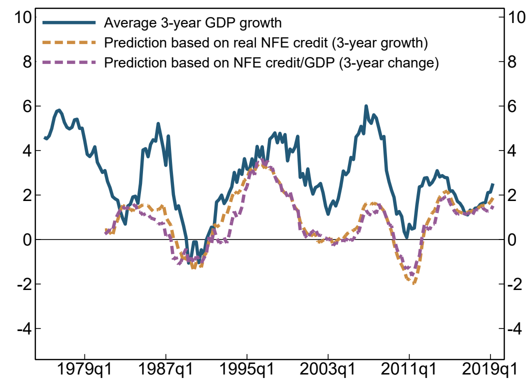
(a) Equity prices and real estate



(b) Total credit



(c) Household credit



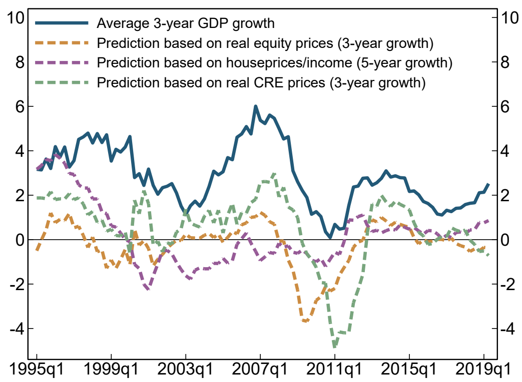
(d) Non-financial enterprise credit

Notes: In-sample three-years ahead prediction for the 5th percentile of three-year average GDP growth from single-indicator models.

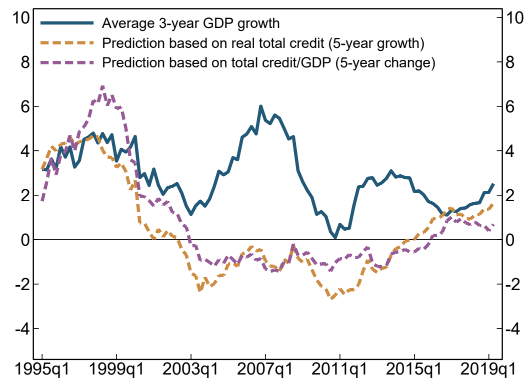
Moreover, Figure 6 shows the in-sample prediction for three-year growth-at-risk based on explanatory variables three years ago for all of the single-indicator models estimated using Norwegian data. Actual average growth over the past three years is plotted for comparison. To summarise our findings for financial indicators that broadly cover the same sectors or related markets, we divide the ten single-indicator models into four groups: (a) Equity prices and real estate (house prices-to-income ratio and real CRE prices), (b) total private credit (real total credit and total credit-to-GDP ratio), (c) household credit (real household credit, household credit-to-GDP and household debt service ratio) and (d) non-financial enterprise credit (real non-financial enterprise credit and non-financial enterprise credit-to-GDP ratio).

All of the models presented signal a decline in the 5th percentile of GDP growth leading up to the two most severe economic downturns in Norway in the sample: the banking crisis of 1988-93 and the financial crisis of 2008-09. Predicted growth-at-risk typically deteriorates across all single-indicator models in the years leading up to the financial crisis, reflecting the fact that most the of financial indicators were elevated during this period.

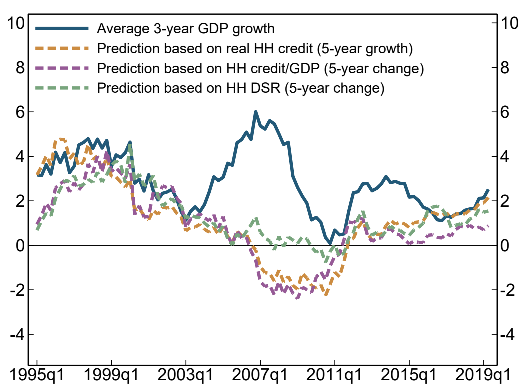
Figure 7: Out-of-sample prediction for Norway from single-indicator models



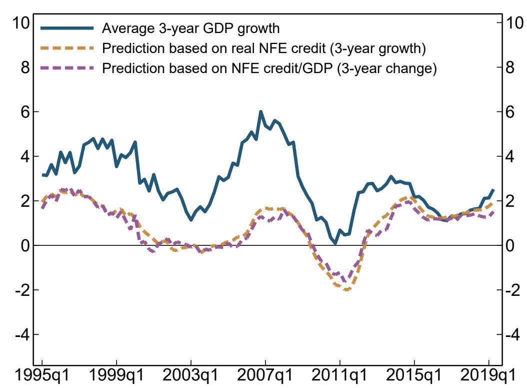
(a) Equity prices and real estate



(b) Total credit



(c) Household credit



(d) Non-financial enterprise credit

Notes: Out-of-sample predictions for 5th percentile of three-year average GDP growth from single-indicator models based on data and estimates from three years ago. Each single-indicator model is estimated recursively starting in 1995Q1.

Next, Figure 7 shows the out-of-sample prediction for three-year growth-at-risk for Norway for the same model groupings. Each single-indicator model is estimated recursively starting in 1995Q1. For each point in time, the figure shows the out-of-sample prediction for the 5th percentile based on data and estimates from three years earlier. The models we consider are generally good at predicting the increase in tail risks before the financial crisis. Model group (b) and (c) predict a gradual increase in tail risks in the period before the financial crisis, while model group (a) and (d) predict that tail risks increase sharply during 2004-2007.

Based on the results presented in this section, we conclude that financial indicators have a significant adverse effect on growth-at-risk and also tend to increase downside risks to growth. Both effects are more significant for Norway than in the panel. Models perform well both in-sample and out-of-sample. The in-sample model predictions for the 5th percentile align closely with the recursive out-of-sample predictions. This suggests that the model estimates for the 5th percentile using Norwegian data are quite robust.

Finally, results presented in Appendix 9.5 suggest that the single-indicator models do a relatively good job in predicting the growth distribution.[27]

6.2 Multivariable models

While single-indicator models can be used to explore the relationship between financial indicators and growth-at-risk for Norway, a multivariable model is necessary to incorporate information from several financial indicators and important macroeconomic control variables to avoid omitted variable bias in our estimates. We employ the international panel dataset to incorporate a richer set of macroeconomic variables and for improving our understanding of the marginal contribution of the different indicators to the predictions of medium-term risks to GDP.

Table 3 shows coefficient estimates for different model specifications for both the 5th percentile and the 50th percentile of three-year average GDP growth. We consider real private credit growth (five-year), house prices-to-income growth (five-year) and real equity price growth (three-year) as potential financial indicators to include in our multivariable model. This group of indicators have the advantage that they cover both credit and asset prices, which have been identified as key drivers of the financial cycle. They also feature somewhat different dynamics over time (see Section 5.1), bringing in additional information to the model.

[27] We evaluate the out-of-sample accuracy of the density forecasts by analysing the probability integral transforms (PITs). PITs show the cumulative distribution of model predictions evaluated at the outturn and thus inform how the out-of-sample predictions from different models fit the actual growth distribution. The models based on real total credit, total credit/GDP and real HH credit perform somewhat better than the other models.

Table 3: Estimated coefficients (5th and 50th percentile) from multivariable models

Explanatory variables	1 5th	1 50th	2 5th	2 50th	3 5th	3 50th
Real total credit	-0.77**	-0.29**				
(5-year growth)	(0.11)	(0.04)				
House prices/income			-0.49**	-0.28**		
(5-year growth)			(0.09)	(0.06)		
Real equity prices					-0.22	-0.05
(3-year growth)					(0.13)	(0.06)
GDP	0.18**	0.14**	0.15**	0.12**	0.21**	0.17**
(1-year growth)	(0.04)	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)
Short-term interest rate	-0.52**	-0.44**	-0.31*	-0.34**	-0.44**	-0.41**
(1-year change)	(0.11)	(0.05)	(0.12)	(0.05)	(0.09)	(0.07)
Inflation	-0.16	-0.13*	-0.28*	-0.32**	-0.31*	-0.27**
	(0.12)	(0.06)	(0.15)	(0.05)	(0.18)	(0.05)
Exchange rate regime	-2.11**	-1.76**	-2.26**	-1.65**	-2.87**	-2.16
	(0.28)	(0.12)	(0.25)	(0.12)	(0.36)	(0.13)
Number of observations	2886	2886	2597	2597	2285	2285

Explanatory variables	4 5th	4 50th	5 5th	5 50th	6 5th	6 50th
Real total credit	-0.55**	-0.24**	-0.57**	-0.23**	-0.63**	-0.20**
(5-year growth)	(0.13)	(0.05)	(0.14)	(0.06)	(0.13)	(0.07)
House prices/income	-0.22*	-0.14*	-0.18	-0.08	-0.14	-0.18**
(5-year growth)	(0.10)	(0.06)	(0.12)	(0.06)	(0.11)	(0.07)
Real equity prices			-0.13	-0.13*		
(3-year growth)			(0.12)	(0.06)		
GDP	0.17**	0.12**	0.20**	0.14**	0.21**	0.14**
(1-year growth)	(0.04)	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)
Short-term interest rate	-0.35**	-0.36**	-0.29*	-0.29**	-0.55**	-0.44**
(1-year change)	(0.13)	(0.05)	(0.14)	(0.06)	(0.13)	(0.06)
Inflation	-0.19	-0.25**	-0.15	-0.28**	-0.09	-0.16**
	(0.11)	(0.04)	(0.14)	(0.04)	(0.09)	(0.06)
Exchange rate regime	-2.20**	-1.66**	-2.72**	-2.04**		
	(0.26)	(0.12)	(0.29)	(0.16)		
Number of observations	2582	2582	2099	2099	2101	2101

*Notes: The table shows estimates of the average annual impact of a one standard deviation change in each variable on the 5th and 50th percentiles of average GDP growth over the following three years. Exceptions are real GDP growth, which is measured in percentage terms, and the exchange rate regime variable. Standard errors are shown in parentheses. ** denotes significance at the 1 percent level and * denotes significance at the 5 percent level.*

In model (1)-(3), the financial indicators are used one at a time. Real credit growth has the largest negative effect on the 5th percentile of GDP growth, followed by house prices-to-income growth. Equity price growth also has a negative effect on the 5th percentile, but it is not significant. All of the financial indicators have a larger effect on the 5th percentile than on the 50th percentile, but the difference is significantly larger for total credit.

In model 4 we combine real credit growth with house prices-to-income growth and in model 5 we also add real equity price growth. In both models, coefficient estimates for credit and house prices are lower (compared with models 1 and 2), reflecting the correlation between these two indicators. Adding equity prices in model 5 does not affect the other coefficients significantly, but the coefficient estimate for equity price growth is higher and has lower statistical significance (compared with model 3). All financial indicators have negative effects on the 5th percentile of GDP growth, but it is only credit growth and to a lesser extent house price growth that has a significantly larger effect on the 5th percentile than on the 50th percentile. Based on these results, we identify model 4 as our baseline multivariable model, featuring two key financial indicators that have negative and significant effects on both growth-at-risk and downside risks to growth.[28]

All of the macroeconomic control variables also have significant effects on medium-term GDP growth. An increase in the short-term interest rate or higher inflation is associated with lower growth. The effect is broadly similar for the 5th and 50th percentiles for the short-term interest rate, while inflation has a larger effect on the median.

Having a fixed exchange rate has a large negative effect on both the 5th and the 50th percentile, but the effect is significantly larger for the 5th percentile, suggesting larger downside risks associated with less flexible exchange rate regimes. This is consistent with the idea that exchange rate flexibility and monetary policy independence can play a dampening role in macroeconomic adjustments. We interpret the large negative coefficient for the 50th percentile on the exchange rate regime as capturing other structural factors that are correlated with the exchange rate regime. For the euro-area countries in our sample, exchange rate regimes have become less flexible over time, which coincides with a gradual decline in potential growth.[29]

To further investigate the role of the exchange rate regime, we estimate our baseline model (model 4) without the exchange rate regime. The last two columns in Table 3 show

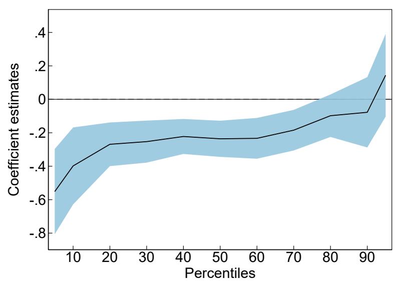
[28] Recursive estimates of model 5 suggest that the coefficient for equity price growth is not stable over time and model 5 does not perform well out-of-sample.

[29] Indeed, including a time trend in the model reduces the estimated effect of the exchange rate regime, but does not affect the estimated effect on downside risks.

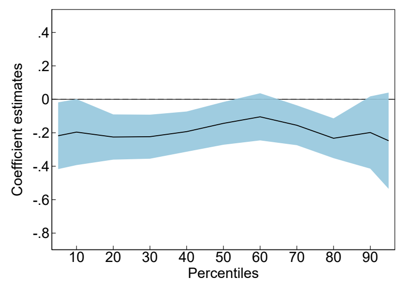
the results. As expected, the estimated effect of both credit growth and the change in short-term interest rates on downside risks to growth is higher in the model without the exchange rate regime.

The main conclusion we draw from this set of models is that while all financial indicators and macroeconomic control variables have an effect on the 5th percentile of GDP growth, it is real credit growth and the exchange rate regime that have the largest effects on *downside risks*. This can also be seen in Figure 8 where coefficient estimates for different percentiles are plotted for different explanatory variables for model 4. Real credit and the indicator for the exchange rate regime have a clear upward slope.[30]

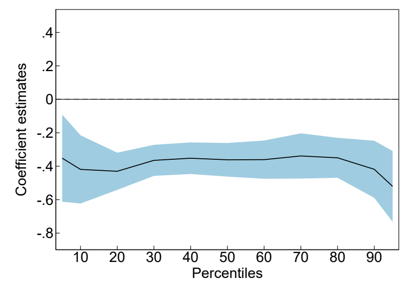
Figure 8: Estimated impact of financial indicators and macroeconomic control variables on different percentiles of three-year average GDP growth.



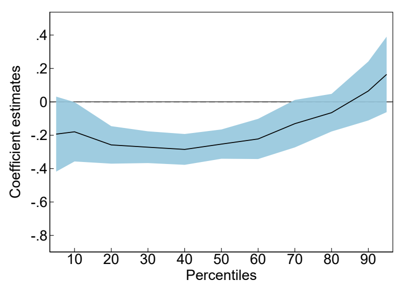
(a) Real total credit (5Y-growth)



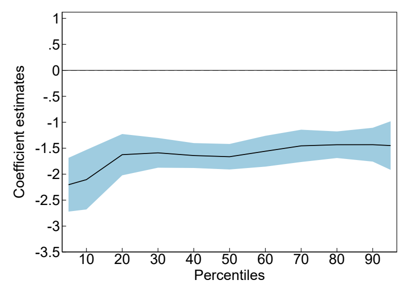
(b) House prices/income (5Y-growth)



(c) Short-term int. rate (1Y-change)



(d) Inflation



(e) Exchange rate regime

Notes: Results from the baseline multivariable model (model 4). Shaded area shows coefficient estimate +/- 2 standard errors.

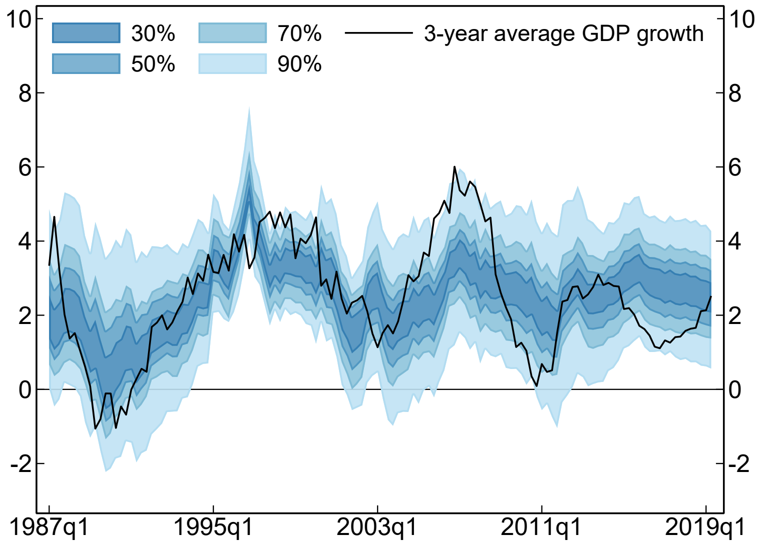
Next, we consider the in-sample and out-of-sample performance of a baseline multivariable model. We use model 4 as our baseline model since it incorporates a set of financial indicators that have a significant effect on both growth-at-risk and downside risks to growth.

[30]We can reject the null hypothesis that coefficients for the 5th and 50th percentiles are equal at the 1 percent level for both variables.

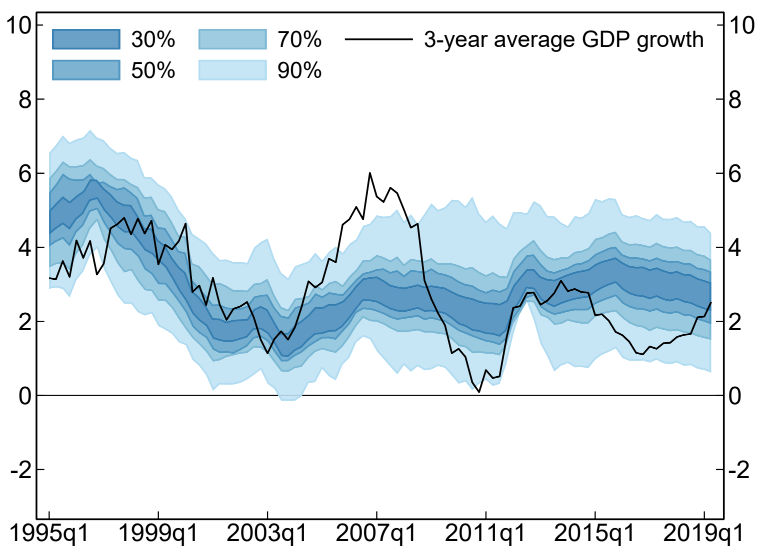
Figure 9a shows the in-sample prediction for different percentiles of GDP growth based on information as of three years earlier along with the realised average three-year GDP growth. The multivariable model does a good job capturing key turning points in the Norwegian data. The 5th percentile prediction declines considerably leading up to both the banking crisis and the financial crisis. Furthermore, downside risks (i.e. larger left tail) are also high leading up to these episodes. The out-of-sample predictions (Figure 9b) show that the multivariable model would have done a good job during the period leading up to the financial crisis in signalling the slowdown in growth between 2007 and 2010. Similar to the single-indicator models, we evaluate the out-of-sample accuracy of the density forecasts from the baseline multivariable model by analysing the probability integral transforms (PITs) for both Norway and the panel. Results presented in Appendix 9.5 suggest that the multivariable model does overall a decent job of predicting the growth distribution for Norway and the panel. However, for the lower percentiles, the model tends to have more optimistic predictions.

Finally, we conduct two robustness exercises for the multivariable model. First, we consider the robustness of our coefficient estimates with respect to the country sample. We re-estimate the multivariable model, taking out one country at a time from the sample, and analyse the robustness of our coefficient estimates. Results from this exercise (Appendix 9.6) reveal that the estimated coefficients are not driven significantly by any single country. As a second robustness exercise and to analyse the effects of the financial crisis on our coefficient estimates, we look at how the coefficient estimates vary over time when the model is estimated recursively (Appendix 9.7). This exercise reveals that the financial crisis has had a significant effect on our coefficient estimates, especially for inflation and the exchange rate regime.

Figure 9: In-sample and out-of-sample prediction for three-year average GDP growth



(a) In-sample prediction



(b) Out-of-sample prediction

Notes: Fans show the predicted three-years ahead distribution based on the baseline multivariable model (model 4). The shaded areas indicate the distribution centred around the median prediction.

7 Policy applications

In this section, we demonstrate how the growth-at-risk framework can be used by policymakers. In Section 7.1, we present an assessment of the evolution of financial indicators and medium-term tail risks in Norway over time as well as tools that policymakers can use to communicate such risks. In Section 7.2, we use the framework to guide the calibration of cyclical stress tests, where the focus is on establishing a link between financial indicators and stress test severity using two complementary measures of growth-at-risk.

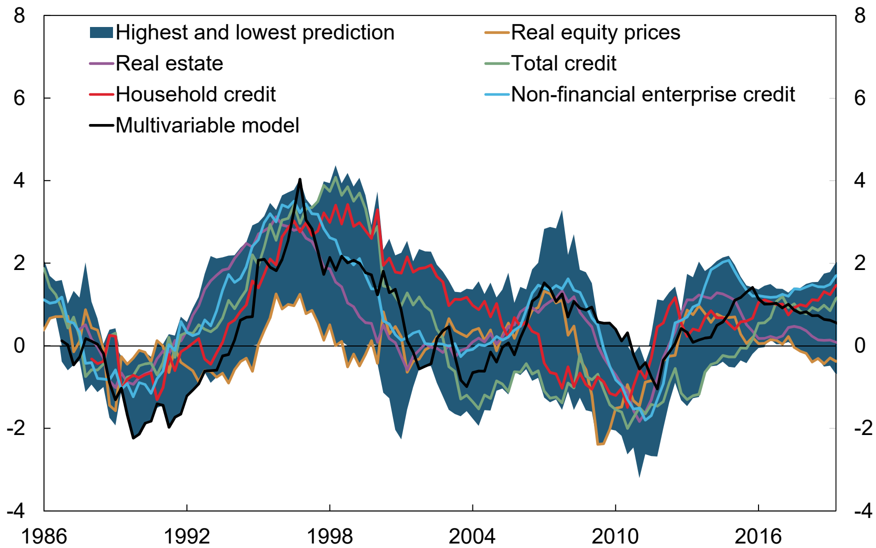
7.1 Medium-term tail risks in Norway

We use the growth-at-risk framework to provide an assessment of how tail risks related to financial indicators have evolved over time in Norway. We first present how predictions from single-indicator models and our baseline multivariable model can be used together for an overall assessment of tail risks. We then show how a policymaker equipped with the baseline multivariable model can present an assessment of tail risks and their drivers.

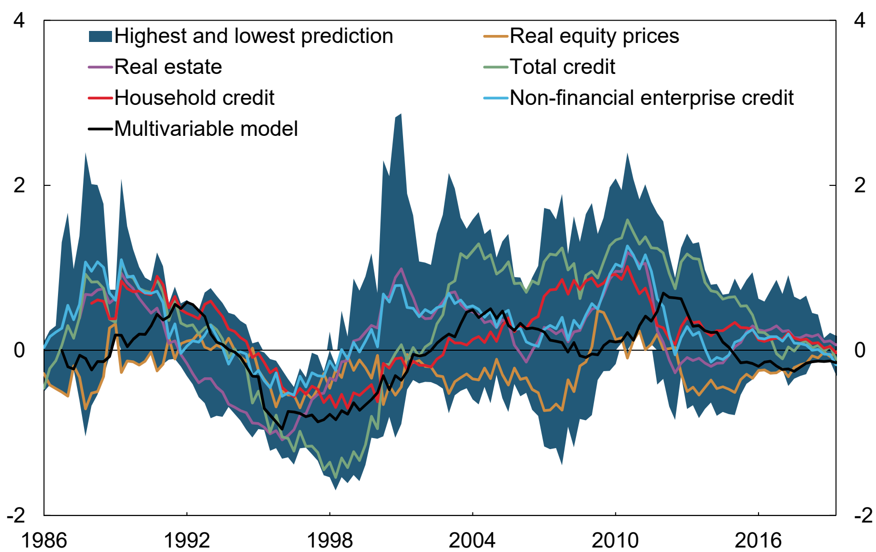
Predictions over time from the single-indicator models and the multivariable model are shown in Figure 10. As expected, the predictions from different single-indicator models tend to move together since our explanatory variables are generally highly correlated. Furthermore, predictions from the multivariable model align well with the predictions from single-indicator models using Norwegian data. This gives us confidence in the overall assessment of growth-at-risk from these models.

Degree of agreement between different models with respect to predictions varies over time. It is reasonable to assume that the analysis should be given a larger weight in policy discussions when many indicators give the same signal. Figure 10 shows that predictions for the latter half of the 1980s, including the banking crisis, show little disagreement. There is a general tendency among the models to forecast low growth-at-risk. Furtermore, the figure shows that growth-at-risk predictions deteriorate more than median growth predictions for the period leading up to and including the banking crisis.

Figure 10: Predictions from different single-indicator models and the multivariable model



(a) Predicted 5th percentile



(b) Predicted difference between 50th and 5th percentile

Notes: Predictions for three-year average real GDP growth based on data three years earlier. The lines depict the average of predictions from single-indicator models in the same group. The shaded area depicts minimum and maximum predictions from all models. The difference between 50th and 5th percentile excludes the difference due to constant terms.

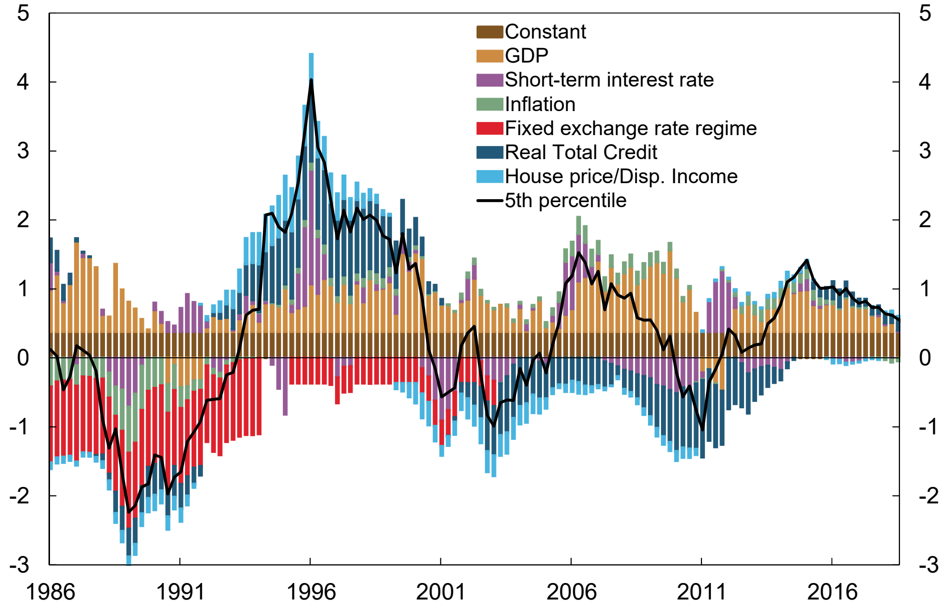
The model forecasts for the financial crisis episode and its aftermath also show relatively little disagreement. The economy was booming in the run-up to the financial crisis, and this boom was accompanied by a rapid development in credit indicators and asset prices, leading to higher risk of low-growth events. The lower panel in Figure 10 shows that tail risks were steadily increasing from the late 1990s. After the financial crisis, the risk outlook for medium-term growth improved due to a slower development in credit and asset prices. The growth-at-risk prediction around 2016 show little disagreement and lower downside risks than before the financial crisis.

To further demonstrate how the growth-at-risk framework can be used, we estimate our baseline multivariable model for different percentiles of the growth distribution ranging from the 5th to the 95th percentiles. We then follow Adrian et al. (2019) and fit a skewed t-distribution developed by Azzalini and Capitanio (2003) in order to recover a smooth probability density function.[31] The predicted distributions using this approach for the periods preceding and following the banking crisis and the financial crisis in Norway are presented in Figure 12. Using the predicted densities together with the contributions from different explanatory variables to growth-at-risk and downside risks to growth (Figures 11a and 11b respectively), it is possible to assess developments in the risk outlook and their drivers, and communicate such risks.

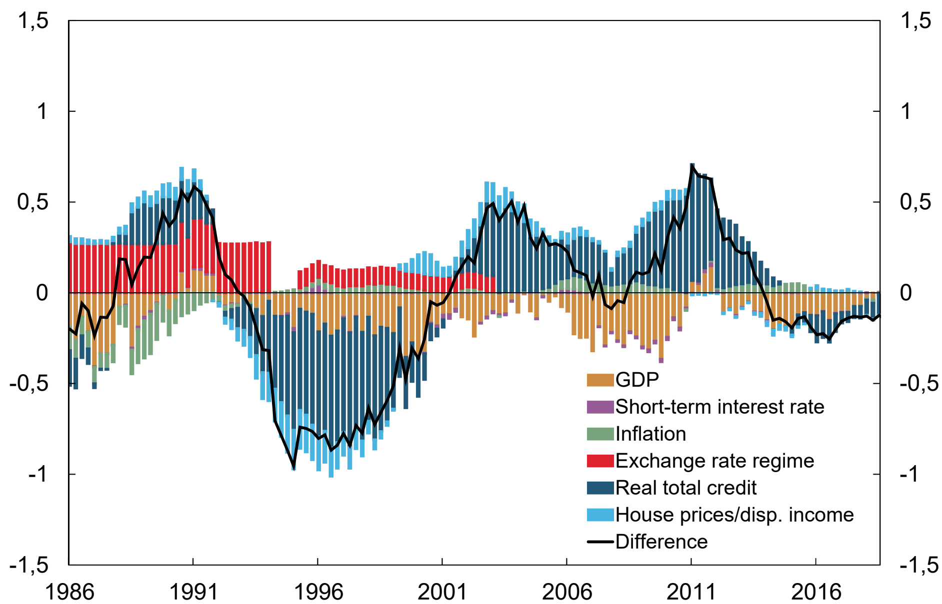
Starting with the banking crisis, the risk outlook prior to the crisis was relatively subdued, but still showing relatively higher upside risks than downside risks (see prediction in 1983Q4 for 1986Q4, Figure 12a). Three years later, there is a marked shift to the left and higher uncertainty in the growth distribution in 1986Q4 for growth over the next three years ending in 1989Q4. Consequently, the 5th percentile is reduced somewhat more than the median in this period. With the benefit of hindsight, we see that the less flexible exchange rate regime in the 1980s and early 1990s has contributed to higher downside risks during this period (Figure 11b). The increase in credit and house price growth between 1983 and 1986 has contributed to a further fattening of the left tail, whereas an increase in interest rates and higher inflation contributed to a negative shift in the predicted growth distribution for the latter half of the 1980s (Figure 11a).

[31] In particular, for each quarter we obtain a fitted t-skew distribution by minimising the square distance between the predicted quantiles and the quantiles of the skewed t-distribution to match the 5th, 25th, 75th and 95th percent quantiles. The median and the 5th percentile in these distributions coincide with those in Figure 9a (apart from smaller approximation errors). See Adrian et al. (2019) for more details on smoothing of the quantile function using a skewed t-distribution.

Figure 11: Contribution of different explanatory variables to predictions for three-year average GDP growth



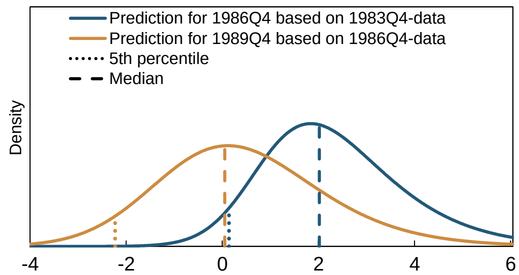
(a) Decomposition of predicted 5th percentile



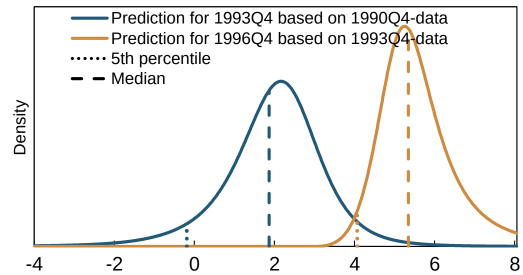
(b) Decomposition of predicted difference between 50th and 5th percentile

Notes: Contribution of different explanatory variables to the predicted 5th percentile (a) and predicted lower tail risks (difference between 50th and 5th percentile) (b) of three-year average GDP growth, both using the baseline multivariable model. Decomposition of the difference between 50th and 5th percentile excludes the difference due to constant terms.

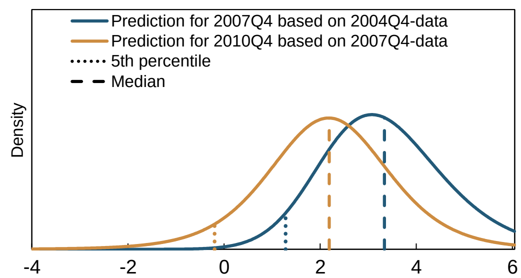
Figure 12: Three-years ahead prediction of three-year average growth in GDP



(a) Predictions before the banking crisis



(b) Predictions after the banking crisis



(c) Predictions before the financial crisis

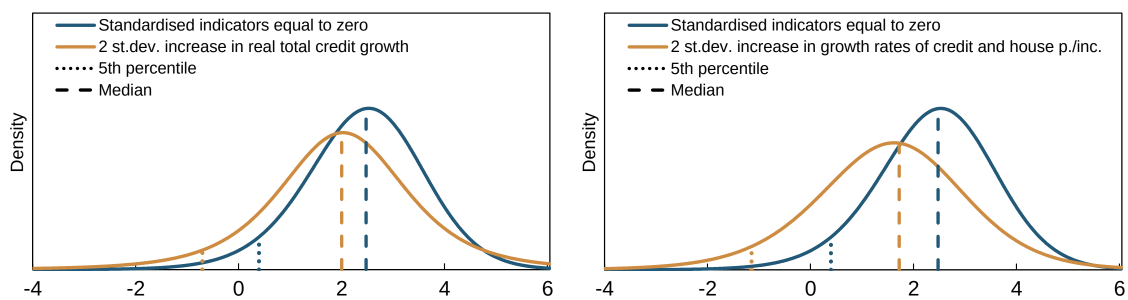
Notes: Distributions are based on fitted t-skew distributions and the predictions from the baseline multivariable model. The 5th percentile and the median are based on the fitted t-skew distribution.

Predicted growth for the period following the start of banking crisis was still relatively low, and the distribution had a relatively fat left tail (see Figure 12b). The prediction made after the banking crisis, in 1993Q4, show a marked shift to the right in the forecast distribution. This also turned out to be a period with strong GDP growth. Key drivers of this change were a more flexible exchange rate, lower real credit and house prices-to-income growth, which reduced left tail risks (Figure 11b), and a lower interest rate, which shifted the whole distribution to the right (Figure 11a).

Moreover, the fattening of left tail risks from the late 1990s and leading up to the financial crisis is mainly ascribed to a long period of persistently high credit growth. Higher interest rates led to a higher risk of low-growth events for the period 2007 to 2010 (Figure 11). In Figure 12c we zoom in on predicted growth distributions for 2007Q4 and 2010Q4. During this period, the predicted densities shift markedly to the left, and we see a further fattening of the left tail. Finally, after the financial crisis, left tail risks are predicted to have fallen due to lower real credit growth (Figure 11b). This has led to a more benign outlook for growth-at-risk (Figure 11a)).

To illustrate the sensitivity of the risk outlook, we show changes in our baseline multivariable model under two scenarios. Figure 13a shows predicted growth distribution when all standardised explanatory variables are equal to zero, i.e. the explanatory variables are equal to their average growth rate in the sample period. We contrast this baseline prediction with a scenario where five-year average real credit growth is two standard deviations higher, which corresponds to an increase in five-year average real credit growth of about 8.5 percentage points. This alternative scenario clearly shows a fatter left tail, but also somewhat lower median growth. The 5th percentile of the growth distribution declines considerably, reaching a level that was more adverse than that experienced during the financial crisis.

Moreover, figure 13b shows a more adverse scenario where both real credit growth and house prices increase considerably (again by two standard deviations, which constitute an increase in five-year average growth in house prices-to-income by about 8.7 percentage points). In this case, the whole growth distribution shifts to the left in addition to a fatter left tail. The predicted growth-at-risk is quite severe, corresponding to the experience during Norway's banking crisis.



(a) Higher growth in credit (b) Higher growth in credit and house prices

Figure 13: *Two different scenarios for growth in financial variables. Distributions are based on fitted t-skew distributions and the predictions from the baseline multivariable model. The 5th percentile and the median are based on the fitted t-skew distribution.*

7.2 Calibrating severity of cyclical stress test scenarios

In the following exercise we use the growth-at-risk framework to map financial indicators to the severity of a cyclical stress scenario.[32] The relevant left-hand side variable depends on the application at hand. To guide the severity of a stress scenario, we are interested in measures that inform the characteristics of the GDP path, where increased severity is associated with more severe outcomes for banks' key reporting variables such as loan losses, earnings and capital.

We measure crisis severity along two dimensions and apply both transformations of GDP as left-hand side variables in single-indicator growth-at-risk regressions:

- **Severity measure 1:** Lowest annual GDP growth over the stress period.
- **Severity measure 2:** Total GDP shortfall during the first three years of the stress period measured as the deviation from pre-crisis GDP.

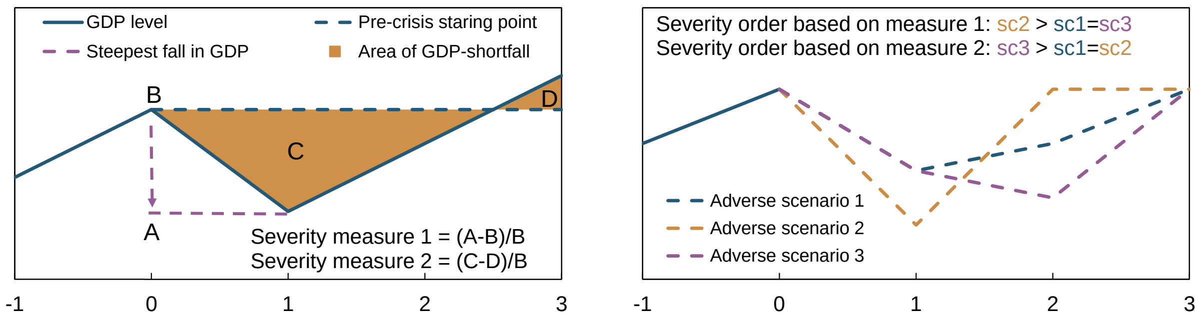
Figure 14a illustrates the two measures of severity. Lowest annual GDP growth (severity measure 1) captures the largest decline in GDP over the stress test horizon, and negative values are associated with the typical V-shape of the crisis GDP path. The GDP shortfall (severity measure 2) is measured by the area between the adverse path and the pre-crisis level of GDP, and it informs us on the persistence of negative shocks to the economy. The GDP shortfall is also a measure of the cumulative loss of output over the first three years of the stress scenario. Together, the two measures are largely sufficient to identify a path for GDP in the stress test scenario.

Next, Figure 14b explores the two severity measures using three different scenarios for GDP. According to severity measure 1, scenario 2 is more severe as it has the steepest fall in GDP. We would expect that the faster deterioration of economic activity is associated with a more rapid increase in credit risk and loan losses than in scenario 1 and 3. According to severity measure 2, scenario 3 is more severe as the cumulative output loss is larger. In the case of scenario 3, we would expect that the more persistent negative shock to the economy probably puts a larger strain on Norwegian banks and their customers than in scenarios 1 and 2. Combined, both measures point to scenario 1 as the least severe scenario, while scenarios 2 and 3 are more severe along different dimensions.[33]

[32] Prasad et al. (2019) suggest that the growth-at-risk approach can provide a useful benchmark for the adverse scenario in a stress test, and it has the additional advantage of taking into account existing macro financial vulnerabilities.

[33] If we applied the three-year average growth, all three scenarios would show zero growth over the first three years of the stress scenario.

Figure 14: Illustration of severity measures



(a) Illustration of severity measures (b) Example based on three adverse scenarios

Notes: Illustration of severity measures and example using three different stress scenarios for GDP. Years after crisis start (horizontal scale)

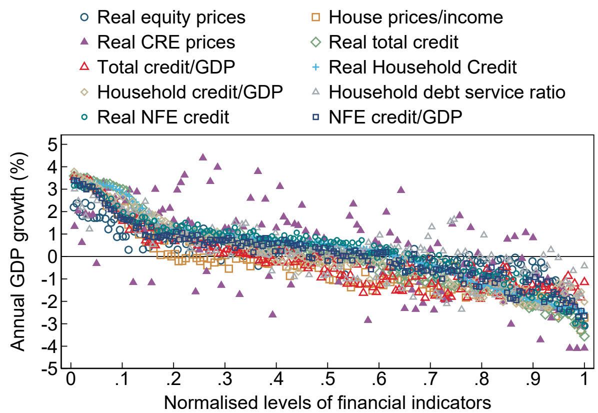
Next, we apply the single-indicator models described in Section 6.1 and estimate the relationships between each severity measure as left-hand side variables and the different financial indicators based on Norwegian and international data. In this regression, we are interested in capturing the link between our financial indicators and the severity of financial crises. Therefore we only report the results for the 5th percentile[34], and we apply the left-hand side variables that corresponds to a crisis in one year time, i.e. two years ahead annual growth and the one year ahead GDP shortfall over the next three years. By projecting the severity of a potential tail event in the medium-term, we capture the strong connection shown in our previous results (see Section 6) between our financial indicators and the severity of a GDP tail event that is often associated with financial distress.[35]

Finally, we let the regression results inform the design of our cyclical stress test scenario, and we construct a range of GDP paths that vary with the level of financial indicators. In particular, we use the regression results for the 5th percentile to inform the relationship between financial indicators and crisis severity. In the last step, we also adjust the range of GDP paths based on a cross-check against the unconditional distribution of the severity measures for mainland GDP in Norway, international crises and previous stress test exercises.

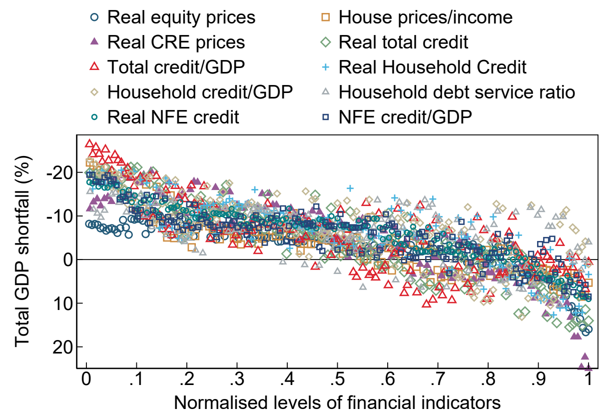
[34]The GDP shortfall increases with the degree of severity. We therefore report the 95th percentile to estimate the relationship between tail events and financial indicators.

[35]Our three left-hand side variables are highly correlated if we apply three-years ahead three-year average growth, two-years ahead annual growth and the one-year ahead GDP shortfall over the next three years. The last column in Figure 3 confirms that annual growth tends to lead the tail events of three-year average growth by one year and the GDP shortfall leads by two years.

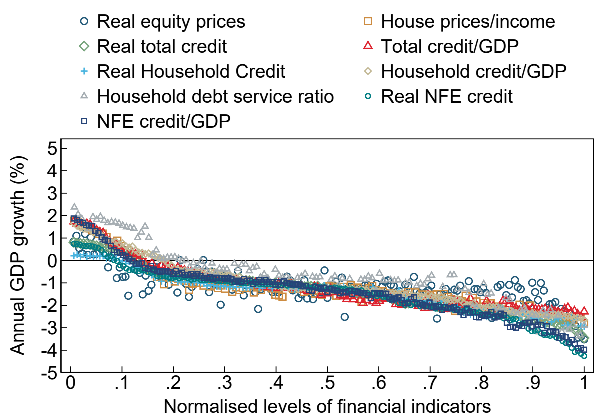
Figure 15: Predicted crisis severity measures based on different financial indicators



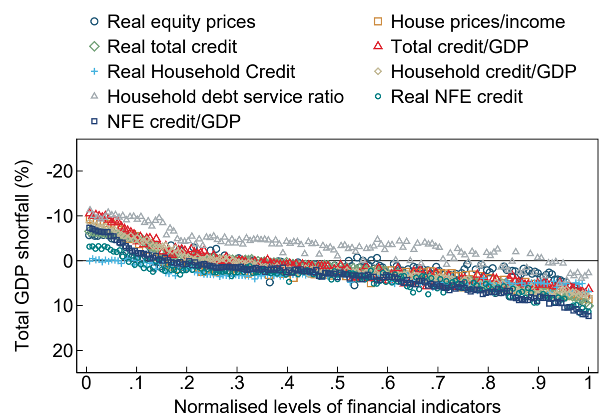
(a) Steepest fall in GDP, Norwegian data



(b) Total GDP shortfall, Norwegian data



(c) Steepest fall in GDP, panel data



(d) Total GDP shortfall, panel data

Notes: Steepest fall in GDP is predicted two years ahead. Total GDP shortfall is predicted one year ahead. Quantile regressions are applied to quantify the correlation between tail events (5th percentile) for mainland GDP and various measures of financial imbalances. Financial indicators are three-year and five-year changes and are normalised based on their empirical cumulative distribution (1975Q1-2019Q2)

Figures 15a and 15b report the regression results based on Norwegian data for each financial indicator. Each indicator is normalised based on its historical distribution in the period 1975Q1-2019Q2, resulting in the same scale for all of the indicators. The steepness of the slope informs us how the severity measures have varied with the level of financial imbalances. As expected, historical observations show that predicted GDP growth usually declines, and predicted total GDP shortfall usually widens as the financial indicators increase.

Figures 15c and 15d report the regression results based on the international panel data. In line with the findings in Section 6, the coefficient for the 5th percentile is negative and generally somewhat smaller for the panel data. This leads to less steep slopes for both measures of severity. The estimates based on the panel data often indicate a more severe crisis for low levels of the financial indicators than the estimates based on the Norwegian data.

Finally, we let the growth-at-risk results inform us on the relationship between financial imbalances and crisis depth. Figure 16a shows the potential range of GDP paths for the cyclical stress scenario.[36] The potential GDP paths are also adjusted based on a cross-check against unconditional distributions described below. In particular we adjust the least severe paths (in yellow) to be more severe than our regression results. Our predictions for the events with historically low financial imbalances, and especially the predictions for Norway, indicate a GDP path that we do not consider to be a severe economic downturn.

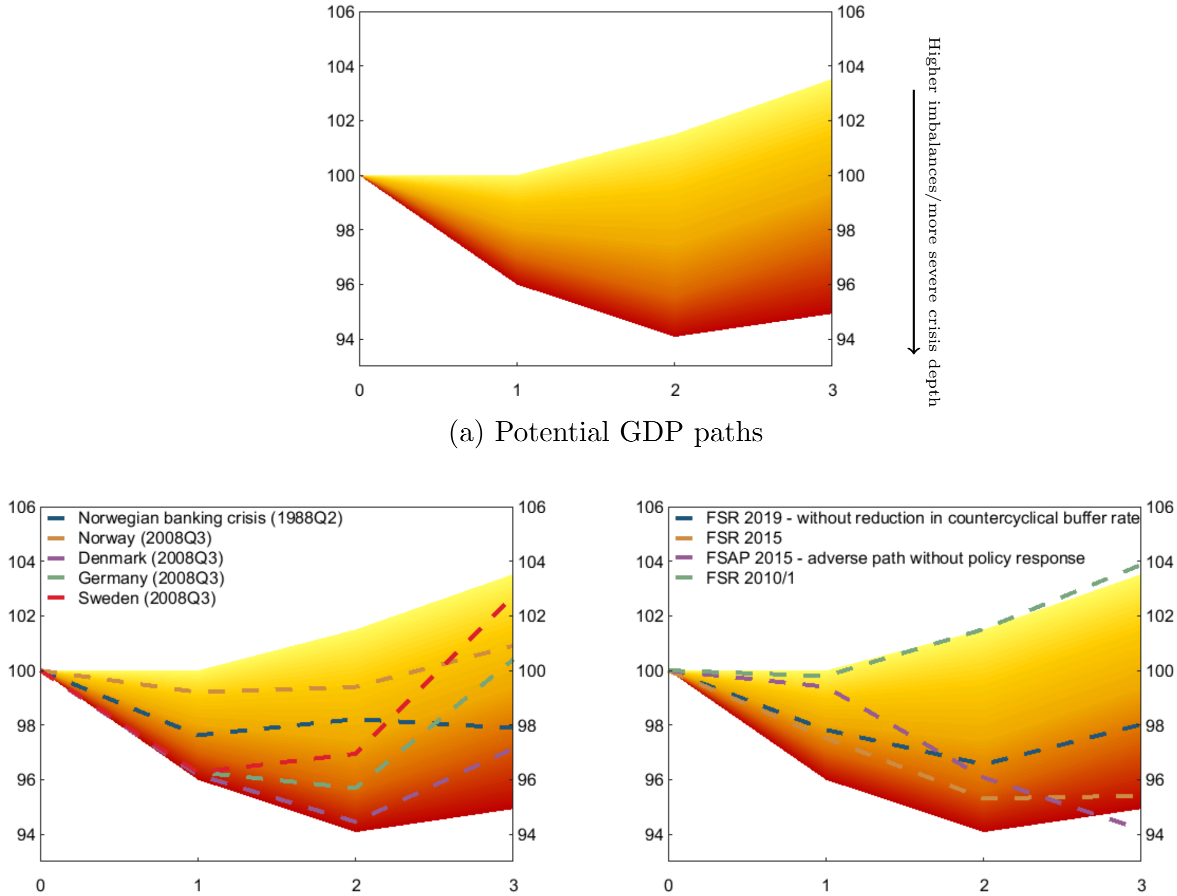
For the cyclical scenario shown in Figure 16a, we let annual growth in GDP in the first year (the year with the largest decline) decrease gradually from 0 percent for the least severe paths (in yellow) to -4 percent for the most severe paths (in red). This is based on the finding in the first row in Figure 15: For Norway the steepest fall in GDP decreases from around 3 percent to around -3 percent as financial indicators increase, whereas the panel data indicates a decrease from around 1 percent to around -3 percent. For the GDP shortfall, we let the cyclical scenario increase gradually from -5 for the least severe GDP paths (in yellow) to 15 percent for the most severe paths (in red). The second row in Figure 15 also reports an increase in severity for the GDP shortfall as financial indicators increase: For Norway, the shortfall increases from around -20 percent to around 15 percent, whereas the panel data show an increase from around -5 percent to around 10 percent.

The last column in Figure 16 reports selected crisis events and stress-testing exercises that we use to cross-check the range of our severity measures and GDP paths. The cross-check against a larger set of crises and stress testing exercises are reported in Appendix 9.8. The GDP paths in levels have been adjusted so that the most severe events (in red) largely cover the developments observed in international crises for comparable countries, see Figure 16b. The least severe GDP paths (in yellow) is limited to zero growth in the first year and a total GDP shortfall of minus 5 in the first three years as a share of pre-crisis GDP. Figure 16c and Figure 23 in Appendix 9.8 show that the least severe GDP paths are in line with

[36] For more information on the assessment of financial imbalances and on how the growth-at-risk framework informed the stress scenario in Financial Stability Report 2019, see Norges Bank (2019c).

the stress-testing exercises performed in the period after the financial crisis.

Figure 16: Potential GDP paths in the stress scenario and variation in financial imbalances



(a) Potential GDP paths

(b) Selected financial crises

(c) Selected stress test exercises

Notes: Years after crisis start (horizontal scale). GDP is indexed. Year 0 = 100. Starting date of selected financial crises (in parenthesis) are based on Anundsen et al. (2016). Selected stress test exercises are based on International Monetary Fund (2015) and Norges Bank (2019b).

8 Conclusion

We develop a growth-at-risk framework to examine how financial indicators affect macroeconomic tail risks over the medium-term in Norway. We use a wide range of financial indicators and different quantile regression models estimated using data for Norway and a panel of 21 OECD countries.

Models were identified based on two main criteria that are useful from a policy perspective: Financial indicators have a significant negative effect on growth-at-risk three years ahead (5th percentile of the growth distribution), and increase downside risks to growth (difference between the median and the 5th percentile of growth distribution).

We estimate both single-indicator models and multivariable models. The simplicity of the single indicator models allows us to estimate the relationship between different financial indicators and growth-at-risk for Norway and the panel data separately. The estimates provide important insights into how financial indicators affect growth-at-risk for Norway. The multivariable models incorporate a broader set of financial indicators and macroeconomic control variables and are estimated using panel data. The multivariable models allow us to study the drivers of growth-at-risk over time and function as a robustness check for the single-indicator models.

Our analysis shows that selected financial indicators are associated with macroeconomic tail risks. This relationship exists for both Norway and the broader sample of advanced economies. Credit growth and to a lesser extent house prices are the main determinants of higher downside risks to growth. We also find that downside risks are higher in countries with a fixed exchange rate regime.

Two policy-relevant exercises illustrated how the growth-at-risk framework can be a useful input in assessing the medium-term risk outlook in Norway. The first exercise showed that our models signal both higher risk of low growth and increased downside risks to growth in periods leading up to the banking crisis (1988-93) and the financial crisis (2008-09). In the second exercise, we used the growth-at-risk framework to link stress test severity to an assessment of financial imbalances.

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9 Appendix

9.1 Data

Table 4: Overview of data sources

Indicator name	Norwegian data	Panel data (excluding Norway)
Real GDP	OECD, Statistics Norway and Norges Bank	OECD
Nominal GDP	OECD, Statistics Norway and Norges Bank	OECD
Equity prices	Thomson Reuters Datastream	Thomson Reuters Datastream
House prices/ disposable income	Eiendomsverdi, Finn.no, Real Estate Norway, Norwegian Association of Real Estate Agents (NEF), Statistics Norway and Norges Bank	OECD
Commercial real estate prices	CBRE, Dagens Næringsliv, OPAK, Statistics Norway and Norges Bank	
Total private credit	Statistics Norway and Norges Bank	Bank for International Settlements
Household credit	Statistics Norway and Norges Bank	Bank for International Settlements
Household debt service ratio	Statistics Norway and Norges Bank	Bank for International Settlements
Non-financial enterprise credit	Statistics Norway and Norges Bank	Bank for International Settlements
Short-term interest rates	Norges Bank	OECD
Inflation	Statistics Norway and Norges Bank	OECD
Exchange rate regime	International Monetary Fund	International Monetary Fund

9.2 Summary statistics

Table 5: Summary statistics of the data

	Obs.	Mean	Std. Dev.	Min	Max	50th perct.
Australia						
GDP (3Y average growth (%))	178	3.2	1.0	0.7	5.3	3.2
Real Equity Price (3Y average growth (%))	97	3.2	7.5	-11.9	22.2	2.8
House Price/Disp. Income (5Y average growth (%))	178	1.5	3.0	-4.0	9.7	0.3
Real Private Credit (5Y average growth (%))	174	6.5	3.5	-0.5	14.4	6.8
Private Credit/GDP (5Y average change (p.p.))	174	3.0	2.8	-2.2	8.7	2.9
Real Household Credit (5Y average growth (%))	146	7.4	3.8	3.2	15.0	5.8
Household Credit/GDP (5Y average change (p.p.))	146	2.2	1.7	0.0	6.1	1.8
Household Debt Service Ratio (5Y average change (p.p.))	61	0.3	0.5	-0.5	1.1	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	154	5.6	6.0	-5.0	20.2	5.5
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	154	1.0	3.0	-5.1	8.2	1.3
Austria						
GDP (3Y average growth (%))	178	2.2	1.0	-0.5	4.5	2.3
Real Equity Price (3Y average growth (%))	122	7.8	20.1	-20.6	75.1	1.3
House Price/Disp. Income (5Y average growth (%))	57	2.2	2.8	-2.2	6.2	3.2
Real Private Credit (5Y average growth (%))	174	4.9	3.1	0.1	13.2	4.3
Private Credit/GDP (5Y average change (p.p.))	174	2.0	1.5	-1.7	5.1	2.1
Real Household Credit (5Y average growth (%))	74	2.6	2.2	-0.6	5.8	3.5
Household Credit/GDP (5Y average change (p.p.))	74	0.4	0.7	-0.8	1.5	0.7
Real Non-Financial Enterprise Credit (3Y av. growth (%))	82	3.3	2.8	-0.2	9.8	2.1
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	82	1.2	1.6	-1.2	4.3	0.8
Belgium						
GDP (3Y average growth (%))	178	2.0	1.0	-0.2	4.6	2.1
Real Equity Price (3Y average growth (%))	106	5.0	13.6	-18.8	39.6	4.5
House Price/Disp. Income (5Y average growth (%))	177	1.3	3.2	-6.9	7.4	1.6
Real Private Credit (5Y average growth (%))	174	4.8	3.3	-3.3	11.2	5.5
Private Credit/GDP (5Y average change (p.p.))	174	3.3	3.0	-3.0	9.7	3.0
Real Household Credit (5Y average growth (%))	134	4.4	2.7	-2.6	10.0	3.9
Household Credit/GDP (5Y average change (p.p.))	134	0.9	0.8	-0.8	2.6	0.9
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.1	-0.1	0.2	0.2
Real Non-Financial Enterprise Credit (3Y av. growth (%))	142	5.4	4.7	-3.1	16.4	4.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	142	3.1	3.5	-3.9	13.7	2.3
Canada						
GDP (3Y average growth (%))	178	2.6	1.4	-0.5	5.9	2.9
Real Equity Price (3Y average growth (%))	178	3.1	9.0	-13.5	24.7	2.4
House Price/Disp. Income (5Y average growth (%))	178	1.3	3.0	-4.1	9.6	1.1
Real Private Credit (5Y average growth (%))	174	4.9	2.5	-0.5	11.0	4.9
Private Credit/GDP (5Y average change (p.p.))	174	2.6	2.4	-2.1	7.0	2.6
Real Household Credit (5Y average growth (%))	174	5.7	3.7	-2.9	12.6	5.3
Household Credit/GDP (5Y average change (p.p.))	174	1.4	1.4	-1.9	4.9	1.4
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.2	-0.1	0.6	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	4.4	3.3	-3.8	13.9	4.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	1.3	2.5	-4.7	6.5	1.2

Table 5: Summary statistics of the data (continued)

	Obs.	Mean	Std. Dev.	Min	Max	50th perct.
Denmark						
GDP (3Y average growth (%))	178	1.8	1.3	-2.1	4.8	1.9
Real Equity Price (3Y average growth (%))	107	9.7	14.0	-13.7	44.2	8.7
House Price/Disp. Income (5Y average growth (%))	133	1.7	4.5	-6.0	9.4	1.8
Real Private Credit (5Y average growth (%))	174	3.8	3.8	-1.8	11.8	2.8
Private Credit/GDP (5Y average change (p.p.))	174	2.7	4.7	-4.3	14.0	1.6
Real Household Credit (5Y average growth (%))	78	2.1	3.3	-3.3	7.2	2.7
Household Credit/GDP (5Y average change (p.p.))	61	-0.1	0.7	-1.2	1.3	-0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	86	4.8	4.7	-0.7	16.5	3.1
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	86	2.4	2.9	-2.7	8.8	2.0
Finland						
GDP (3Y average growth (%))	178	2.3	2.3	-3.8	6.5	2.8
Real Equity Price (3Y average growth (%))	118	12.4	31.5	-23.3	147.0	7.6
House Price/Disp. Income (5Y average growth (%))	157	0.1	3.3	-8.0	7.3	0.1
Real Private Credit (5Y average growth (%))	174	4.9	3.4	-2.4	12.7	5.1
Private Credit/GDP (5Y average change (p.p.))	174	2.3	3.8	-9.4	11.1	2.4
Real Household Credit (5Y average growth (%))	174	6.9	5.8	-4.5	19.3	7.8
Household Credit/GDP (5Y average change (p.p.))	174	1.1	1.6	-2.9	3.6	1.3
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	3.9	3.9	-7.7	14.3	4.0
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	1.1	4.1	-12.5	15.9	1.0
France						
GDP (3Y average growth (%))	178	2.0	1.0	-0.4	4.6	1.9
Real Equity Price (3Y average growth (%))	116	5.1	14.0	-18.6	44.6	2.8
House Price/Disp. Income (5Y average growth (%))	145	1.0	4.0	-3.9	11.4	-0.2
Real Private Credit (5Y average growth (%))	174	3.6	1.7	0.2	7.8	3.4
Private Credit/GDP (5Y average change (p.p.))	174	2.0	1.8	-1.5	5.4	2.2
Real Household Credit (5Y average growth (%))	146	5.1	2.7	0.3	9.4	5.2
Household Credit/GDP (5Y average change (p.p.))	146	1.0	0.7	-0.6	2.7	1.0
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.1	-0.1	0.3	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	154	3.1	2.4	-0.9	9.2	2.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	154	1.4	1.7	-1.9	4.5	1.6
Germany						
GDP (3Y average growth (%))	178	1.9	1.3	-1.0	6.1	1.9
Real Equity Price (3Y average growth (%))	178	7.5	13.9	-21.8	50.7	5.8
House Price/Disp. Income (5Y average growth (%))	137	-1.2	1.9	-4.3	3.6	-1.8
Real Private Credit (5Y average growth (%))	174	2.5	2.1	-1.6	5.9	3.3
Private Credit/GDP (5Y average change (p.p.))	174	0.5	1.8	-3.1	3.8	0.8
Real Household Credit (5Y average growth (%))	174	2.8	2.9	-2.2	8.2	3.9
Household Credit/GDP (5Y average change (p.p.))	174	0.4	1.3	-2.1	2.6	0.6
Household Debt Service Ratio (5Y average change (p.p.))	61	-0.2	0.0	-0.3	-0.1	-0.2
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	2.2	2.3	-2.5	7.1	2.2
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	0.2	1.0	-2.1	3.0	0.2
UK						
GDP (3Y average growth (%))	178	2.2	1.5	-1.2	5.3	2.6
Real Equity Price (3Y average growth (%))	131	3.6	8.6	-14.9	29.9	3.7
House Price/Disp. Income (5Y average growth (%))	110	1.8	5.3	-7.1	11.8	1.2
Real Private Credit (5Y average growth (%))	174	5.7	5.4	-2.5	18.5	5.3
Private Credit/GDP (5Y average change (p.p.))	174	2.5	3.7	-5.8	8.0	2.7
Real Household Credit (5Y average growth (%))	174	5.6	5.3	-2.0	16.7	3.9
Household Credit/GDP (5Y average change (p.p.))	174	1.2	1.8	-2.2	4.5	1.0
Household Debt Service Ratio (5Y average change (p.p.))	61	0.0	0.4	-0.6	0.8	-0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	161	5.8	6.3	-4.7	24.5	5.1
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	161	1.4	2.6	-5.7	6.9	1.6

Table 5: Summary statistics of the data (continued)

	Obs.	Mean	Std. Dev.	Min	Max	50th perct.
Greece						
GDP (3Y average growth (%))	178	1.4	3.1	-7.4	7.5	1.8
Real Equity Price (3Y average growth (%))	112	3.9	29.0	-25.1	142.4	-4.3
House Price/Disp. Income (5Y average growth (%))	69	0.4	3.2	-4.1	8.9	-0.1
Real Private Credit (5Y average growth (%))	174	5.5	8.1	-4.7	21.0	2.4
Private Credit/GDP (5Y average change (p.p.))	174	1.9	3.4	-5.2	9.1	0.7
Real Household Credit (5Y average growth (%))	78	20.5	21.6	-4.7	52.6	22.1
Household Credit/GDP (5Y average change (p.p.))	78	2.6	2.4	-2.7	5.9	2.9
Real Non-Financial Enterprise Credit (3Y av. growth (%))	86	4.7	7.5	-7.7	16.8	7.0
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	86	1.5	2.0	-4.0	4.9	1.4
Italy						
GDP (3Y average growth (%))	178	1.6	1.6	-2.0	4.7	1.6
Real Equity Price (3Y average growth (%))	75	-2.5	11.1	-19.3	25.6	-2.5
House Price/Disp. Income (5Y average growth (%))	177	0.3	4.3	-8.3	8.3	0.5
Real Private Credit (5Y average growth (%))	174	3.3	3.9	-2.8	10.7	2.8
Private Credit/GDP (5Y average change (p.p.))	174	0.8	3.0	-5.0	6.6	0.8
Real Household Credit (5Y average growth (%))	174	4.6	5.3	-4.1	16.3	3.1
Household Credit/GDP (5Y average change (p.p.))	174	0.5	1.1	-1.6	2.6	0.4
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.2	-0.2	0.4	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	1.9	3.5	-2.8	9.4	1.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	-0.1	2.3	-5.3	5.1	-0.2
Japan						
GDP (3Y average growth (%))	178	2.4	2.0	-2.1	6.9	1.7
Real Equity Price (3Y average growth (%))	178	4.2	14.9	-18.9	43.9	1.9
House Price/Disp. Income (5Y average growth (%))	177	-1.3	2.4	-6.8	3.9	-1.3
Real Private Credit (5Y average growth (%))	174	2.4	4.4	-3.2	12.8	0.8
Private Credit/GDP (5Y average change (p.p.))	174	0.5	4.0	-6.6	9.1	0.1
Real Household Credit (5Y average growth (%))	174	3.6	5.0	-2.7	13.7	1.6
Household Credit/GDP (5Y average change (p.p.))	174	0.6	1.4	-2.2	3.3	0.3
Household Debt Service Ratio (5Y average change (p.p.))	61	-0.1	0.1	-0.2	0.0	-0.2
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	1.6	4.4	-5.0	12.8	0.5
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	-0.2	3.2	-7.1	7.4	-0.4
Korea						
GDP (3Y average growth (%))	178	2.2	1.0	-0.5	4.5	2.3
Real Equity Price (3Y average growth (%))	106	4.1	12.3	-23.6	39.3	3.2
House Price/Disp. Income (5Y average growth (%))	156	2.1	4.0	-6.1	11.5	1.4
Real Private Credit (5Y average growth (%))	174	13.5	8.1	2.3	29.0	15.7
Private Credit/GDP (5Y average change (p.p.))	173	3.1	3.1	-4.6	8.4	3.0
Real Household Credit (5Y average growth (%))	174	17.1	9.8	4.6	32.6	15.6
Household Credit/GDP (5Y average change (p.p.))	173	1.8	0.9	-0.2	3.5	1.9
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.2	-0.3	0.6	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	10.4	8.0	-4.0	31.7	9.7
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	176	1.2	3.9	-10.2	8.4	1.6
Netherlands						
GDP (3Y average growth (%))	178	2.2	1.4	-1.5	5.1	2.5
Real Equity Price (3Y average growth (%))	134	6.9	15.0	-20.4	54.0	5.8
House Price/Disp. Income (5Y average growth (%))	137	1.8	4.2	-7.1	9.9	1.1
Real Private Credit (5Y average growth (%))	174	6.0	3.7	0.7	14.5	5.1
Private Credit/GDP (5Y average change (p.p.))	174	4.8	2.4	-2.8	9.9	4.8
Real Household Credit (5Y average growth (%))	94	6.0	5.3	-1.5	15.2	6.6
Household Credit/GDP (5Y average change (p.p.))	94	2.3	2.4	-2.6	5.2	2.8
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.4	-0.6	0.7	0.3
Real Non-Financial Enterprise Credit (3Y av. growth (%))	102	3.4	2.0	-0.3	8.6	3.1
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	102	2.0	3.6	-3.4	11.5	1.5

Table 5: Summary statistics of the data (continued)

	Obs.	Mean	Std. Dev.	Min	Max	50th perct.
New Zealand						
GDP (3Y average growth (%))	178	2.5	1.9	-2.0	6.7	2.8
Real Equity Price (3Y average growth (%))	63	3.0	8.4	-14.1	15.3	6.2
House Price/Disp. Income (5Y average growth (%))	113	3.1	3.8	-2.7	11.4	2.8
Real Private Credit (5Y average growth (%))	174	7.5	5.3	-0.9	22.7	7.4
Private Credit/GDP (5Y average change (p.p.))	173	3.3	3.4	-5.5	10.0	3.4
Real Household Credit (5Y average growth (%))	94	8.8	5.4	-0.1	18.7	9.0
Household Credit/GDP (5Y average change (p.p.))	93	2.3	1.9	-1.2	5.5	2.6
Real Non-Financial Enterprise Credit (3Y av. growth (%))	72	3.6	4.2	-4.4	11.6	3.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	71	0.2	3.1	-6.0	6.2	-0.5
Norway						
GDP (3Y average growth (%))	178	2.8	1.6	-1.1	6.0	2.8
Real Equity Price (3Y average growth (%))	178	7.6	16.7	-19.0	69.5	6.4
House Price/Disp. Income (5Y average growth (%))	143	2.3	4.4	-10.4	9.4	3.0
Commercial Real Estate (3Y average growth (%))	140	5.5	14.8	-15.0	50.6	6.1
Real Private Credit (5Y average growth (%))	158	5.8	4.1	-2.6	14.5	5.8
Private Credit/GDP (5Y average change (p.p.))	158	2.4	3.4	-6.8	6.9	3.1
Real Household Credit (5Y average growth (%))	158	6.4	4.1	-1.6	13.8	5.8
Household Credit/GDP (5Y average change (p.p.))	158	1.6	2.0	-3.4	4.6	2.0
Household Debt Service Ratio (5Y average change (p.p.))	138	0.2	0.5	-1.0	1.3	0.2
Real Non-Financial Enterprise Credit (3Y av. growth (%))	166	5.5	6.0	-6.6	20.8	4.1
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	166	0.6	1.8	-4.1	4.4	0.6
Portugal						
GDP (3Y average growth (%))	178	2.2	2.2	-2.4	7.4	1.9
Real Equity Price (3Y average growth (%))	95	2.5	18.0	-20.8	64.0	-3.2
House Price/Disp. Income (5Y average growth (%))	78	-1.0	2.0	-3.8	4.3	-1.2
Real Private Credit (5Y average growth (%))	174	4.6	5.9	-3.8	18.7	4.7
Private Credit/GDP (5Y average change (p.p.))	174	1.9	6.3	-11.6	13.6	3.4
Real Household Credit (5Y average growth (%))	138	11.1	10.9	-4.2	33.3	9.4
Household Credit/GDP (5Y average change (p.p.))	138	1.8	2.8	-4.4	6.1	1.4
Household Debt Service Ratio (5Y average change (p.p.))	61	-0.1	0.3	-0.6	0.5	-0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	146	2.7	5.6	-7.7	14.6	2.7
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	146	0.1	5.9	-15.9	9.5	1.4
Spain						
GDP (3Y average growth (%))	178	2.4	1.9	-1.7	6.0	2.7
Real Equity Price (3Y average growth (%))	118	4.2	16.7	-17.9	64.3	-0.8
House Price/Disp. Income (5Y average growth (%))	173	2.0	6.2	-6.3	16.3	0.1
Real Private Credit (5Y average growth (%))	174	5.6	7.5	-4.8	20.9	3.4
Private Credit/GDP (5Y average change (p.p.))	174	2.2	6.1	-10.4	14.4	1.0
Real Household Credit (5Y average growth (%))	134	7.3	8.1	-4.8	20.5	6.8
Household Credit/GDP (5Y average change (p.p.))	61	0.1	0.6	-0.7	1.0	0.0
Real Non-Financial Enterprise Credit (3Y av. growth (%))	142	4.6	8.7	-6.6	27.0	1.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	142	0.9	4.9	-7.8	11.4	0.5
Sweden						
GDP (3Y average growth (%))	178	2.2	1.4	-2.0	4.9	2.6
Real Equity Price (3Y average growth (%))	122	9.7	16.1	-22.1	53.3	5.3
House Price/Disp. Income (5Y average growth (%))	177	0.8	3.9	-6.8	7.3	2.0
Real Private Credit (5Y average growth (%))	174	4.8	4.1	-3.1	14.2	4.4
Private Credit/GDP (5Y average change (p.p.))	174	2.8	4.5	-5.4	15.0	2.3
Real Household Credit (5Y average growth (%))	134	5.1	4.2	-4.5	10.4	6.1
Household Credit/GDP (5Y average change (p.p.))	134	1.1	1.7	-2.6	3.9	1.4
Household Debt Service Ratio (5Y average change (p.p.))	61	0.1	0.1	-0.1	0.5	0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	142	6.2	5.6	-3.2	18.8	4.6
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	142	2.7	4.5	-6.3	16.6	1.9

Table 5: Summary statistics of the data (continued)

	Obs.	Mean	Std. Dev.	Min	Max	50th perct.
Switzerland						
GDP (3Y average growth (%))	178	1.6	1.4	-2.6	4.4	1.8
Real Equity Price (3Y average growth (%))	113	7.7	14.6	-13.7	58.0	4.4
House Price/Disp. Income (5Y average growth (%))	178	-0.3	2.8	-5.9	4.0	0.5
Real Private Credit (5Y average growth (%))	174	3.4	2.4	-1.2	9.7	3.5
Private Credit/GDP (5Y average change (p.p.))	174	2.6	2.5	-1.6	7.5	2.6
Real Household Credit (5Y average growth (%))	58	3.4	0.7	2.3	4.7	3.5
Household Credit/GDP (5Y average change (p.p.))	58	1.3	1.2	-1.3	3.0	1.7
Real Non-Financial Enterprise Credit (3Y av. growth (%))	66	4.0	3.6	-1.5	12.1	4.2
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	66	1.7	2.6	-2.3	7.4	2.0
US						
GDP (3Y average growth (%))	178	2.8	1.4	-0.4	6.2	2.6
Real Equity Price (3Y average growth (%))	178	5.1	10.6	-14.6	32.4	6.0
House Price/Disp. Income (5Y average growth (%))	178	-0.4	2.3	-6.0	5.0	-0.4
Real Private Credit (5Y average growth (%))	174	3.7	2.8	-2.0	9.7	3.4
Private Credit/GDP (5Y average change (p.p.))	174	1.3	2.3	-4.2	5.1	1.0
Real Household Credit (5Y average growth (%))	174	4.0	3.5	-2.9	10.4	3.9
Household Credit/GDP (5Y average change (p.p.))	174	0.8	1.9	-3.4	4.6	0.7
Household Debt Service Ratio (5Y average change (p.p.))	61	-0.1	0.3	-0.6	0.4	-0.1
Real Non-Financial Enterprise Credit (3Y av. growth (%))	177	3.3	3.4	-3.7	10.1	3.3
Non-Financial Enterprise Credit/GDP (3Y av. change (p.p.))	177	0.5	1.5	-2.8	3.3	0.5

9.3 Normality tests

Table 6: Shapiro-Wilk test for normality of three-year average GDP growth

Country	Number of observations	W *	V **	z	Prob>z ***
Australia	178	0.993	0.925	-0.178	0.571
Austria	178	0.987	1.817	1.366	0.086
Belgium	178	0.986	1.872	1.435	0.076
Canada	178	0.972	3.762	3.030	0.001
Denmark	178	0.984	2.194	1.798	0.036
Finland	178	0.954	6.252	4.192	0.000
France	178	0.989	1.471	0.883	0.189
Germany	178	0.984	2.186	1.788	0.037
UK	178	0.955	6.062	4.122	0.000
Greece	178	0.932	9.202	5.076	0.000
Italy	178	0.975	3.361	2.773	0.003
Japan	178	0.959	5.534	3.913	0.000
Korea	178	0.918	11.006	5.486	0.000
Netherlands	178	0.979	2.768	2.329	0.010
New Zealand	178	0.972	3.777	3.039	0.001
Norway	178	0.981	2.525	2.119	0.017
Portugal	178	0.983	2.232	1.836	0.033
Spain	178	0.962	5.189	3.766	0.000
Sweden	178	0.952	6.533	4.293	0.000
Switzerland	178	0.962	5.105	3.729	0.000
US	178	0.982	2.412	2.013	0.022

Sample: 1975Q1 - 2019Q2.
* Shapiro-Wilk test statistic.
** Index for departure from normality. V = 1 for normal populations, large values indicate non-normality.
*** Reject the null hypothesis of normality if Prob>z is smaller than 0.1 for 10 % significance level, 0.05 for 5 % significance level, and 0.01 for 1% significance level.

Table 7: Skewness and kurtosis test for normality* of three-year average GDP growth

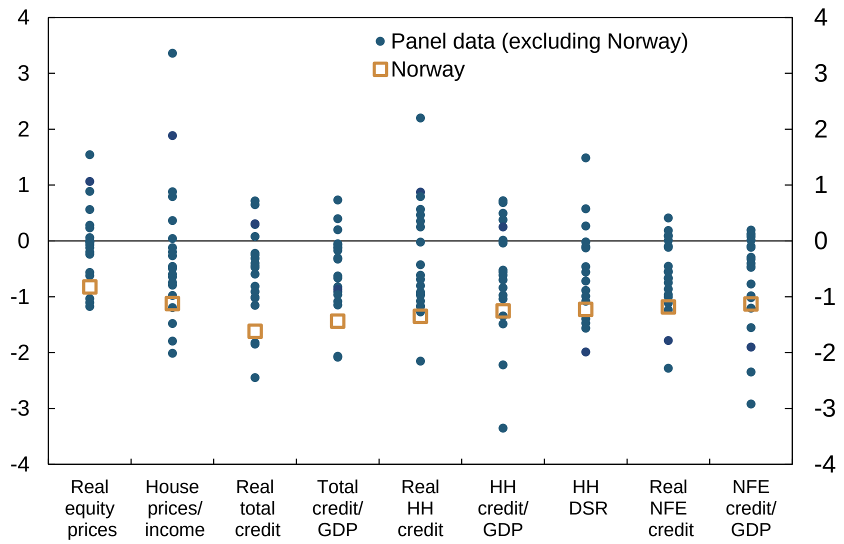
Country	Number of observations	Pr(Skewness)	Pr(Kurtosis)	Adjusted $\chi(2)$	Prob>χ^2 *
Australia	178	0.443	0.820	0.648	0.723
Austria	178	0.088	0.631	3.189	0.203
Belgium	178	0.906	0.009	6.466	0.039
Canada	178	0.029	0.216	6.064	0.048
Denmark	178	0.052	0.705	3.966	0.138
Finland	178	0.001	0.629	10.507	0.005
France	178	0.565	0.684	0.503	0.778
Germany	178	0.079	0.233	4.571	0.102
UK	178	0.011	0.175	7.623	0.022
Greece	178	0.000	0.058	19.691	0.000
Italy	178	0.075	0.271	4.440	0.109
Japan	178	0.209	0.001	10.619	0.005
Korea	178	0.160	0.000	0.000	0.000
Netherlands	178	0.180	0.018	6.935	0.031
New Zealand	178	0.010	0.406	6.896	0.032
Norway	178	0.589	0.009	6.667	0.036
Portugal	178	0.425	0.025	5.579	0.061
Spain	178	0.009	0.095	8.643	0.013
Sweden	178	0.000	0.992	11.041	0.004
Switzerland	178	0.000	0.036	14.857	0.001
US	178	0.540	0.697	0.532	0.766

Sample: 1975Q1 - 2019Q2

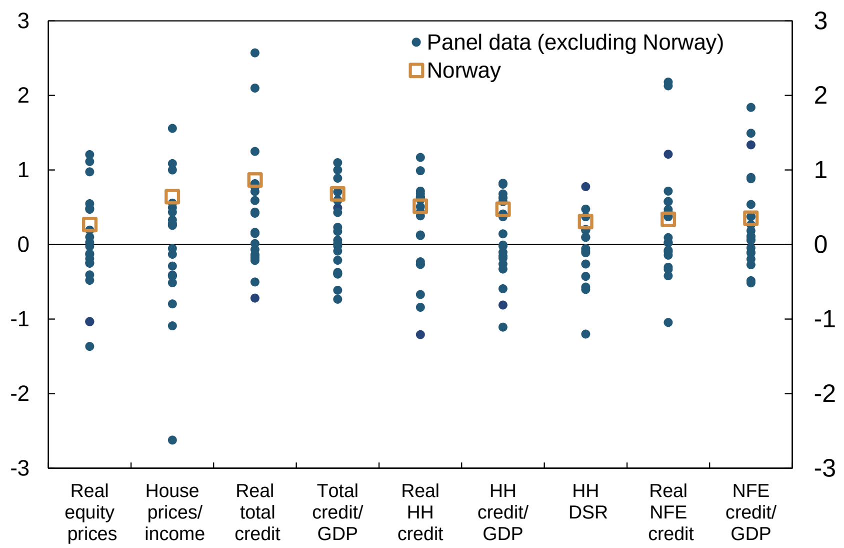
* Reject the null hypothesis of normality if Prob> χ^2 is smaller than 0.1 for 10% significance level, 0.05 for 5% significance level, and 0.01 for 1% significance level

9.4 Country-specific results from single-indicator models

Figure 17: Country-specific results from single-indicator models



(a) 5th percentile

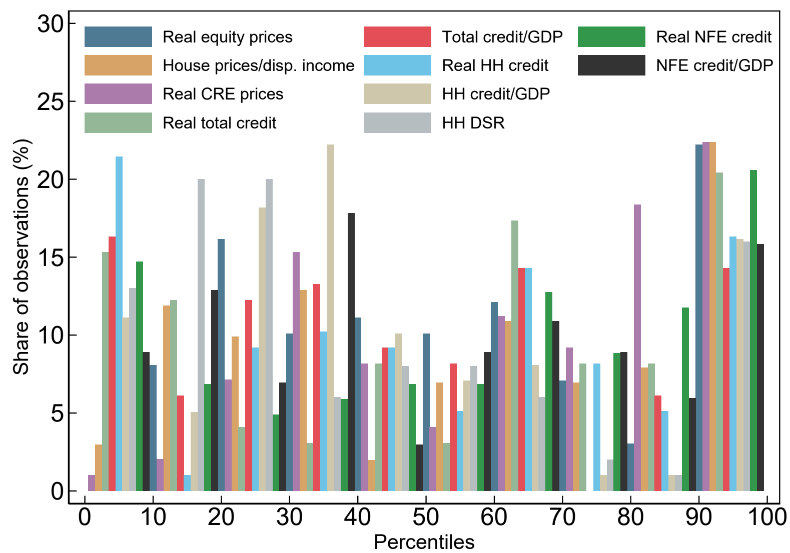


(b) Difference between the 50th and 5th percentiles

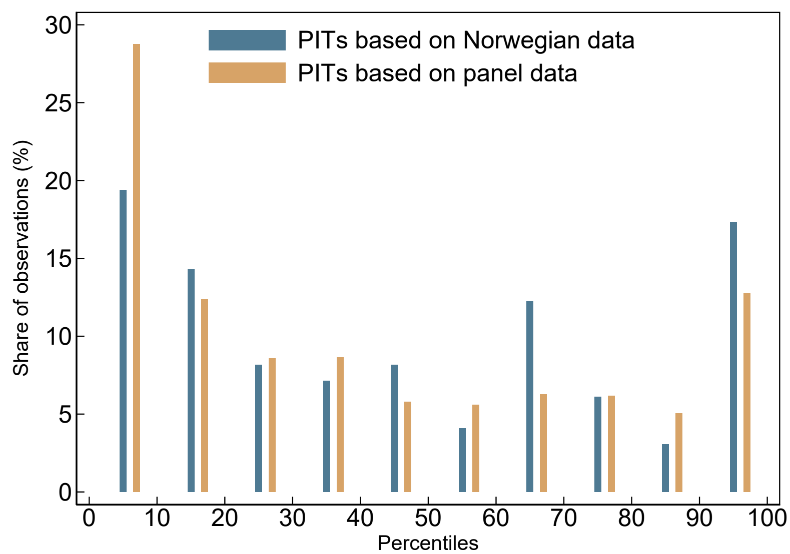
Notes: Coefficients are estimated for each country in the panel data separately. Each blue dot indicates the result from one of the countries in the panel data excluding Norway. The yellow squares indicate the coefficient estimates for Norway.

9.5 Probability integral transforms (PITs)

Figure 18: PITs based on recursive out-of-sample predictions (three years ahead)



(a) Single-indicator models (based on Norwegian data)

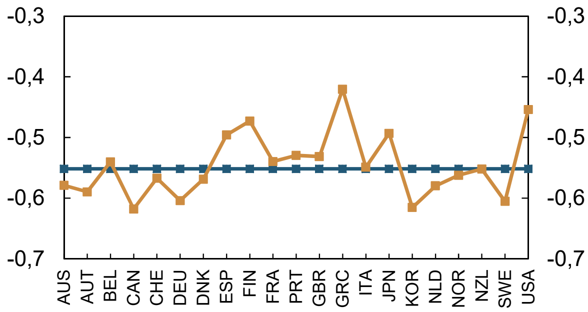


(b) Baseline multivariable model (model 5)

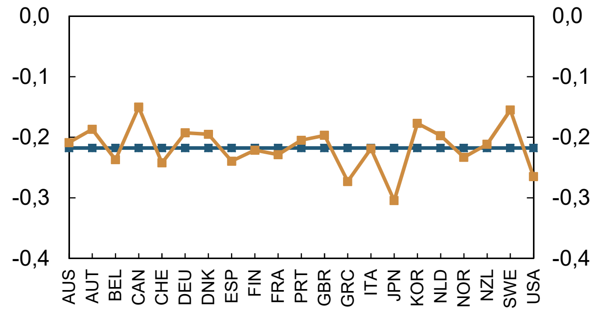
Notes: Based on predictions for 1995Q1-2019Q2. The PITs should have a standard uniform distribution if the model is correctly specified.

9.6 Robustness of results to different country samples

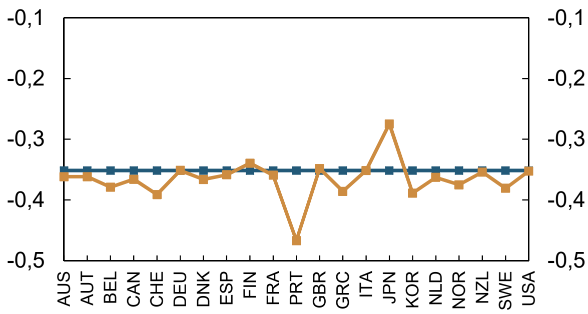
Figure 19: Results based on the baseline multivariable model



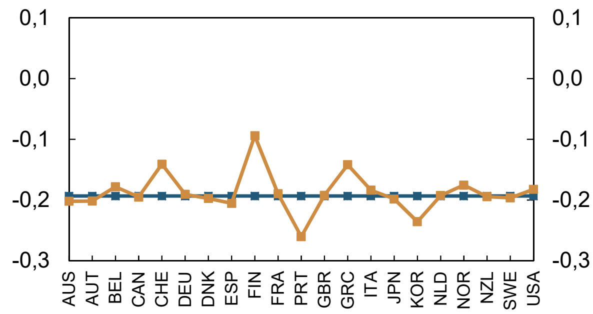
(a) Real total credit (5Y-growth)



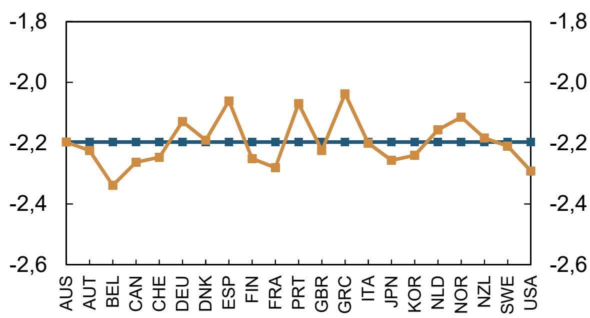
(b) House prices/income (5Y-growth)



(c) Short-term int. rate (1Y-change)



(d) Inflation

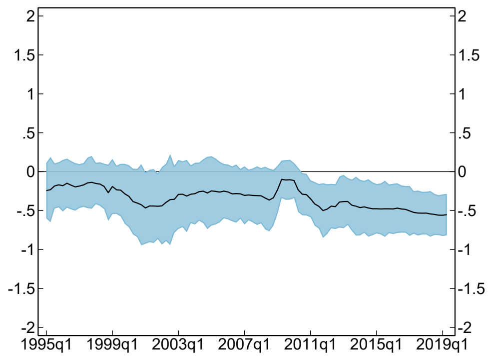


(e) Exchange rate regime

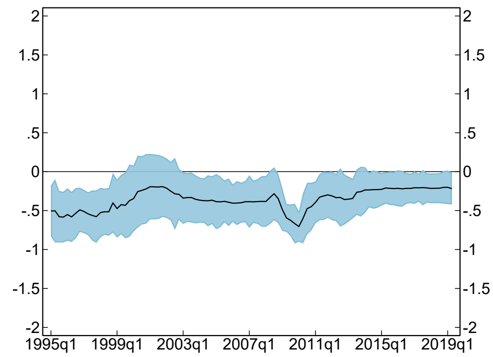
Notes: Blue lines show the estimated coefficients for the sample of 21 OECD countries. Yellow lines show the re-estimated coefficients by taking out one country at a time from the sample.

9.7 Recursive coefficient estimates

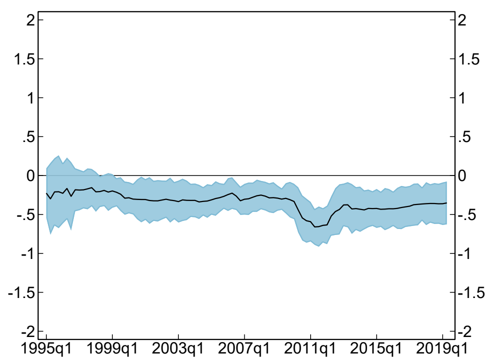
Figure 20: Recursively estimated 5th percentile coefficients for the baseline multivariable model



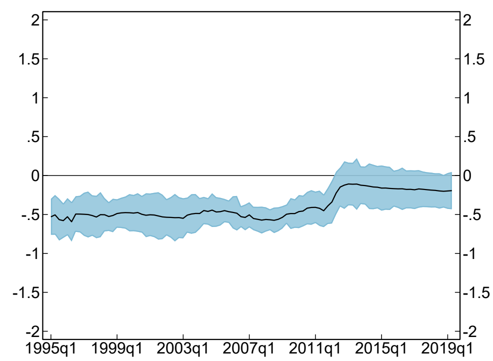
(a) Real total credit (5Y-growth)



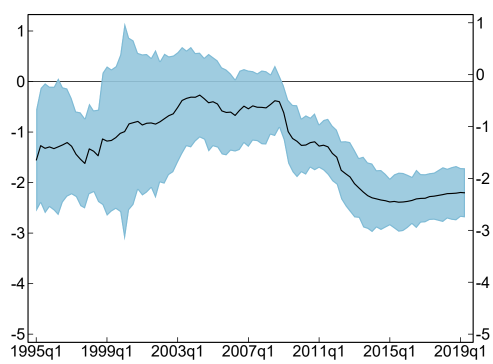
(b) House prices/income (5Y-growth)



(c) Short-term int. rate (1Y-change)



(d) Inflation

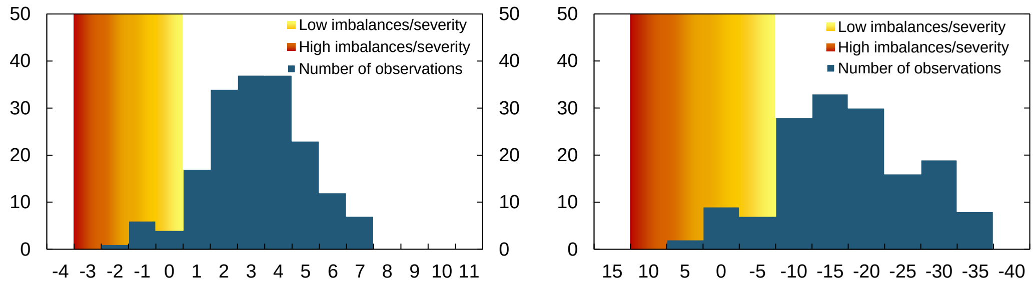


(e) Exchange rate regime

Notes: Recursive estimates for the period 1995Q1-2019Q2 and +/- two standard errors. Standard errors are computed recursively based on 100 bootstrap replications.

9.8 Unconditional distributions

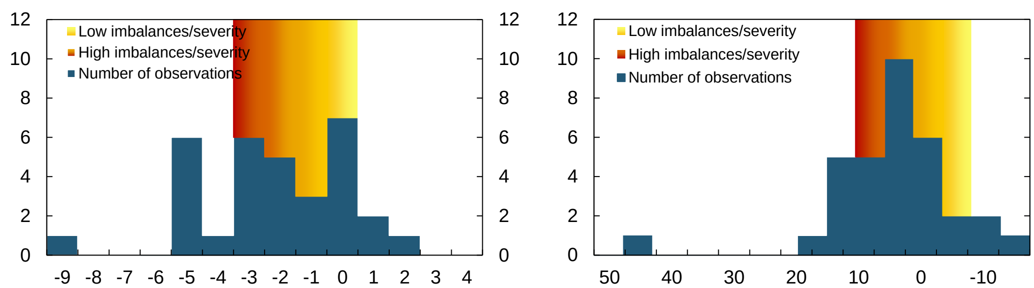
Figure 21: The unconditional distribution of severity measures for Norwegian mainland-GDP



(a) Severity measure 1: Annual GDP growth (%) (b) Severity measure 2: Total GDP shortfall (%)

Notes: Based on data for the period 1975Q1-2019Q2. Fan indicates cyclical scenario relationship between severity and financial imbalances.

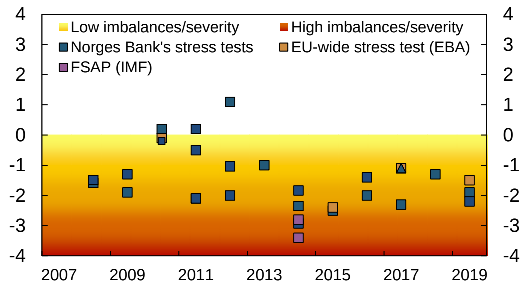
Figure 22: The unconditional distribution of severity measures during crisis episodes in OECD countries



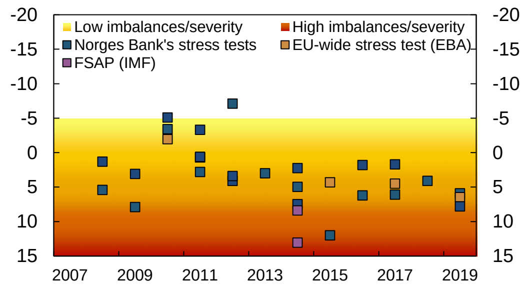
(a) Severity measure 1: Annual GDP growth (%) (b) Severity measure 2: Total GDP shortfall (%)

Notes: We have identified the most severe outcomes during 33 crisis episodes in 21 OECD countries. Crisis dating is based on Anundsen et al. (2016). Fan indicates cyclical scenario relationship between severity and financial imbalances.

Figure 23: The unconditional distribution of severity measures based on previous stress test exercises for Norway



(a) Severity measure 1: Annual GDP growth (%)



(b) Severity measure 2: Total GDP shortfall (%)

Notes: Previous stress tests include European Banking Authority (2011), European Banking Authority (2016), European Banking Authority (2018), European Banking Authority (2020), International Monetary Fund (2015) and Norges Bank (2019b). Fan indicates cyclical scenario relationship between severity and financial imbalances.