Is a macroprudential reaction function emerging and is it sensible?

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[WORKING DRAFT: DO NOT CIRCULATE]

Abstract

A decade on from the global financial crisis, is a macroprudential reaction function emerging and is it sensible? We address this question in two parts. First, we assess the responsiveness of the countercyclical capital buffer (CCyB) and housing tools to developments in the risk environment. We find that both tools are tightened in response to rapid household credit growth, with a one standard deviation increase approximately doubling the probability that tools are tightened in the following year. CCyB use also responds to rapid house price growth and low equity market volatility. Second, we compare the weight policymakers have given to different risk indicators with the indicators' predictive power over severe recessions in the past, as measured by the "GDP-at-risk" framework. In practice, countries have tended to overweight household credit relative to its GDP-at-risk weights and put too little weight on other indicators, including households' debt service ratios and corporate credit growth. While the risk indicators we consider can explain around 30% of variation in the CCyB, their explanatory power over housing tools is much more limited. This may indicate that housing tools are in part put in place as structural guardrails rather than to address current vulnerabilities.

Key words: Macroprudential policy; financial cycle; financial stability
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1 Introduction

The global financial crisis was a stark illustration of the real economy danger posed by unchecked financial vulnerabilities. In the immediate aftermath of the crisis, GDP fell by 5% across advanced economies and the unemployment rate rose 3pp. Output losses continued to accumulate and – a decade later – economic activity is in many cases yet to regain its pre-crisis trend.

Financial amplification mechanisms can account for much of the severity of the crisis. A fragile financial sector meant that banks had to cut back on lending to protect their capital ratios, which led to a credit crunch. And a heavily indebted household sector had to cut back consumption to continue servicing its debt, precipitating a debt-driven collapse in aggregate demand. Taken together, Aikman et al (2019a) estimate that these two channels can account for as much as three-quarters of the output loss in the US between 2007 and 2010.

The lesson was clear: the financial system needed to be significantly better prepared ahead of the next global shock. That way it could absorb rather than dramatically amplify the economic fallout. The first phase of the regulatory response has been largely structural. Over the past decade, a raft of regulatory reform and balance sheet adjustment has taken place, in order to address the financial system's resilience deficit. Across advanced economies, bank leverage ratios (ie the ratio of tangible common equity to tangible assets held on banks' balance sheet) have nearly doubled from less than 3% to nearly 6%. Households too have repaired their balance sheets, with advanced economy household debt relative to income drifting down on average, despite ultra-low low interest rates encouraging borrowers to take on more debt.

A decade on, structural reforms of the banking sector are either already in place or well underway.[1] Bank capital ratios in many countries have begun to level off. The advanced economy risk environment has emerged from its relatively benign post-crisis repair stage, with the warning signs from many financial indicators returning to around their historical norms. However, as time has passed, dispersion in the risk environment has grown across advanced countries. For example, while the average growth rate of non-financial credit and the average portion of income that households spend on servicing their debt have remained subdued relative to the pre-crisis period, some countries have seen a significant pick-up in these indicators. Aggregate indicators of vulnerabilities in the financial system – such as "GDP-at-risk", which weights together indicators based on their predictive power over severe recessions in the past – exhibit similar time-trends, with advanced economy risks around historical norms on average, but with growing international dispersion around that.[2]

As financial vulnerabilities re-emerge and dispersion in risks grows, the second – more cyclical – phase of the regulatory response has become increasingly relevant. Around the world, financial stability committees (FSCs) have been tasked with monitoring and taking action to address emerging risks to financial stability: these committees represent the institutional

[1] There remains, however, further to go on the growing non-bank financial sector.
[2] See Cecchetti (2006) and De Nicolo and Lucchetta (2012) for early expositions of the GDP-at-risk approach. See Adrian et al. (2019), Adrian et al. (2018) and Aikman et al. (2019b) for more recent contributions to this literature.

memory of the crisis. FSCs have been endowed with a new macroprudential toolkit, which aim to allow the committees either to damp financial vulnerabilities as they emerge or to ensure sufficient resilience is built across the financial system in response to risks that would mitigate the impact on the real economy if risks crystallise.

In this paper, we focus on the usage of two leading elements of the toolkit. One is the time-varying adjustments to bank capital resilience that can be made with the countercyclical capital buffer (CCyB). These buffers are increments to the internationally agreed minimum capital levels that can be deployed nationally. The extra capital requirements are intended to be built up as risks build, and can be released by authorities when risks crystallize. In principle, the release can encourage banks to draw down their capital rations in a stress, so that even in difficult times banks can continue to lend to support the economy.

The second set of tools relate to limiting household debt. We conduct a detailed data collection of housing tool interventions made across our advanced economy panel, drawing on national *Financial Stability Reports* and other sources. We bucket the array of housing interventions into tools focused on addressing borrower resilience, and those concerned first and foremost with ensuring lender resilience. The policies in the borrower resilience suite focus on limits to debt levels (compared to incomes), on the fraction of income that can be pledged to service debts, or on related affordability tests. These restrictions are intended to ensure that households do not become so overextended that in a downturn they have to scramble to continuing making repayments. In the crisis, this type of borrower stress led to defaults in some countries that harmed lenders, as well as to cutbacks in spending that amplified the initial downtown. The policies captured in our lender resilience suite of housing tools include loan to value limits, mortgage risk weight floors and amortisation restrictions. These tools can limit losses to banks and reduce the probability of a credit crunch. We consider both types of intervention in our empirical analysis.

By October 2019, these macroprudential tools had been “switched on” in about two-thirds of our advanced economy panel of 15 countries. Within our sample, 9 had activated the CCyB, with the average CCyB setting amongst those countries reaching around 1.5% of risk-weighted assets. Policy actions to limit household debt have also grown in prominence, with 10 of our 15 countries having activated at least one form of housing tool. There have been 34 instances of new housing tools either being “switched on” or tightened in our sample over the past decade.

Our first contribution is to explore which risk indicators have predicted tool use so far – the beginnings of a macroprudential reaction function. Our regression estimates suggest that both the CCyB and housing tools have been tightened in response to rapid non-financial sector credit growth, particularly when it emanates from the housing sector. The impact is economically meaningful: a one standard deviation increase in household credit growth is found to nearly double the probability that macroprudential tools will be tightened in the following year. With respect to the likely change in the *size* of the CCyB we find that a one standard deviation increase in household credit growth is associated with a CCyB hike of 30bps.

Macroprudential authorities' reactions to other risk indicators is less clear cut, however. Episodes of rapid house price growth tend to be followed by a tightening in the CCyB – a one standard deviation increase in house price growth doubles the probability of a CCyB hike in the subsequent year, and is associated with an average hike of 22bps. Credit-fuelled housing bubbles are widely viewed as a leading indicator of previous financial crises (Jorda et al. (2015)). By contrast, we find no systematic response in the application or calibration of macroprudential housing measures to house price developments. This finding is somewhat surprising, given that these tools are more directly addressing housing-specific risks than the CCyB. We find no evidence either that the CCyB or housing measures are responsive to developments in the household debt service ratio, despite this indicator's strong correlation with macrofinancial tail risks in the past (Drehmann et al. (2019)). Finally, we find that the CCyB is more likely to be tightened in periods of low equity market volatility – a one standard deviation fall in equity market volatility doubles the probability of a CCyB hike in the subsequent year, with an average increase of 15bps. This may reflect a fear that low volatility might breed risk-complacency, presaging greater risk taking and leverage (Brunnermeier and Sannikov (2014), Danielsson et al. (2018)).

Our second contribution is to show that the aggregate risk indicator "GDP-at-risk" provides a useful summary measure of the factors driving macroprudential tool use in practice.[3] Cross-country variation in GDP-at-risk estimates are well correlated with macroprudential tool use in recent years. Since 2014, countries that have activated the CCyB or housing tools have had, on average, higher levels of GDP-at-risk (ie more severe prospective downturns) than those that have not. A 1pp deterioration in GDP-at-risk is associated with a 30bp hike in the CCyB and a 23pp increase in the probability that a housing tool will be tightened next year (relative to an unconditional probability of 17% in our sample).

GDP-at-risk weights household and corporate credit growth, house prices and equity market volatility in a way that is proportional to their marginal explanatory power over the severity of past downturns. We can compare this to the relative weights that policymakers appear to be placing on these indicators in practice. Our results suggest countries have put more weight on household credit growth and equity market volatility than the GDP-at-risk weights of these indicators would imply, and less weight on house price growth (housing tools), corporate credit growth (the CCyB) and the household debt service ratio (both tools).

Taken together, we find that credit growth, house price and volatility indicators explain around 30% of variation in the CCyB to date. However, the explanatory power of these indicators over housing tool use is much more limited. One interpretation of this is that housing policies are typically put in place as structural guardrails, rather than being responsive to fluctuations in vulnerabilities. Another is that countries are yet to converge towards a common reaction function when deciding which tools to deploy or tighten.

[3] Our GDP-at-risk model includes household credit growth, corporate credit growth, house price growth and a measure of equity price volatility; we estimate each indicator's marginal contribution in explaining variation in the 5th percentile of GDP growth 12 quarters ahead in our advanced economy panel over the past 40 years.

The remainder of the paper is organized into five sections. In **section 2**, we introduce the sample of countries and tools that we will analyse. We also document some basic patterns about where and when the tools have been deployed. In **section 3**, we describe the risk environment that has emerged since the crisis. In **section 4**, we analyse how individual risk indicators relate to the usage of our key tools, and how this compares to their performance at explaining tail risks in the past. In **section 5**, we check the ability of the aggregate GDP-at-risk indicator to predict the use of macro-prudential tools, and compare the weight the GDP-at-risk framework would put on different factors to the weights authorities appear to use in practice. In addition, we look at the specific cases where the decision to (not) tighten tools appears most surprising in light of the risk environment. We believe that studying these "outliers" can help us judge the extent to which a common reaction function is emerging. **Section 6** presents our conclusions. Even though we are in the early days of using macroprudential policy, there are already some interesting patterns of usage that are emerging.

2 Macroprudential tool usage, a decade on

2.1 Our choice of countries and tools

We focus our analysis of post-crisis macroprudential tool usage along two dimensions.

First, we restrict our analysis to macroprudential policy action in advanced economies. We are interested in analysing the extent to which a consensus policy reaction function is emerging, which can help explain tool use with respect to common developments in the risk environment. In selecting our sample, we therefore face a trade-off. The widest possible set of countries would maximise the instances of tool use with which to glean information about the reaction function. That is a useful feature, particularly given that macroprudential regimes are new, such that we will rely heavily on cross-sectional rather than time-series variation in tool use. On the other hand, the wider the country sample, the more heterogeneous the macro-financial features of the economies within it and the less plausible it is to expect a common macroprudential reaction function.[4] A somewhat narrower sample of countries also allows us to draw on a longer – and more balanced – panel of financial indicators. This gives us more confidence in characterising the risk environment, relative to country-specific historical norms. In balancing this trade-off, we select a sample of 15 advanced economies where we have the best coverage of financial indicators, drawing on the dataset of Aikman et al (2019b).[5]

Our second judgement is to focus on two classes of macroprudential intervention: i) time-varying bank capital interventions (via the CCyB); and ii) housing marked-related interventions, which come in two forms: *lender-resilience tools* and *borrower-resilience tools*. The primary purpose of the CCyB is to increase banks' capital resilience in the light of any increase in the losses the banking system may face. This can reduce the probability that in a downturn, banks

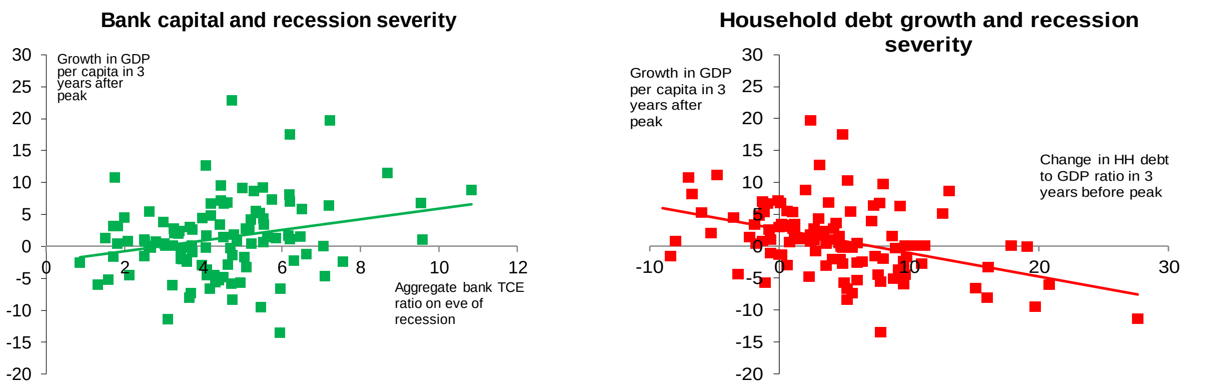
[4] For example, in emerging economies, the relative importance of international capital flows in driving the domestic risk environment – and hence the appropriate focus on the macroprudential reaction function – is likely to be significantly higher.

[5] Our sample includes: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, UK, USA. Relative to Aikman et al (2019b) we exclude Ireland from our sample, where recent moves in risk indicators have been extremely volatile, owing to GDP reclassifications and associated sharp moves in credit relative to GDP.

have to cut back on lending to credit-worthy borrowers to protect their capital ratios. The aim of lender-resilience housing tools is to ensure lenders are resilient to a slowdown in the housing market, which reduces the probability of a credit crunch. As such, the objectives of lender-focussed tools are similar to the objectives of the CCyB. However, lender-focussed housing tools are more targeted in nature, in that they have a bigger impact on lenders that are more exposed to the housing market. Examples of tools in this category include maximum loan-to-value limits, minimum risk weights and restrictions on loan maturity and amortisation. The aim of borrower-resilience tools is to limit unsustainable build-ups in household debt that increase the sensitivity of borrowers to income and interest rate shocks and have the potential to amplify macroeconomic downturns. Limits on debt-service costs (which covers both interest payments and amortisation of the loan) to income ratios and loan to income ratios fall into this category.[6]

We focus on these interventions given our assessment that the amplification mechanisms which they seek to address – a credit crunch and a debt-driven collapse in aggregate demand – were pivotal in making the global financial crisis so severe (see for example: Bernanke (2018), Gertler and Gilchrist (2018), Aikman et al (2019a)). More generally, Figure 2.1 illustrates that across our advanced economy panel since 1980, rapid household credit growth and low levels of bank capital in the run-up to a recession episode has typically been associated with a more severe GDP fall-out.

Figure 2.1: Correlation between the severeity of recessions and two key fault-lines



2.2 Use of the countercyclical capital buffer

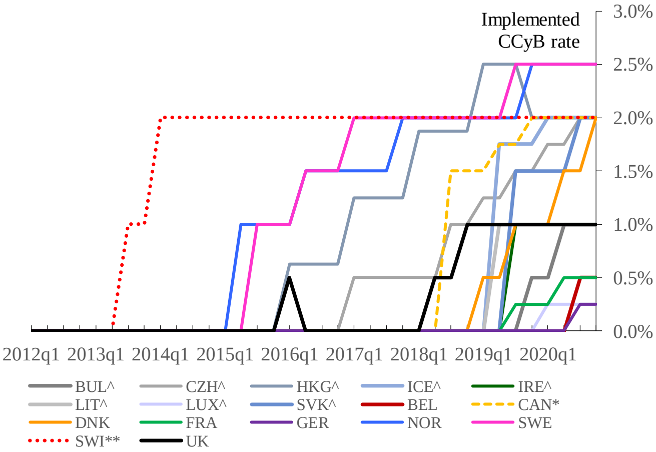
The countercyclical capital buffer (CCyB), introduced as part of the Basel III framework, provides national authorities with a means to vary bank capital requirements as macro-financial risks vary over time.[7] When financial indicators point to larger macro-financial vulnerabilities or increased bank risk-taking, an increase in the CCyB allows additional banking sector resilience to be built, commensurate with growing medium-term vulnerabilities across the banking system as a whole.

[6] We classify tools in the borrower-resilience category when their calibration depends on characteristics of the borrower, for instance their income or other debt obligations. We classify tools in the lender-resilience category if their calibration is uniform across borrowers and instead depends on features of the contract only (such as LTV ratios, amortisation periods, etc.).
[7] The CCyB was introduced in December 2010, as part of: [Basel III: A global regulatory framework for more resilient banks and banking systems](#).

As of October 2019, a positive CCyB rate had been announced in 17 countries worldwide. Figure 2.2 documents the number of positive CCyB rates through time and the path of the tool for each country. We also include in our analysis both the sectoral CCyB applied to the housing market in Switzerland[8] and the "Domestic Stability Buffer" set in Canada[9], both of which share close similarities with the aggregate CCyB tool activated in other jurisdictions.

Across our sample of 15 advanced economies, 9 (60%) had announced a positive CCyB rate by late 2019.[10] The latest positive announced rates range from 0.25% in Germany to 2.5% in Norway and Sweden, with an average rate of around 1.5%. The first countries to implement the CCyB were Norway and Sweden in mid-2015, followed by Hong Kong in 2016.[11] It was not until 2018, however, that CCyB use began to expand more rapidly. Taking into account the typical one-year lag between announcement and implementation, that means that the CCyB has only come into effect very recently in many jurisdictions (see Figure 2.2). A further three countries announced a positive CCyB rate in 2019, which is due to come into effect in 2020. Consistent with this recent uptick in CCyB activity, awareness and discussion of the CCyB appears to have risen. For example, interest in "countercyclical capital buffer" as a *Google Trends* search term doubled between 2014 and 2019.

Figure 2.2: Worldwide CCyB use



*Canadian Domestic Stability Buffer.
** Swiss Secotral CCyB
^ Countries not in our later risk indicator sample

The implication of recent CCyB announcements is that we now have a rapidly growing body of case law on the conditions under which national authorities have opted to activate the CCyB. We do not, however, have as much evidence yet on the impact of the CCyB on financial and macroeconomic variables, which will take time to accumulate. The focus of our study is

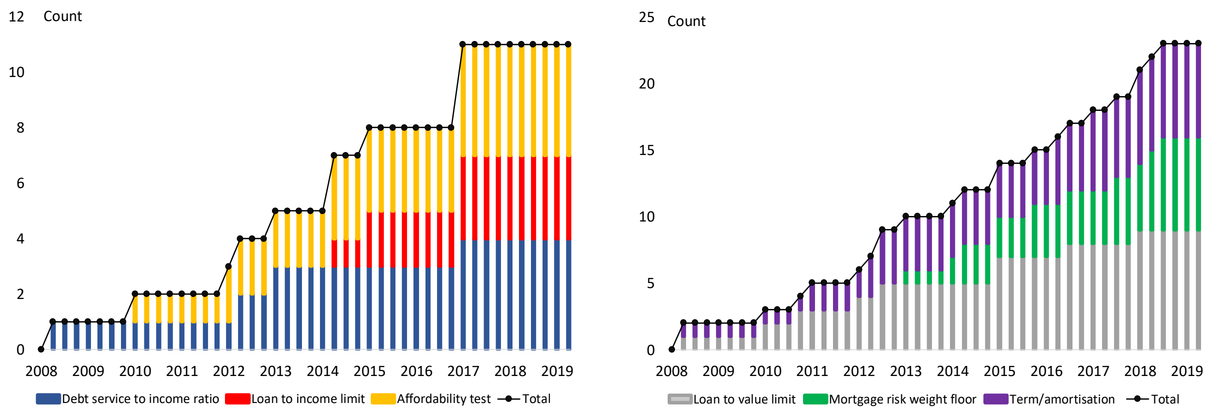
[8] See SNB (2017) for an overview of the Swiss sectoral CCyB (Link) and BIS (2019) for a general discussion of sectoral CCyBs (Link).
[9] See OSFI (2019) for information on the Canadian Domestic Stability Buffer (Link).
[10] As of October 2019, the countries not included in our sample which we are aware have set a positive CCyB rates were: Bulgaria (1%); Czechia (2%); Hong Kong (2%); Iceland (2%); Ireland (1%); Lithuania (1%); Luxembourg (0.25%) and Slovakia (2%). For international CCyB listings, see https://www.bis.org/bcbs/ccyb/
[11] Switzerland implemented their sectoral CCyB tool earlier, in late 2013. In the UK, although a positive CCyB rate was announced in 2016Q1, to be implemented a year later, that was subsequently superseded by a CCyB cut back to zero in 2016 Q2, following the referendum on the UK's membership of the EU.

therefore on the extent to which there are commonalities in the risk environment which has typically prompted CCyB activation or a change in the CCyB level.

2.3 Use of housing market-related tools

Figure 2.3 documents the usage of borrower resilience and lender resilience housing measures since the global financial crisis across the countries in our dataset. In constructing the chart, we have focused on measures that apply to new owner-occupier mortgage borrowers, rather than those re-mortgaging or buying for investment purposes. We have also abstracted from measures that apply only in specific regions, focusing instead on measures that apply at the nationwide level. Finally, we have classified measures from the date at which they were announced, rather than when they take effect. The full list of measures recorded is documented in the annex.

Figure 2.3: Use of borrower and lender-based macroprudential housing measures



Note: covers actions by Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, UK, USA. Actions are classified based on accouchement date.

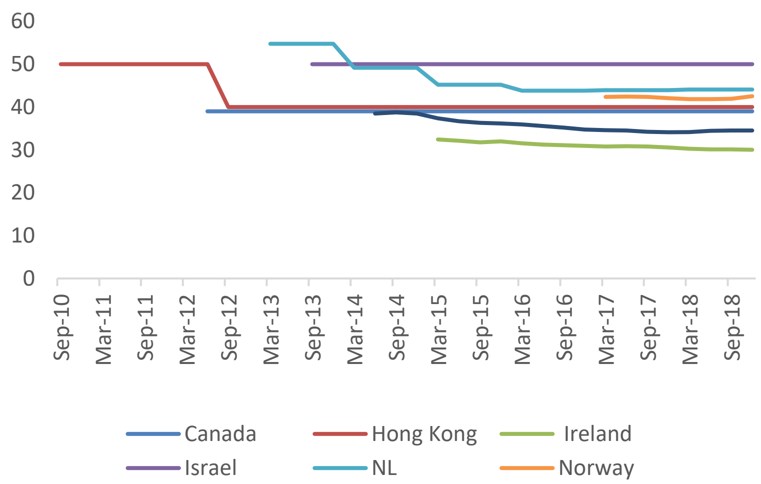
Of the 15 advanced economies in our sample, at the time of writing 9 (60%) had implemented lender-resilience measures, while only 5 (33%) had implemented borrower-resilience measures. There is substantial overlap between these groups, with 4 (27%) countries having implemented both types of measure – the UK is the only country in the sample to have implemented only borrower-resilience measures. Figure 2.3 also illustrates that many housing interventions were introduced before countries started to make active use of the CCyB.

The most common lender resilience tool is a maximum loan to value limit, applied in 7 (47%) countries. The most common borrower resilience tool is a maximum debt-service to income ratio, applied in 3 countries via an explicit quantitative limit, and a further 2 via a requirement for lenders to assess affordability, either under current interest rates or stressed rates. Several countries (UK, Ireland and Norway) have also put in place loan to income ratios.
For a given mortgage term and interest rate, there is a correspondence between measures that establish limits on loan to income ratios and those that establish limits on debt service to income

ratios.[12] We use this correspondence to compare the calibration of the borrower-resilience measures that have been applied to date. There are two further complications in comparing these measures. First, loan to income limits are specified relative to borrowers' gross (ie pre-tax) income, while debt service to income ratios are specified relative to net income. To account for this, we scale loan to income measures using information from the OECD on average personal income tax and social security contribution rates on gross labour income. Second, while loan to income limits apply to mortgage debt only, many of the debt service limits in our dataset apply to overall debt, taking into account non-mortgage borrowing. We lack information on the marginal mortgage applicants' other borrowing to account for this, so in the analysis below we assume the borrower has no other debt obligations.

With these caveats in mind, Figure 2.4 places each country's borrower resilience measure on a common footing. To provide some context we also include Hong Kong, Ireland and Israel, in this chart though they are not included in our sample for our regression analysis. The figure records the maximum (implied) debt service ratio a borrower seeking a 25 year mortgage with no other debt can obtain in each country. Debt service limits are highest (least stringent) in Israel and most stringent in Ireland. While loan to income limits have remained fixed in the three countries that have applied them (UK, Ireland, Norway), with falling interest rates the maximum implied debt service ratio has tightened in these countries over time. Of the countries that have applied debt service ratios, only Netherlands and Hong Kong have actively recalibrated the measures over time.

Figure 2.4: Actual and implied maximum mortgage payments as % of post-tax income



Note: Estimates of the effective maximum debt service to income ratios for a borrower seeking a 25 year mortgage with no other debt. Covers all countries in our sample of 15 countries that have in place either debt service to income ratio or loan to income limits, plus Ireland, Israel and HK.

3 How has the advanced economy risk environment evolved post-crisis?

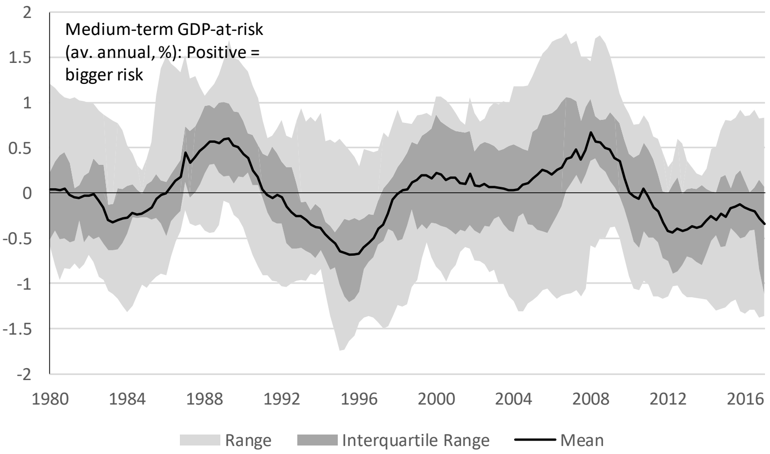
In theory, the deployment of both time-varying capital tools and measures targeting household debt should reflect changes in the financial risk environment. This is because when financial risk

[12] In particular, if m is the mortgage term, r is the interest rate on the loan (assumed to be fixed), and LTI is the maximum loan to income ratio, the implied maximum debt-service to income ratio is given by: $DSTI = LTI \cdot r \cdot (1-(1+r)^{-m})^{-1}$.

indicators are elevated, a raft of evidence suggests that both the probability and potential severity of future macroeconomic downturns is increased. In other words, the left hand tail of the future GDP growth distribution gets fatter, and macroprudential policy interventions may be needed to reduce these risks, or ensure the financial system is resilient against them. The financial risk environment can potentially be driven by a large number of vulnerabilities, with relevant indicators spanning financial and non-financial sector leverage, the terms and conditions under which credit is provided and real and financial sector asset prices.

Figure 3.1 presents a time-series of "GDP-at-risk", which provides a simple summary measure of the overall impact of developments in individual risk indicators. The measure of GDP-at-risk we use is based on Aikman et al (2019b) and is a forecast of the 5th percentile of the GDP distribution three years in the future. This estimate is obtained by weighing a range of macro-financial indicators based on their historical relationship with the left tail of the GDP distribution.[13] Increases in the series imply a fatter tail of the forecast distribution 3 years ahead. Note that our framework does not account for the various *non*-financial factors that also affect the 5th percentile of future GDP, such as geopolitical risks. Hence, Figure 3.1 should be read as showing *changes in the severity of a future downturn that can be explained by changes in macro-financial variables*.

Figure 3.1: GDP-at-risk across countries and time



There are three key takeaways from this figure. First, the summary metric of macro-financial risks that we use captures the increase in risks ahead of the global financial crisis, as shown by the increase in the cross-country mean between 2004 and 2008. Second, in the years after the crisis risks in most countries have fallen below their long-run average. Third, over the past 5 years some countries have seen risks build again, as shown by the increase in the range of GDP-at-risk estimates across our sample of advanced economies (light grey swath). We find similar patterns when looking at other aggregate risk indicators, including a simple average of key vulnerability metrics and their first principal component.

A hypothesis we examine below is that the increasing use of macroprudential tools in recent years can be viewed as a response to increases in some countries' GDP-at-risk since the crisis.

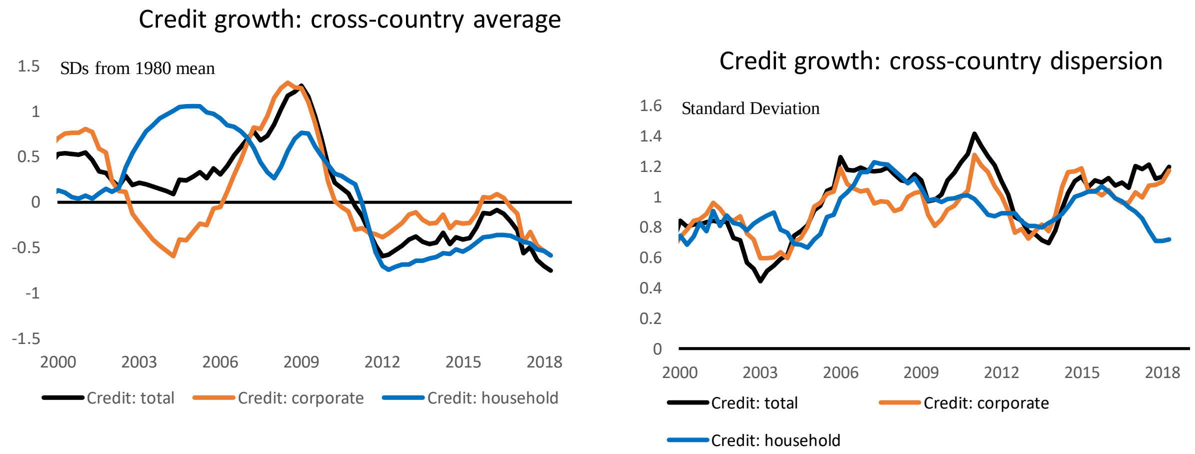
[13] The relationship between individual risk factors and GDP-at-risk is estimates using a panel of 16 advanced economies from 1980-2018. It considers the following risk indicators: 3 year change in credit-to-GDP ratio, 3 year house price growth, current account deficit, and equity market volatility. See Aikman et al (2019b) for a detailed description of the underlying mythology.

Individual risk indicators

In addition to considering the evolution of GDP-at-risk, we consider disaggregated developments in other well-established risk indicators.[14] In selecting these indicators, we draw on the vast literature on financial crisis early warning indicators (for early contributions, see for example Kaminsky and Reinhasrt (1999) and Borio and Lowe (2002)).[15] We pay particular attention to developments in credit growth to the non-financial private sector relative to nominal GDP, an indicator that has received considerable attention in the early warning literature.[16] We also investigate the split of credit growth between borrower type, separating household and corporate sector borrowing. That allows us to distinguish the extent of re-leveraging in different sectors post-crisis and assess how that has related to macroprudential tool use in general and targeted sectoral tool use in particular.

Figure 3.2 demonstrates that the aggregate patterns for these indicators mirror the ones for GDP-at-risk: While the cross-country averages for these indicators are currently low relative to their levels in the run-up to the crisis (left panel) we observe increasing dispersion in many of the indicators, with some countries experiencing a build-up in risks related to corporate debt in particular (right panel).

Figure 3.2: The mean levels of individual vulnerability indicators and their dispersion



We augment our assessment of risks from rapid credit growth with indicators of debt serviceability. Clearly, credit growth and debt serviceability are closely related. However, changes in the level of interest rates could mean that even if the total amount of credit falls, the average debt servicing cost could still rise (and vice-versa). Elevated debt serviceability burdens are a natural indicator of the risk that consumers have to cut back on spending in the

[14] Note that many of these individual indicators form the component parts of our GDP-at-risk aggregate measure, which simply acts as an adding up device, with an indicator's weighting based on its ability to forecast GDP tail risks in the past.
[15] For a wider review of the literature, see for example Aikman et al (2018).
[16] See for example Gavin and Hausmann (1996); McKinnon and Pill (1996); Honohan (2000); Eichengreen and Arteta (2000); Bordo et al. (2001); Borio and Lowe (2002a,6 and 2004)); Borio and Drehmann (2009); Drehmann et al. (2011); Mendoza and Terrones (2014); Baron and Xiong (2017); Bridges et al. (2017) for a discussion of the link between credit growth and the subsequent probability and severity of financial crises.

event of stress, in order to meet their debt obligations.[17] As discussed in Section 2, many housing sector macroprudential tools have been designed specifically to target elevated debt service ratios in order to mitigate the risk of aggregate demand externalities that can arise if a large number of borrowers cut back on consumption in a stress. The overall pattern for household debt servicing ratios (DSRs) mirrors the trends for credit growth indicators: while the average level of DSRs has been trending downwards since the crisis, their dispersion has recently started to grow.

Two additional indicators that we consider are real house price growth and the size of the current account deficit (relative to GDP). Twin booms in credit and house prices were observed in several advanced economies pre-crisis and such synchronised booms (or "leveraged bubbles") have been found to be associated with particularly toxic economic tail risks (see Jordà et al (2015)). So rapid house price growth may induce countries to take action even if there are no signs of increased debt levels or stretched affordability metrics. Similarly, given a strong historic correlation between large current account deficits and subsequent crises, countries may look at the current account deficit as a simple summary indicator of the macroeconomic vulnerabilities associated with more fragile funding when deciding whether to take any macro-prudential actions.[18]

As a final indicator, we consider equity market volatility. Importantly, we invert this measure in our analysis, since our focus is on the build-up of financial vulnerabilities over the medium-term, which may be fostered by extended periods of low volatility and an associated under-pricing of risk.[19]

4 Relationship between individual risk indicators and tool usage

In order to investigate whether macro-prudential tools are in fact deployed or tightened in response to changes in the risk environment we run a number of univariate regressions that aim to establish the relationship between risk indicators and the calibration of tools (see Panel A of Table 4.1).

We consider three specifications. First, we consider univariate probit regressions that estimate the relationship between various risk indicators and the probability of a county activating or tightening any of its housing tools[20]:

$$(1)\quad \Pr\{H_{i,t} = 1 | X_{i,t-1}\} = \varphi(c + \beta X_{i,t-1})$$

[17] Drehmann and Juelius (2012) find that debt serviceability is a key indicator with which to capture household financial constraints. See Korinek and Simsek (2016) and Bianchi and Mendoza (2016) for models which capture the aggregate demand externalities associated with elevated indebtedness.

[18] While foreign capital inflows can come in the form of stable long-term funding (eg foreign direct investment), cross-country evidence suggests that *on average*, foreign capital inflows are often less stable than domestically provided capital. For advanced economies, the evidence that the current account deficit is a useful risk indicator, when other key indicators are controlled for, is mixed (see Aikman et al 2018 for a review). Aikman et al (2019b) do find, however, that the current account deficit is a significant determinant of advanced economy GDP tail risks.

[19] Elevated volatility is, in contrast, a useful indicator of very near-term risks to GDP. For a further discussion of this "term structure" of risks, see Adrian et al (2018) and Aikman et al (2019b).

[20] Note that in order to maximise our sample size, we consider all types of housing tool together, covering measures targeted at both borrower and lender resilience.

where X is a set of risk indicators (tested individually at this stage); t is the year (within the period from 2012 to 2019 when most tools where activated or tightened); i is the country index, and $H_{i,t}$ is an indicator variable that is set equal to one if country i's housing tools were activated or tightened in year t. Given that housing tools tend to be bespoke measures that may require additional legislation and are likely to be agreed with a lag, we consider the relationship between an announcement to tighten the tools and risk indicators in the previous year t-1.

Note that we focus on whether countries choose to activate or tighten housing tools, rather than the level at which they are calibrated. This reflects two things: First, countries have used a range of housing tools that are not easily comparable. While we can translate most borrower-focussed tools into a common metric, the same is not necessarily possible across borrower- and lender-focused tools: eg, it is difficult to compare the tightness of a 75% LTV limit to the tightness of a 40% DSR limit. Second, we have demonstrated above that countries do not tend to recalibrate borrower-focussed housing tools once they have been put into place. So the exact calibration is likely to reflect country-specific factors and is unlikely to be a reflection of the risk environment.

Second, we consider a range of univariate regressions that establish similar relationships between risk indicators and the decision of whether to activate or tighten the CCyB:

$$(2)\quad \Pr\{C_{i,t} = 1|X_{i,t-1}\} = \varphi(c + \beta X_{i,t-1})$$

where $C_{i,t}$ is an indicator variable that is set equal to one if country i's CCyB activated or tightened in year t. Again, we focus on the relationship between changes in the applicable CCyB and risk indicators in the previous year. While changes in the CCyB do not typically require additional legislation, in many countries any changes in the applicable CCyB are subject to a statutory one-year implementation period.

Finally, we consider a range of simple linear regressions that regress the level of the CCyB onto the various risk indicators:

$$(3)\quad CCyB_{i,t} = c + \beta X_{i,t-1}$$

where $CCyB_{i,t}$ denotes the CCyB rate in country i at time t. This specification exploits the fact that in contrast to housing tools, there is a straightforward cardinal interpretation of the setting of the CCyB which is comparable across time and countries. Moreover, the discussion in Section 2 demonstrates that countries regularly change the applicable CCyB rates, and may do so in a way that reflects changes in the risk environment.

Below we discuss the results for the use of housing tools and the CCyB separately.

4.1 Factors determining the use of housing-related tools

Panel A of Table 4.1 demonstrates that when deciding whether to deploy or tighten housing tools, countries appear to put weight on credit growth.[21] This indicator is statistically significant at the 1% level and the coefficient is also economically meaningful. The marginal effect from this unconditional probability of a one standard deviation increase in total credit growth is a 15 percentage point increase in the likelihood of a country activating or tightening housing tools. As context, the unconditional probability that a housing tool is tightened in our sample is 17%.[22] This headline finding is intuitive, given the well-established result that credit growth is a good indicator of the level of financial stability risks.

However, there are a number of more surprising results: first, countries appear to pay attention to the growth in credit to non-financial corporates, which should not necessarily be related to risks in the housing market. That said, non-financial credit may simply be correlated with household credit growth (see below). And non-financials often use credit to fund commercial real estate investments, which can interact with the residential real estate market (e.g. because investments in one lead to an increase in prices in the other). Second, countries do not appear to react to average household DSRs when calibrating housing measures. This is perhaps surprising given that some housing tools are explicitly aimed at ensuring that households have sufficient disposable income to be able to continue servicing their debt without cutting back on consumption in a downturn. It may reflect the fact that many countries have acted pre-emptively by tightening housing tools while average household DSRs have remained modest, reflecting the current low interest rate environment. Finally, countries do not appear to react to house price growth when deciding whether to activate or tighten housing tools. While this also appears unintuitive, it may again reflect the fact these tools have been implemented as structural measures in a number of jurisdictions.

Finally, unsurprisingly each of the indicators in isolation has a low predictive power, with total credit growth performing best (pseudo R^2 = 12%). This may reflect the fact that authorities consider a range of indicators when deciding whether to tighten housing tools. It may also reflect the fact that other non-conjunctural factors determine whether countries deploy housing tools. For example, the willingness to implement these measures may reflect whether countries experienced a painful crisis in the past, and/or if their macroprudential frameworks have been designed to avoid inaction bias. Relatedly, it may also reflect the fact that housing tools are put in place as structural safeguards before risks start to emerge. This would be consistent with the fact that once borrower-focussed tools have been put in place, countries are unlikely to recalibrate them in light of changes in the risk environment.

[21] Throughout, our credit growth measure is the three-year change in the credit to GDP ratio. We also ran this analysis on a more timely, one-year credit growth measure, but found it to have less explanatory power over tool use. This is consistent with policymakers looking through high frequency noise in credit data and waiting to see clear signs of an emerging trend. It is also consistent with the literature linking credit growth measures to the severity of past downturns, which typically find a three-year smoothed credit measure to contain the strongest signal (see, for example, Bridges et al (2017)).

[22] There are 20 country-year instances in which tools our tightened across our sample of 120 observations spanning 15 countries over 8 years (2012-2019).

4.2 Factors determining the use of the CCyB

Similarly, when deciding whether to tighten the CCyB and agreeing the absolute level of capital buffers, countries also put weight on household credit growth and, to a lesser extent, total credit growth. A one standard deviation increase in household credit growth is associated with a 14 percentage point increase in the probability of a CCyB tightening in the following year, doubling the unconditional probability in our sample of 13%. In our linear model, a one standard deviation increase in household credit growth is on average associated with a 30bps increase in the CCyB. The fact that household credit growth appears to be a better predictor of a broad-based tool like the CCyB than total credit growth may be related to the fact that the CCyB only applies to banks, and in many countries, households are more reliant on bank credit than corporates (who are more reliant on bond markets).

Table 4.1 also provides some evidence that house price growth may inform countries' decision to tighten the CCyB. As discussed above, this may be related to the fact that house price growth has in the past been correlated with credit booms, and may be a leading indicator of build-ups in risky household borrowing (as first-time buyers need to take out larger mortgages to buy properties that have stretched valuations). In addition, house price growth is a very salient indicator that attracts a lot of public attention. However, it is surprising that this indicator appears to be better at predicating the use of the CCyB than the use of more targeted housing interventions.

Table 4.1: Univariate relationships between tool usage and risk indicators

Panel A: What are policymakers responding to in practice…

	Total credit growth	NFC credit growth	HH credit growth	HH DSR	Real house price	Current Account	Volatility (inverted)
	Housing probit: probability of tool tightening next year:						
Coeff†	0.5***	0.36**	0.39**	0.17	0.00	0.06	-0.08
Marginal effect p(tigthen)^	15%	11%	12%	4%	0%	2%	-2%
Pseudo R^2	0.12	0.06	0.06	0.01	0.00	0.00	0.00
	CCyB probit: probability of CCyB increase next year:						
Coeff†	0.16	-0.07	0.51***	0.03	0.48**	0.16	0.42**
Marginal effect p(tigthen)^	4%	-1%	14%	1%	13%	4%	13%
Pseudo R^2	0.01	0.00	0.09	0.00	0.06	0.01	0.06
	CCyB Linear: explanatory variable for CCyB setting:						
Coeff†	0.15***	0.03	0.3***	0.02	0.22***	0.01	0.15***
Marginal effect (CCyB rate)	15bps	3bps	30bps	2bps	22bps	1bp	15bps
Pseudo R^2	0.06	0.00	0.17	0.00	0.06	0.00	0.05

Panel B: Materiality of the variables in explaining tail risk

	Total credit growth	NFC credit growth	HH credit growth	HH DSR	Real house price	Current Account	Volatility (inverted)
GDP-at-risk impact †‡	0.6	0.6	0.6	1.0	0.3	0.6	-0.2

† All coefficients show impact of a 1SD increase in the risk indicator labelled. Indicators standardised at country level using 1980-2018 distribution. Growth rates 3yr averages.
^ Impact of 1SD increase in risk indicator on probability tool is tightened next year. Marginal effect shown is from the unconditional probability of tightening (13% for housing tools, 17% for CCyB).
‡ Based on Aikman et al (2019). Coefficients show average annual impact on 5th percentile of GDP distribution over next three years. Impact of each indicator estimated in turn, with macro controls.

Finally, periods of low equity price volatility appear to be a reasonable predictor of CCyB usage. This is consistent with empirical evidence which suggests that periods of low volatility provide the breeding ground for financial stability risks (Brunnermeier and Sannikov (2014)), as value-at-risk constraints encourage leveraged intermediaries to expand their balance sheets (Adrian and Shin (2013)).

4.3 Comparing practice and evidence: factors that determined tail risk in the past

Next, we compare the financial indicators that appear to drive the use of macro-prudential tools in practice to the factors that have affected GDP tail risk most in the past. Unless there have been profound structural changes in the economy, we might think that these are the factors that *should* drive the usage of macro-prudential tools – in particular broad-based tools such as the CCyB.

Panel B of Table 4.1 draws on the GDP-at-risk methodology in Aikman et al (2019b) to consider how well the various indicators perform at explaining past tail risks to GDP. More specifically, the numbers represent the coefficients of quantile regressions that regress the 5th percentile of GDP at a three-year horizon on the relevant risk indicator.[23] While the absolute size of the coefficients in panel A and B is not directly comparable, the relative size of the coefficients of different risk indicators are still instructive.[24] This exercise yields four interesting observations:

i) First, these regressions confirm that credit growth and house price growth are important determinants of tail risk to GDP, and may therefore warrant a macro-prudential policy response.

ii) Second, the results in Panel B show that low equity market volatility is not a strong predictor of the build-up of medium-term risks, once macroeconomic controls are accounted for. While volatility indicators can still be useful in informing whether policy should be loosened in response to volatility spikes, such decisions are not the focus of our analysis.[25]

iii) Third, our regressions suggest that higher current account deficits were historically associated with more severe downturns in the medium-term, possibly because foreign capital inflows were more unstable in nature than domestically provided funding. To the extent that this pattern persists, large current account deficits should arguably be associated with some form of macro-prudential response. However, it is not clear that housing tools could help lean against these risks. And in the context of ensuring banks' resilience to the associated risks it might be more appropriate to ensure that banks rely on sufficiently stable funding than to tighten capital requirements.

iv) Fourth, it is notable that household debt service ratios historically were powerful leading indicators of subsequent crises. Indeed, the DSR measure is estimated to load most heavily of all the indicators on tail risk, with a one standard deviation DSR increase associated with a full 1 percentage point deterioration in the forecasted 5th percentile of GDP growth over each of the next three years. Yet, from the univariate regressions, it seems that financial stability committees have not been using DSR information in the setting of tools. Given current levels of interest rates in most countries, even large levels of debt would translate into modest debt service ratios. So the absence of a connection

[23] In each case, the relevant risk indicator is included alongside macroeconomic controls (lagged GDP growth, inflation and the change in central bank policy rate), this follows Aikman et al (2019b). Estimates are obtained from a panel quantile regression spanning our sample of 15 advanced economies across forty years (1980-2018).

[24] For example, the fact that a one standard deviation increase in total credit growth makes a severe downturn in GDP growth 0.6 percentage points worse in each year over a three-year horizon does not imply that the CCyB should be increased by 0.6 percentage points.

[25] Note that the estimates in Panel B do not necessarily tell us anything about loosening decisions: the coefficients focus on the medium-term impact of volatility on tail risks. Any decision to loosen in response to volatility spikes is more likely to be linked to the near-term impact of heightened volatility.

could be a consequence of the level of low interest rates that have prevailed in most of world during our sample period.

5 Relationship between the aggregate risk environment and tool usage

In addition to considering the relationship between individual risk indicators and tool usage, in this section we explore the relationship between the overall risk environment and the usage of macro-prudential tools. This approach has two key advantages: first, as we have noted above, our univariate regressions may be subject to considerable omitted variable bias. For example, credit to non-financial corporates may be a good predictor of housing tool usage because it is correlated with household credit. Looking at the entire risk environment simultaneously helps mitigate this issue. Second, we have observed that individual indicators have a fairly low predictive power for tool usage. The multivariate setting allows us to check if the joint predictive power of the various risk indicators that countries appear to consider when setting their tools is materially higher.

We take two approaches to assessing the impact of the overall risk environment on tool usage. First, we produce an aggregate indicator, which weights together the individual indicators that appear to feature in the macroprudential reaction function. To do this, we estimate a model of GDP-at-risk that jointly considers all of the indicators that individually appeared to predict tool usage (household credit growth, non-financial corporate credit growth, house price growth and volatility).[26] We use the estimated GDP-at-risk coefficients on in each individual indicator as the weights for our aggregate indicator. Subsequently we test whether this measure of aggregate risk performs well at predicting tool usage. Second, we use a simple multivariate regression that regresses tool usage on all of these four individual risk indicators.

The key difference between those two approaches is that the GDP-at-risk approach imposes the restriction that policymakers weight the four indicators according to their marginal performance at predicting the severity of past downturns. This has two key advantages: First, it increases the degrees of freedom in our subsequent regression that tries to explain tool usage during the past 7 years. This is helpful given the limited number of observations that we have. Second, our GDP-at-risk weights provide a “sensible” benchmark for the relative weights that policymakers should place on the four indicators when forming a view on the aggregated risk environment, given macroprudential policy’s focus on addressing tail risks to the real economy. Subsequently, we can compare these “sensible” weights to the actual weights that policymakers appear to be placing on different indicators as determined by the multivariate regression.

5.1 Predictive power of the aggregate risk environment, using GDP-at-risk weights

In order to construct an aggregate indicator based on GDP-at-risk weights, we estimate the 5th percentile of the forecasted GDP growth distribution over the next three years as a joint function of the four risk indicators that individually appear to be related to tool usage. We follow directly the methodology of Aikman et al (2019b), estimating the following quantile regression:

[26] Note that total credit growth is nested within this as total credit growth is simply the sum of household and private non-financial corporate credit growth.

$$\hat{\beta}_\tau^h = argmin_{\beta^h} \sum_{i,t} \rho_\tau \left(y_{i,t+h} - X_{i,t}\beta_\tau^h \right)$$

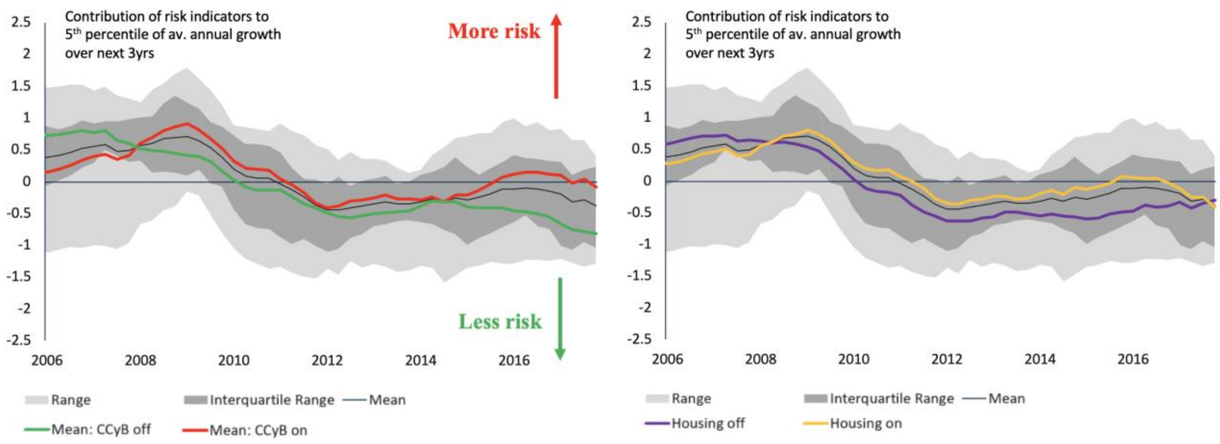
Where τ is the quantile under consideration (5th), h is the horizon (3 years), ρ_τ is the standard asymmetric absolute loss function, $y_{i,t+h}$ is average annual GDP growth in country i over the next h periods and X is a vector of risk indicators X^F and macro controls X^M. Our X^F vector includes our four indicators: i) the three year change in the household credit to GDP ratio; ii) the three year change in the corporate credit to GDP ratio; iii) three year real house price growth; and iv) the quarterly volatility of daily equity market returns. Our X^M vector includes three macroeconomic controls: lagged GDP growth; inflation and the change in central bank policy rate. We estimate this model across our advanced economy panel of 15 countries over the past forty years (1980-2018).[27] All our explanatory variables are standardised at the country level so, for example, the units of our risk indicators are in standard deviations from own-country 1980-2018 average.

Our aggregate risk indicator for each country in our panel follows directly from this GDP-at-risk model. We construct it as *the joint contribution of our four risk indicators to GDP-at-risk*: that is: $X_{i,t}^F . \beta_{5^{th}}^{3yr}$. Our coefficient estimates are as follows:

$$X_{i,t}^F . \beta_{5^{th}}^{3yr} = 0.39 * \dot{HHcredit} + 0.35 * \dot{NFCcredit} + 0.06 * \dot{HousePrice} - 0.02 * Volatility$$

For brevity, we will refer to this measure below simply as "GDP-at-risk." The black line in the left panel of Figure 5.1 shows how the mean level of GDP at risk developed over the past forty years, and the swathes shows the amount of cross-sectional variation around this mean within our advanced economy panel.[28] The overall patterns are consistent with the results of the benchmark model of GDP-at-risk that we presented above and that includes a slightly larger set of explanatory variables.

Figure 5.1: Relationship between GDP-at-risk and tool usage



[27] We also include Ireland in this estimation, increasing our country panel to 16 to be directly consistent with Aikman et al (2019b) – this does not materially affect our results, since this exercise draws on 40 years of data and the volatility in Irish credit to GDP data mentioned previously only affects the very recent data.

[28] Given that each input indicator is standardised, a GDP-at-risk value of zero denotes that the contribution of our risk indicators to GDP-at-risk is at the historical (1980-2018) average.

In the left panel of Figure 5.1, the red (and green) line shows the average level of GDP-at-risk conditional on countries having (and not having) put in place a positive CCyB by the end of the sample period. The figure demonstrates that countries that have currently set positive CCyB rates have indeed seen higher aggregate vulnerabilities (as measured by GDP-at-risk) than other countries. By end-2018, the divergence in the risk environment between these two country groupings was substantial, with the forecasted 5th percentile of the GDP growth distribution amongst CCyB users being ¾ pp worse in each of the next three years (cumulating to a 2.2pp more severe tail risk for the level of GDP).

The right panel of Figure 5.1 repeats this exercise for countries that have (not) switched on housing tools. Again, we see that countries that have switched on housing tools appear to have done so in light of a somewhat riskier aggregate environment than other countries: GDP-at-risk has been more severe amongst the housing tool users for much of the previous decade. The fact that the two lines start to diverge at an earlier stage is consistent with the fact that many housing tools were put in place before countries started raising the CCyB. The fact that over the past years the gap between the two groups of countries has been narrowing might be because housing tools, once implemented, have successfully leaned against a build-up of risks in the housing sector. This is consistent with the notion that housing tools are often thought of as addressing risks at source by actively "leaning" against a build-up in risks, rather than fatalistically building resilience to higher macro-financial vulnerabilities (a role often ascribed to the CCyB).

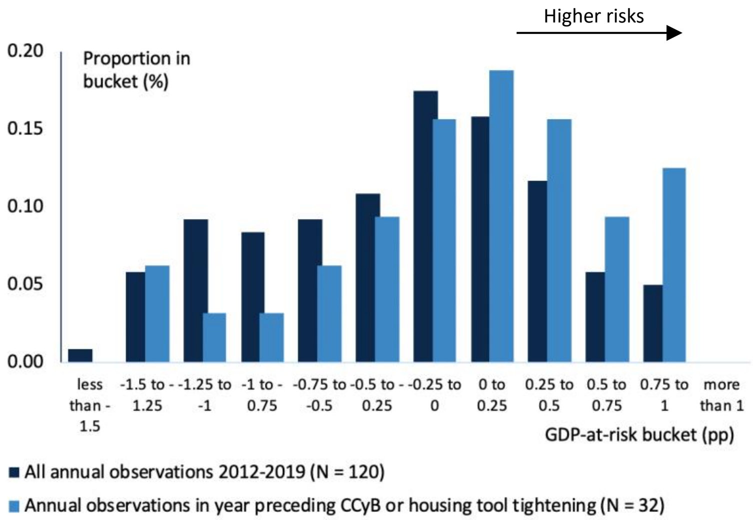
In this illustrative exercise, we have used static "tool-user" versus "non-user" country groupings, which ignores the exact timing of the macroprudential actions. Ignoring the time-dimension is likely to be a reasonable simplification for the CCyB groupings, given that we focus on a fairly short time-period since countries have started activating their CCyBs. However, ignoring the timing is more problematic for the housing grouping, given the tools have been in place for longer and are more likely affect the risk environment (rather than just being a function of the risk environment). Such reverse causality means that Figure 5.1 may underestimate any causal relationship between risk indicators and subsequent tool usage. We therefore explore the timing of the decisions in more detail below.

Risk environment ahead of policy tightening

Next, we drill down into the timing of decisions to tighten macroprudential policy and consider whether in the years *before* agreeing a macro-prudential action, countries had seen a build-up of risks. In line with the approach explained above, we assume that agreeing and/or implementing policy decisions takes about one year, so we analyse the relationship between tightening decisions at time t and the level of GDP-at-risk at time t-1.

Figure 5.2 demonstrates that ahead of tightening decisions, GDP-at-risk was considerably more skewed to the right (i.e. was more risky) than across the entire sample. The dark blue bars shows the overall distribution of GDP-at-risk across our full sample of 120 country-year observations from 2012-2019. The light blue bars show the equivalent distribution for the sub-sample of 32 country-year pairings where a macroprudential tightening occurred in the following year. This reveals that in 56% of cases preceding tool tightening, GDP-at-risk was at or above average (bins above zero in Figure 5.2), compared to 38% for the full distribution. Moreover, in 22% of cases, GDP-at-risk was 0.5 percentage points above its long-run averages or worse before tools were tightened, double the 11% share of such observations across the full distribution.

Figure 5.2: Distribution of GDP at risk one year ahead of policy tightening



Regressing tightening decisions on our aggregate measure of GDP-at-risk demonstrates that this indicator is indeed a useful summary statistic with which to predict tool use. Table 5.1 repeats the regressions run in Section 4 on individual indicators for our aggregate GDP-at-risk measure. It shows that a higher level of GDP-at-risk increases the probability of a tightening of housing tools at a confidence level of 1%. Moreover, the coefficient is economically significant. It implies that a 1pp deterioration in GDP-at-risk has a marginal effect of 23pp on the probability that a housing tool will be tightened next year (relative to an unconditional probability of 17% in our sample).

Table 5.1: Relationships between tool usage and GDP-at-risk

	Housing tool probit	**CCyB probit**	**CCyB linear**
GDP-at-risk coefficient	0.71***	0.37	0.3***
P-value	0.005	0.13	0.002
(Pseudo) R^2	0.08	0.03	0.08
N	120	120	120

While our GDP-at-risk measure is not a good predictor in our CCyB tightening probit model, Table 5.1 also shows that it has stronger predictive power over the level of the CCyB in our linear model. This effect is significant at the 1% confidence level and suggests that a 1pp deterioration in GDP-at-risk is associated with a 30bps tightening in the CCyB during the following year, on average across our full sample. This coefficient estimate is likely to be biased downwards by the fact that for the first two/three years of our 2012-2019 sample, CCyB frameworks had not been operationalised in many countries. Limiting the sample to 2014-2019 (reflecting the fact that the CCyB was raised in several jurisdictions in 2015) increases the marginal effect from 30bps to 50bps, still significant at the 1% level.

Note that while we do find strongly significant effects of GDP-at-risk on tool usage, the (pseudo) R^2 of the regressions is not much higher than in the univariate regressions above. This suggests that countries do not systematically follow the same approach to calibrating their tools, and/or that our benchmark model of risk aggregation may not fully describe how countries aggregate risks in practice.

Individual outliers

Having established a link between the level of GDP-at-risk and macroprudential tool use, it is possible to investigate instances where the degree of macroprudential activism has been unusually high / low relative to the sample average. For example, the left panel of Table 5.2 documents the ten instances in our sample where GDP-at-risk was highest but no macroprudential action followed in the subsequent year. And conversely, the right panel documents the ten instances where tools were tightened with the lowest prevailing level of GDP-at-risk.[29]

Table 5.2: Instances of macroprudential inaction (action) at surprisingly high (low) levels of GPD-at-risk

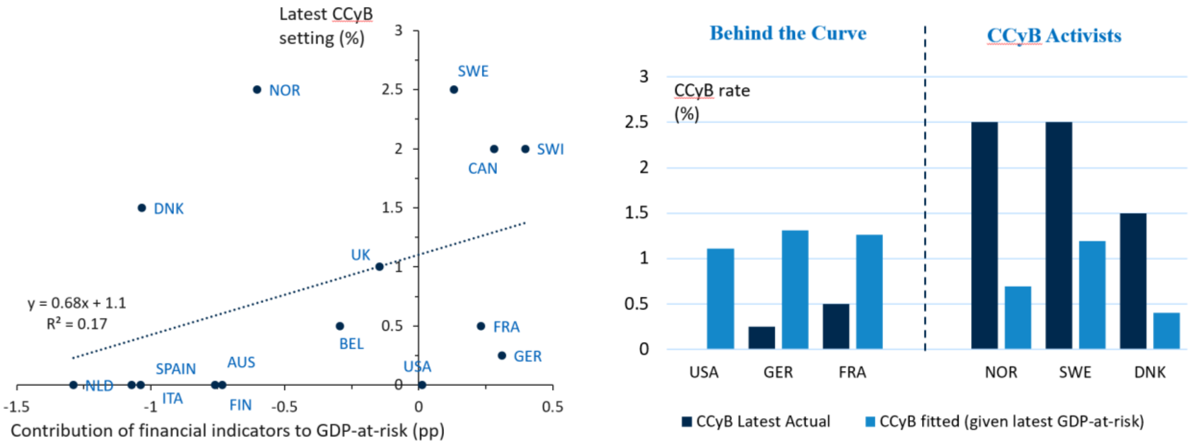
	Instances of high GDP-at-risk and no subsequent action						**Instances of low GDP-at-risk and subsequent action**		
	Full sample (2012-2019)			Sub-sample (2015-2019)			Full sample (2012-2019)		
Rank	**Country**	**Year**	**GDP-at-risk level**	**Country**	**Year**	**GDP-at-risk level**	**Country**	**Year**	**GDP-at-risk level**
1	CAN	2017	0.85	CAN	2017	0.85	UK	2016	-1.48
2	FRA	2012	0.80	AUS	2016	0.69	UK	2014	-1.36
3	AUS	2016	0.69	CAN	2016	0.58	DNK	2019	-1.03
4	CAN	2016	0.58	NOR	2018	0.57	DNK	2015	-0.80
5	NOR	2018	0.57	SWI	2018	0.48	DNK	2017	-0.71
6	ITA	2012	0.50	SWI	2019	0.40	NOR	2019	-0.60
7	BEL	2012	0.49	FRA	2018	0.33	SWE	2016	-0.31
8	SWI	2018	0.48	SWI	2017	0.31	UK	2018	-0.29
9	SWE	2012	0.46	GER	2019	0.31	SWE	2017	-0.26
10	FIN	2012	0.45	BEL	2017	0.25	SWE	2018	-0.11

While Table 5.2 is a useful way of identifying potentially surprising macroprudential inaction, it does not account for the fact that perhaps the countries identified had *already* acted in the concurrent (or previous) years in response to the developing risk environment. Similarly, macroprudential authorities may subsequently "catch up" with later tool tightening.

[29] Note that this exercise relates directly to the histogram in Figure 5.2: the left panel of Table 5.2 identifies the dark blue bars furthest to the right in the histogram where no action was taken; the right panel of Table 5.2 identifies the light blue bars furthest to the left.

One way of addressing the first concern is to compare the latest *level* of the CCyB with the latest level of GDP-at-risk across our sample. The left panel of Figure 5.3 illustrates the simple correlation between the current CCyB setting and the level of GDP-at-risk. On average, it suggests that the emerging CCyB reaction function is to set a CCyB of around 1% when GDP-at-risk is around its historical average and to increase the CCyB by about 70bps for each 1pp deterioration in GDP-at-risk. However, there is substantial international heterogeneity in CCyB activism with respect to GDP-at-risk. This confirms some of the patterns in Table 5.2, eg with Norway, Sweden and Denmark appearing to be very activist relative to the aggregate risk environment they are facing. To illustrate that further, the right panel of Figure 5.3 simply plots the actual CCyB settings versus those implied by the line of best fit on the left panel for the three countries with the lowest CCyB relative to its fitted value (USA, Germany and France) and for the three countries with the highest CCyB relative to its values (Norway, Sweden and Denmark).

Figure 5.3: The latest CCyB setting and GDP-at-risk



In summary

Taken together, this section illustrates that estimates of "GDP-at-risk" can provide a useful aggregate measure with which to summarise a multi-dimensional risk environment. Moreover, our GDP-at-risk measure does a reasonable job at capturing the factors that have driven macroprudential tool use in practice and provides a means to compare macroprudential activism across countries on a consistent basis.

5.2 Comparing the GDP-at-risk benchmark to what is being done in practice

Throughout Section 5.1, our GDP-at-risk approach imposed the restriction that policymakers weight the four indicators according to their marginal performance at predicting the severity of past downturns. Our final illustrative exercise relaxes this restriction on indicator weighting and explores the weight placed on each indicator in practice, in a multivariate setting.

Table 5.3 presents the results of multivariate counterparts to the regressions described in Section 4. Each model seeks to explain tool usage as a function of the four vulnerability indicators that individually appeared to predict tool usage in section 4 (that is household credit growth, corporate credit growth, house price growth and low volatility). This approach determines the weight of individual indicators endogenously, in a way that most accurately predicts tool usage. By design, this approach will perform better at predicting the tool usage we observe in the data than the GDP-at-risk weights we imposed in section 5.1. However, by estimating the weights endogenously we decreases the degrees of freedom in our regression, which makes it more difficult to establish statistical significance.

Table 5.3: Multivariate regression of tool usage on individual vulnerability indicators

	Housing (Probit)	CCyB (Probit)	CCyB (Linear)	**Memo:** GDP-at-risk coefficients (impact on GDP tails)
Coeffs:				
HH credit growth (3yr)	0.30	1.02***	0.38***	0.39
NFC credit growth (3yr)	0.25	-0.7***	-0.14**	0.35
Real house price growth (3yr)	-0.10	0.55*	0.09	0.06
Volatility	0.00	0.56**	0.19***	-0.02
Constant	-0.88***	-1.37***	0.43***	
R-squared	0.09	0.29	0.30	
Number of obs	120	120	120	
Coeffs (share of total):				
HH credit growth (3yr)	67%	72%	73%	49%
NFC credit growth (3yr)	56%	-49%	-26%	45%
Real house price growth (3yr)	-23%	38%	17%	8%
Volatility	0%	39%	36%	-2%
	100%	100%	100%	100%

We draw three conclusions from the top half of the Table 5.3. First, even using the multivariate specification, it is difficult to predict the usage of housing tools. In fact, when all the indicators are added together, none of them are individually significant and the pseudo R^2 is no better than for the univariate specifications in the last section. Second, the multivariate analysis works much better for predicting the moves in the CCyB. The (pseudo) R^2 for either the probit specification or the linear model are much higher, explaining around 30% of CCyB variation and most of the variables are significant. The magnitude of several imply large effects, with a one standard deviation increase in household credit, decrease in volatility and increase in house prices typically pushing the CCyB up by 38bps, 19bps and 9bps respectively.

Third, there is an odd correlation between non-financial credit growth and CCyB usage. In both specifications, high levels of NFC growth *reduce* the likelihood of a CCyB move. This could reflect collinearity, given the small sample size, or perhaps just an omitted variable problem. This is something we will investigate further in subsequent versions of this paper.

The bottom section of Table 5.3 compares the relative weight put on different indicators to the GDP-at-risk benchmark we considered in section 5.1. There are three key differences. First, countries appear to put less weight on non-financial credit growth when deciding whether to tighten the CCyB than our benchmark approach would suggest. Second, relative to our benchmark, real house price growth is underweighted when countries decide whether to tighten housing tools, but is over weighted in the context of CCyB decisions. Finally, consistent with the univariate regressions discussed above, countries appear to tighten the CCyB in response to lower equity price volatility, when our benchmark suggests there should be little reaction. Alongside these comparisons on the relative weighting of the four included indicators, recall from Table 4.1 that GDP-at-risk analysis would also suggest including the household DSR and perhaps the current account deficit in the macroprudential reaction function, which there is currently no evidence of in practice.

There are a number of reasons why countries may optimally deviate from indicator weightings implied by GDP-at-risk analysis. First, they may take into account changes in the structure of the financial system that mean indicators that mattered in the past are less likely to determine the severity of future downturns. Second, the different weights may reflect the fact that the calibration of tools should not be linked to the aggregate risk environment, but should instead reflect vulnerabilities that can be addressed via the specific tools in question. However, the evidence for the second explanation is mixed at best: arguably housing tools should be driven by risks specific to the household sector and/or the housing market. However, when determining whether to deploy housing tools countries appear to be placing less rather than more weight on more targeted indicators, such as household credit growth and house price growth (relative to the CCyB reaction function). Third, housing policies may be put in place as structural guardrails, rather than being responsive to fluctuations in vulnerabilities over the cycle, such that the link between risk indicators and tool action might not be expected to be tight.

It is also worth bearing in mind that macro-prudential policy remains – at best – in its adolescence, so it should not be surprising that countries are yet to converge towards a common reaction function when deciding which tools to deploy or tighten and are continuing to learn about which indicators to attach most weight to.

6 Conclusion

The analysis in this paper is an early attempt to assess whether there is any evidence of a common reaction function beginning to emerge in use of some macroprudential tools. We recently started to see both increasing tool usage and increasing dispersion in the macro-financial risk environments of different countries, so there is now a growing evidence base that we can draw on. However, given the limited time in which macroprudential tools have been deployed there are still serious data limitations in doing any empirical work on this topic.

With this caveat in mind, there are still several interesting relationships that are apparent in the data. First, we find that both the CCyB and housing tools tend to be tightened in response to rapid household credit growth, with a one standard deviation increase approximately doubling the probability that tools are tightened in the following year. Credit growth has been discussed as an early warning indicator for financial crises for many year before the financial crisis, so it seems sensible for countries to consider household credit growth when deciding whether to activate or tighten policy. However, a couple of the financial variables that have helped predict severe recessions do not seem to predict the actions of macro-prudential policymakers, notably the household debt service ratio. It will be interesting to see whether these patterns hold up once we have gone all the way through another financial cycle and more data accumulates.

We also find that a measure of financial stability risks that aggregates credit growth and other macro-financial vulnerabilities into on *overall level of risk* ("GDP-at-risk") performs well at predicting when some macroprudential tools are deployed. However, when comparing the relative weights that policymakers appear to be putting on various indicators in practice to the weight that we would need to put on the indicators to predict tail risk in the past we find a number of differences. In particular, countries have tended to overweight household credit relative to its GDP-at-risk weights and put too little weight on other indicators, including corporate credit growth.

While the risk indicators we consider can explain around 30% of variation in the CCyB, their explanatory power over housing tools is much more limited. This may indicate that housing tools are in part put in place as structural guardrails rather than to address current vulnerabilities. The limited explanatory power also indicates that there are other important factors affecting the use of macro-prudential tools. For example, the willingness to implement these measures may reflect whether countries experienced a painful crisis in the past, and/or if their macroprudential frameworks have been designed to avoid inaction bias. Exploring these factors will be the subject of further work.

Our analysis also points to other questions that warrant further work. One is around the exact timing of policy interventions. Most financial risks build slowly, so the exact timing of when they might be deployed might not matter. But it will still be interesting to consider heterogeneity in how long countries take to implement effective policy responses to emerging vulnerabilities. Finally, there are a number of data challenges that limit our analysis of reaction functions. For example, there are no standard measures of the distribution of DSRs across borrowers that are available consistently across countries. To the extent that such data is being collected by individual countries, it would be useful to produce a consistent dataset that helps compare statistics on the tail of the most highly indebted borrowers across countries.

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Annex

A.1. Record of macroprudential housing policy actions by country

Table A1.1: Australian macroprudential housing measures

Announcement date	Policy measure	Set by
December 2014	• 10% benchmark on annual growth of mortgage lending to investors (trigger point for more intense supervisory action)	Australian Prudential Regulation Authority (APRA)
March 2017 (implemented 6 months later)	• 30% benchmark on the flow of new interest-only lending as a share of total new residential mortgage lending.	APRA

Source: Review of APRA's prudential measures for residential mortgage lending
https://www.apra.gov.au/sites/default/files/review_of_apras_prudential_measures_for_residential_mortgage_lending_risks_-_january_2019.pdf

Table A1.2: Belgian macroprudential housing measures

Announcement date	Policy measure	Set by
May 2014	• Risk weight add-on of 5pp for IRB banks' residential mortgage exposures.	Banque Nationale de Belgique (NBB)
April 2018	• 33% scalar multiplier on IRB banks' residential mortgage risk weights.	NBB

Source: The measures are described in the NBB's submission to the European Systemic Risk Board,
https://www.esrb.europa.eu/pub/pdf/other/esrb.notification180314_crr_be.en.pdf

Table A1.3: Canadian macroprudential housing measures

Announcement date	Policy measure	Set by
July 2008 (implemented October)	• Maximum LTV for new mortgages reduced from 100% to 95%. Maximum Total Debt Service (TDS) ratio of 45% introduced.[30] • Maximum amortisation lowered from 40 to 35 years.	Canada Mortgage Housing Corporation (CMHC)
February 2010 (implemented April)	• Maximum LTV for refinanced mortgages reduced from 95% to 90%. • Maximum LTV for investment properties reduced from 95% to 80%.	CMHC
January 2011 (implemented March)	• Maximum amortisation reduced from 35 to 30 years. • Maximum LTV for refinanced mortgages lowered from 90% to 85%.	CMHC
June 2012 (implemented July)	• Maximum TDS ratio reduced to 44%. • Maximum Gross Debt Service (GDS) ratio capped at 39%. • Maximum amortisation reduced from 30 to 25 years. • Maximum LTV for refinanced mortgages lowered from 90% to 85%.	CMHC
December 2015 (implemented February 2016)	• Maximum LTV for new mortgages reduced from 95% to 90% for portion of house price above CA$500k.	CMHC

[30] Canada's Total Debt Service (TDS) ratio defined as the ratio of principal + interest + taxes + heating costs + other debt obligations to gross annual income. The Gross Debt Service (GDS) ratio defined as the ratio of principal + interest + taxes + heating costs to gross annual income.

December 2015 (introduced November 2016)	• Introduction of a downturn LGD floor in mortgage risk weight calculation.	Office of the Superintendent of Financial Institutions (OSFI)

Source: 'Appendix: Mortgage Finance Policy Changes in Canada' in Bank of Canada Financial System Review, June 2017
https://www.bankofcanada.ca/wp-content/uploads/2017/06/fsr-june2017.pdf

Table A1.4: Denmark's macroprudential housing measures

Announcement date	Policy measure	Set by
2012 (effective 2013)	• Affordability test: borrowers must be able to service a 30 year fixed interest rate amortising mortgage.	Ministry of Industry, Business and Financial Affairs
2014 (effective as of 2018)	• 25% Cap on fraction of mortgages with interest rate fixed for less than 2 years and where LTV is three-quarters or more of the LTV limit (80% for residential property to qualify for covered bonds).	
2015	• Minimum downpayment of 5%.	
2016	• Higher interest rate stress test and net wealth requirements where mortgage > 4 times income (Copenhagen and Aarhus).	
2017 (effective 2018)	• For households with debt-to-income > 4 and LTV > 60%: interest rate fixation must be at least 5 years and deferred amortisation only an option on 30-year fixed rate loan.	

Source: Table 1, 'Policies to mitigate excessive credit growth and leverage', in
https://www.nationalbanken.dk/en/publications/Documents/2018/11/ANALYSIS_Discussion%20paper%20for%20Macroprudential%20policy%20conference.pdf

Table A1.5: Finland's macroprudential housing measures

Announcement date	Policy measure	Set by
July 2016	• Maximum LTV set at 90%.	Fin-FSA
June 2017 (effective from January 2018)	• Mortgage risk weight floor set at 15%.	Fin-FSA
March 2018 (effective July 2018)	• Maximum LTV reduced to 85% (other than for first-time buyers).	Fin-FSA

Source:
For details of the risk weight floor, see 'Notification of measure taken pursuant of Article 458 of the Capital Requirements Regulation', https://www.esrb.europa.eu/pub/pdf/other/esrb.notification_other170627_Finland.en.pdf
For details of the LTV regulations, see 'Bank of Finland Bulletin', June 2015
https://www.bofbulletin.fi/en/archive/?issue=2015-2 and
'Template for notifying national macroprudential measures not covered by CRR/CRD'
https://www.esrb.europa.eu/pub/pdf/other/esrb.notification180321_FI_ltc.en.pdf?0fb8f6b482a144952ca148d0899bcf11

Table A1.6: Netherlands' macroprudential housing measures

Announcement date	Policy measure	Set by
January 2012 (phased in over subsequent 6 years)	• Maximum LTV ratio of 106-100%	Ministry of Finan
January 2013	• Cap on debt service to income ratio (differentiated by income group)	

Sources: 'Kingdom of the Netherlands: Financial Sector Assessment Program: Technical Note – Macroprudential Policy Framework, 2017
https://www.imf.org/en/Publications/CR/Issues/2017/04/13/Kingdom-of-the-Netherlands-Netherlands-Financial-Sector-Assessment-Program-Technical-Note-44818

Table A1.7: Norway's macroprudential housing measures

Announcement date	Policy measure	Set by
March 2010 (converted to regulation in June 2015)	• Maximum LTV for new mortgages set at 85% (guideline). • Interest rate stress of 5% points in mortgage affordability assessment. • Principal repayment requirement of 2.5% annually for mortgages with LTV above 60%	Finanstilsynet (Financial Supervisory Authority of Norway)
January 2017	• Maximum total debt to income ratio of 5x.	Finanstilsynet

Source: 'Table 1.1 Measures to mitigate vulnerabilities in Norway', in Norges Bank Financial Stability Report 2017
https://static.norges-bank.no/contentassets/f3a45cb94d334c4cb619cc549952d553/fs_report_2017.pdf?v=11/02/2017091700&ft=.pdf

Table A1.8: Sweden's macroprudential housing measures

Announcement date	Policy measure	Set by
October 2010	• Maximum LTV ratio of 85% on new mortgages.	Finansinspektionen (FI)
June 2016	• New mortgages with LTV > 70% must amortise by a minimum of 2% annually and those with LTV between 50% and 70% must amortise by at least 1% annually.	FI
March 2018	• Amortisation requirement tightened. New mortgages greater than 4.5x gross income must amortise by a minimum of 3% annually (if LTV > 70%) or 2% annually (if 50% < LTV < 70%).	FI
August 2018	• Risk weight floor of 25% on banks' mortgage exposures.	FI

Source:
On the LTV cap, see 'Sweden: Financial Sector Assessment Program Update—Technical Note on Household Indebtedness: Implications for Financial Stability', https://www.imf.org/external/pubs/ft/scr/2011/cr11289.pdf
On the amortisation requirement, see 'The mortgage market in Sweden – November 2018'
https://www.swedishbankers.se/media/3906/1809_bolaanemarknad-2018_en.pdf
On the 25% risk weight floor, see 'Risk weight floor for Swedish mortgage exposures',
https://www.fi.se/contentassets/85100a98bf914e219f4f39bb0a58741d/art458-beslut-2018-08-22_eng.pdf

Table A1.9: Switzerland's macroprudential housing measures

Announcement date	Policy measure	Set by
July 2012	• Self-regulation: maximum LTV of 90% • Self-regulation: mortgages must be amortised to two-thirds of collateral value at origination over 15 years.	Swiss Bankers' Association
January 2013	• Increase in mortgage risk weights: 100% risk weight for mortgage amount above 80% of property value; bank-specific multiplier for IRB banks; 100% risk weight for mortgages that do not meet minimum standards	FINMA
February 2013 (effective September 2013)	• Mortgage sectoral CCyB set at 1%	Federal Council (SNB proposal)
January 2014 (effective end-June)	• Mortgage sectoral CCyB set at 2%.	Federal Council (SNB proposal)

Source:'Macroprudential policy in Switzerland: the first lessons', Jean-Pierre Danthine May 2016
https://voxeu.org/article/macropru-policy-switzerland

Table A1.10: UK's macroprudential housing measures

Announcement date	Policy measure	Set by
June 2014	• Maximum LTI for new mortgages set at 4.5x. • Interest rate stress of 3% points in mortgage affordability assessment.	Bank of England

Jurisdictions in our sample that are classified as *not* having implemented macroprudential housing measures:

France
Germany
Italy
Spain
The United States

Sources:
For European countries, *Table 2 Overview of active macroprudential measures in Europe (Q4 2018)* in 'A Review of Macroprudential Policy in the EU in 2018', April 2019
https://www.esrb.europa.eu/pub/pdf/reports/esrb~32aae4bd95.report190430_reviewofmacroprudentialpolicy.pdf

A.2. Principles underpinning the classification of policy actions

We document six types of macroprudential housing measures: (1) debt-service ratio (DSR) limits, (2) loan-to-income (LTI) limits, (3) affordability tests, (4) amortisation and maturity constraints, (5) loan-to-value (LTV) limits, and mortgage risk weight increases (6).
To qualify as a 'DSR limit', a policy must include a quantitative limit on the ratio of mortgage debt or total debt obligations to the borrowers' income (net or gross). If instead the obligation falls on the lender to check affordability, either under current rates or under a prescribed stressed interest rate, we classify this in the 'affordability test' category.

We group these policies into two buckets: *borrower-resilience tools* and *lender-resilience tools*. The defining characteristic of *borrower-resilience tools* is that their calibration depends on characteristics of the borrower, for instance their income or other debt obligations. The calibration of *lender-resilience tools*, by contrast, is uniform across borrowers. On this basis, loan-to-income limits, debt service limits and affordability measures can all be described as borrower-resilience tools; while loan-to-value limits, risk weight floors and amortisation/term limits are lender-resilience tools.

Many of the policies are calibrated in a highly granular way, with restrictions differing according to the status of the borrower (eg whether a first-time buyer, a property investor and so on). We focus on measures that apply to new owner-occupier mortgage borrowers, rather than those remortgaging or buying for investment purposes. We also abstract from measures that apply only in specific regions, focusing instead on measures that apply at the nationwide level.

Finally, we classify measures from the date at which they are announced, rather than when they take effect.