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## Financial Stability Notes

# Growth at Risk & Financial Stability

Martin O'Brien and Michael Wosser

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# Growth at Risk and Financial Stability

Martin O'Brien<sup>1</sup>

Michael Wosser<sup>2</sup>

Central Bank of Ireland

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## Abstract

Growth at Risk (GaR) provides a methodology for understanding how financial conditions and the level of financial vulnerabilities contribute to the possibility of future episodes of weak economic growth. Using the GaR framework, we show that the likelihood and severity of future weak or negative economic growth in Ireland rises during periods where risks to financial stability are growing. In particular, we show that near term tail risks are heavily influenced by prevailing financial market conditions, but that medium horizon risks are more dependent upon systemic financial vulnerabilities, such as when credit growth is excessive. Our empirical analysis also suggests that structural characteristics of Ireland's economy or financial system make it more exposed to potential weak growth outcomes, compared with other countries in our sample. We discuss how macroprudential policy can be better informed by tracking developments in the severity and likelihood of weak or negative economic outcomes made possible by a GaR framework.

## 1 Introduction

A fundamental part of financial stability analysis and policy is considering the magnitude of potential downside risks related to the gradual build-up of financial vulnerabilities or instances of acute financial market stress. Macroprudential policy is intended to provide resilience against those risks. However, consistently measuring the extent of downside economic risks, or 'tail-risk' in a systematic way is inherently difficult, not least because the extreme outcomes of financial crises are (thankfully) relatively rare. This can make appropriate measurement of the tail-risk of financial instability to inform policy mitigants challenging in real time. In this Note, we introduce in the Irish context an empirical method known as Growth at Risk (GaR) which can overcome this challenge.<sup>3</sup> By systematically tracking the evolution of lower expected growth outcomes and their financial stability drivers continuously through time, authorities are better informed on the relative severity of the current macro-financial risk environment and, potentially, the need for policy to mitigate those risks. For example, during the build-up phase of the financial cycle, the potential for future tail-outcomes gradually increases alongside the gradual build-up of vulnerabilities. In these instances macroprudential policies can be introduced to build resilience commensurate to the severity of potential tail-outcomes.

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<sup>1</sup> Head of Function, Macroprudential Policy, Macro-Financial Division. [Martin.O'Brien@centralbank.ie](mailto:Martin.O'Brien@centralbank.ie). Thanks to Robert Kelly, Neill Killeen, Fergal McCann, Vasileios Madouros, Caroline Mehigan, Sharon Donnery, Matei Kubinschi, Joana Passinhas and other colleagues. All views expressed in this Note are those of the authors alone and do not represent the views of the Central Bank of Ireland or the ESCB.

<sup>2</sup> Economist, Macro-Financial Division. [Michael.wosser@centralbank.ie](mailto:Michael.wosser@centralbank.ie). Corresponding author.

<sup>3</sup> For the purposes of this Note, the terms GaR and tail-risk are synonymous.

Broadly, we explore the potential for harmfully weak economic growth in the future based on:

- Current financial conditions. These emerge as more useful indicators of near-term tail outcomes, as stressed financial market conditions are more likely related to the materialisation of risks. In turn, this can help guide the setting of macroprudential policy when shocks have hit.
- Current financial vulnerabilities. These emerge as more useful indicators of tail outcomes over a longer horizon, as they relate to the build-up of risks. This can help guide the setting of macroprudential policy in this build-up phase.]

The GaR framework has recently been made prominent through the work of Adrian et al. (2019). Its use does not require us to limit our data to crisis episodes exclusively, but neither does it require us to omit or ignore them. Adrian et al. (2019) examine US GDP growth relative to financial conditions up to 16 quarters in advance.<sup>4</sup> Aikman et al. (2018) augment this model to show how weak UK output is influenced by the extent of leverage in the private non-financial sector as well as by residential and commercial real-estate valuations. Using a panel dataset approach, Adrian et al. (2018) examine how the term structure of interest rates impacts fifth percentile GDP growth outcomes in 11 OECD and 11 developing countries over the period 1970Q1 to 2017Q4. Macroprudential policy actions are examined in Galán (2020), who finds that the positive effect of policy actions in minimising the left tail of GDP growth outcomes outweigh the negative consequences at median growth outcomes for EU countries.

In this *Note*, we examine the extent to which expectations of future weak Irish output growth is shaped by current financial conditions as well as cyclical systemic risk as a measure of financial vulnerabilities (the gap between the ratio of private-sector credit to GNI\* and its long run trend). Additionally, current growth rates and Ireland-specific factors are included as controls in our analysis. The role played by each indicator in the variation of expected economic growth projections through time is of particular interest.

Our results for Ireland align with much of the wider GaR literature. We find a significant role for financial conditions, which typically tighten as risks to financial stability materialise, and broad-based measures of the build-up of cyclical systemic risk in determining expected weak growth outcomes (downside economic risk, or 'tail-risk'). These financial stability-related indicators exert more of an influence on the lower part of the distribution of expected growth outcomes than on the baseline, or median growth forecasts. We also find evidence of the build-up of cyclical systemic risk on potential weak expected output growth out to at least four years, pointing to the benefit of policy action to build resilience in the financial system early in the financial cycle. Our empirical analysis also suggests that structural characteristics of Ireland's economy or financial system make it more exposed to potential weak growth outcomes, compared with other countries in our sample. This could relate to characteristics such as being a small, highly globalised economy or the degree of market and exposure concentration in the banking sector, and is an active area of ongoing research.

In the remainder of the *Note* we discuss the GaR model and the data used in the analysis (Section 2), the results of our analysis in more detail (Section 3), and finally conclude with the potential implications and extensions of this work (Section 4).

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<sup>4</sup> Prior to its publication in 2019, Adrian et al. published a working paper version of their model and preliminary results in 2015, which became widely leveraged and cited. Figueres and Jarocinski (2020) applies a similar approach for the euro area.

## 2 Model and Data

The GaR framework builds on the Central Bank’s Early Warning System (EWS) dataset.<sup>5</sup> The EWS tracks a variety of macro-financial indicators in 27 OECD countries, measured quarterly, from 1990 to the present. Year-on-year GDP growth rates (GNI\* in the case of Ireland) are included as the dependant variable.<sup>6</sup> In order to capture measures of financial conditions or stress we include the Country-Level Indices of Financial Stress (CLIFS), or most relevant equivalent.<sup>7</sup> As a measure of broad build-up of cyclical systemic risk we use the credit-to-GDP gap, which in the case of Ireland we replace with the more appropriate alternative credit-to-GNI\* gap published by the Central Bank.<sup>8</sup> By making use of the extensive cross-country panel dataset, the GaR framework produces a comprehensive set of conditional, time-varying, projected economic growth distributions for each country.<sup>9</sup>

First used in the Central Bank’s Financial Stability Review (2020:I), our model is similar to, but builds upon, the “vulnerable growth” model of Adrian et al. (2019).<sup>10</sup> The authors describe the mechanism by which a tightening of financial conditions significantly affects the left (i.e. the “at risk”) tail of the forward-looking GDP growth distribution. Their model allows conditional forecasts of each percentile of the future GDP growth distribution from the 1<sup>st</sup> to the 100<sup>th</sup> percentile to be estimated.<sup>11</sup> Particular attention is paid to the 5<sup>th</sup> percentile forecasts which we use as the reference GaR threshold, although monitoring developments in the left tail of the expected growth distribution in general is informative. We estimate the following empirical model:

$$\Delta GDP_{t+h,i,j} = \alpha_j + \beta_{1,j}\Delta GDP_{t,i} + \beta_{2,j}FinCond_{t,i} + \beta_{3,j}CycSysRisk_{t,i} + FE_i + \epsilon_j$$

Here,  $\Delta GDP_{t+h,i,j}$  represents the future output growth over the horizon “h” at time “t” for country “i” at percentile “j”. We include current GDP growth, our measure of financial conditions and cyclical systemic risk variables as additional controls, in a country fixed effects (FE) framework. To recover forecasts at the percentile level, the model is estimated via quantile regressions. This allows the relationship between the explanatory and control variables to be explored across the forecast economic growth distribution, not just the expected (or median) outcomes. A sub-sample of quantile regression coefficients and their accompanying standard errors are presented in Table 1 of the Appendix.

In this way it is possible to generate forecasts, at horizon “h”, of each percentile of the expected growth distribution, for each country in the sample. These forecasted percentile-level growth rates are then sorted by frequency and smoothed according to a skewed-T distribution function. As a result, the GaR output yields both the expected rate of growth at different points in the forecast distribution, but also the likelihood of that growth outcome dependent on current conditions.

<sup>5</sup> See O’Brien and Wosser (2018) for a full description of the EWS and the data that underpins the model.

<sup>6</sup> See Table 2 in the Appendices for more details on sample composition. Real GNI\* growth rates on a quarterly frequency are interpolated using Modified Domestic Demand available from the CSO. Real GDP growth for other countries is sourced from the ECB Statistical Data Warehouse.

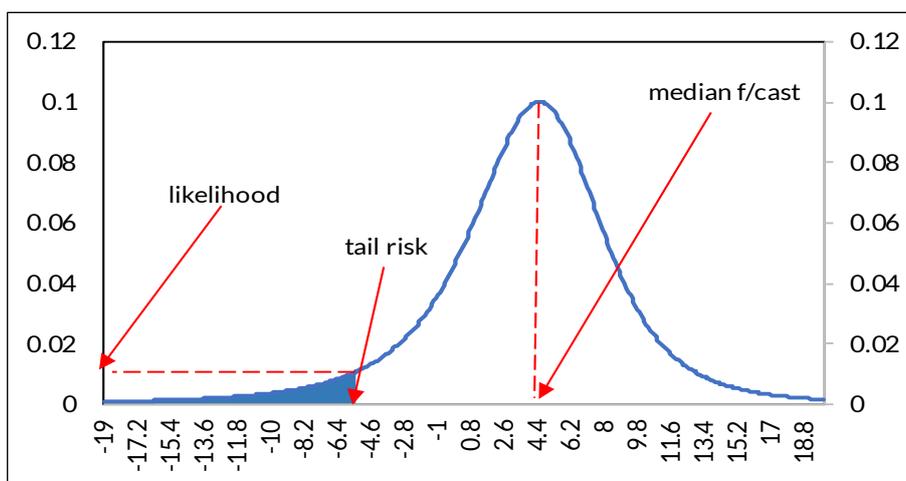
<sup>7</sup> We use the Irish Composite Stress Index (ICSI) instead of CLIFS in the case of Ireland. This is available on a more timely basis than the CLIFS and also has several more favourable attributes for our purposes.

<sup>8</sup> Credit-to-GDP gaps are available via the Bank for International Settlements. The Central Bank’s alternative credit gap measure used for Ireland is available at <https://www.centralbank.ie/financial-system/financial-stability/macro-prudential-policy/countercyclical-capital-buffer>.

<sup>9</sup> There are 1,942 country/time observations used in the estimation overall, covering the 27 OECD countries included in the sample from 1990 onwards.

<sup>10</sup> Adrian et al. (2019) make use of a National Financial Conditions Index (see Brave and Butters (2011)) whereby tighter financial conditions correspond to a higher value of the index, similar to CLIFS and ICSI.

<sup>11</sup> The model allows the user to determine the forecast horizon “h” such that the distribution of GDP growth at time “t+h” can be estimated based upon prevailing conditions at time “t”. One example is h=4 quarters.



**Fig. 1 Example of a forecast (t+4Q ahead) GNI\* growth distribution**

An example of a one year ahead forecast distribution is shown in Figure 1. Included are the forecast distribution (blue curve) with growth rates depicted on the X axis and likelihood on the Y axis. The tail risk is shaded in blue with the threshold 5<sup>th</sup> percentile forecast highlighted with the red arrow. Also shown is the forecast at the median of the distribution. Each dimension of these forecasts has a role in the analysis to follow. By considering these dimensions for different forecast horizons (t+8 quarters, t+12 quarters, and so on), and through time, we can build up a consistent measurement of the risk environment which can in turn inform policy discussions.

Given the above, the main outputs of interest from the framework are:

1. The relative role of financial conditions and cyclical systemic risk on the distribution of expected growth outcomes, with a particular focus on the left-tail of the distribution.
2. Tracking through time particular parts of that distribution of expected growth, and the likelihood of those outcomes over a given forecast horizon.

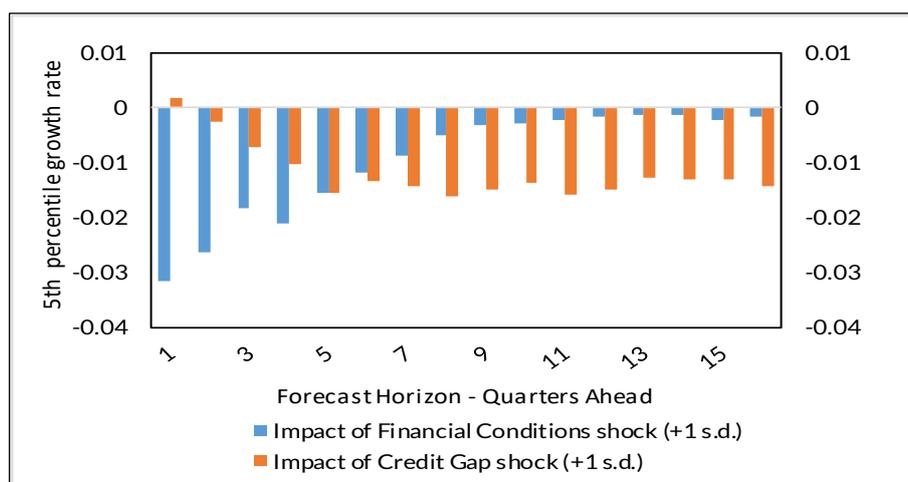
### 3 Growth-at-risk estimation and results

#### **Role of financial conditions and cyclical systemic risk in expected “tail” outcomes**

First we consider the general role of financial conditions and cyclical systemic risk on forecast growth distributions, particularly the left-tail, or downside growth. There are two key aspects to this. The first addresses the impact of a 1 standard deviation shock involving these variables and their impact on left tail outcomes over the term structure of our forecasting horizon (t+1Q to t+16Q ahead). The second deals with the relative contribution of these variables toward left tail outcomes and how these contributions evolve over time.

Shocks to the key control variables have different tail-risk consequences, in terms of scale and timing. We allow the forecast horizon to vary from 1 quarter to 16 quarters ahead, with output growth rates annualised over these horizons. The results in Figure 2 track the difference between the 5<sup>th</sup> percentile GNI\* growth forecast, had the shock not occurred, and what it would be

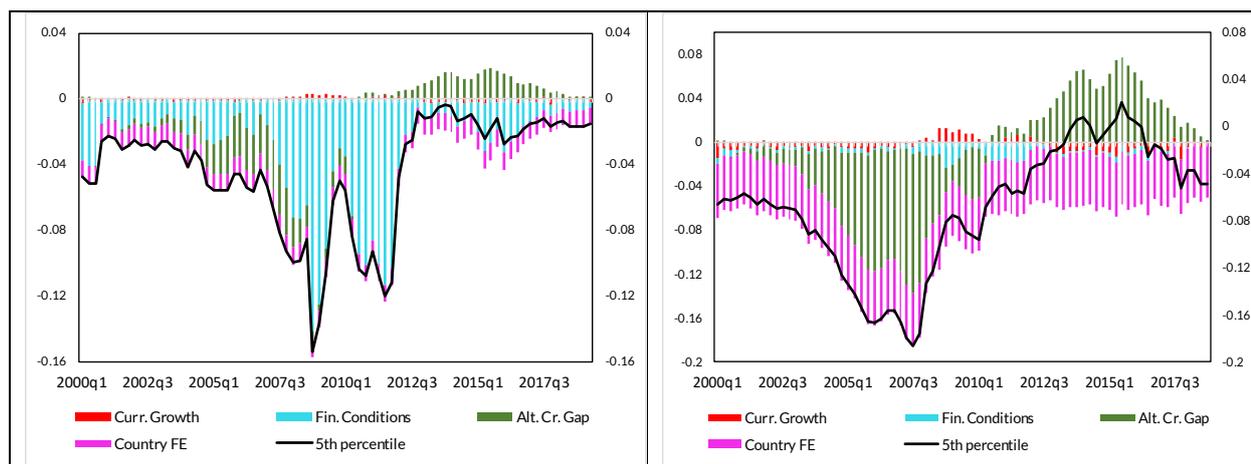
subsequent to the shock occurring “h” (horizon) periods earlier. As can be seen, a financial conditions shock, reflecting sharply tighter financial conditions, negatively impacts tail risk in the near term, with the effect dissipating after approximately 8 quarters. The most adverse outcome is a 3 percentage points left shift of the 5th percentile forecast, one quarter ahead. This is not surprising as a financial conditions index is, by construction, a contemporaneous measure of financial stress whose influence ought to be more pronounced in the shorter term.



**Fig. 2 Tail risk repercussions from financial conditions and credit shocks**

By contrast, a shock to the credit-to-GNI\* gap has little immediate impact, but becomes relatively more pronounced as time progresses. Once it filters through to output growth, its effect does not materially dissipate over the remainder of our forecasting horizon, reflecting the persistent influence of systemic risk accumulations through the financial cycle. The shock is associated with a circa 1.6 percentage points deterioration in tail risk, commencing 5 quarters ahead. All else being equal, this would suggest that an early policy response to build resilience to emerging cyclical systemic risk may be beneficial in minimising the negative impact of left-tail growth outcomes (see Lozej and O’Brien (2018)).

As shown above, the GaR framework allows us to examine changes in the shape of growth forecast distributions insofar as these relate to critical threshold point movements. The extent to which the contraction and expansion of the distribution evolves, and the factors responsible for this evolution, is revealed by a dynamic factor decomposition of the 5<sup>th</sup> percentile GaR.



**Fig. 3A and 3B Explanatory variables' effect on Ireland's GNI\* growth**

Note: Chart 3A shows the contribution of the explanatory variables toward Ireland's 5<sup>th</sup> percentile GNI\* forecast distributions (t+4Q ahead). Chart 3B shows their impact three years ahead (t+12Q). Similar charts covering the t+8Q horizon as well as a t+4Q (10<sup>th</sup> percentile) forecast decomposition are outlined in the Appendices. Y axis is GNI\* growth rate.

This is illustrated in Figures 3A and 3B. We estimate the model over the full sample time-frame at 1 year ahead (Fig. 3A) and three years ahead (Fig. 3B) intervals. These Figures track the dynamic influence of the main explanatory variables by multiplying the 5<sup>th</sup> percentile regression coefficients by their respective values as the latter unfold through time. With respect to Figure 3A, the most significant factor appears to be the financial conditions measure. Whereas the *extent* of its contribution to tail risk is shown to be time dependent, particularly during the period of the 2008 Global Financial Crisis (GFC), the relationship is *invariably negative*, even across the term structure of the forecast horizon (Figure 3B). This implies that tightening financial conditions are associated with significantly weaker future GNI\* growth at risk forecasts, one year ahead. This is consistent with the findings of Adrian et al. (2019) and Aikman et al. (2018).

By contrast, the t+4Q ahead influence of the credit gap varies over the course of the financial cycle. The green bars highlight the GaR contribution stemming from Ireland's alternative credit gap. At certain times, such as in the pre-GFC period, there is a negative contribution to GaR. This implies that the credit gap, during those periods consistent with increasing cyclical systemic risk, weighs against GNI\* growth tail risk. Thus, credit booms foreshadow more severe economic downturns, whenever these eventually emerge (see Schularick and Taylor (2012)). The importance of this variable is stark in that its influence is visible circa. 2005 and it pre-dates the 2008 financial crisis by at least two years. In recent quarters, the credit gap exerts relatively little influence over the t+4Q tail risk, with financial conditions presently the more dominant factor.

As shown in Figure 2, shocks to the conditioning variables have contrasting impacts over time. This is also evident in Figure 3B, where the three year ahead (t+12Q) factor decomposition of the 5<sup>th</sup> percentile GNI\* forecast is shown. All the conditioning variables exert considerably different influence on tail risk over a three year horizon compared with a one year horizon. Financial conditions are no longer to the fore, with the alternative credit gap and country fixed effects appearing to be the most important tail risk determinants.

Over the sample timeframe, regardless of the forecasting horizon, the country fixed effect is persistently negative. This suggests that structural (slow moving) characteristics of Ireland's economy or financial system render it as being more exposed to left-tail growth outcomes, compared with other countries in our sample. These structural factors might include trade and

financial openness, economic size and foreign direct investment (FDI) dependency, as well as measures of banking system concentration.<sup>12</sup> Extending the GaR analysis to further explore the role of macro-financial structure on tail-risk is an active avenue of current research.<sup>13</sup>

### **Distributions of expected growth and “tail” outcomes**

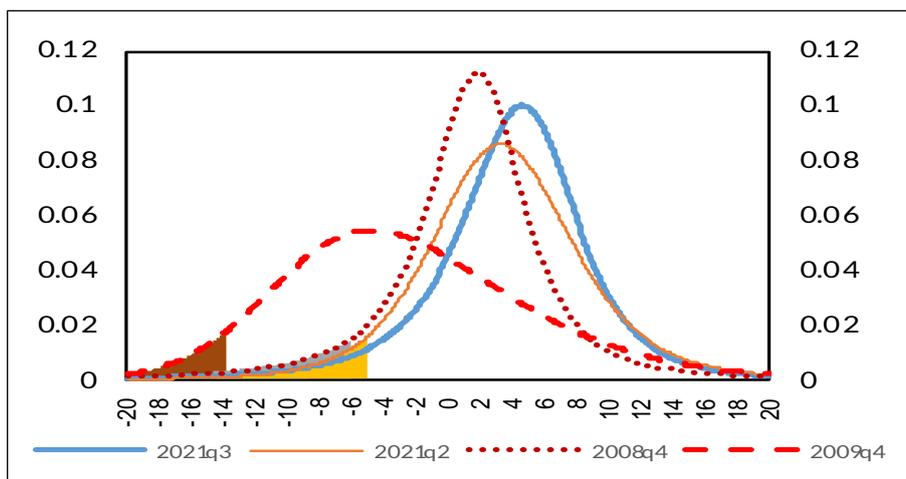
Given the sharp tightening in financial conditions we saw in the initial phases of the COVID-19 crisis, we use it as an example of one of the main outputs of interest from the GaR framework (Fig 4). While on its own this framework is unlikely to capture the full extent of potential tail outcomes related to heretofore unusual events like widespread lockdowns, it is indicative of the impact of materialisation of risks related to more stressed financial conditions. Estimates of the expected growth distributions in 2020Q4 and 2021Q2 are shown given developments up to 2019Q4 and 2020Q2, along with their 5<sup>th</sup> percentile thresholds, which can be derived from the GaR framework. Looking at changes in the distribution for these time periods allow us to illustrate the consequences of deteriorating financial conditions, as transpired during the first phase of Ireland’s COVID-19 outbreak. These led to an increase in expected output growth tail risk in Ireland’s case. The 5th percentile “at-risk” threshold shifts left from a value of -1.8 per cent to -5.6 per cent over this period. The likelihood has also increased slightly. This implies that both the severity and likelihood of downside economic outcomes as a result of tightening financial conditions in Ireland increased with the onset of the pandemic. While this is not necessarily surprising, the GaR framework provides us with a consistent measurement through time of these “at-risk” metrics, which allow for a more informed discussion of the overall systemic risk environment.

Looking at the specific case of the COVID-19 shock, the median growth forecast also deteriorated (shifted left), but not to the same extent. As a result, there has been a widening of the gap from the 5th percentile forecast to the median forecast, (the 6.2 percentage points gap increased to a gap of 8.6 percentage points over this period). This suggests greater overall outcome uncertainty in the left hand side of the forecast distribution and in central growth forecasts generally, corresponding to the increased variance (flatter distribution with a wider spread) observed in the latter period forecast.

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<sup>12</sup> For robustness, the 10th percentile growth forecast decomposition is available in the Appendix (Fig. 7) where, although country fixed effects are more prominent, the effect of the ICSI and alternative credit gap variables is comparable to those involving the 5th percentile growth forecasts.

<sup>13</sup> Analysis involving the relationship between macro-financial structure, systemic risk and GaR is ongoing (O’Brien and Wosser (2021) mimeo). See also Box 2: Financial stability considerations of being a small, highly globalised economy, in [Financial Stability Review 2019:I](#). The phenomenon of structural characteristics being an important determinant of tail-risk in the Irish context was also discussed by former Governor Philip R. Lane in a number of speeches, for example “Tail Risks and the Irish Economy”, April 2019 (<https://www.centralbank.ie/news/article/tail-risks-and-the-irish-economy-governor-philip-r-lane>).



**Fig. 4 Forecast GNI\* growth distributions (t+4Q) now versus circa 2008**

Note: Solid lines reflect the two most recent forecasts and show deteriorating GaR thresholds at the fifth percentile (blue to mustard). However, adverse outcomes are not expected to be as weak as those of the global financial crisis (dashed lines). X axis is GNI\* growth rate, Y axis is likelihood.

However, changes in the severity of downside risk as a result of the COVID-19 shock are much less significant than those experienced in the run-up to and during the last financial crisis in the late 2000s, as the corresponding series (red dashed lines) relating to the model’s 2008Q4 and 2009Q4 forecasts show.<sup>14</sup> In the case of each of the 2009Q4 and 2021Q2 forecasts, a financial shock had already occurred within the previous six months and their respective growth impact was already materialising by the time the respective forecasts were made, so comparisons are appropriate. The scale of the financial shock in each case appears significantly different. The relatively more severe tail risk stemming from the 2008 global financial crisis is attributed to the higher degree of vulnerability associated with the large credit gap evident at that time. This had accumulated over several years prior to 2008 and resulted in (1) a more severe 5% GaR threshold based on conditions in 2007Q4 than that observed based on conditions in 2019Q4 and (2) a more significant left shift of forecast growth outcomes once the crisis materialised than we are presently observing.

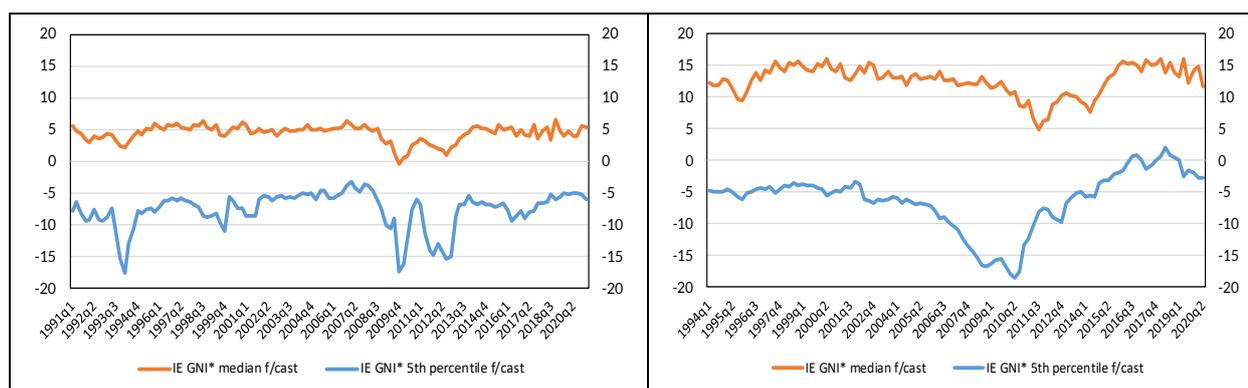
Figures 5A and 5B show the one and three year ahead 5<sup>th</sup> and median percentile forecasts of Ireland’s output growth over our sample timeframe. In each case, the 5<sup>th</sup> percentile appears to be more volatile than the corresponding median forecasts. This higher degree of volatility is an inherent response to changing systemic risk and financial conditions generally. For example, in the case of the t+4Q ahead forecasts, the average 5<sup>th</sup> percentile left shift is -1.02 percentage points, whereas median percentile left shifts average -0.6 percentage points.<sup>15</sup> This suggests that shocks to cyclical systemic risk and financial market conditions are likely to have to have a more pronounced effect in the left tail than they do at the median. As such, the gap between the median and the 5<sup>th</sup> percentile is useful in terms of understanding the nature of the output growth tail risk that exists at any point in time.

A widening gap implies that, periodically, the forecast growth distribution has flattened and central growth outcomes appear less certain. By measuring not just the extent of these left shifts, but also their likelihood, one can quantify this increased risk objectively, via the extent of the gap itself. The

<sup>14</sup> For consistency with our more recent forecasts, the 2008q4 and 2009q4 series were estimated by quantile regression on a recursive basis, meaning only data that was available up to 2007q4 and 2008q4 respectively were included.

<sup>15</sup> Average left-shift of t+12Q 5<sup>th</sup> percentile is -6.5%, median left shift average is -1.2%

spread between the 5<sup>th</sup> and median percentile forecasts widens as the forecast horizon extends (Figure 5B). This can be partially explained by the increased for uncertainty inherent with making longer term forecasts, however the varying uncertainty stemming from the changing shape of the forecast distributions are also evident. The relatively large spread between the series that is present in the 2010 forecast, was already appearing as early as 2007.<sup>16</sup>



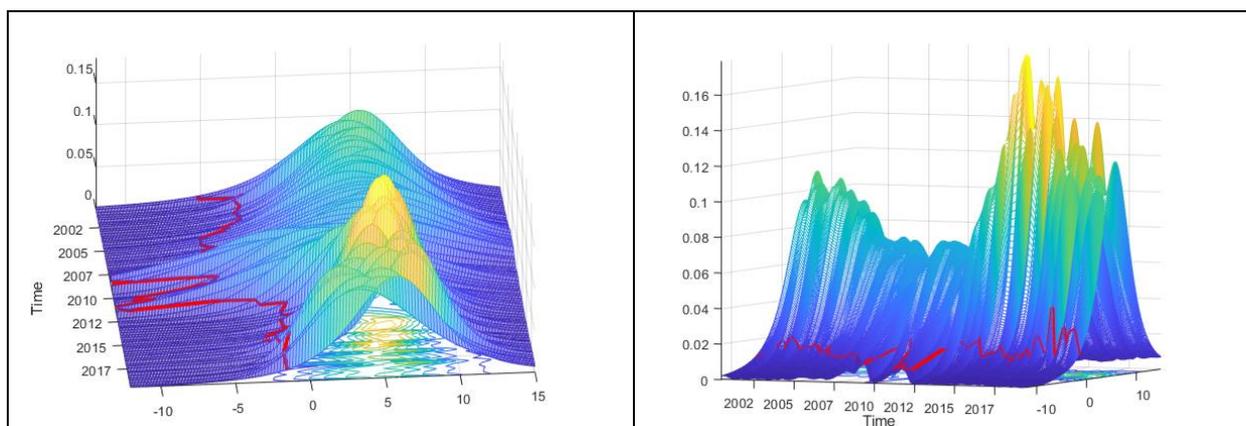
**Figs. 5A and 5B Median and 5<sup>th</sup> percentile of GNI\* growth forecast distribution**

Note: LHS chart reflects one year ahead (t+4Q) fifth and median growth forecasts. RHS chart has the same percentile forecasts for three years ahead (t+12Q). Y-axis is GNI\* growth in percentage points.

The outcome likelihood is another dimension of the tail risk that can be evaluated through time. To see how this evolves consider Figures 6A and 6B, which are identical apart from the viewing angle. These are developed by multiplying the quantile regression coefficients (forecast horizon = t+4Q) by the explanatory variables as the latter evolve through the sample timeframe. Of note is the greater variability present in the left-tail (Fig 6A) compared with the right tail, confirming one of the main findings of Adrian et al. (2019). The evolution of the 5<sup>th</sup> percentile GaR threshold is traced via the red line. A scan of Figure 6A also confirms that, in addition to left tail outcomes exhibiting relatively greater overall uncertainty than right tails (i.e. periods of strong growth), future weak growth prospects appear to be more sensitive to financial conditions fluctuations and systemic risk levels than are strong growth outcomes. This finding is confirmed in Figures 8 and 9 in the Appendices which highlight the greater impact and statistical significance both the financial conditions and the credit gap indicators have at lower growth percentiles, compared with higher percentiles. By adjusting the 3D viewing perspective, Figure 6B reveals how **both** of the key “at-risk” dimensions vary over time, namely the **threshold** at which the 5<sup>th</sup> percentile occurs (shift along the x-axis) as well as the **density** (or likelihood) according to the z-axis of that threshold.

Looking to the foreground of the charts, in particular Figure 6A, the more recent forecasts can be seen and the relative extent of current GaR levels, compared to previous forecasts, can be compared and contrasted. When central outcomes are more likely the peaks are yellow, but this characteristic is absent in the most recent forecasts, highlighting the increased uncertainty surrounding these forecasts, compared with those of the 2016-2018 period.

<sup>16</sup> Note, in this model 2007 forecasts (over a three year horizon) are projected from explanatory data observed in 2004. In this Chart, all forecasts are based on full sample quantile regression estimates rather than recursive estimates.



**Figs. 6A and 6B Time-varying GNI\* growth forecasts (t+4Q) for Ireland (2000-2020)**

Note: Left tails vary more than right tails. Lower percentiles are more sensitive to changing financial conditions and systemic risk than higher percentiles. 5<sup>th</sup> percentile forecast depicted in red. See Appendices, Figs. 8 and 9 for confirmation. Last observation 2020q2.

## 4 Conclusion

The GaR framework complements a variety of economic modelling tools deployed within the Central Bank and enhances our understanding of the source and potential economic cost associated with financial stability risks. The empirical output derived from the framework provides a range of useful information informing policymakers about the possible extent of future vulnerable economic growth. It shows how the latter is related to the build-up and materialisation of financial stability risks, the factors that contribute most to them, and the timeframe during which economic damage is likely to be most severely felt.

The benchmark model of Adrian et al. (2019) showed that left tail growth outcomes tend to be more volatile and pronounced (left shifted) than central or right tail outcomes, taking financial conditions into account. Their model reveals periodic episodes of extremely sharp US growth contractions. Our analysis confirms these findings with respect to Irish data and shows that it is possible to anticipate such outcomes to a certain degree. By augmenting the model with additional factors, such as the alternative credit gap, it is possible to examine the role played by the gradual accumulation of systemic risk levels in terms of future vulnerable economic growth.

The GaR framework can be developed further in several ways. Because GaR forecasts explicitly link current financial conditions and systemic risk levels to future economic tail outcomes, GaR forecasts are helpful in the meaningful design and benchmarking of adverse scenarios that can inform system-wide resilience assessments. This in turn helps to guide policy instrument choice and calibration. It will also be possible to examine the structural vulnerabilities that coincide with being a small, open economy, whose retail banking system happens to be heavily concentrated in real estate lending. The enhanced financial system resilience, stemming from other macroprudential policy decisions already introduced by the Central Bank, can be factored into this analysis.

In addition, because the GaR framework is quite tractable, it can be readily adapted to target any economic series exhibiting periodic growth rates. Work is currently ongoing to adapt the model to assess Irish house prices (see Deghi et al. (2020), Alter and Mahoney (2020) and IMF (2019)),

commercial real estate and credit growth-at-risk (see Lang and Forletta (2019) using a consistent framework across each subject area, but allowing important model-specific determinants to inform the results in each case. For instance, in the house price at risk model we include a price misalignment indicator within the estimation process.<sup>17</sup> Capital flows at risk and their relationship with financial asset prices have also featured in recent literature (see Eguren-Martin et al. (2020)). These in turn will also contribute to policymakers' assessment of macroprudential policy effectiveness within an overall empirics-based architecture.

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<sup>17</sup> The core results from this model is included in the Bank's Financial Stability Review 2020 II, Box C.

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Appendix

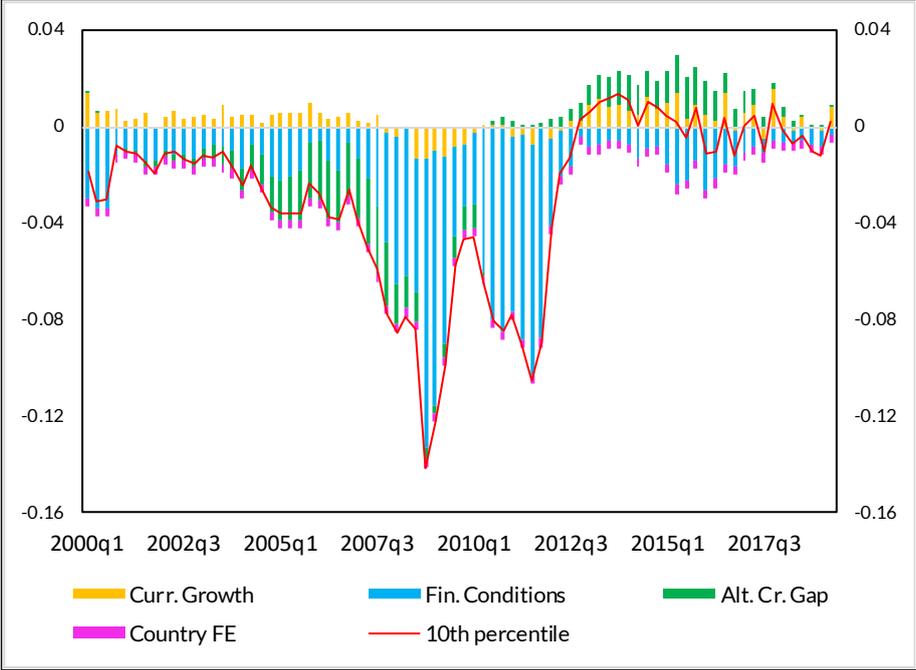


Fig. 7 Explanatory variables effect on Ireland's expected GNI\* two year ahead growth (t+8Q) tenth percentile forecasts. Y axis is GNI\* growth rate.

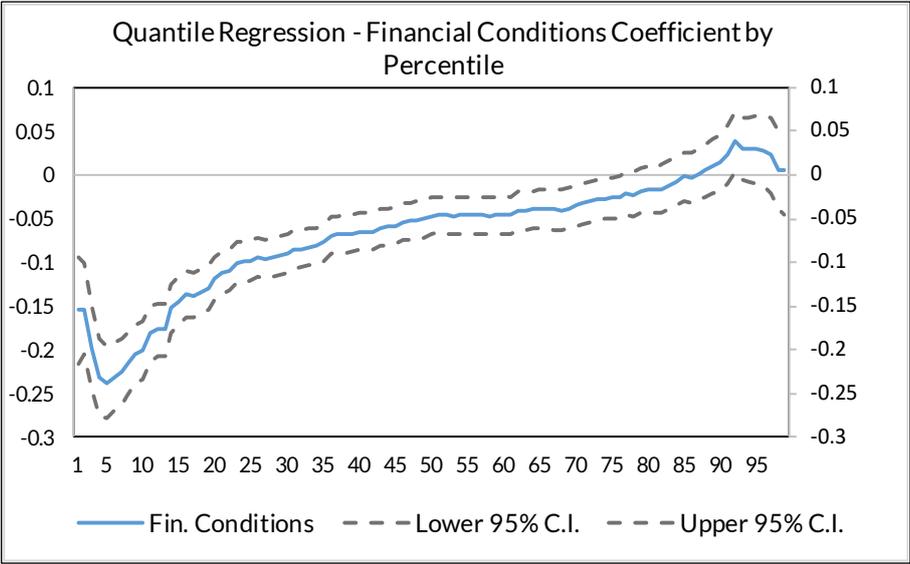


Fig. 8 Financial Conditions coefficient value and significance by percentile

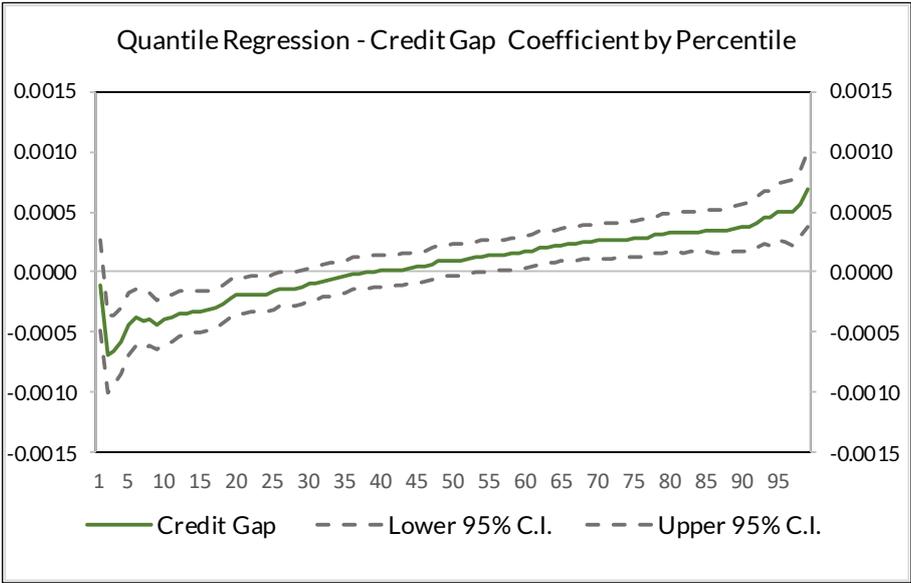


Fig. 9 Credit gap coefficient value and significance by percentile

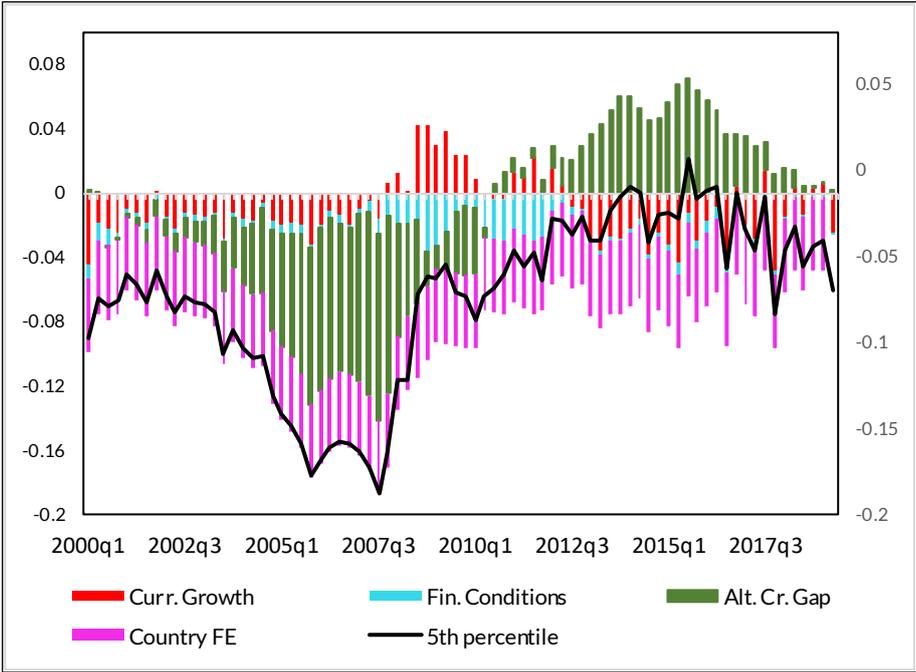


Fig. 10 Explanatory variables effect on Ireland's expected GNI\* growth two year ahead (t+8Q) fifth percentile forecasts. Y axis is GNI\* growth rate.

|                                     | Forecast Horizon: (t+h) quarters ahead |                    |                    |                    |                    |                    |                   |                   |                   |
|-------------------------------------|--|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------|-------------------|-------------------|
|                                     | 5th Percentile                         |                    |                    | Median Percentile  |                    |                    | 95th Percentile   |                   |                   |
|                                     | 4                                      | 8                  | 12                 | 4                  | 8                  | 12                 | 4                 | 8                 | 12                |
| <b>Current Growth<sub>t-4</sub></b> | -0.0264                                | <b>-0.3522 ***</b> | -0.1103            | <b>0.1709 ***</b>  | <b>0.2377 ***</b>  | <b>0.2685 ***</b>  | <b>0.0691 *</b>   | -0.1034           | -0.1200           |
| (Std. Err)                          | 0.0485                                 | 0.0795             | 0.0951             | 0.0247             | 0.0384             | 0.0482             | 0.0455            | 0.0727            | 0.0908            |
| <b>Fin. Conditions</b>              | <b>-0.2383 ***</b>                     | <b>-0.0614 **</b>  | -0.0382            | <b>-0.0472 ***</b> | <b>-0.0834 ***</b> | <b>-0.0709 ***</b> | 0.0289            | 0.0506            | 0.0178            |
| (Std. Err)                          | 0.0206                                 | 0.0338             | 0.0407             | 0.0105             | 0.0163             | 0.0206             | 0.0193            | 0.0309            | 0.0389            |
| <b>Credit Gap</b>                   | <b>-0.0004 ***</b>                     | <b>-0.0017 ***</b> | <b>-0.0003 ***</b> | <b>0.0001 *</b>    | 0.0000             | <b>-0.0003 *</b>   | <b>0.0005 ***</b> | <b>0.0008 ***</b> | <b>0.0008 ***</b> |
| (Std. Err)                          | 0.0001                                 | 0.0002             | 0.0003             | 0.0001             | 0.0001             | 0.0001             | 0.0001            | 0.0002            | 0.0003            |
| <b>IE Country Fixed Effect</b>      | -0.0105                                | <b>-0.0460 ***</b> | <b>-0.0493 ***</b> | <b>0.0451 ***</b>  | <b>0.0845 ***</b>  | <b>0.1260 ***</b>  | <b>0.1232 ***</b> | <b>0.2179 ***</b> | <b>0.3008 ***</b> |
| (Std. Err)                          | 0.0087                                 | 0.0142             | 0.0171             | 0.0044             | 0.0069             | 0.0087             | 0.0082            | 0.0130            | 0.0163            |

**Table 1. Explanatory variables' coefficients, standard errors and significance across term structure of forecast horizon and growth distribution percentiles.**

Note: Coefficients and standard errors are based on quantile regressions of growth distributions at the 5<sup>th</sup>, 50<sup>th</sup> and 95<sup>th</sup> percentiles. Estimates are based on full data sample. Negative coefficients are associated with increased downside growth risk, particularly in the left tail of the growth distribution (5<sup>th</sup> percentile). Statistical significance is denoted at the 1%, 5% and 10% level with \*\*\*, \*\* and \* respectively.

| Country       | GDP growth rate | Credit Gap | Financial Conditions | GDP Coverage    |
|---------------|-----------------|------------|----------------------|-----------------|
| Argentina     | 105             | 101        | -                    | 1994Q1 - 2020Q1 |
| Australia     | 163             | 160        | -                    | 1980Q1 - 2020Q2 |
| Austria       | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Belgium       | 164             | 157        | 124                  | 1980Q1 - 2020Q3 |
| Brazil        | 99              | 56         | -                    | 1996Q1 - 2020Q3 |
| Canada        | 164             | 160        | -                    | 1980Q1 - 2020Q3 |
| China         | 110             | 97         | 59                   | 1993Q1 - 2020Q2 |
| Denmark       | 163             | 160        | 164                  | 1980Q1 - 2020Q2 |
| Finland       | 163             | 157        | 164                  | 1980Q1 - 2020Q2 |
| France        | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Germany       | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Greece        | 163             | 157        | 113                  | 1980Q1 - 2020Q2 |
| Hungary       | 103             | 157        | 88                   | 1995Q1 - 2020Q3 |
| Ireland       | 163             | 160        | 152                  | 1980Q1 - 2020Q2 |
| Italy         | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Japan         | 163             | 160        | -                    | 1980Q1 - 2020Q2 |
| Luxembourg    | 163             | 44         | 109                  | 1980Q1 - 2020Q2 |
| Netherlands   | 163             | 160        | 164                  | 1980Q1 - 2020Q2 |
| New Zealand   | 134             | 160        | -                    | 1980Q1 - 2020Q2 |
| Norway        | 163             | 160        | -                    | 1980Q1 - 2020Q2 |
| Poland        | 103             | 72         | 86                   | 1995Q1 - 2020Q3 |
| Portugal      | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Spain         | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Sweden        | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |
| Switzerland   | 163             | 160        | -                    | 1980Q1 - 2020Q2 |
| United        | 163             | 160        | 164                  | 1980Q1 - 2020Q2 |
| United States | 164             | 160        | 164                  | 1980Q1 - 2020Q3 |

**Table 2. Countries comprising sample and key variable coverage**

Note: The countries comprising the sample are from the Central Bank's Early Warning System Dataset. The table shows the number of observations (quarterly frequency) per country and period of coverage for GDP growth. Irish growth data refers to GNI\*.

T: +353 (0)1 224 6000

[www.centralbank.ie](http://www.centralbank.ie)

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Bosca PO 559, Baile Átha Cliath 1, Éire  
PO Box 559, Dublin 1, Ireland



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