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JEL Classification: G01, G18, G21

Keywords: Financial Stability, GDP-at-Risk, macroprudential policy, quantile regressions, local projections

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Credit, capital and crises: a GDP-at-Risk approach◇

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1 Introduction

What is the relationship between vulnerabilities associated with elevated debt and asset prices and downside risks to economic growth? Recent research has established a strong relationship between indicators of financial conditions derived from asset prices and downside risks to growth in the *near term* up to one year ahead (Adrian et al. (2019)). In this paper, we augment this programme of research by considering a wider set of macroprudential indicators, including measures of credit, house prices, external imbalance, and banking system resilience information routinely monitored by central banks. We find that these indicators have forecasting power over downside risks to economic growth over the medium-term, specifically 3 to 5 years ahead.

We first construct a novel cross-country panel dataset covering 16 advanced economies over the period 1980:Q4-2017:Q4. For each country, we collect information on credit-to-GDP ratios, house price growth, current account imbalances and a fast-moving measure of financial conditions. We also construct a measure of banking sector leverage computed as tangible common equity ratios, which we obtain by aggregating individual bank balance sheet information in each country. This permits us to assess the impact of the substantial increase in capital requirements, and hence banks' capital, following the Global Financial Crisis on downside risks. We apply quantile regressions (Koenker and Bassett (1978)) to estimate the relationship between these indicators and the shape of the GDP growth distribution across our panel. Using local projections (Jordà (2005)), we explore how this relationship varies up to 20 quarters ahead, focusing on the 12-quarter horizon as a benchmark. Given implementation and transmission lags, this arguably is the relevant policy horizon for implementing macroprudential policy responses to address the impact of building vulnerabilities.[1]

We find significant relationships between each of the vulnerability metrics and the 5$^{\text{th}}$ quantile of the future GDP growth distribution (which we refer to as "GDP-at-Risk").[2] Moreover, these relationships are both economically intuitive and meaningful in magni-

[1]For instance, unless in exceptional circumstances, the countercyclical capital buffer has an implementation lag of one year. Moreover, macroprudential authorities may prefer to vary their countercyclical tools in a gradual manner (see, for example, Bank of England (2016)).

[2]See Cecchetti (2006) and De Nicolò and Lucchetta (2012) for early expositions of this approach, and Adrian et al. (2018, 2019) for more recent contributions to this literature.

tude. Forecasting 12 quarters ahead, we find that GDP-at-Risk cumulatively deteriorates by 0.9, 0.75 and 1.5 percentage points following one-standard-deviation increases in the 3-year change in the credit-to-GDP ratio, 3-year real house price growth and the current account deficit (as a proportion of GDP) respectively. These results are consistent with findings from the early-warning literature that analyses the precursors of banking and currency crises (e.g. Reinhart and Kaminsky (1999), Schularick and Taylor (2012)).

In a novel result, we find that higher bank capital mitigates these increases in risk: a one-standard-deviation increase in bank capitalisation, as measured by tangible common equity ratios, leads to a cumulative 0.9 percentage point improvement in GDP-at-Risk over three years. By contrast, the median projection does not significantly change in response to higher bank capital. This finding is consistent with theories that emphasise the role of bank capital as a buffer to absorb losses in a stress. Franta and Gambacorta (2020) provide collaborating evidence on the positive and significant role of macroprudential policies, in the context of loan-to-value ratio and loan provisions, in mitigating the risks to output growth. Similarly, Galán (2020) shows the benefits of macroprudential policies on the left-hand tail of GDP growth distribution.

In contrast to Adrian et al. (2018), we find no impact on 3-year-ahead GDP-at-Risk from movements in financial conditions or asset price volatility. The impact of these indicators is apparent only in the near term (i.e. at horizons of up to one year), over which time a tightening in financial conditions depresses GDP-at-Risk. This finding is in line with evidence from Plagborg-Møller et al. (2020) that financial variables have limited forecasting power. Our findings are robust to alternative specifications of our regression equation such as the inclusion of the Miranda-Agrippino and Rey (2015) measure of the global financial cycle and single variable quantile regression setups.

Using our estimates, we illustrate the significant time variation in medium-term tail risks in advanced economies over the past four decades, decomposing the contributions of each of our vulnerability indicators. In the United States, our estimates point to a sharp deterioration in the 3-year-ahead forecast of GDP-at-Risk prior to both the early 1990s recession and the Global Financial Crisis driven by rapid growth in credit and house prices and, on the latter occasion, a widening current account deficit.

While this retrospective analysis is encouraging, we find that including the crisis episode and its aftermath is key to uncovering the impact of bank leverage on tail risk in our sample. When calculated over subsamples, we find an unstable relationship between these variables prior to 2007. This finding is perhaps unsurprising given that the Global Financial Crisis was the first simultaneous full-blown banking crisis hitting advanced economies since the Great Depression. More promisingly, the relationships between other vulnerability metrics and GDP tail risk are robust across subsamples. In particular, estimates of the impact of house prices, current account deficits and financial conditions remain stable. While there is some instability in the estimated impact of credit growth in our full baseline model, we find the impact of this indicator to be stable in single variable regressions.

These findings may be of interest to policymakers in central banks and other policy institutions charged with monitoring systemic risks in the financial system. Since the crisis, a plethora of such macroprudential frameworks and associated policy committees have been set up for this purpose. Edge and Liang (2019) document that such committees now exist in 47 countries around the world. A key challenge in operationalising these frameworks is improving our understanding of the impact of indicators of underlying vulnerabilities observable today on the potential for destabilising financial instability in future. Our findings contribute to our collective understanding of these relationships, and hence can inform the inferences policymakers draw from developments in different macroprudential indicators. They suggest the potential for conditioning the stance of macroprudential policy on such vulnerability indicators. These findings will also be of interest to researchers working to develop macroeconomic models that can generate crisis dynamics (Adrian and Boyarchenko (2012), Brunnermeier and Sannikov (2014) and He and Krishnamurthy (2014)). Our results can inform the development and calibration of these models by providing some basic empirical facts about the precursors of tail risk events.

Our paper relates to three main strands of the literature: first, and most directly, we build on a strand of studies that use quantile regressions to estimate the distribution of GDP growth conditional on financial and economic conditions (Adrian et al. (2018), Aikman et al. (2018), Adrian et al. (2019), Franta and Gambacorta (2020) and Galán

(2020)).[3] We contribute to this body of work by exploring how downside risk changes with respect to multiple indicators, including the effect of measures of banking system resilience.

Second, our work relates to the large literature on early warning indicators of financial crises, which seeks to find empirical regularities in the run-up to financial crises. Perhaps the most important result in this literature is the importance of credit-based variables as leading indicators of both the likelihood and severity of crises (see e.g. Schularick and Taylor (2012) and Jordà et al. (2013)).[4] In this paper, we provide new evidence on the relationship between banking system capital ratios and macroeconomic tail risk. The closest empirical work to ours is Jordà et al. (2017), who examine the relationship between bank capital ratios and the probability and severity of crises using a large cross-country data set. While they find no relationship between measures of bank capital and the probability of crises, they show that conditional on being in a crisis, countries with better capitalised banking systems experience faster recoveries. While our procedure does not condition on crisis states, our results are qualitatively consistent with theirs in that we find that higher capital ratios improve tail growth outcomes over the medium term. Our finding is also consistent with microeconometric evidence that banks that entered the financial crisis with higher capital ratios contracted their lending by less (Carlson et al. (2013)) and with work documenting the transmission of bank distress to real economic activity (see, for example, Chodorow-Reich (2014), who shows that bank distress led to an economically significant reduction in employment at small and medium-sized US firms reliant on bank credit). Third, our work relates to the growing literature on the real effects of macroprudential policy actions (e.g. International Monetary Fund (2011); Kuttner and Shim (2016); Bruno et al. (2017); Akinci and Olmstead-Rumsey (2018); Richter et al. (2018)).

The rest of the paper is organised as follows: Section 2 introduces our data and Section 3 describes our quantile regression methodology. Section 4 presents our results,

[3]Previously, the impact of housing and equity price booms on tail risks were explored by Cecchetti (2006) and Cecchetti and Li (2008). Similarly, Giglio et al. (2016) employs quantile regressions to assess the predictive power of various systemic risk indicators.

[4]For research on the relationship between credit growth and financial crisis risk, see Gavin and Hausmann (1996); McKinnon and Pill (1996); Eichengreen and Arteta (2000); Honohan (2000); Bordo et al. (2001); Borio and Lowe (2002b,a, 2004); Borio and Drehmann (2009); Drehmann et al. (2011); Mendoza and Terrones (2014); Baron and Xiong (2017); and Bridges et al. (2017).

while Section 5 concludes. Appendices A and B provide additional analysis and details of the dataset respectively.

2 Data

Our analysis is based on a cross-country panel dataset using time series from 16 advanced economies over the period 1980:Q4-2017:Q4. These countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States.[5]

For each country, we collect time series for five vulnerability measures: *i)* the 3-year percentage point change in the private non-financial sector credit-to-GDP ratio; *ii)* 3-year real house price growth; *iii)* the current account deficit as a percentage of GDP; *iv)* realised volatility over one quarter in equity prices (we also report results replacing this with a financial conditions index); *v)* banking system tangible common equity (TCE) to total asset ratios as a measure of the resilience of the financial system. The TCE ratio is a widely-used measure of banks' resilience (see Basel Committee on Banking Supervision (2010) and Demirgüç-Kunt et al. (2013)).[6] The measurement of indicators *i)* - *iii)* is relatively standard, but *iv)* and *v)* warrant some further discussion.

Bank capital

To construct a cross-country dataset for the TCE ratio, we first collect individual bank balance sheet data on group-level TCE (defined as common equity minus preference shares and intangible assets) and total tangible assets for banks in each of the aforementioned countries.[7] This information is obtained from Thomson Reuters Worldscope.[8] The TCE

[5]We experimented with including Japan in this sample, but found that its inclusion generated implausibly large moves in some of the estimated coefficients. We re-ran our estimation removing each country individually, and the results did not change significantly when any other country was removed.

[6]The TCE measure we use is strongly correlated with other measures of banking system leverage. For instance, it has a correlation of 0.75 with the Bank of England's leverage indicator for the United Kingdom.

[7]Total assets here covers total cash and due from banks, investments, net loans, customer liability on acceptances, investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment and other assets.

[8]In general, Worldscope targets publicly quoted companies, and its coverage depends on certain criteria being met such as a market capitalisation of over $100m or belonging to one of the major stock indices.

ratio for a bank is the ratio of its tangible common equity to tangible assets. To aggregate these data into a single country-level TCE ratio that is comparable over time, we use a chain-weighted approach, which allows us to take into account the entry and exit of banks each period. Details of this approach are provided in Appendix B with summary statistics on the banks in our sample provided in Table B.III. Data are available at annual frequency – our measure for year t is taken at the end of year t, and is linearly interpolated to create a quarterly series. As we discuss later, our results do not change significantly if we use the annual series.

Financial conditions

To estimate the impact of country-specific financial conditions, we explore two alternative variables. We first use equity price volatility as a proxy for financial conditions in our baseline specification to make use of its longer data availability. This series can be extended back to 1980 with the other variables in our specification. The volatility series is measured as the monthly standard deviation of daily returns in each country's equity price index. For robustness, we also show results using a financial conditions index (FCI) with a sample beginning in 1991 as in Eguren-Martin and Sokol (2020). This FCI is a modified version of that constructed by International Monetary Fund (2017), which follows the methodology of Koop and Korobilis (2014). The headline FCIs comprise of term spreads, interbank spreads, corporate spreads, sovereign spreads, long-term interest rates, policy rates, equity returns and equity volatility. House price and credit growth variables are removed as they are introduced to the specification separately to isolate their impact.[9] The FCI and equity volatility series are strongly correlated; for the US, the correlation is 0.92, while for the UK it is 0.72.

We also use the central bank's policy rate and inflation rate alongside lagged quarterly GDP growth for each country in the empirical analysis as macroeconomic control variables. All variables are standardised by their country-level means and standard deviations. We provide details of the data sources and descriptive statistics in Appendix B.

[9]We would like to thank Fernando Eguren-Martin for providing these data. Eguren-Martin and Sokol (2020) discuss the properties of a related FCI measure and its global component.

3 Quantile regression methodology

In this section, we turn to quantile regressions to explore how the full distribution of real GDP growth varies with the vulnerability metrics described in the preceding section. Quantile regression is a widely-used technique that allows researchers to analyse how changes in a set of conditioning variables influence the shape of the distribution of the variable of interest (Koenker and Bassett (1978)). In our application, we estimate quantile regressions for a panel of advanced economy countries, requiring the treatment of country-specific fixed effects to avoid estimation bias. We follow Canay (2011) and assume that country fixed effects are locational shifts for the entire distribution (i.e. country fixed effects are the same across different quantiles). Under this assumption, we are able to employ a two-step procedure to eliminate country fixed effects and estimate our coefficients of interest.[10]

The first stage involves using a standard within estimator to estimate the fixed effects. We estimate the following linear pooled panel model by OLS:

$$y_{i,t+h} = \alpha_i^h + \gamma^h X_{i,t} + \epsilon_{i,t}, \tag{1}$$

The left-hand-side of Equation 1 is the average annualised growth rate of real GDP over h quarters, $y_{i,t+h}$, where $y_{i,t+h} = \frac{(Y_{i,t+h} - Y_{i,t})}{h/4}$ and $Y_{i,t+h}$ denotes the *log* level of real GDP of country i at time $t+h$ for horizons $h = 1, 2, \ldots, 20$ quarters. Our coefficient units are thus comparable across horizons. Fixed effects are denoted by α_i^h and X_{it} contains our vulnerability metrics and control variables described in Section 2 for country i measured at time t.[11]

Canay (2011) shows that the fixed effects can be estimated as:

$$\hat{\alpha}_i^h = \frac{1}{N} \sum_{i,t} (y_{i,t+h} - \hat{\gamma}^h X_{i,t})$$

In the second stage, we define the dependent variable as $y^*_{i,t+h} = y_{i,t+h} - \hat{\alpha}_i^h$. We then

[10] There are other ways of treating fixed effects in quantile regression setting, e.g. Galvao (2011). However, these methods rely on larger panel datasets to estimate fixed effects accurately at each quantile.

[11] In our baseline model, the y variable is not standardised which means that coefficients can be interpreted as percentage point changes in real GDP growth. The results do not change significantly if we standardise GDP growth as well as the explanatory variables.

proceed with quantile regressions as follows to estimate β^h_τ,

$$\hat{\beta}^h_\tau = \underset{\beta^h}{\operatorname{argmin}} \sum_{i,t} \rho_\tau (y^*_{i,t+h} - X_{i,t}\beta^h_\tau)$$

where τ denotes the quantile under consideration and ρ_τ is the standard asymmetric absolute loss function: $\rho_\tau(u) = u \times (\tau - \mathbb{1}\{u < 0\})$. The model is estimated from 1 to 20 quarters ahead using local projections (Jordà (2005)) to understand how the left tail of GDP growth develops over the forecast horizon. For inference, we follow the block bootstrapping method of Kapetanios (2008) (see also Lahiri (2003)). This method resamples the data over blocks of different time series dimensions to generate the standard errors of the estimated coefficients for respective quantiles. In our application, we resample the time series observations with replacement using 8 blocks (corresponds to 2 years), although changing the block size to 4 or 12 blocks does not alter our results.

4 Results

We first focus on the relationship between our vulnerability indicators and the projected 5$^{\text{th}}$ percentile of GDP growth (henceforth referred to as "GDP-at-Risk"). Figure 1 plots local projections of the estimated change in GDP-at-Risk at various horizons. The results are reported for common annualised GDP growth units. Note that we invert the sign of the current account balance and equity volatility following our priors that an increase in the current account deficit and periods of low volatility may bring about a deterioration in GDP-at-Risk over the medium term.

Overall, the coefficients for credit and the current account are always negative. Therefore, stronger increases in credit-to-GDP ratios or a wider current account deficit has a detrimental effect on tail risk across our entire forecast horizon. Stronger house price growth appears to have a beneficial effect in the short term, but in the medium term this effect is more than offset and the coefficient is negative after around two years. The fast moving volatility measure is only significant in the short term, indicating that a sharp spike in this indicator increases tail risk immediately but has little impact in the medium term. Finally, an increase in the capital ratio has a beneficial effect for GDP-at-Risk in the medium term. Our baseline specification also includes an intercept and controls, results for which are reported in Figure A.I.

We proceed by discussing these results in two stages: first, we focus on the impact of innovations in vulnerabilities on GDP-at-Risk over the medium term, which we take as a three-year horizon. Given that the local projections presented in Figure 1 are relatively flat between quarters 12 and 20, our focus on the 12$^{\text{th}}$ quarter is representative of a broader medium-term (3 to 5 year) horizon.[12] Second, we discuss our results across the GDP growth distribution, expanding our attention beyond the 5$^{\text{th}}$ percentile GDP-at-Risk measure.

4.1 Downside risks to growth over the medium term

In Figure 2, we summarise the impact of each of our vulnerability indicators and macroeconomic controls on GDP-at-Risk at the three-year horizon. We discuss each indicator in turn.

Credit, house prices and current account deficits

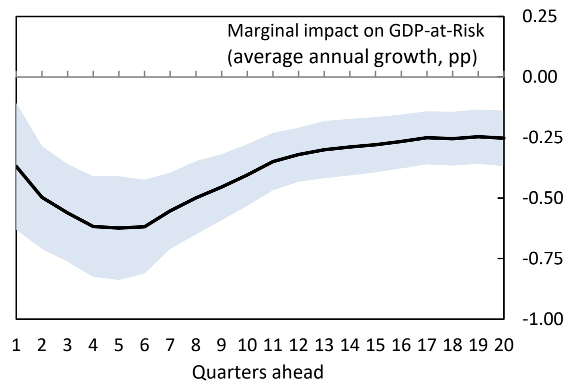
We find that medium-term tail risks to growth are aggravated by periods of rapid credit growth, house price growth and large current account deficits. This chimes with insights from the voluminous literature on early warning indicators of financial crises, a typical finding of which is that credit booms accompanied by rapid house price inflation tend to increase the probability and severity of crises (see, for example, Kaminsky and Reinhart (1999), Schularick and Taylor (2012), Jordà et al. (2013) and Aikman et al. (2018)).

The estimated impacts of each of these three vulnerabilities on GDP-at-Risk are both statistically and economically significant. For example, a one-standard-deviation increase in the 3-year change of the credit-to-GDP ratio is associated with a 0.3 percentage point weaker GDP-at-Risk per annum over the next 3 years, thus cumulating to 0.9 percentage

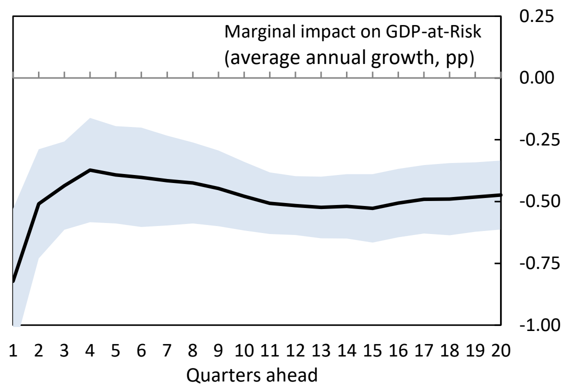
[12] Note that the local projections in Figure 1 give the average annual growth impact at each horizon. A flat, non-zero projection therefore implies a building cumulative level effect over time. For example, a coefficient of 0.25pp at the 4-year (16-quarter) horizon implies a total level effect of 1pp on GDP-at-risk. At the 5-year horizon it would imply a 1.25pp cumulative effect. If, instead, the level effect were permanent at 1pp, we would expect to see the projection gradually decay at longer horizons (to 0.2 in year 5, 0.17 in year 6, 0.14 in year 7, and so on).

Figure 1: Baseline results: local projections showing impact of each variable on 5^{th} percentile of GDP growth at horizons from one quarter to five years ahead

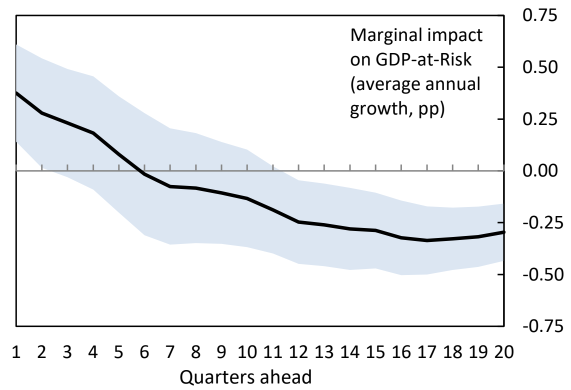
(a) Credit-to-GDP (3 year pp change)



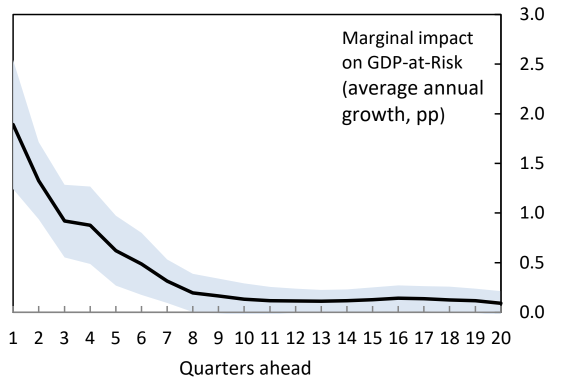
(b) Current account deficit



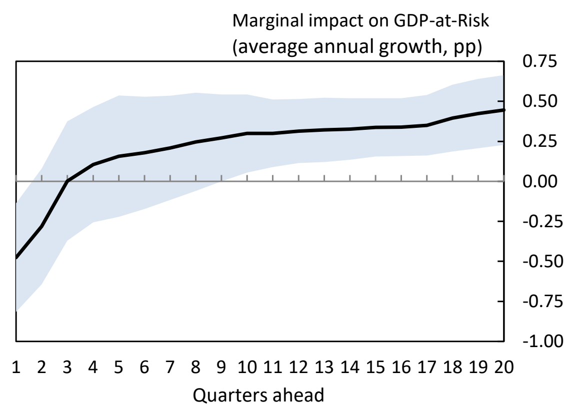
(c) Real house price growth (3 year)



(d) Volatility



(e) Bank capital (TCE) ratio



Note: These charts show the impact of a one-standard-deviation increase in a given indicator at time t on the 5^{th} percentile of real GDP growth at each horizon on the x-axis. GDP growth is measured as the average annual growth rate at each horizon. Confidence intervals represent ± 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

points over this period.[13] To give a sense of scale, between 2004 and 2007, the UK's credit-to-GDP ratio rose by 23 percentage points, 1.3 standard deviations above the mean change over the sample. Our credit result thus suggests that this was associated with a cumulative 1.2 percentage point deterioration in 3-year-ahead GDP-at-Risk over this period.

The estimated coefficient on real house price growth is similar in magnitude (−0.75 percentage points cumulatively), but somewhat less precisely estimated. The estimated impact of current account deficits on tail risk is twice as large, with a one-standard-deviation increase in the deficit increasing the severity of GDP-at-Risk in the medium term by 1.5 percentage points cumulatively. This is qualitatively consistent with potential amplification mechanisms associated with a heavy reliance on foreign funding. For example, to the extent that foreign flows prove relatively flighty, a large deficit may be associated with greater amplification of asset price and funding cost adjustments in the event of an adverse shock.

As a cross-check on these results, Appendix A reports results from an alternative specification of quantile regressions where the impact of each vulnerability indicator is estimated individually (see Figure A.III).[14] We obtain broadly similar results in this exercise. The medium-term coefficients for real house price growth and the current account change very little, but the magnitude of the coefficient for credit increases by two-thirds.

Volatility and financial conditions

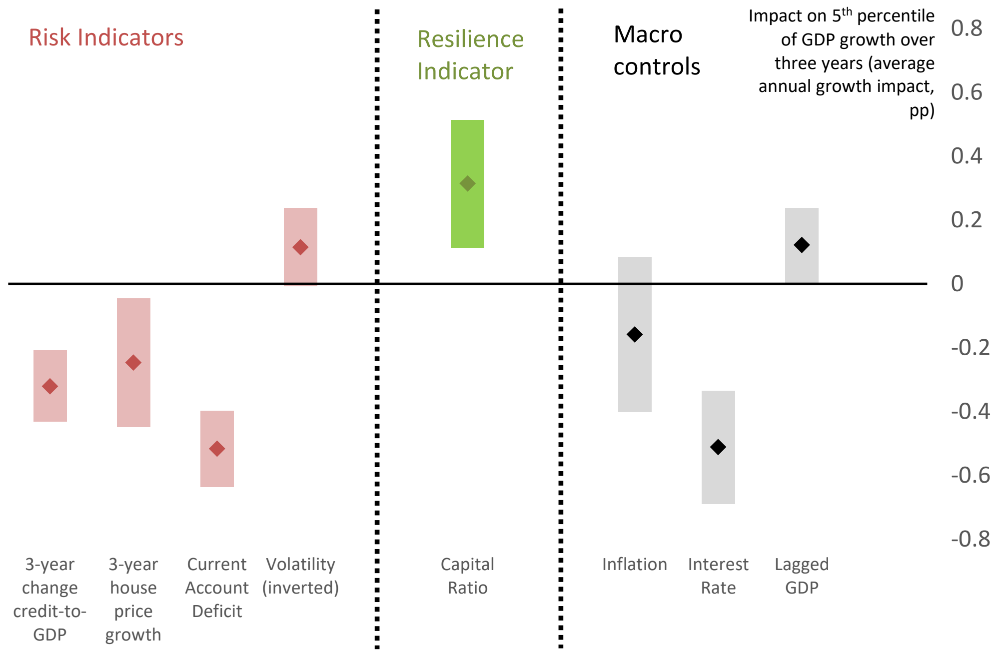
We find that a reduction in volatility is associated with a small decrease in the severity of GDP-at-Risk three years ahead. However this relationship is not statistically significant. As a cross-check on this finding, Table A.I (column 2) reports results from a regression where we replace our volatility measure with an index of financial conditions from Eguren-Martin and Sokol (2020).[15] Due to the availability of the index, we start

[13] As a robustness check, Figure A.II reports results of our baseline specification with credit split into its contributions from household and corporate borrowers. We find that after 20 quarters the effect of the changes in household credit is twice as severe as that of corporate credit.

[14] These regressions with individual vulnerability indicators also include macroeconomic controls.

[15] Eguren-Martin and Sokol (2020) follow the same methodology that the IMF employ in constructing cross-country FCIs which they regularly publish in their Global Financial Stability Reports, see e.g. https://www.imf.org/en/Publications/GFSR/Issues/2017/03/30/global-financial-stability-report-april-2017.

FIGURE 2: Impact of each variable on 5^{th} percentile of GDP growth at 3-year horizon



Note: This figure shows the impact of a one-standard-deviation increase in a given indicator at time t on the 5^{th} percentile of real GDP growth after 12 quarters. The impact on GDP growth is measured as the average annual growth rate over 3 years. Confidence intervals represent a ± 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

our sample in 1991. Reassuringly, our baseline results do not materially change in this variant, and we continue to find only a small relationship between financial conditions and medium-term GDP-at-Risk.[16]

Adrian et al. (2018) show that loose financial conditions create an intertemporal trade-off in that they reduce tail risks in the near term at the expense of a modest deterioration in GDP-at-Risk in the medium term. We observe very similar results when our regression specification is stripped down to include just the financial conditions index and lagged GDP growth. However, the medium-term impact on GDP-at-Risk cannot be distinguished from zero when we add our various vulnerability indicators and further macroeconomic controls, with the change in the policy rate having a noticeable impact.[17]

[16] An exception is the coefficient on real house price growth, which loses significance in this shorter sample.

[17] Adrian et al. (2018) include credit growth and house price measures within their FCI measure. In contrast, we strip these out of our FCI measure to avoid overlap with our slow-moving credit and house price vulnerability measures.

This finding is in line with evidence from Plagborg-Møller et al. (2020) that financial variables might have limited power on forecasting downside risks.

To the extent that the transmission of loose financial conditions to larger macroeconomic tail risks operates via boosting property prices and fostering excessive credit growth, we capture these channels directly with the inclusion of these variables. Indeed, Adrian et al. (2018) find that the impact of loose financial conditions on GDP-at-Risk in the medium term is amplified in the event of credit boom, defined as a dummy variable when credit growth is in the top 30 percent of its distribution. For the purposes of informing the gradual application of countercyclical macroprudential policy, our preferred approach is to estimate a continuous mapping from building credit vulnerabilities to GDP-at-Risk directly rather than relying on a binary credit boom indicator.

Given that changes in downside risks may be driven by global developments, we consider how fluctuations in the global financial cycle influence GDP-at-Risk. Our hypothesis is that when risk appetite is heightened globally, downside risks to growth over the medium term are more severe than if this is only a domestic development.[18] We explore this in the third column of Table A.I by re-estimating our baseline model with the global factor of Miranda-Agrippino and Rey (2015) replacing domestic equity volatility.[19]

As reported in Table A.I, this global factor is found to have a material impact on GDP-at-Risk at the 3-year horizon. An increase in global asset prices (i.e. a loosening in global financial conditions) is estimated to increase the severity of a downturn by about -2 percentage points cumulatively over this horizon. This is consistent with Eguren-Martin and Sokol (2020), who find an important role for the global factor in their FCI measure. The coefficients on the other variables in our regression are broadly unaffected by the inclusion of a global factor: the coefficients on credit and the current account are of a similar magnitude, and the coefficients on house prices and capital have the same sign, but a smaller size. Overall, this relative stability in our estimates indicates that the global factor provides additional information over our sample that is uncorrelated with our other regressors.

[18] Alessi and Detken (2011) find measures of global liquidity to be amongst the best leading indicators of financial crises in OECD countries. Cesa-Bianchi et al. (2019) report a similar finding.

[19] The results are broadly unchanged in an alternative specification where the global factor is included in addition to domestic equity volatility.

Bank capital

Turning to the impact of financial system resilience, we find that higher levels of banking system capital significantly improve GDP-at-Risk in the medium term. This is a novel finding, consistent with the notion that credit crunch amplification mechanisms are a key driver of severe macroeconomic tail events and that higher banking sector capitalisation can forestall these adverse dynamics. We find that a one-standard-deviation increase in the banking sector's TCE ratio improves GDP-at-Risk by 0.9 percentage points cumulatively over the following three years. As an illustration, the United Kingdom's TCE ratio averaged 4.1% over our full sample with a standard deviation of 0.9 percentage points. In 2007, this ratio had fallen to 1.9%, 2.5 standard deviations below its average level. We estimate that this diminution in resilience alone is sufficient to account for a 2.3 percentage point deterioration in GDP-at-Risk cumulatively from 2008 to 2010.

One potential concern is that our bank capital measure is based on annual bank reports and has been interpolated to a quarterly frequency in order to match the frequency of other series in our panel. When we repeat our analysis with annual data, we obtain a near-identical 0.3 percentage point coefficient on capital at the three-year horizon and the coefficient remains statistically significant (see Table A.I column 4).[20]

4.1.1 Decomposing GDP-at-Risk

In Figure 3, we use our baseline regression results for the medium term (3 years ahead) as a lens through which to view the drivers of tail risks to growth in the United Kingdom and United States over our sample. The upper panel shows the time series of predicted UK GDP-at-Risk, while the lower panel shows the estimated series for the United States. The black solid line shows the level of tail risk 3 years after each point in time as predicted by our model. For example, the reading for 2005:Q1 is the 5$^{\text{th}}$ percentile of the distribution of average annual GDP growth over the period 2005:Q1-2008:Q1 as predicted in 2005:Q1. One important caveat to this exercise is that we do not identify orthogonal disturbances.

[20] We take end-year measures of our risk indicators and macroeconomic controls to match the frequency of the bank capital series.

Rather, the contributions in this case show the impact on the risk projection of "news" in the time series of each of the right-hand-side variables of our regression.

Our model suggests that medium-term tail risks to growth have fluctuated significantly in both countries over our sample period. In the United Kingdom, GDP-at-Risk reached highly elevated levels prior to the 1990-1991 recession, driven by rapid growth in credit and house prices, an expanding current account deficit and extremely tight monetary conditions following increases in Bank Rate from 7% in May 1988 to almost 15% in October 1989. Each of these factors went into reverse following the recession, ushering in a prolonged period where risks to growth were subdued.

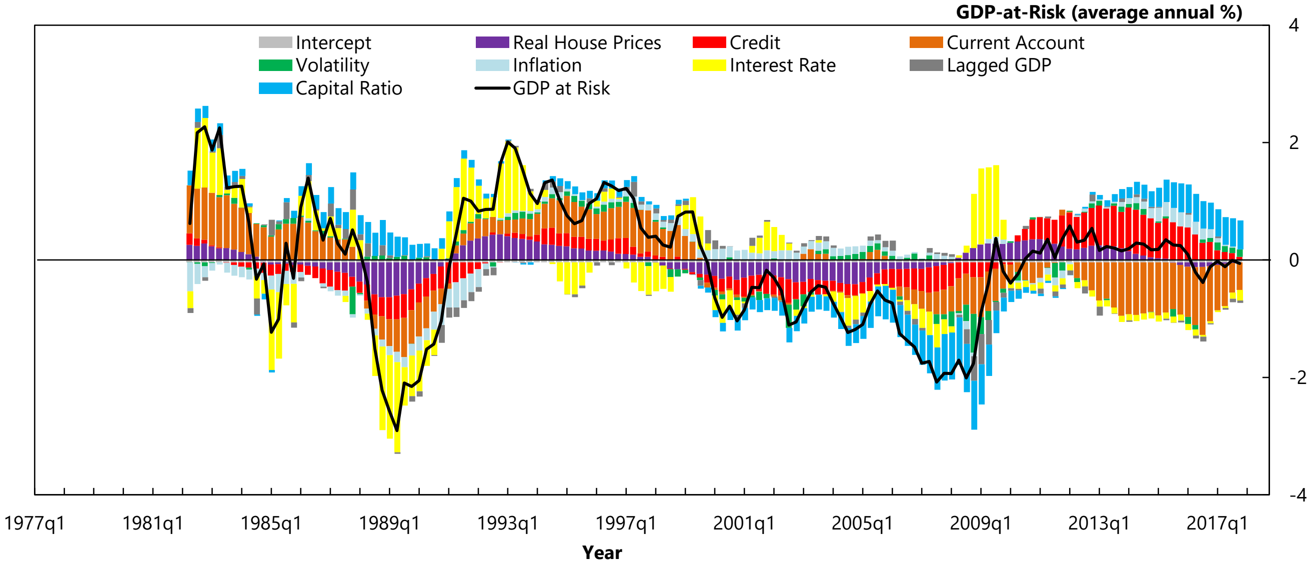
This benign period continued up until the late 1990s/early 2000s, when rapid growth in credit and house prices resumed, this time accompanied by weaker bank capital adequacy. This created a large and persistent increase in growth tail risks by the mid-2000s. By 2006:Q2, over two years before the failure of Lehman heralded the worst of the global financial crisis, our model predicts that GDP-at-Risk was -3.9% cumulatively over the subsequent 3 years. In the aftermath of the crisis, our model views risks to the economy as having declined significantly, driven by modest increases in credit and house prices and the strengthening in banking system capital. The increase in bank capital is estimated to have reduced tail risks to growth by nearly 4 percentage points cumulatively. Offsetting these positive developments to some extent, however, has been the increasing current account deficit.

Our estimate of GDP-at-Risk for the United States shares a remarkably similar time path. Risks to growth are estimated to have built significantly in the mid-to-late 1980s, driven by rapid growth in credit and house prices and against the backdrop of a weakly capitalised banking system. These risks were increased materially by the tightening in monetary policy in the late 1980s, culminating in the 1990-1991 recession. Just as for the United Kingdom, a benign period followed where tail risks to growth remained persistently subdued. Unsurprisingly given the absence of equity valuations in our model, we miss the mild recession in 2001 that followed the collapse of the dot-com bubble.

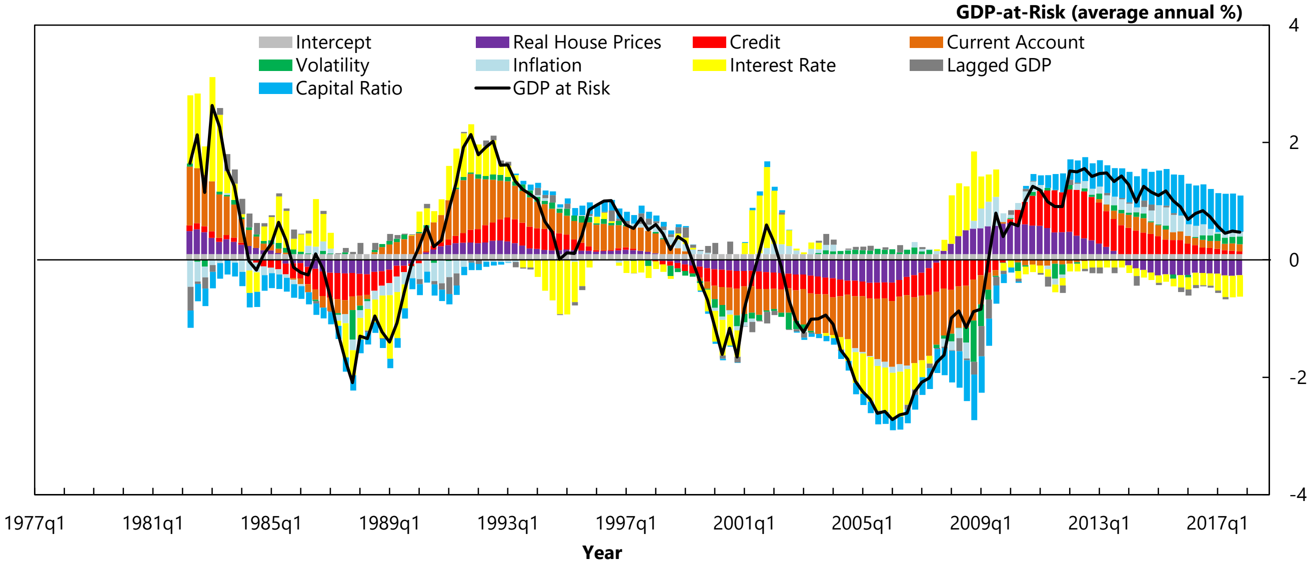
We do, however, capture an unprecedented build-up in GDP-at-Risk from the mid-2000s onwards, driven by rapid growth in credit and house prices, and notably the widen-

Figure 3: Decomposition of GDP-at-Risk at the 3-year horizon

(a) UK 3 years ahead



(b) USA 3 years ahead



Note: The black solid line shows the average annual 5^{th} percentile of GDP growth 3 years after each point in time, as predicted by our model and using coefficients estimated from the full sample. The bars shows the contribution of each indicator to that total. The cumulative impact at each point can be calculated by multiplying by 3.

ing in the current account deficit.[21] Many contemporaneous accounts emphasised risks

[21] In contrast to the United Kingdom, our measure of banking system capital does not contribute to the deterioration in US GDP-at-Risk over this period. Commercial bank leverage, which our metric captures, was relatively stable over this period, with the increase in leverage concentrated in the large

associated with the build-up in the US external deficit, which exceeded 6% of GDP in 2006. Our perspective, similar to Obstfeld and Rogoff (2009), is that the US current account deficit and its counterpart, abundant inflows of capital to the US economy, intermediated by the financial system was a strong signal of building internal imbalances over this period, which manifested themselves via an explosion in leverage in the shadow banking system and via a build-up in indebtedness in the household sector. By 2006:Q2, our model predicts that US GDP-at-Risk over the subsequent 3 years had reached -8% cumulatively. In the post-crisis period, we estimate that the severity of GDP-at-Risk has fallen substantially, driven to a large extent by the strengthening in banking system capitalisation, the slowing of credit growth and narrowing of the current account deficit.

4.1.2 Measuring GDP-at-Risk over subsamples

Figure 4 presents coefficients for GDP-at-Risk 3 years ahead estimated using different subsamples of our dataset. In particular, the far-left bar for each variable reports the 3-year-ahead coefficient estimate for the truncated sample period of right-hand-side variables observed from 1980:Q4 to 1992:Q1 (that is, including their impact on GDP realisations up to 1995:Q1); subsequent bars then expand the sample with an incremental 5 years of data. Figure 4a presents results using sub-samples of our full baseline model, while Figure 4b presents results using a simpler models only including each vulnerability indicator in turn (including controls).

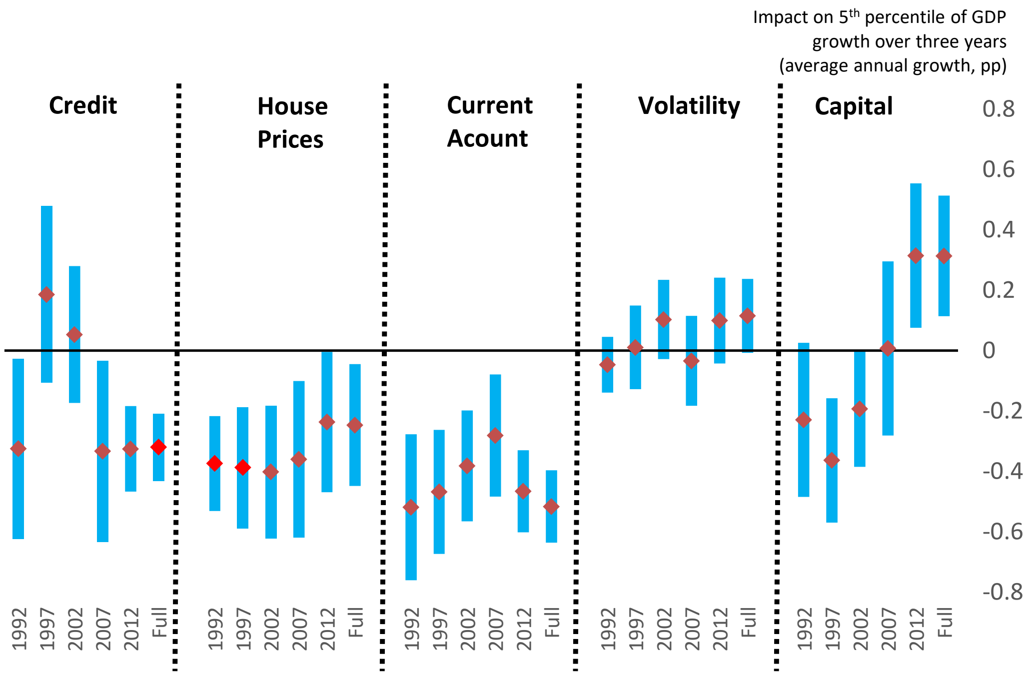
Overall, while the coefficient estimates for house prices, credit, current account deficits and volatility are relatively stable over these sub-samples, the estimated impacts of bank capital can vary significantly, both in terms of magnitude and sign. In particular, a researcher estimating this regression in the early 2000s would have found a *negative* relationship between banking system capitalisation and GDP-at-Risk (i.e. more bank capital increases recession severity). This is perhaps unsurprising given that the Global Financial Crisis was the first simultaneous full-blown banking crisis hitting advanced economies since the Great Depression.

We offer two considerations for interpreting these results: first, the instability of our estimated capital coefficient emphasises the challenges involved in uncovering the impact

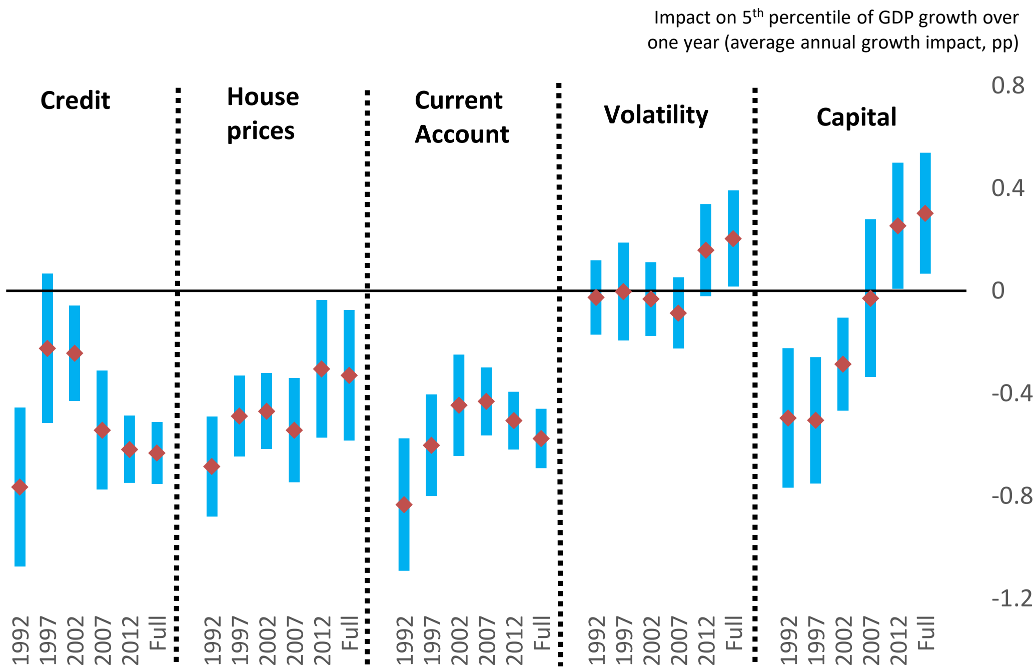
dealer institutions (Duffie (2019)).

Figure 4: Impact of each variable on 5^{th} percentile of GDP growth at 3-year horizon over different sub-samples

(a) Full model



(b) Single variable model



Note: The figure shows how the 12 quarter coefficients in our baseline model (A) and a simpler model (B) which includes each variable individually (with macroeconomic controls) change if we restrict the vulnerabilities sample at each of the points on the x-axis.

of vulnerability metrics on extreme tails of the distribution of growth, using what remains a relatively small sample of data.[22] As such, caution is required when using results from such exercises to inform real-time risk assessment.[23] Second, it is plausible that having seen genuinely extreme observations in indicators and growth before and after the global financial crisis, the 5^{th} percentile coefficients in this regression will be less responsive to new data henceforth.

4.2 Characterising the full predicted GDP growth distribution

Our last set of results compares estimates of the tail of the predicted distribution of GDP growth with other parts of the distribution. We focus on comparisons with the 50^{th} percentile (the median) and the 95^{th} percentile. Figure 5 presents coefficient estimates for the 5^{th}, 50^{th} and 95^{th} percentiles, as well as OLS estimates, at the 3-year-ahead horizon. Our main finding here is that the impact of our vulnerability measures on growth is, by and large, estimated to have the same sign across all percentiles. It is notable that the current account loads more heavily on the left-hand tail in the medium term than on other parts of the distribution.

To illustrate the economic significance of these estimates, Figure 6a presents time series estimates of predicted percentiles of UK GDP growth 3 years ahead. The dotted lines shows the actual outturn of real GDP growth at each horizon. In order to aid comparison with actual outturns, we have shifted our GDP estimates forward relative to Figure 3. For example, the point labelled 2008 gives our forecast for 2008 GDP made three years ahead (in 2005).

The outturns of GDP growth do not fall outside the lower 5% region of the predicted density. We find that innovations in vulnerability indicators act more like location shifters for the entire predicted density of GDP growth 3 years ahead, with both the 5^{th} and

[22]This is reminiscent of the observation in Mendoza and Terrones (2014) in their analysis of credit booms, which updated an earlier analysis from 2008 with data from 2007-2010. The additional four years data had generated a *"a critical change from our previous findings because, lacking the substantial evidence from all the recent booms and crises, we had found only 9 percent frequency of banking crises after credit booms for emerging markets and zero for industrial countries."*.

[23]Challenges posed by real-time assessments of cyclical fluctuations are by no means unique to our approach or application. For example, real-time assessments of economic slack differ notably from such estimates made with the benefit of hindsight (e.g., Orphanides and van Norden (2002) and Edge and Rudd (2016)). This concern has also been emphasized in the literature on the credit-to-GDP gap (e.g., Edge and Meisenzahl (2011)).

Figure 5: Impact of each variable on the 5th, 50th and 95th percentiles and conditional mean of GDP growth

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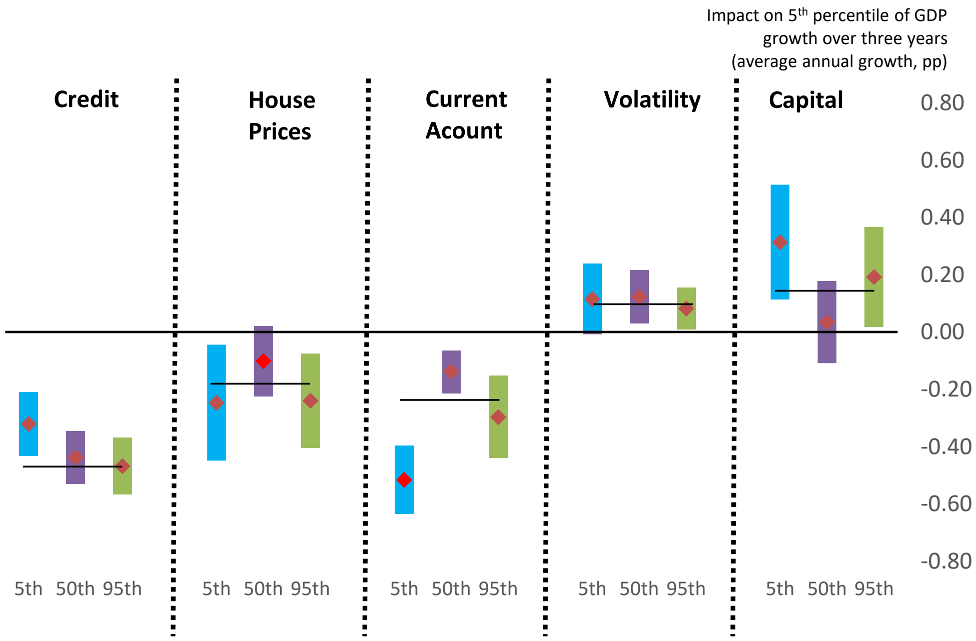


Note: This figure shows the impact of a one-standard-deviation increase in a given indicator at time t on a particular percentile of real GDP growth after 12 quarters. The OLS estimates are given by the horizontal black line for each indicator. Impact on GDP growth is measured as the average annual growth rate impact at the labelled percentile. Confidence intervals represent ± 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

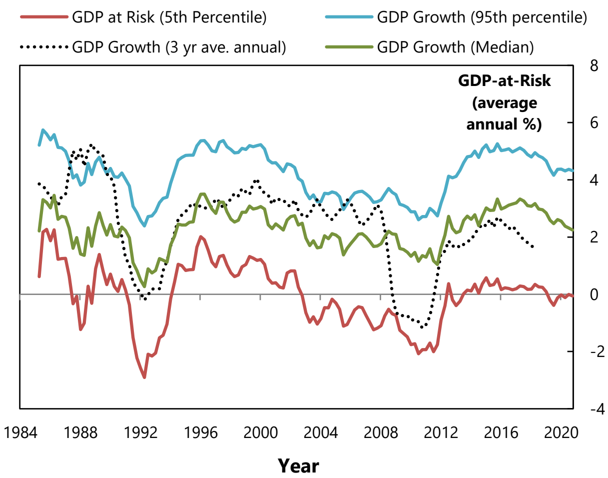
95th percentiles varying significantly (although the distance between these points of the distribution does increase in the run up to stress events).[24]

Finally, Figure 6b plot predicted densities of UK growth for 2008:Q3 as of 3 years beforehand. These are obtained by applying a kernel density estimator to our full-sample quantile regression coefficients (estimated at the 5th percentile, 95th percentile, and every decile in between). Relative to a baseline predicted density for the year 2000 (shown for comparison), a researcher armed with this model in 2005:Q3 would have predicted a marked leftward shift in the entire distribution and a fattening in the left-hand tail, well

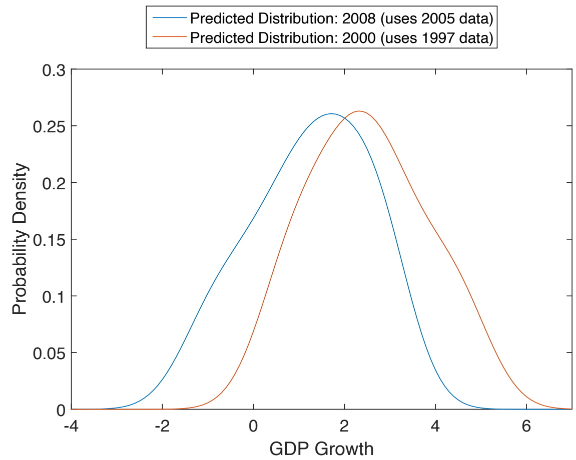
[24] In Appendix A.3, we broaden the analysis in Figure 6a by calculating the 3-year-ahead forecast for GDP growth at *every* decile in the distribution, as well as at the 1st, 5th, 95th and 99th percentiles. Figure A.IV illustrates the proportion of actual GDP observations falling into each percentile bucket predicted by our baseline model, and shows that the fraction of observations falling into each part of the predicted distribution are closely aligned with the expected proportions.

Figure 6: Predicted GDP growth density

(a) Forecast from 3 years previously vs. actual outturn



(b) Predicted density (3 years ahead)



Note: The left panel shows the predicted 5^{th}, 50^{th} and 95^{th} percentiles of GDP growth using data 12 quarters ahead of each point in time as well as the realised observations. The right panel shows the full predicted distribution of GDP growth in 2008 and 2000 using data from 2005 and 1997.

in advance of the crisis that was to follow. These are retrospective estimates that rely on coefficients estimated using the full sample that would not have been obtainable at the time, and as such care should be taken in interpreting their utility for real-time risk assessment purposes.

5 Conclusion

The provision of sufficient early warning when downside risks to future growth increase is crucial for the successful operationalisation of the macroprudential frameworks that have been established worldwide as a legacy of the global financial crisis. In this paper, we have developed a rich empirical framework within which we trace the impact of a set of vulnerability measures on the real GDP growth distribution at various horizons. Our primary focus has been on the tail of the GDP distribution – GDP-at-Risk – and its determinants in the medium-term (at the 3-5 year horizon). Most importantly, we provide a framework within which a lack of financial system resilience is linked explicitly to downside risks to economic growth.

Drawing on our panel data across 16 advanced economies, we establish that familiar indicators of macrofinancial imbalance systematically increase GDP tail risks in the medium-term. Credit booms, which have preceded around three-quarters of the worst GDP catastrophes in our sample, are found to materially worsen GDP-at-Risk in the medium term. We also find significant roles for rapid house price growth and a large current account deficit in affecting GDP tail risks three years out. We demonstrate that an increase in bank capital can improve GDP-at-Risk in the medium-term.

Our paper contributes to a programme of research that is required in order to deepen the evidence base underpinning macroprudential strategy. The framework we present could and should be extended in several dimensions: first, our set of vulnerability indicators is by no means exhaustive. Taking credit as an example, fruitful extensions include analysis of the relative roles of different types of credit (by sector or type of lender), the role of debt serviceability and the importance of the distribution of a given level of debt. The global nature of the financial cycle and the importance of international spillovers between our vulnerabilities should also be explored further. Moreover, our bank capital indicator is only one measure of financial system resilience and extensions to capture the role of liquidity both within the banking sector and in market-based finance are warranted.

A second dimension for future work is to establish structural counterparts to our empirical framework, which are able to generate the observed links between vulnerabilities and the GDP distribution. This would allow us to better understand the joint determination of our vulnerability indicators, thresholds above which they signal particular concern and to learn more about the underlying drivers of GDP-at-Risk.

Finally, we need to establish tools to better understand the transmission of macroprudential policy onto the GDP distribution. That transmission might operate directly as in the link we have established from bank capital to GDP-at-Risk in this paper. Transmission may also operate indirectly, perhaps by leaning on the build-up of certain vulnerabilities or changing the extent to which a given aggregate imbalance transmits to risks at the borrower level. Assessing the transmission mechanism of different macroprudential tools through a common lens of their impact on the GDP distribution at different horizons would help to advance policy decisions on tool selection, the potential for tool interaction and the cost-benefit analysis critical for policy calibration.

References

Adrian, T., and N. Boyarchenko (2012): "Intermediary leverage cycles and financial stability," Staff Reports 567, Federal Reserve Bank of New York.

Adrian, T., N. Boyarchenko, and D. Giannone (2019): "Vulnerable Growth," *American Economic Review*, 109(4), 1263–89.

Adrian, T., F. Grinberg, N. Liang, and S. Malik (2018): "The Term Structure of Growth-at-Risk," Working Paper 180, International Monetary Fund.

Aikman, D., J. Bridges, S. Burgess, R. Galletly, I. Levina, C. O'Neill, and A. Varadi (2018): "Measuring risks to UK financial stability," Bank of England working papers 738, Bank of England.

Akinci, O., and J. Olmstead-Rumsey (2018): "How effective are macroprudential policies? An empirical investigation," *Journal of Financial Intermediation*, 33, 33 – 57.

Alessi, L., and C. Detken (2011): "Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity," *European Journal of Political Economy*, 27(3), 520 – 533.

Bank of England (2016): "The Financial Policy Committee's approach to setting the countercyclical capital buffer," Policy statement, Bank of England.

Baron, M., and W. Xiong (2017): "Credit Expansion and Neglected Crash Risk," *The Quarterly Journal of Economics*, 132(2), 713–764.

Basel Committee on Banking Supervision (2010): "Calibrating regulatory minimum capital requirements and capital buffers: a top-down approach," Working paper, Bank of International Settlements.

Bordo, M., B. Eichengreen, D. Klingebiel, M. S. Martinez-Peria, and A. K. Rose (2001): "Is the Crisis Problem Growing More Severe?," *Economic Policy*, 16(32), 53–82.

Borio, C., and M. Drehmann (2009): "Assessing the risk of banking crises - revisited," BIS Quarterly Review March 2009, Bank of International Settlements.

Borio, C., and P. Lowe (2002a): "Assessing the risk of banking crises," BIS Quarterly Review December 2002, Bank of International Settlements.

——— (2002b): "Asset prices, financial and monetary stability: exploring the nexus," BIS Working Papers 114, Bank of International Settlements.

——— (2004): "Securing sustainable price stability: should credit come back from the wilderness?," BIS Working Papers 157, Bank of International Settlements.

Bridges, J., C. Jackson, and D. McGregor (2017): "Down in the slumps: the role of credit in five decades of recessions," Bank of England working papers 659, Bank of England.

Brooke, M., O. Bush, R. Edwards, J. Ellis, B. Francis, R. Harimohan, K. Neiss, and C. Siegert (2015): "Measuring the macroeconomic costs and benefits of higher UK bank capital requirements," Financial Stability Paper 35, Bank of England.

Brunnermeier, M. K., and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104(2), 379–421.

Bruno, V., I. Shim, and H. S. Shin (2017): "Comparative assessment of macroprudential policies," *Journal of Financial Stability*, 28, 183 – 202.

Canay, I. A. (2011): "A simple approach to quantile regression for panel data," *The Econometrics Journal*, 14(3), 368–386.

Carlson, M., H. Shan, and M. Warusawitharana (2013): "Capital ratios and bank lending: A matched bank approach," *Journal of Financial Intermediation*, 22(4), 663 – 687.

Cecchetti, S. G. (2006): "Measuring the Macroeconomic Risks Posed by Asset Price Booms," Working Paper 12542, National Bureau of Economic Research.

Cecchetti, S. G., and H. Li (2008): "Measuring the impact of asset price booms using quantile vector autoregressions," Mimeo, Brandeis University.

Cesa-Bianchi, A., F. E. Martin, and G. Thwaites (2019): "Foreign booms, domestic busts: The global dimension of banking crises," *Journal of Financial Intermediation*, 37, 58 – 74.

Chodorow-Reich, G. (2014): "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis," *Quarterly Journal of Economics*, 129(1), 1–59.

De Nicolò, G., and M. Lucchetta (2012): "Systemic Real and Financial Risks : Measurement, Forecasting, and Stress Testing," *IMF Working Paper*, 58.

Demirgüç-Kunt, A., E. Detragiache, and O. Merrouche (2013): "Bank Capital: Lessons from the Financial Crisis," *Journal of Money, Credit and Banking*, 45(6), 1147–1164.

Drehmann, M., C. Borio, and K. Tsataronis (2011): "Anchoring countercyclical capital buffers: the role of credit aggregates," BIS Working Papers 355, Bank of International Settlements.

Duffie, D. (2019): "Prone to Fail: The Pre-crisis Financial System," *Journal of Economic Perspectives*, 33(1), 81–106.

Edge, R. M., and J. N. Liang (2019): "New Financial Stability Governance Structures and Central Banks," Finance and Economics Discussion Series 2019-019, Board of Governors of the Federal Reserve System (US).

Edge, R. M., and R. R. Meisenzahl (2011): "The Unreliability of Credit-to-GDP Ratio Gaps in Real Time: Implications for Countercyclical Capital Buffers," *International Journal of Central Banking*, 7(4), 261–298.

Edge, R. M., and J. B. Rudd (2016): "Real-Time Properties of the Federal Reserve's Output Gap," *The Review of Economics and Statistics*, 98(4), 785–791.

Eguren-Martin, F., and A. Sokol (2020): “Attention to the tail(s): Global financial conditions and exchange rate risks,” ECB Working Paper 2387, Frankfurt a. M.

Eichengreen, B., and C. Arteta (2000): “Banking Crises in Emerging Markets: Presumptions and Evidence,” Center for International and Development Economics Research (CIDER) Working Papers C00-115, UC Berkeley.

Franta, M., and L. Gambacorta (2020): “On the effects of macroprudential policies on Growth-at-Risk,” *Economics Letters*, 196, 109501.

Galán, J. E. (2020): “The benefits are at the tail: Uncovering the impact of macroprudential policy on growth-at-risk,” *Journal of Financial Stability*, p. 100831.

Galvao, A. F. (2011): “Quantile regression for dynamic panel data with fixed effects,” *Journal of Econometrics*, 164(1), 142 – 157, Annals Issue on Forecasting.

Gavin, M., and R. Hausmann (1996): “The Roots of Banking Crises: The Macroeconomic Context,” IDB Publications (Working Papers) 6067, Inter-American Development Bank.

Giglio, S., B. Kelly, and S. Pruitt (2016): “Systemic risk and the macroeconomy: An empirical evaluation,” *Journal of Financial Economics*, 119(3), 457 – 471.

He, Z., and A. Krishnamurthy (2014): “A Macroeconomic Framework for Quantifying Systemic Risk,” Working Paper 19885, National Bureau of Economic Research.

Honohan, P. (2000): “Banking System Failures in Developing and Transition Countries: Diagnosis and Prediction,” *Economic Notes*, 29(1), 83–109.

International Monetary Fund (2011): “Macroprudential Policy; What Instruments and How to Use them? Lessons From Country Experiences,” IMF Working Papers 11/238, International Monetary Fund.

——— (2017): “Global Financial Stability Report October 2017: Is Growth at Risk?,” Report, International Monetary Fund.

Jordà, O. (2005): “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 95(1), 161–182.

Jordà, O., B. Richter, M. Schularick, and A. M. Taylor (2017): “Bank Capital Redux: Solvency, Liquidity, and Crisis,” Working Paper 23287, National Bureau of Economic Research.

Jordà, O., M. Schularick, and A. M. Taylor (2013): “When Credit Bites Back,” *Journal of Money, Credit and Banking*, 45(s2), 3–28.

Kaminsky, G. L., and C. M. Reinhart (1999): “The Twin Crises: The Causes of Banking and Balance-of-Payments Problems,” *American Economic Review*, 89(3), 473–500.

Kapetanios, G. (2008): “A bootstrap procedure for panel data sets with many cross-sectional units,” *The Econometrics Journal*, 11(2), 377–395.

Koenker, R., and G. Bassett (1978): “Regression Quantiles,” *Econometrica*, 46(1), 33–50.

Koop, G., and D. Korobilis (2014): "A new index of financial conditions," *European Economic Review*, 71, 101 – 116.

Kuttner, K. N., and I. Shim (2016): "Can non-interest rate policies stabilize housing markets? Evidence from a panel of 57 economies," *Journal of Financial Stability*, 26, 31–44.

Lahiri, S. N. (2003): *Resampling Methods for Dependent Data*. Springer Series in Statistics.

McKinnon, R. I., and H. Pill (1996): "Credible liberalizations and international capital flows: the overborrowing syndrome," in *Financial Deregulation and Integration in East Asia*, ed. by T. Ito, and A. O. Krueger. Chicago University Press.

Mendoza, E. G., and M. E. Terrones (2014): "An Anatomy of Credit Booms and their Demise," in *Capital Mobility and Monetary Policy*, ed. by M. F. D., C. E. Raddatz, and C. M. Reinhart, vol. 18 of *Central Banking, Analysis, and Economic Policies Book Series*, chap. 6, pp. 165–204. Central Bank of Chile.

Miranda-Agrippino, S., and H. Rey (2015): "US Monetary Policy and the Global Financial Cycle," NBER Working Papers 21722, National Bureau of Economic Research, Inc.

Obstfeld, M., and K. Rogoff (2009): "Global Imbalances and the Financial Crisis: Products of Common Causes," CEPR Discussion Papers 7606, Centre for Economic Policy Research.

Orphanides, A., and S. van Norden (2002): "The Unreliability of Output-Gap Estimates in Real Time," 84(4), 569–583.

Plagborg-Møller, M., L. Reichlin, G. Ricco, and T. Hasenzagl (2020): "When is growth at risk?," *Brookings Papers on Economic Activity,*, (4).

Reinhart, C. M., and G. L. Kaminsky (1999): "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems," *American Economic Review*, 89(3), 473–500.

Richter, B., M. Schularick, and I. Shim (2018): "The macroeconomic effects of macroprudential policy," Working Paper 740, Bank of International Settlements.

Schularick, M., and A. M. Taylor (2012): "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," *American Economic Review*, 102(2), 1029–61.

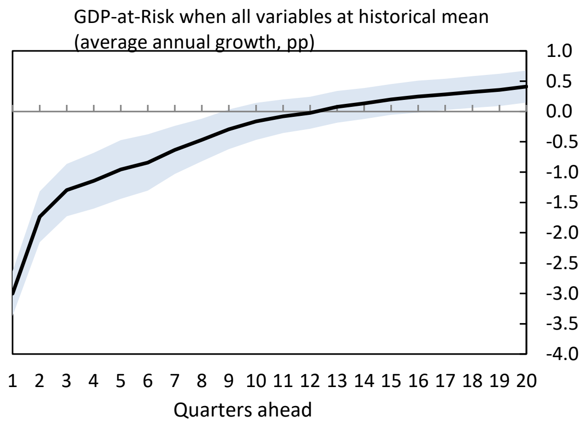
A Appendix - Robustness checks and additional material

A.1 Results for the intercept and control variables in baseline model

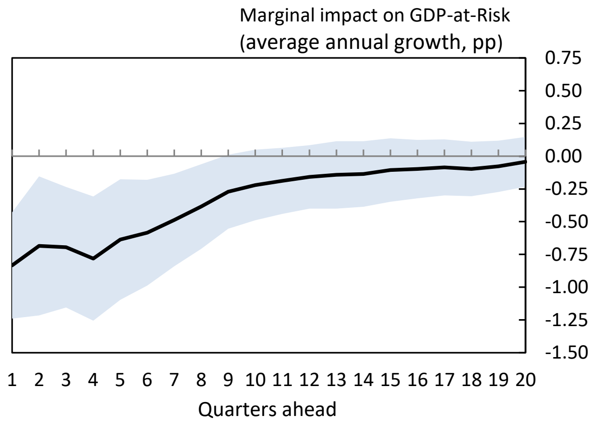
Figure 1 plots local projections of the estimated change in the GDP-at-Risk at various horizons, conditional on a one-standard-deviation change in each of the vulnerability indicators in our baseline model. In Figure A.I, we report results for the intercept and control variables from the same specification.

Figure A.I: Baseline results - 5th percentile: intercept and controls

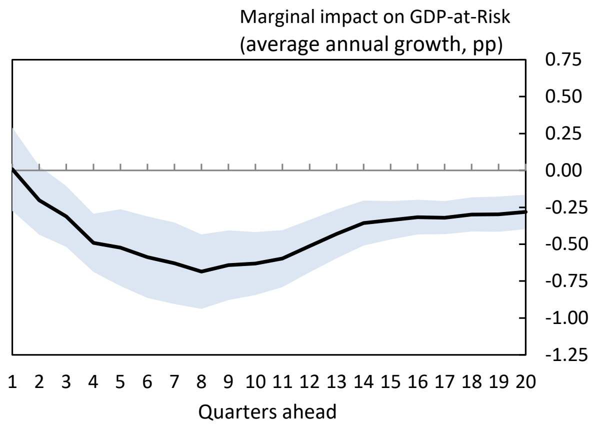
(A) Intercept



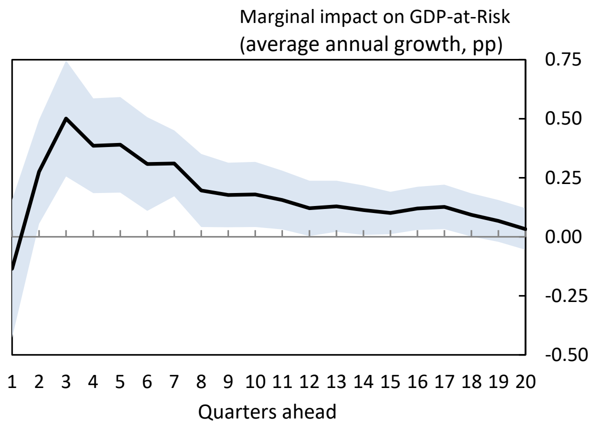
(B) Inflation



(C) Policy Rate



(D) Lagged GDP Growth



Note: Charts display coefficients for the intercept and control variables that were included in our baseline specification in Figure 1. Charts show the impact of a one-standard-deviation increase in a given indicator at time t on the 5th percentile of real GDP growth at each horizon on the x-axis. GDP growth is measured as the average annual growth rate at each horizon. Confidence intervals represent ± 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

A.2 Alternative specifications of baseline model

A.2.1 Global Factor

As outlined in Section 4.1, Table A.I reports results where we re-estimate our baseline model with the FCI (replacing equity volatility); with the global factor of Miranda-Agrippino and Rey (2015) (replacing equity volatility) and with all variables in annual space.

The global factor proposed in Miranda-Agrippino and Rey (2015) is extracted from a large panel of risky asset prices across various geographical areas, and is available from 1980 to 2018.[25] It uses a Dynamic Factor Model to summarise fluctuations in global financial markets and includes asset prices traded on all the major global markets covering North and Latin America, Europe, Asia and Australia.

A.2.2 Households and corporate credit

In Figure 1, we plot local projections showing the impact of a one-standard-deviation increase in each indicator on GDP-at-Risk in our baseline model. Figure A.II repeats this estimation, but splits total credit into its household and corporate credit components. The top row of Figure A.II presents the impact of a change in household or corporate credit-to-GDP on GDP-at-Risk and shows that after 20 quarters, the impact of an increase in household credit on tail risk is twice as large as the impact of corporate credit. The main messages from other indicators in relatively similar to our baseline results in Figure 1, although the coefficient on the current account is generally smaller.

[25]We thank the authors for providing us with extended data on the global factor. The time series used in Miranda-Agrippino and Rey (2015) covers the shorter period of 1990-2012.

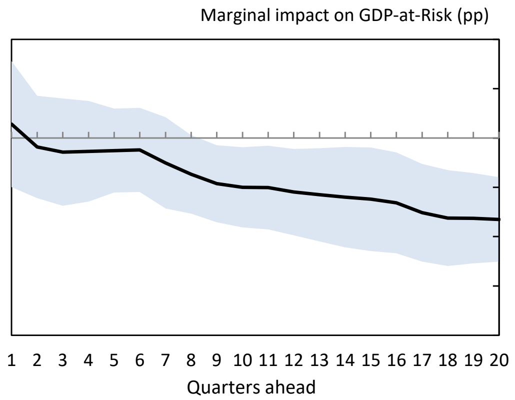
Table A.I: Estimated impact on 5^{th} percentile of GDP growth after 12 quarters

	Baseline (1)	2	3	4
Credit-to-GDP (3yr pp change)	-0.32	-0.30	-0.35	-0.27
	(-0.21, -0.43)	(-0.15, -0.46)	(-0.23, -0.46)	(0.01, -0.54)
Real House Prices (3yr growth)	-0.25	0.03	-0.15	-0.17
	(-0.04, -0.45)	(0.21, -0.16)	(0.03, -0.33)	(0.22, -0.56)
Current account (% of GDP)	-0.52	-0.63	-0.68	-0.52
	(-0.4, -0.64)	(-0.46, -0.8)	(-0.57, -0.8)	(-0.32, -0.72)
Volatility (SDs from Mean)	0.11			0.02
	(0.24, -0.01)			(0.22, -0.19)
FCI		0.09		
		(0.25, -0.08)		
Global Factor			-0.67	
			(-0.42, -0.92)	
Capital Ratio (quarterly)	0.31	0.57	0.14	
	(0.51, 0.11)	(0.73, 0.4)	(0.31, -0.03)	
Capital Ratio (annual)				0.31
				(0.58, 0.04)

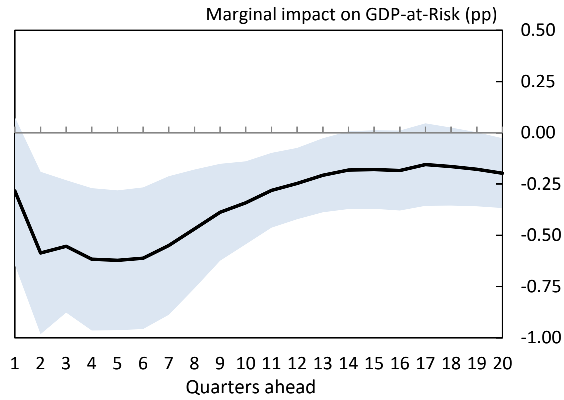
Note: This table shows estimates of the average annual impact of one-standard-deviation increases in each variable on the 5^{th} percentile of GDP growth over the following 12 quarters. Four separate specifications are used: (1) our baseline, (2) our baseline with the FCI replacing equity volatility, (3) our baseline with a global factor (see Miranda-Agrippino and Rey (2015)) replacing equity volatility, and (4) our baseline but with all variables in annual space. Numbers in brackets refer to one-standard-deviation confidence bands.

Figure A.II: Baseline results with credit split into household and corporate contributions

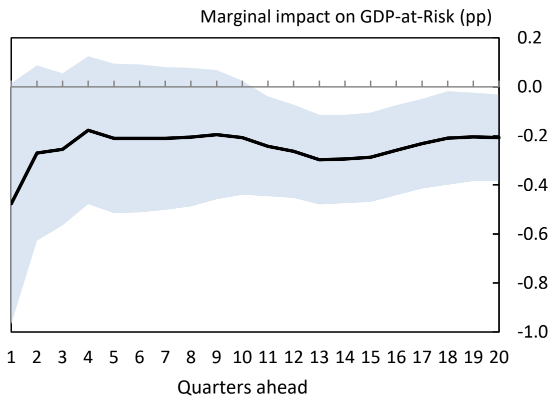
(a) Household credit-to-GDP (3 year pp change)



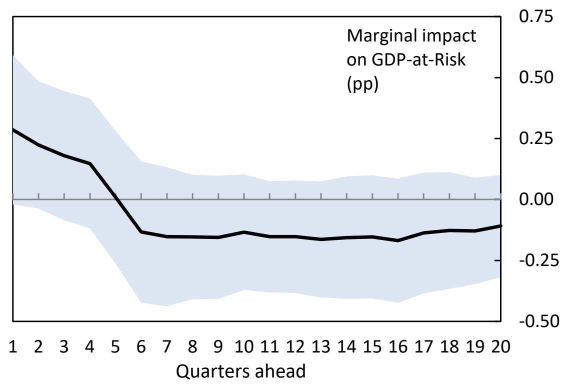
(b) Corporate credit-to-GDP (3 year pp change)



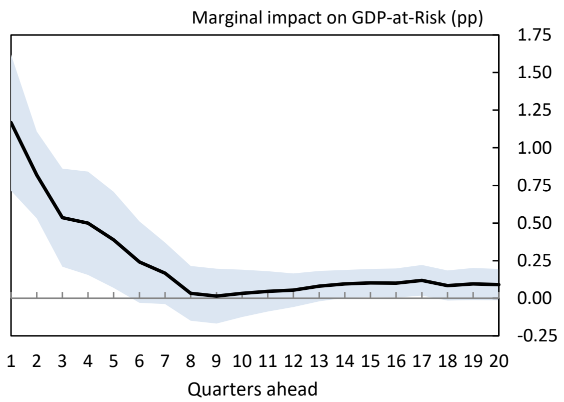
(c) Current account deficit



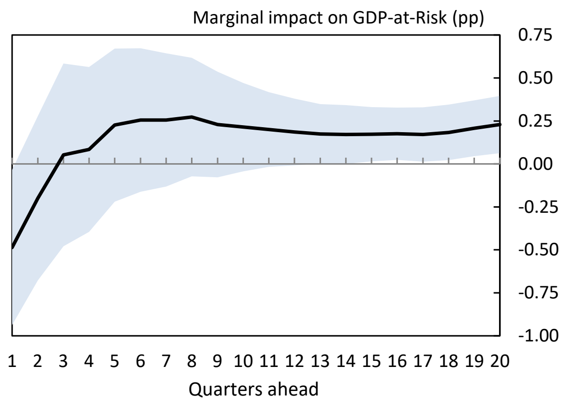
(d) Real house price growth (3 year)



(e) Volatility



(f) Capital ratio

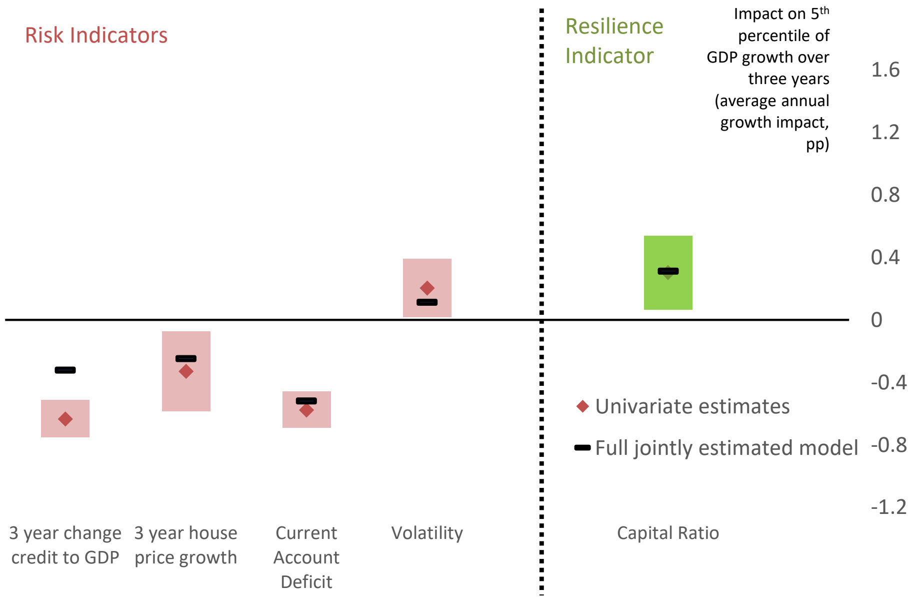


Note: these charts show the impact of a change in the indicator at time t on the 5^{th} percentile of real GDP growth at each horizon on the x-axis. GDP growth is measured as the average annual growth rate at each horizon. Confidence intervals represent ± 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

A.2.3 Single indicator models

As a cross-check on the baseline results in Figure 2, Figure A.III reports results from an alternative specification of quantile regressions where the impact of vulnerability indicators is estimated individually.[26] We obtain broadly similar results to our baseline model in this exercise. The medium-term coefficients for house price growth and the current account change very little, but the magnitude of the coefficient on credit growth increases by two-thirds.

FIGURE A.III: Baseline results and single-indicator model



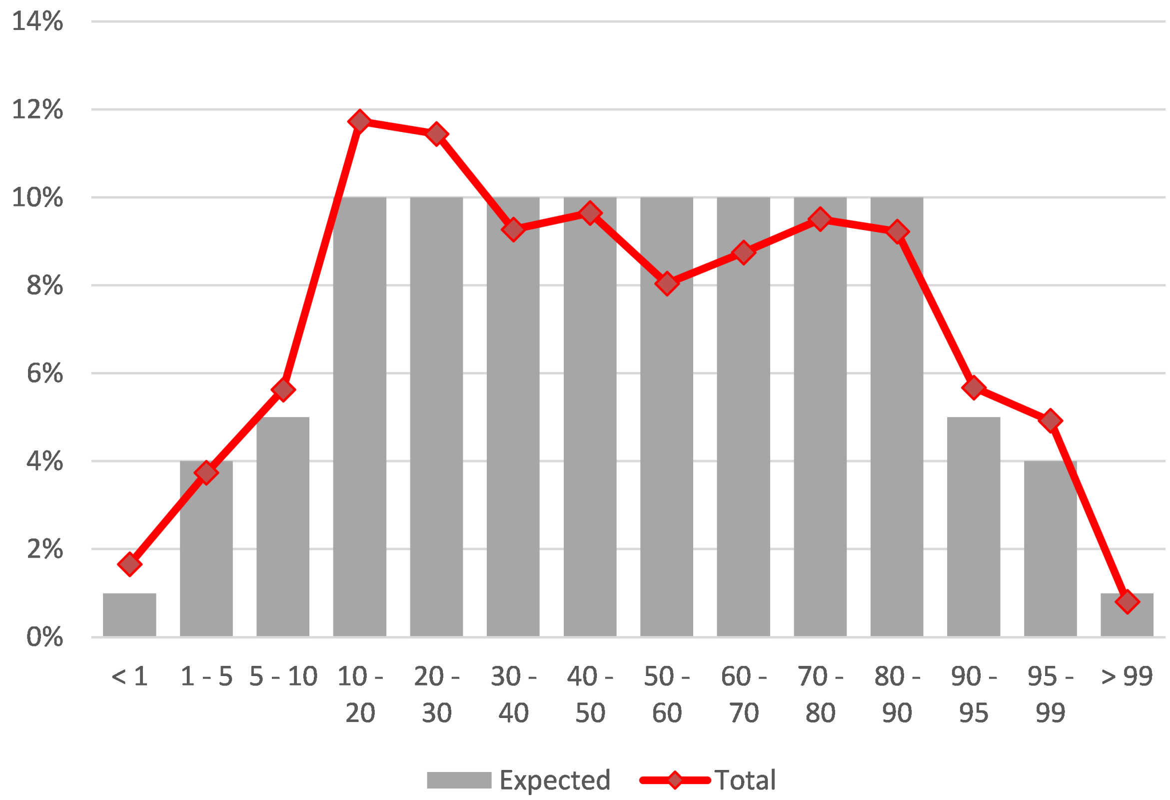
Note: this figure shows the impact of a one-standard-deviation increase in a given indicator at time t on the 5^{th} percentile of real GDP growth after 12 quarters. GDP growth is measured as the average annual growth rate at the 3-year horizon. Confidence intervals represent ± 1 standard deviation and correspond to the single-indicator model. Standard errors are generated using block bootstrapping following Kapetanios (2008). The coefficients labelled single indicator estimates are those obtained when each vulnerability indicator is included individually in the specification, alongside our macroeconomic controls (lagged GDP growth, inflation and the annual change in central bank policy rate). The black bars denote the coefficients obtained from our full baseline model, where all five vulnerabilities indicators are included jointly (the results from Figure 2).

[26]These regressions with individual vulnerability indicators also include macroeconomic controls.

A.3 Comparing actual GDP outturns with the full predicted GDP growth distribution

Here we compare actual GDP realisations against the full predicted GDP growth distribution based on our baseline model. The 3-year-ahead forecast horizon is used such that the actual GDP growth outturn is allocated to a percentile bucket based on the GDP growth distribution predicted 3 years previously. For example, suppose that in 1994:Q3, our baseline model had predicted that the 60th percentile for GDP growth over the next 3 years in Country X would average 2.73% and the 70th percentile would average 2.88%. Then if the actual outturn for GDP growth in that country between 1994:Q3 and 1997:Q3 averaged 2.79%, then the 1997:Q3 growth observation would be allocated to the 60-70th percentile bucket. This process is repeated for each GDP growth observation for each country in our sample. Figure A.IV shows that the proportion of GDP observations across all countries in our sample falling within each percentile bucket is broadly in line with the expected proportions. While this is an in-sample exercise with the coefficients coming from our baseline model estimated at each quantile using the full data sample, it nevertheless provides a reassuring check of the overall goodness of fit of our model.

Figure A.IV: Proportion of actual GDP growth outturns across all countries falling into each part of the GDP distribution predicted 3 years previously



Note: the red line shows the proportion of actual GDP growth outturns falling into each percentile bucket, based on the predicted GDP distribution from 3 years earlier. The predicted GDP distribution is based on our baseline model, estimated over the full sample of countries and the full time series. The grey bars simply show the expected proportion of observations falling into each bucket (i.e. 10% to fall into each decile). Irelands observations are excluded from the red line given a heavy loading at the extreme right-hand tail of the distribution. This reflects GDP data reclassifications and does not affect our analysis in this paper, which is focused on the left tail.

B Data Appendix

B.1 Capital ratios

We construct an annual cross-country measure of the tangible common equity (TCE) ratio that builds on Brooke et al. (2015). First, for each country, we obtain annual data on total assets, equity and intangible assets for each banking group operating in a given year from Thomson Reuters Worldscope. Measures of tangible assets and tangible equity for each bank are then obtained by subtracting intangible assets from each of total assets and total equity.

To account for the entry and exit of banks at different points in time within the financial system, we adopt a "chain-weighting" approach to produce a "spliced" country-level measure of tangible assets and tangible equity. For the year 2005, our spliced measure of tangible assets is simply the raw sum of tangible assets across banks in 2005 as we use 2005 as the base year. For the year 2004, the spliced measure of tangible assets is calculated as:

$$\text{Spliced TA in 04} = \text{Spliced TA in 05} \times \frac{\text{Raw 04 sum for banks operating in both 04 \& 05}}{\text{Raw 05 sum for banks operating in both 04 \& 05}}$$

Similarly for the year 2003, the formula becomes:

$$\text{Spliced TA in 03} = \text{Spliced TA in 04} \times \frac{\text{Raw 03 sum for banks operating in both 03 \& 04}}{\text{Raw 04 sum for banks operating in both 03 \& 04}}$$

The process continues back to the initial year. For years after 2005, the calculation is very similar. For example, for the year 2006:

$$\text{Spliced TA in 06} = \text{Spliced TA in 05} \times \frac{\text{Raw 06 sum for banks operating in both 05 \& 06}}{\text{Raw 05 sum for banks operating in both 05 \& 06}}$$

The same construction applies for tangible equity. The TCE ratio is then computed as spliced tangible assets divided by spliced tangible equity. We apply linear interpolation to obtain quarterly values from the annual series.

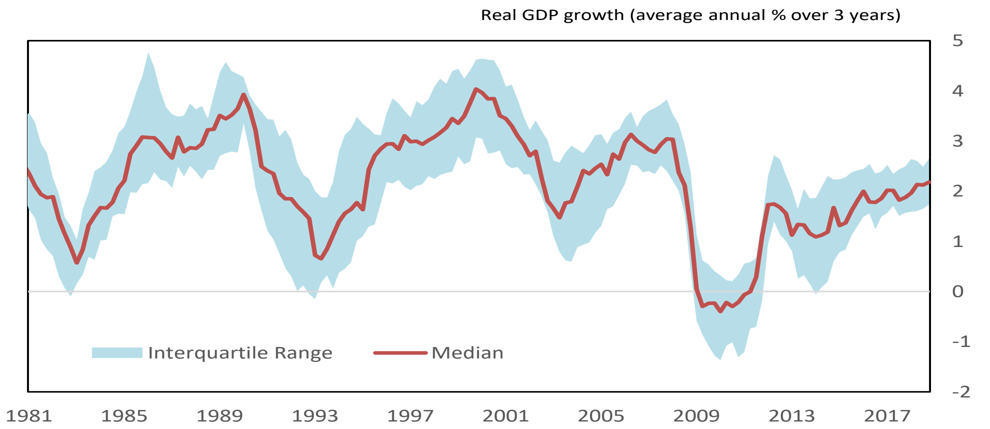
Table B.I documents data sources for each variable, Table B.II reports summary statistics on our dataset, and Figure B.I plots the median and interquartile range of real GDP growth, changes in credit-to-GDP and the TCE ratio across our panel of countries. Table B.III reports summary statistics on the banks used to construct the capital ratios across countries, in particular summary statistics on the number of banks, market capitalisation, bank tangible assets and total assets across the banking sector. The average number of banks per year across country-year pairs is 18, although Table B.III shows that there is heterogeneity across countries and over time. The US has the most banks per year with 88.6 banks on average, while Ireland has the least with 3.4 banks on average. Summary statistics at the bank level on tangible assets (in terms of local currency) and market capitalisation (in terms of US dollars for publicly-traded banks in our sample) are also reported. In addition, we report summary statistics on aggregate assets across all banks in a given country and year. For example, at end-2017, total assets in our data were £5.6 trillion in the UK, which covered 90% of total banking system assets as measured by the denominator in the Financial Policy Committee's leverage indicator.

Table B.I: Data sources

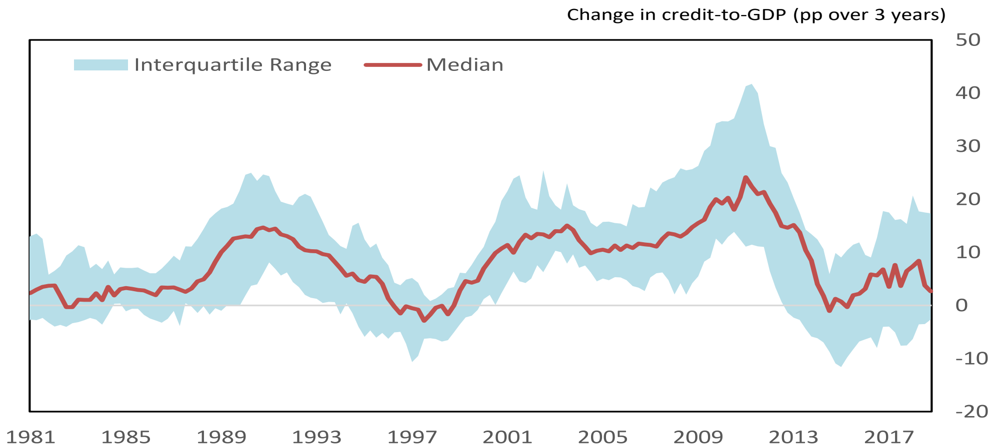
Variable	Data Source	Frequency	Notes
Real GDP	OECD	Quarterly	
Credit-to-GDP	BIS	Quarterly	3 year change in ratio of private non-financial credit to GDP
House prices	OECD	Quarterly	3 year growth in real house prices
Current Account	OECD	Quarterly	Per cent of GDP
Volatility	Datastream	Daily	Quarterly standard deviation of daily return in national equity market
Capital Ratio	Worldscope	Annual	Ratio of tangible common equity to tangible assets
Inflation	OECD	Quarterly	Annual growth of CPI
Policy Rate	BIS	Quarterly	Annual change in central bank policy rate

FIGURE B.I: Median and Interquartile range of selected indicators across sample of countries

(A) Real GDP growth



(B) 3-year change in credit-to-GDP



(C) Capital ratio

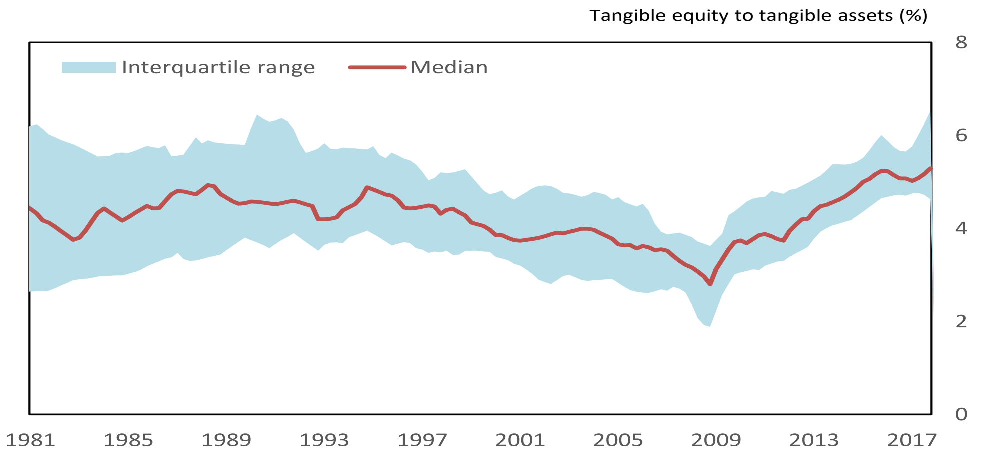


Table B.II: Summary statistics by country

		N	Mean	Std Dev.	Min	p25	p75	Max
Australia	Credit-to-GDP (3yr change)	149	10.2	10.9	-13.4	4.4	18.3	29.8
	Real House Prices (3yr growth)	149	11.5	13.6	-10.7	0.6	19.5	53.8
	Current account (% of GDP)	149	-4.3	1.2	-6.9	-5.1	-3.3	-2.1
	Volatility (SDs from Mean)	149	0.0	1.0	-7.5	-0.3	0.6	1.3
	Capital Ratio	149	5.0	0.7	3.5	4.4	5.7	6.3
	Inflation	149	4.0	3.0	-0.4	1.9	6.1	12.4
	Policy Rate (1yr change)	149	-0.4	2.9	-15.0	-1.3	0.5	7.8
Belgium	Credit-to-GDP (3yr change)	149	10.5	11.9	-12.1	2.2	16.7	47.6
	Real House Prices (3yr growth)	149	5.6	15.6	-37.9	0.4	15.3	28.7
	Current account (% of GDP)	149	1.9	2.2	-3.2	0.2	3.5	5.2
	Volatility (SDs from Mean)	149	0.0	1.0	-4.5	-0.4	0.7	1.1
	Capital Ratio	149	3.3	0.7	1.2	2.8	3.7	4.5
	Inflation	149	2.7	2.1	-1.1	1.3	3.1	9.9
	Policy Rate (1yr change)	149	-0.3	1.3	-5.0	-1.3	0.3	3.0
Canada	Credit-to-GDP (3yr change)	149	7.6	10.0	-14.5	0.5	14.9	30.6
	Real House Prices (3yr growth)	149	8.5	15.2	-25.5	-1.0	19.0	56.0
	Current account (% of GDP)	149	-1.5	2.1	-4.2	-3.3	0.5	3.0
	Volatility (SDs from Mean)	149	0.0	1.0	-6.7	-0.3	0.6	1.1
	Capital Ratio	149	3.6	0.4	2.6	3.3	3.9	4.3
	Inflation	149	3.1	2.6	-0.9	1.5	4.0	12.8
	Policy Rate (1yr change)	149	-0.3	2.1	-7.2	-1.3	0.8	8.4
Denmark	Credit-to-GDP (3yr change)	149	9.4	16.6	-13.9	-4.9	20.2	47.8
	Real House Prices (3yr growth)	149	5.4	23.5	-48.5	-14.6	21.9	57.6
	Current account (% of GDP)	149	1.8	3.7	-5.3	-1.1	3.5	9.3
	Volatility (SDs from Mean)	149	0.0	1.0	-6.9	-0.3	0.6	1.4
	Capital Ratio	149	5.4	1.4	2.8	4.3	6.6	7.9
	Inflation	149	3.0	2.5	0.2	1.7	3.4	12.2
	Policy Rate (1yr change)	149	-0.3	1.3	-6.3	-0.9	0.2	3.5
Finland	Credit-to-GDP (3yr change)	149	7.9	15.7	-45.1	3.7	15.5	48.1
	Real House Prices (3yr growth)	149	8.5	21.8	-46.7	-0.7	21.6	70.9
	Current account (% of GDP)	149	0.8	3.7	-5.8	-1.8	4.0	8.4
	Volatility (SDs from Mean)	149	0.0	1.0	-3.9	-0.4	0.7	1.2
	Capital Ratio	149	5.1	1.1	2.5	4.1	5.8	7.6
	Inflation	149	3.2	2.9	-0.5	1.2	3.9	13.8
	Policy Rate (1yr change)	149	-0.2	1.0	-4.0	-0.5	0.0	2.0

Summary statistics by country

		N	Mean	Std Dev.	Min	p25	p75	Max
France	Credit-to-GDP (3yr change)	149	7.2	6.4	-7.1	2.0	12.4	18.8
	Real House Prices (3yr growth)	149	6.0	16.4	-22.6	-7.7	20.1	44.5
	Current account (% of GDP)	149	0.0	1.3	-4.0	-0.8	0.8	3.8
	Volatility (SDs from Mean)	149	0.0	1.0	-5.1	-0.4	0.6	1.3
	Capital Ratio	149	2.8	0.7	1.4	2.5	3.2	4.1
	Inflation	149	3.0	3.1	-0.4	1.4	3.2	14.2
	Policy Rate (1yr change)	149	-0.3	1.4	-3.3	-1.2	0.2	5.6
Germany	Credit-to-GDP (3yr change)	149	1.2	6.3	-10.7	-3.1	6.6	11.7
	Real House Prices (3yr growth)	149	-0.7	6.8	-12.6	-5.9	3.7	15.2
	Current account (% of GDP)	149	2.7	3.4	-2.2	-0.9	5.7	9.1
	Volatility (SDs from Mean)	149	0.0	1.0	-5.0	-0.5	0.7	1.3
	Capital Ratio	149	2.7	0.7	1.7	2.3	2.8	5.2
	Inflation	149	2.0	1.5	-1.1	1.1	2.7	7.2
	Policy Rate (1yr change)	149	-0.2	1.1	-3.5	-0.5	0.5	2.5
Ireland	Credit-to-GDP (3yr change)	149	19.4	32.9	-43.1	-0.3	28.2	111.4
	Real House Prices (3yr growth)	149	10.4	28.4	-42.0	-10.1	29.8	73.7
	Current account (% of GDP)	149	-1.5	3.8	-12.5	-3.7	1.0	8.2
	Volatility (SDs from Mean)	149	0.0	1.0	-5.2	-0.4	0.7	1.1
	Capital Ratio	149	5.5	1.6	3.2	4.5	6.4	9.7
	Inflation	149	3.6	4.6	-2.8	1.5	4.0	23.3
	Policy Rate (1yr change)	149	-0.4	1.8	-6.8	-1.3	0.3	4.5
Italy	Credit-to-GDP (3yr change)	149	4.6	8.4	-11.7	-2.7	10.6	22.1
	Real House Prices (3yr growth)	149	4.2	24.4	-41.0	-14.5	20.5	66.7
	Current account (% of GDP)	149	-0.3	1.8	-3.7	-1.6	1.3	3.3
	Volatility (SDs from Mean)	149	0.0	1.0	-4.1	-0.5	0.7	1.5
	Capital Ratio	149	4.7	0.7	3.4	4.3	5.0	6.7
	Inflation	149	4.6	4.4	-0.3	2.0	5.5	19.6
	Policy Rate (1yr change)	149	-0.4	1.5	-6.5	-1.0	0.3	4.0
Netherlands	Credit-to-GDP (3yr change)	149	14.1	9.3	-9.9	7.2	19.4	41.0
	Real House Prices (3yr growth)	149	5.2	22.1	-48.1	-8.0	17.8	47.7
	Current account (% of GDP)	149	4.8	2.7	-0.4	2.7	6.9	10.8
	Volatility (SDs from Mean)	149	0.0	1.0	-5.2	-0.3	0.7	1.1
	Capital Ratio	149	3.8	0.8	2.5	3.0	4.5	5.5
	Inflation	149	2.1	1.6	-1.2	1.3	2.7	7.3
	Policy Rate (1yr change)	149	-0.3	1.2	-5.0	-0.8	0.3	3.0

Summary statistics by country

		N	Mean	Std Dev.	Min	p25	p75	Max
Norway	Credit-to-GDP (3yr change)	149	9.5	16.2	-22.5	-1.7	23.4	44.3
	Real House Prices (3yr growth)	149	12.1	20.6	-31.6	-0.1	26.8	68.8
	Current account (% of GDP)	149	6.8	6.0	-6.6	2.9	12.1	17.3
	Volatility (SDs from Mean)	149	0.0	1.0	-6.3	-0.3	0.6	1.3
	Capital Ratio	149	4.5	1.1	1.6	3.9	5.4	6.8
	Inflation	149	3.7	3.1	-1.4	1.9	4.5	14.7
	Policy Rate (1yr change)	149	-0.2	1.8	-6.0	-0.8	0.3	5.5
Spain	Credit-to-GDP (3yr change)	149	7.6	21.1	-35.3	-3.3	23.7	53.8
	Real House Prices (3yr growth)	149	11.5	33.8	-43.5	-13.5	34.1	111.7
	Current account (% of GDP)	149	-2.4	3.0	-10.2	-3.9	-0.5	2.3
	Volatility (SDs from Mean)	149	0.0	1.0	-4.2	-0.4	0.7	1.5
	Capital Ratio	149	5.1	0.8	3.1	4.7	5.5	6.9
	Inflation	149	4.6	3.8	-1.1	2.3	6.1	16.1
	Policy Rate (1yr change)	149	-0.4	2.8	-10.6	-1.5	0.5	11.7
Sweden	Credit-to-GDP (3yr change)	149	10.4	16.7	-26.6	0.4	16.7	63.1
	Real House Prices (3yr growth)	149	8.8	21.7	-34.2	-7.0	27.1	42.9
	Current account (% of GDP)	149	2.7	3.4	-3.1	-0.2	5.4	8.4
	Volatility (SDs from Mean)	149	0.0	1.0	-4.5	-0.5	0.7	1.2
	Capital Ratio	149	3.6	0.7	1.8	3.2	3.9	5.0
	Inflation	149	3.3	3.5	-1.2	0.8	5.2	14.8
	Policy Rate (1yr change)	149	-0.3	3.9	-32.0	-1.0	1.0	30.0
Switzerland	Credit-to-GDP (3yr change)	149	7.1	9.1	-9.7	0.2	13.4	30.0
	Real House Prices (3yr growth)	149	3.8	12.9	-26.1	-3.2	11.9	35.0
	Current account (% of GDP)	149	7.8	3.7	-0.6	4.5	10.9	15.1
	Volatility (SDs from Mean)	149	0.0	1.0	-4.8	-0.3	0.6	1.3
	Capital Ratio	149	4.4	1.8	1.7	2.9	6.3	7.0
	Inflation	149	1.7	2.0	-1.4	0.4	2.8	7.1
	Policy Rate (1yr change)	149	-0.1	1.1	-2.4	-0.9	0.3	3.0
UK	Credit-to-GDP (3yr change)	149	7.0	11.7	-20.2	-0.2	16.5	23.4
	Real House Prices (3yr growth)	149	13.4	23.0	-28.2	-6.0	31.1	69.4
	Current account (% of GDP)	149	-2.1	1.7	-5.9	-3.5	-0.7	2.3
	Volatility (SDs from Mean)	149	0.0	1.0	-5.8	-0.3	0.7	1.2
	Capital Ratio	149	4.1	0.9	1.8	3.5	4.7	5.5
	Inflation	149	3.4	2.6	0.0	1.6	4.4	15.2
	Policy Rate (1yr change)	149	-0.4	1.8	-5.0	-1.3	0.5	4.9
USA	Credit-to-GDP (3yr change)	149	4.1	8.8	-18.2	-1.0	11.6	18.4
	Real House Prices (3yr growth)	149	2.7	11.9	-22.3	-5.9	13.6	22.0
	Current account (% of GDP)	149	-2.6	1.5	-6.1	-3.3	-1.6	0.3
	Volatility (SDs from Mean)	149	0.0	1.0	-6.2	-0.2	0.6	1.2
	Capital Ratio	149	5.5	1.1	2.8	4.8	6.0	8.1
	Inflation	149	3.1	2.0	-1.6	1.9	3.7	12.5
	Policy Rate (1yr change)	149	-0.4	2.0	-8.9	-1.3	0.8	8.2
All Sample	Credit-to-GDP (3yr change)	2384	8.6	15.2	-45.1	-0.2	15.4	111.4
	Real House Prices (3yr growth)	2384	7.3	20.9	-48.5	-5.7	19.5	111.7
	Current account (% of GDP)	2384	0.9	4.5	-12.5	-2.3	3.5	17.3
	Volatility (SDs from Mean)	2384	0.0	1.0	-7.5	-0.3	0.7	1.5
	Capital Ratio	2384	4.3	1.4	1.2	3.3	5.1	9.7
	Inflation	2384	3.2	3.1	-2.8	1.4	3.9	23.3
	Policy Rate (1yr change)	2384	-0.3	2.0	-32.0	-1.0	0.5	30.0

Table B.III: Banking system data: summary statistics by country

		N	Mean	Std Dev.	Min	p25	p75	Max
Australia	Number of banks per year	38	9.3	3.1	4	8	12	13
	Market capitalisation ($m)	308	15449	25048	8.2	419	17133	123289
	Tangible assets (billions AUD)	353	150.5	243.4	0.08	4.9	148.6	965.4
	Aggregate total assets (billions AUD)	38	1414	1303	48.0	378	2564	3913
Belgium	Number of banks per year	38	4.0	2.1	2	2	6	8
	Market capitalisation ($m)	148	5740	9197	21.4	238	6386	47703
	Tangible assets (€bn)	153	113.5	144.9	0.008	5.7	212.7	644.8
	Aggregate total assets (€bn)	38	459	301	66.3	160	695	1000
Canada	Number of banks per year	38	10.0	2.2	6	9	12	14
	Market capitalisation ($m)	333	15089	23892	12.8	1015	16252	113668
	Tangible assets (billions CAD)	380	178.0	259.1	0.0001	6.5	253.1	1317
	Aggregate total assets (billions CAD)	38	1798	1474	312	558	2718	5368
Denmark	Number of banks per year	38	27.3	13.4	4	20	38	44
	Market capitalisation ($m)	1009	583	2870	2.5	19.4	159	34810
	Tangible assets (billions DKK)	1039	69.4	380.2	0.3	1.4	11.4	3532
	Aggregate total assets (billions DKK)	38	1904	1417	80.6	845	3606	4089
Finland	Number of banks per year	38	3.9	1.3	2	3	5	6
	Market capitalisation ($m)	122	820	1145	6.7	161	961	6417
	Tangible assets (€bn)	147	11.2	13.0	0.04	1.7	14.8	62.2
	Aggregate total assets (€bn)	38	43.6	23.5	10.5	18.7	63.9	77.6
France	Number of banks per year	38	23.1	9.4	7	18	30	42
	Market capitalisation ($m)	745	4991	13710	6.3	215	1915	98706
	Tangible assets (€bn)	879	120.6	329.9	0.07	3.1	46.5	2059
	Aggregate total assets (€bn)	38	2807	2085	265	1118	5518	6012
Germany	Number of banks per year	38	17.3	6.9	8	11	25	29
	Market capitalisation ($m)	530	5213	10171	2.3	360	4228	66666
	Tangible assets (€bn)	659	118.9	270.5	0.003	8.4	108.5	2184
	Aggregate total assets (€bn)	38	2071	1176	360	842	3009	4020
Ireland	Number of banks per year	38	3.4	1.3	1	3	4	6
	Market capitalisation ($m)	93	3603	4701	1.7	392	4759	20628
	Tangible assets (€bn)	131	50.8	54.6	0.1	7.0	80.4	196.4
	Aggregate total assets (€bn)	38	176	162	5.7	38.0	281	554
Italy	Number of banks per year	38	26.7	10.0	9	19	35	43
	Market capitalisation ($m)	904	3896	9686	0.1	339	3061	110084
	Tangible assets (€bn)	1015	48.1	122.8	0.004	3.4	38.0	1009
	Aggregate total assets (€bn)	38	1301	878	93.6	420	2264	2459
Netherlands	Number of banks per year	38	7.3	2.7	2	6	10	11
	Market capitalisation ($m)	121	9205	16446	35.4	232	9301	99754
	Tangible assets (€bn)	279	162.9	277.9	0.2	6.0	141.4	1311
	Aggregate total assets (€bn)	38	1198	984	142	365	1733	3451

Banking system data: summary statistics by country

		N	Mean	Std Dev.	Min	p25	p75	Max
Norway	Number of banks per year	38	17.4	8.0	4	13	23	29
	Market capitalisation ($m)	613	767	3144	3.8	20.0	253	30175
	Tangible assets (billions NOK)	660	85.8	300.2	0.2	5.1	48.5	2692
	Aggregate total assets (billions NOK)	38	1494	1359	63.8	559	2791	4316
Spain	Number of banks per year	38	14.4	5.6	6	9	19	23
	Market capitalisation ($m)	501	8239	19225	5.3	424	6115	136121
	Tangible assets (€bn)	546	84.6	197.7	0.04	2.9	62.6	1392
	Aggregate total assets (€bn)	38	1232	1216	46.3	182	2385	3386
Sweden	Number of banks per year	38	4.4	1.2	3	4	5	7
	Market capitalisation ($m)	136	12873	12886	22.2	2528	20170	54071
	Tangible assets (billions SEK)	168	1217	1453	1.8	140.3	2037	6368
	Aggregate total assets (billions SEK)	38	5413	4958	229	1000	11265	13886
Switzerland	Number of banks per year	38	19.4	6.4	4	20	23	26
	Market capitalisation ($m)	585	5926	15539	6.1	140	2282	117800
	Tangible assets (billions CHF)	738	92.1	281.8	0.9	5.3	25.2	2378
	Aggregate total assets (billions CHF)	38	1800	1130	233	621	2589	3954
UK	Number of banks per year	38	12.0	1.9	8	11	13	15
	Market capitalisation ($m)	343	26813	42647	4.0	1784	40748	210836
	Tangible assets (£bn)	456	226.5	399.1	0.003	23.6	206.9	2375
	Aggregate total assets (£bn)	38	2741	2487	123	645	5621	8186
USA	Number of banks per year	38	88.6	44.3	38	45	132	162
	Market capitalisation ($m)	3308	7905	28444	0.001	240	3599	366302
	Tangible assets ($bn)	3365	61.8	236.1	0.003	3.7	31.7	2517
	Aggregate total assets ($bn)	38	5616	3686	1041	2427	9810	12111

Note: This table provides summary statistics across countries on the banks used to construct the capital ratio series in Sections 2 and B.1. "Number of banks per year" shows summary statistics on the number of annual bank observations available for a given country. "Market capitalisation" shows summary statistics on the market capitalisation at the bank level for those banks in our sample that are publicly traded, and is expressed in terms of US dollars. "Tangible assets" shows summary statistics on total tangible assets at the bank level, where tangible assets are calculated as total assets minus intangible assets and are expressed in terms of the local currency. "Aggregate total assets" gives the sum of total assets across the banks in a given country and year and is expressed in terms of the local currency.