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Abstract

How can macroeconomic tail risks originating from financial vulnerabilities be monitored systematically over time? This question lies at the heart of operationalising the macroprudential policy regimes that have developed around the world in response to the global financial crisis. Using quantile regressions applied to a panel dataset of 16 advanced economies, we examine how downside risk to growth over the medium term, GDP-at-Risk, is affected by a set of macroprudential indicators. We find that credit booms, property price booms and wide current account deficits each pose material downside risks to growth at horizons of three to five years. We find that such downside risks can be partiall y mitigated, however, by increasing the capitalisation of the banking system. We estimate that across our sample of countries, GDP-at-Risk, defined as the 5th quantile of the projected GDP growth distribution over three years, on average deteriorated by around 4.5 percentage points cumulatively in the run-up to the crisis. Our estimates suggest that an increase in bank capital equivalent to a countercyclical capital buffer rate of 2.5% (5%) would have been sufficient to mitigate up to 20% (40%) of this increase in medium-term macroeconomic tail risk.

Key words: Financial stability, GDP-at-Risk, macroprudential policy, quantile regressions, local projections.

JEL classification: G01, G18, G21.

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1 Introduction

What is the relationship between vulnerabilities in the real and financial sectors and downside risks to economic growth? In particular, do measures of credit growth, external deficits, asset valuations and financial system leverage affect tail risks to economic growth, and could this information be used by policymakers to inform the setting of macroprudential and other policies? Recent research has established a strong relationship between indicators of financial conditions (derived from asset prices) and downside risks to growth at *near-term* horizons of up to one year (Adrian et al. (2019)).

In this paper, we augment this programme of research along two dimensions. First, we analyse a broader set of vulnerability indicators such as banking sector leverage ratios, credit to the non-financial sector, external imbalances and property prices. Second, we focus on the forecasting ability of these indicators at a *medium-term* horizon of 3-5 years, recognising that undertaking policy measures to mitigate developing risks requires significant advanced warning due to implementation lags.

Our analysis is based on a novel cross-country panel dataset of 16 advanced economies over the period 1980:Q4-2017:Q4. For each country, we collect time series information on credit growth, 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 divided by tangible assets, 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, since the 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 from 0 to 20 quarters ahead, focusing on the 12 quarter horizon as a benchmark. This is a policy horizon relevant for implementing macroprudential policy responses to address the impact of building vulnerabilities.

We find significant relationships between each of the vulnerability metrics in this study and the 5^{th} quantile of the future GDP growth distribution (which we refer to as GDP-at-Risk).[1] That is, there is no more than a 1-in-20 chance of experiencing a worse decline in GDP than this. Moreover, these relationships are both economically intuitive and meaningful in magnitude. Forecasting 12 quarters ahead, we find that GDP-at-Risk cumulatively deteriorates by 0.9 percentage points following a one standard deviation increase in 3-year credit growth (relative to GDP); by 0.75 percentage points following a similarly scaled increase in 3-year real house prices; and by 1.5 percentage points following a one standard deviation increase in the current account deficit. These results are consistent with findings from the early-warning literature that analyses the precursors of banking and currency crises (e.g. Schularick and Taylor (2012), Reinhart and Kaminsky (1999)).

In a novel result, we find that higher bank capital mitigates these increases in risk: a one standard deviation increase in bank capitalisation leads to a cumulative 0.9 percentage point improvement in GDP-at-Risk over three years. By contrast, the median projection deteriorates 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.

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. These findings are robust to alternative specifications of our regression equation such as the inclusion of Miranda-Agrippino and Rey (2015)'s measure of the global financial cycle, and simpler univariate analysis.

To understand what drives these results, we examine the behaviour of these vulnerability metrics prior to the largest growth catastrophes in our sample – in particular, the 30 largest declines in standardised real GDP growth over 3-year windows. Conditioning on this subset of the data, we find that in 73% of these catastrophes credit growth (relative to GDP) over the preceding 3 years is above its country-specific sample mean. Furthermore, 71% of catastrophes are preceded by real house price growth above its sample mean, and in 77% of cases, the banking system's tangible common equity ratio is below its sample

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

mean. We find similar results if we instead examine the behaviour of these measures prior to financial crises (as dated by Baron et al. (2019)). The current account deficit and financial conditions, in contrast, have less impressive signalling power.

Using these 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 Kingdom, 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, a widening current account deficit, and, on the latter occasion, declining banking system capital ratios. On average our 3-year ahead forecasts of GDP-at-Risk deteriorated by 4.5 percentage points cumulatively between 2002 and 2007. As an illustrative exercise, we consider the impact that a countercyclical capital buffer of 2.5% (5%) might have had over this period. Under the assumption that the impact of applying the countercyclical capital buffer on tail risk is well approximated by the marginal impact of bank capital in our quantile regressions, we find that such a policy could have offset around 20% (40%) of the deterioration in GDP-at-Risk on average across the countries in our sample.

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 sub-samples, we find an unstable relationship between these variables prior to 2007. This is also evident in our analysis of the precursors of the largest declines in GDP in our sample: our finding that weak bank capital preceded many of these GDP catastrophes is dominated by observations from the global financial crisis. 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 coefficient on credit growth in our full baseline model, we find the impact of this indicator to be stable in univariate regressions.

These findings will 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 macro-prudential indicators. These findings will be of interest as well to researchers working to develop macroeconomic models that can generate crisis dynamics (see Brunnermeier and Sannikov (2014), He and Krishnamurthy (2014) and Adrian and Boyarchenko (2012)). Our results can inform the development and calibration of these models by providing some basic empirical facts about the precursors of tail risk events.

The rest of the paper is organised as follows. Section 2 motivates our contribution in the context of the existing literature; Section 3 introduces our data and associated stylised facts; Section 4 describes our quantile regression methodology; Section 5 presents our results and Section 6 draws out some of the policy implications. Section 7 concludes. Appendices A, B and C provide additional analysis, further policy discussions and data details respectively.

2 Related Literature

Our paper relates to three main strands of the literature. First, and most directly, we build on a strand of studies that Cecchetti (2006) and Cecchetti and Li (2008) initiated with the application of quantile regression techniques to study the impact of housing and equity price booms on tail risks. More recently Adrian et al. (2018), Adrian et al. (2019) and Aikman et al. (2018) apply quantile regressions to estimate the distribution of GDP growth conditional on financial and economic conditions. Using a rich dataset capturing 11 advanced and 11 emerging economies, Adrian et al. (2018) investigate how downside risks to growth change over different horizons. Defining Growth-at-Risk as the 5^{th} quantile of the predicted growth rate, they show a strong relationship between financial conditions and tail risk in the near term. This relationship reverses, however, over the medium term, with looser conditions predicting an increase in tail risk at this horizon.[2] 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. That is, we estimate the joint impact of these vulnerability measures on downside risks to growth. Moreover, to highlight the potential utility of this technique to inform macroprudential authorities' risk assessments, we focus to a greater extent on tail risks over the medium term, which we define to be horizons of 3-5 years ahead.

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 robust result in this literature is the importance of credit-based variables as leading indicators of both the likelihood and severity of crises. In key recent contributions to this literature, Schularick and Taylor (2012) report that, across their sample of 14 developed economies from 1870 to the present day, a persistent one percentage point increase in the credit-to-GDP ratio on average raises the probability of a financial crisis from 4% to 4.3% per year, while Jordà et al. (2013) find that, conditional on a crisis, real GDP is almost 1% lower after five years if the crisis is preceded by a credit boom of this size. This echoes and extends findings from earlier and subsequent research by numerous authors.[3] These findings are consistent with various theories of the drivers of credit booms and their macroeconomic consequences, including theories of the underestimation of tail risks Bordalo et al. (2018), theories of herding behaviour by banks (Rajan (1994) and Aikman et al. (2015)) and theories of implicit government guarantees (Farhi and Tirole (2012)).

In this paper, we provide new evidence on the relationship between banking system capital ratios and macroeconomic tail risk. Recent theories of systemic risk and macroeconomic dynamics predict a highly non-linear relationship between banks' equity capital and activity, driven by the notion of there being an occasionally-binding constraint on bank solvency (see Brunnermeier and Sannikov (2014), He and Krishnamurthy (2014)

[2]See also Giglio et al. (2016) who employ this technique to assess the predictive power of various systemic risk indicators.

[3]For research on the relationship between credit growth and financial crisis risk, see Gavin and Hausmann (1996); McKinnon and Pill (1996); Honohan (2000); Eichengreen and Arteta (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).

and Adrian and Boyarchenko (2012); for an earlier contribution in the same vein, see van den Heuvel (2002)). If the capital constraint is slack in these models, then shocks have only small effects on activity. But as the constraint becomes more proximate, equivalently-sized shocks have far larger effects. Our results provide empirical support for these theories in that we find a weakly capitalised banking system generates a heavy left-hand tail in the distribution of predicted growth over the medium term.

The closest empirical work to ours is Jordà et al. (2017), which examines the relationship between bank capital ratios and the probability and severity of crises using a large cross-country data set. They find no relationship between measures of bank capital and the probability of crises; however, 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 higher capital ratios improve tail growth outcomes over the medium term. Our finding is also consistent with microeconometric evidence that banks that entered the last 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. Kuttner and Shim (2016); Bruno et al. (2017), Richter et al. (2018), Akinci and Olmstead-Rumsey (2018), International Monetary Fund (2011)). Given the limited usage of macroprudential tools over the majority of our sample, we are not able to identify the impact of specific macroprudential policy changes. However, for illustration, we do use our estimates to trace out the intertemporal trade-offs faced by policymakers in contemplating whether to tighten banks' capital ratios. While this exercise is subject to the Lucas Critique, we believe it is nevertheless informative about the potential costs and benefits of macroprudential policy action.

3 Data and Stylised Facts

This section provides details of our data set and examines the behaviour of our vulnerability measures in the lead-up to tail realisations of real GDP growth. We provide details of the data sources and descriptive statistics in Appendix C.

3.1 Description of our dataset

Our analysis is based on a cross-country panel dataset using time series from 16 advanced economies over the period 1980Q4-2017Q4. These countries are: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States.[4]

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 Demirgüç-Kunt et al. (2013) and Basel Committee on Banking Supervision (2010b).[5] 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 firms' group level TCE (defined as common equity minus preference shares and intangible assets) and total tangible assets for each country.[6] This information is obtained from Thomson Reuters Worldscope.[7] The TCE ratio for a bank is the ratio

[4]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.

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

[6]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.

[7]In general, Worldscope targets publicly quoted companies, and its coverage depends on certain

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 C. 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.

Table C.III provides summary statistics on the banks used in our sample across countries. The average number of banks per year across country-year pairs is 18, although Table C.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. For example, across all bank-year pairs in the UK, the average tangible assets holding is £226.5 billion and the average market capitalisation is $26.8 billion. In addition, we report summary statistics on aggregate assets across all banks in a given country and year. For example, aggregate assets across the UK banks in our sample is £2.7 trillion on average in a given year. 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.

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 example, in the United Kingdom, it measures the standard deviation of daily returns in the FTSE All-share index. For robustness we also show results using a financial conditions index (FCI) with a sample beginning in 1991, as in Eguren-Martin

criteria being met such as a market capitalisation of over $100m or belonging to one of the major stock indices.

and Sokol (2019). This FCI is a modified version of that constructed by International Monetary Fund (2017), which follows the methodology of Koop and Korobilis (2014). House price and credit growth variables are removed as they are introduced to the specification separately to isolate their impact.[8] The headline FCIs comprise of term spreads, interbank spreads, corporate spreads, sovereign spreads, long-term interest rates, policy rates, equity returns and equity volatility. In our framework, a lower FCI value indicates tighter financial conditions, while higher FCI indicates looser conditions, which may indicate growing risks in the medium term. 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 bank rate and the inflation rate alongside lagged quarterly GDP growth for each country in the empirical analysis as macroeconomic control variables. We standardise all variables by their country-level means and standard deviations.

3.2 GDP catastrophes

The top panel in Figure 1 plots the unconditional distribution of 3-year growth rates in real GDP pooled across all 16 countries in our dataset, estimated using a kernel density estimator (see the note to Figure 1 for details).. We focus on the 3-year growth rate to filter out noisy observations at the quarterly or annual frequency, and to focus instead on persistent declines. Evidently, this distribution has a pronounced left-hand side skew, and the left-hand tail is heavier than would be the case for a normal (the most severe growth outcome up to a 97.5% confidence level is −2.1 standard deviations from the mean, compared with −1.96 standard deviations for the normal case).

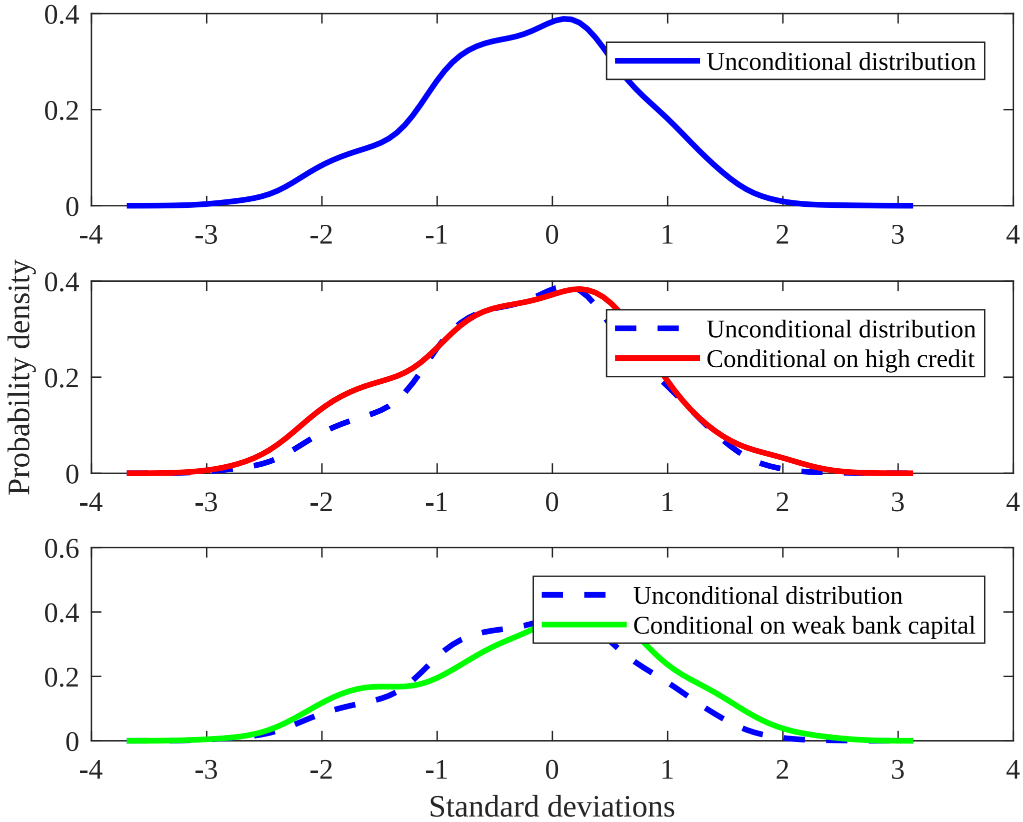
What impact do heightened financial vulnerabilities have on this distribution? The middle panel of Figure 1 plots the distribution of real GDP growth where this time we have conditioned on 3-year credit-to-GDP growth being above its country-specific mean 12 quarters earlier.[9] Visual inspection of these distributions reveals that probability mass has shifted to the left-hand tail: the 2.5% tail of GDP growth deteriorates from −2.1 to −2.3 standard deviations from the mean. The bottom panel in Figure 1 repeats the

[8] We would like to thank Fernando Eguren-Martin for providing these data. Eguren-Martin and Sokol (2019) discuss the properties of a related FCI measure and its global component.

[9] That is it asks, 'in times when 3-year credit-to-GDP growth is above average what is the distribution of GDP growth outturns 12 quarters later"?

exercise, but this time conditioning on the TCE ratio being below its country-specific mean 12 quarters earlier. While the impact is somewhat less pronounced in this case, weak bank capital also shifts probability mass to the left-hand tail, leading the 2.5% tail of GDP growth to deteriorate from −2.1 to −2.2 standard deviations from the mean.

FIGURE 1: Distributions of real GDP growth



Note: This chart presents unconditional and conditional probability densities of 3-year real GDP growth, pooled across the 16 countries in our sample. The densities are estimated using a kernel density estimator with a normal kernel function. The top panel plots the unconditional distribution of real GDP growth, standardised using country-specific means and standard deviations. The middle panel plots the distribution conditional on 3-year credit-to-GDP growth exceeding its sample mean 12 quarters earlier. The bottom panel plots the distribution conditional on banking system capital being below its sample mean 12 quarters earlier. The Jarque-Berra test statistics for each density strongly rejects the null hypothesis of normality; the test statistic for the unconditional distribution is 34 (vs critical value of 5.97); for the distributions conditional on high credit and weak bank capital, the test statistics are 17.2 and 27 respectively (versus a critical value of 5.95 in both cases).

To focus on the relationship between vulnerabilities and growth observations in the tail, we next sort our dataset to find the largest declines in real GDP over 3-year windows in our sample. Recall that all variables have been demeaned and normalised by their standard deviations, so this procedure selects the largest standard deviation GDP declines in our sample relative to country-specific means.

To avoid the resulting data being dominated by clustering at the country level – for instance, the worst growth outcomes being Finland 1990Q1, Finland 1990Q2 and so on – we require that each newly-identified GDP collapse fall outside a window of ±2 years from those previously identified at the country level.[10] Segmenting the data for each of our 16 countries over 37 years generates a total of 294 distinct GDP episodes. We sort these episodes by their severity and truncate the sorted data to find the 30 worst episodes - approximately the bottom decile of the distribution of real GDP growth. The top 5 GDP catastrophes in order of severity are Switzerland 1974-1976, Denmark 2006-2008, Sweden 1990-1992, Finland 1990-1992 and Netherlands 1979-1981.

Table 1: Vulnerability measures and GDP catastrophes

	No. of GDP catastrophes preceded by:	*Memo: No. of financial crises preceded by:*
Credit booms	73% (22 of 30)	*79% (26 of 33)*
House price booms	71% (20 of 28)	*59% (19 of 32)*
Current account deficits	53% (16 of 30)	*55% (18 of 33)*
Volatility spikes	47% (14 of 30)	*63% (20 of 32)*
Weak bank capital	77% (17 of 22)	*74% (23 of 31)*

Note: This table presents summary statistics of the correlations between the largest drops in GDP growth and vulnerability indicators in our dataset. Crises dates for the memo column are those identified in the combined list of Baron et al. (2019). n=30 corresponds to the bottom decile of the distribution of 3-year real GDP growth rates (full sample n=294). We have fewer observations for the correlations with bank capital and house prices because of the shorter time series available for these variables (our data for the former begin in 1980Q4; for the latter in 1975Q1)

What proportion of these GDP catastrophes were preceded by heightened vulnerabilities, as measured by our metrics introduced above? Table 1 presents our baseline results. In our sample, 22 of the 30 (73%) most severe declines in real GDP were preceded by credit booms, where a credit boom is defined by 3-year growth in credit-to-GDP being above its country-specific mean at the onset of the GDP decline. This estimate is close to the finding in Dell'Ariccia et al. (2016) that two credit booms in three are followed by either full-blown banking crises or extended periods of sub-par growth. On the same

[10]While this procedure removes adjacent periods within each country's experience from the sample of largest moves, it does not preclude a clustering of moves across countries in a given period.

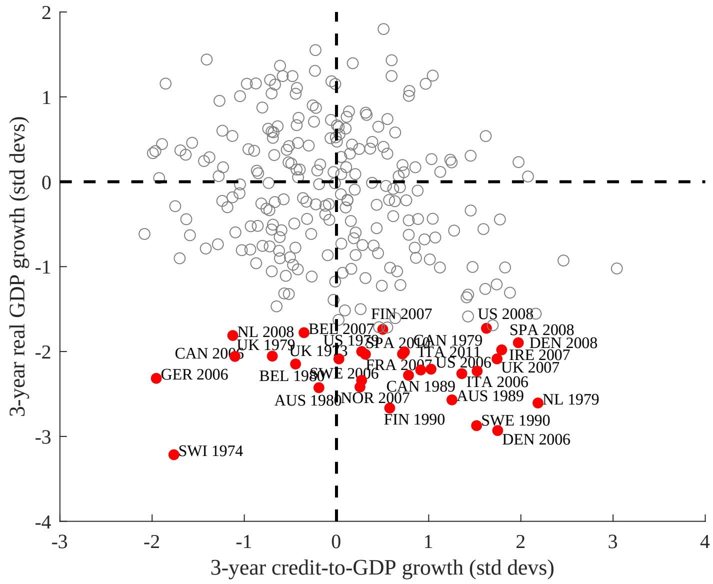
basis, 71% of the most severe GDP declines were preceded by 3-year real house price growth being above its country-specific mean, and an impressive 77% were preceded by banking system TCE ratios being below their country-specific means. The statistics for the current account deficit and for our volatility metric are less impressive, with around 50% of the largest declines preceded by low volatility or a wide current account deficit – about what would be expected in a random draw.

Figure 2 presents this information in scatter plot format. The red filled dots in each panel are the 30 most severe real GDP contractions in our sample; the grey unfilled dots are the remaining 264 observations generated by our procedure. The upper panel plots this against the 3-year growth in credit-to-GDP at the onset of the GDP decline; the lower panel plots GDP against the (standardised) level of banking systems' TCE ratios at the same point.

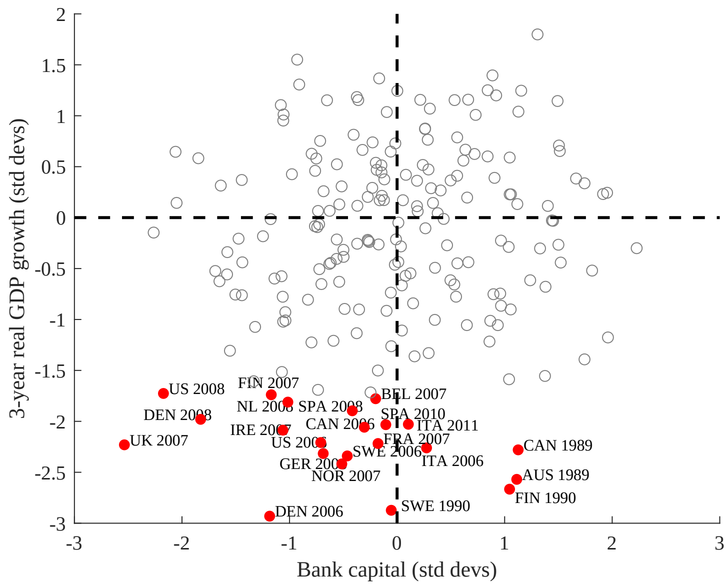
Two points emerge from presenting the information this way. First, while the majority of red filled dots do indeed lie in the south east (credit growth) and south west (bank capital) quadrants, consistent with Table 1, many of the credit growth and bank capital observations prior to GDP collapses are within one standard deviation of the mean. Evidently, many GDP catastrophes have occurred against a backdrop of vulnerability build-ups which, in hindsight, appear modest. Particularly large vulnerability build-ups may provide an even stronger signal of substantial GDP tail risks ahead, which we elaborate on in Appendix A. Second, looking at the GDP collapses that were not preceded by credit booms or weakly capitalised banking systems, (the type 1 errors), many of these cases are recessions caused by factors unrelated to financial instability. This list includes Switzerland 1974-1976 and UK 1979-1981 (tight monetary policy), Germany 2006-2008 (bank losses from foreign exposures), Spain 2010-2012 and Italy 2011-2013 (euro area sovereign debt crisis). We explore this theme further in Table 1 by recording the number of financial crises in our dataset (as defined by Baron et al. (2019)) that are preceded by elevated vulnerabilities. The signalling performance of our indicators does not improve substantially when we condition on financial crises explicitly, reflecting the substantial overlap between these events. Weak bank capital provides the strongest signal ahead of financial crises, with 23 of the 31 crises in our dataset (74%) preceded by weakly capitalised banking systems.

FIGURE 2: Vulnerability indicators prior to the largest GDP catastrophes

(A) Credit growth prior to the largest output declines



(B) Bank capital prior to the largest output declines



Note: The top and bottom panels plot 3-year real GDP growth (with overlaps removed up to+/- 2 years) against 3-year credit growth and bank capital respectively. The scatter points are country-quarter pairs. Data are in terms of country-level standard deviations. The red observations represent the largest GDP declines. Bank capital is measured as tangible common equity relative to total assets.

4 Quantile regression methodology

In this section and the next, 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 the researcher to analyse how changes in a set of conditioning variables influence the shape of the distribution of the dependent variable (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.[11]

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 Eq. 1 is the average annualised growth rate of real GDP over h horizons, $y_{i,t+h}$, 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 for country i measured at time t. The vulnerability indicators are the 3-year percentage point change in the ratio of private nonfinancial credit to GDP, 3-year growth in real house prices, the current account deficit as a percentage of GDP, realised volatility in equity prices, and the banking system's TCE ratio. As controls, we include the annual inflation rate, the annual percentage point change in the central bank's policy rate, and lagged GDP growth. Each variable is standardised using its country level mean and standard deviation.[12]

[11]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.

[12]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

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 $y^*_{i,t+h} = y_{i,t+h} - \hat{\alpha}_i^h$, that is the first-stage dependent variable minus the estimated country fixed effects. We then proceed with quantile regressions as follows to estimate β_τ^h,

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

where τ denotes the quantile under consideration and ρ_τ is the standard asymmetric absolute loss function. 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.

5 Results

To analyse results from our baseline quantile regression, we first focus on the relationship between our vulnerability indicators and the projected 5$^{\text{th}}$ quantile of GDP growth (henceforth referred to as GDP-at-Risk). Figure 3 plots local projections of the estimated change in GDP-at-Risk at various horizons, conditional on a one standard deviation innovation to each of the vulnerability indicators in our model, holding constant all other indicators in the regression.[13] The coefficients are reported in common annualised GDP growth units. So the coefficient of −0.3 percentage points at the 12-quarter horizon for

we standardise GDP growth as well as the explanatory variables.

[13] 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.

credit-to-GDP growth in Figure 3a means that a one standard deviation increase in credit-to-GDP is associated with an average annual deterioration of −0.3 percentage points in GDP-at-Risk over the next 12 quarters, and hence a −0.9% cumulative deterioration in the tail of the projected level of GDP over the next three years.

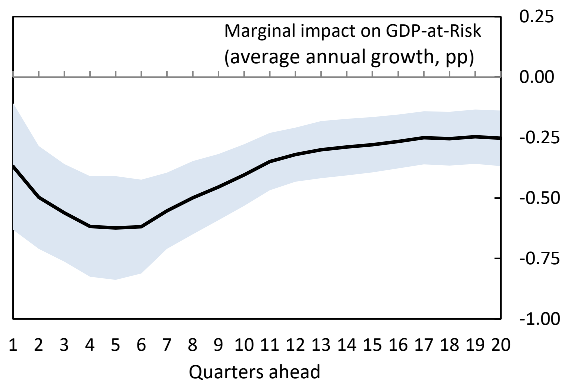
Overall, it is striking that the coefficients for credit and the current account are always negative. So stronger credit growth (relative to GDP growth) or a wider current account deficit has a detrimental effect on tail risk across our entire forecast horizon. Stronger house price growth appears to 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, telling us that a sharp spike in this indicator extends 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 three 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 3 are relatively flat between quarters 12 and 20, our focus on the 12$^{\text{th}}$ quarter is representative of a broader 3-5 year medium-term horizon.[14] This arguably is the relevant policy horizon for implementing macroprudential policy responses to address the impact of building vulnerabilities. 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)). This necessitates a forward-looking approach to monitoring risks. Next, we assess how the information content of vulnerability indicators differs for GDP-at-Risk when we focus on the near-term. Finally, we discuss our results across the GDP growth distribution, expanding our attention beyond the 5% GDP-at-Risk measure.

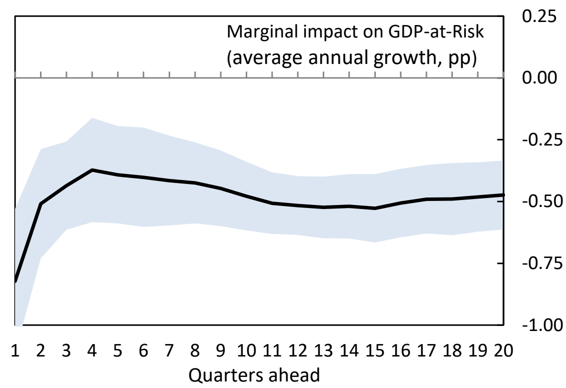
[14]Note that the local projections in Figure 3 give the average annual growth impact at each horizon. A flat, non-zero projection therefore implies a building cumulative level effect over time. For example, a coefficient of 0.25pp at the 4 year (16 quarter) horizon implies a total level effect of 1pp 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 3: Baseline results: local projections showing impact of each variable on 5$^{\text{th}}$ percentile of GDP growth at horizons from one quarter to five years ahead

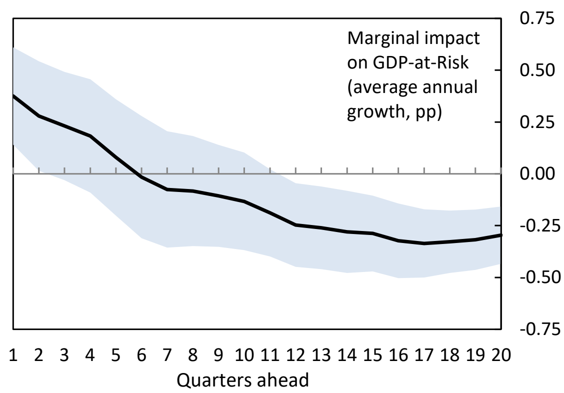
(A) Credit-to-GDP (3 year pp change)



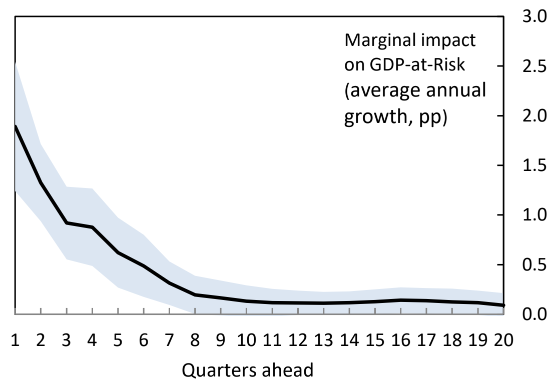
(B) Current account deficit



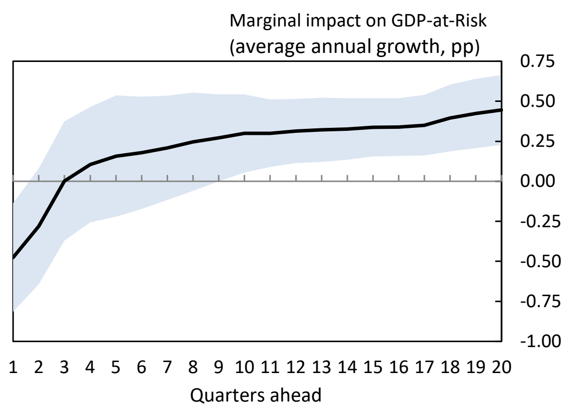
(C) Real house price growth (3 year)



(D) Volatility



(E) Bank capital (TCE) ratio



Note: These charts show the impact of a one standard deviation change in the indicator at time t on the 5$^{\text{th}}$ 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 plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

5.1 Downside risks to growth over the medium term

Figure 4 summarises the impact of each of our vulnerability indicators and macro 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) and Jordà et al. (2013) for key contributions to this literature; see Aikman et al. (2018) for a summary of the wider literature.

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 credit-to-GDP is associated with a 0.3 percentage point weaker GDP-at-Risk per annum over the next 3 years, cumulating to 0.9 percentage points.[15] 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 growth rate over the sample. Our credit result 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 medium-term coefficient on real house price growth is similar in magnitude (-0.25 percentage points per year, or -0.75 percentage points cumulatively), but somewhat less precisely estimated than the credit coefficient. 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 0.5 percentage points per year (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

[15] 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 a one standard deviation change in household credit is twice as severe as that of corporate credit.

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 vulnerability indicators is estimated individually (see Figure A.III).[16] We obtain broadly similar results 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 4: Impact of each variable on 5th percentile of GDP growth at 3-year horizon

Note: This figure shows the impact of a one standard deviation change in each indicator at time t on the 5th 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 ± 1 standard deviation. Standard errors are generated using block bootstrapping.

Volatility and financial conditions

Our results suggest 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.II (column 2) reports results from a regression where we replace our volatility measure with an index of financial condi-

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

tions from Eguren-Martin and Sokol (2019). Due to the availability of the index, we start 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. [17]

These findings are in contrast to the volatility paradox emphasised by Brunnermeier and Sannikov (2014). In their theoretical model, periods of low perceived exogenous risk lead to increased risk-taking, higher leverage and greater endogenous risk. Moreover, Adrian et al. (2018) also provides empirical support 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 increase in GDP-at-Risk in the medium-term. Our results, however, follow from the way in which we specify our model, i.e. we observe very similar results to these existing studies 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.[18]

There are advantages of conditioning future GDP growth on various indicators. To the extent that the transmission of loose financial conditions to larger macroeconomic tail risks operates by 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.

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

[18] 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.

Global asset prices

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 being 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.[19] We do this in column 3 of Table A.II by re-estimating our baseline model with with the global factor of Miranda-Agrippino and Rey (2015) replacing domestic equity volatility.[20]

The global factor proposed in Miranda-Agrippino and Rey (2015) is extracted from a large panel of risky asset prices across various geographical areas, which is available from 1980 to 2018.[21] 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.

As reported in Table A.II, this global factor is found to have a material impact on GDP-at-Risk at the 3-year horizon; a one standard deviation increase in global asset prices (i.e. a loosening in global financial conditions) is estimated to increase the severity of a downturn by -0.67 percentage points per annum over this horizon (or about 2 percentage points cumulatively). This is consistent with Eguren-Martin and Sokol (2019), 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.

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

[19] 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.

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

[21] 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.

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. Our results highlight the economically significant role for bank capital in shaping macroeconomic tail risks. We find that a one standard deviation increase in the banking sector's TCE ratio improves GDP-at-Risk by 0.3 percentage points per year over the following three years, cumulating to 0.9 percentage points. 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 $\frac{3}{4}$ of a percentage point deterioration in GDP-at-Risk relative to average, each year from 2008 to 2010 (or 2.4 percentage points cumulatively).

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.II column 4).[22]

5.1.1 Decomposing GDP-at-Risk

In Figure 5, we use our baseline regression results for the medium term (3-years) as a lens through which to view the drivers of tail risks to growth in the United Kingdom and United States over our sample. This decomposition is an illustrative example of how policy makers can use the GDP-at-Risk framework to monitor the additive impact of various measures on future risks to growth. 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. So the reading for 2005Q1, for instance, is the 5$^{\text{th}}$ quantile of the distribution of average annual GDP growth over the period 2005Q1-2008Q1, as predicted in 2005Q1. Note that we estimate the impacts of our five vulnerabilities on the

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

tail of predicted GDP growth jointly, therefore this exercise is not designed to identify the impact of orthogonal exogenous shocks. We are instead looking at the relationships between endogenous variables at different points and are interested in the additive impact of these vulnerabilities on the left tail of GDP growth over time.

Our model suggests that, retrospectively speaking, 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 – factors which, when combined, created a large and persistent increase in growth tail risks by the mid-2000s. By 2006Q2, over two years before the failure of Lehman heralded the worst of the global financial crisis, our model predicts that GDP-at-Risk over the subsequent 3 years reached -1.3% per year. In the aftermath of the crisis, our model views risks to the economy as having declined significantly, driven by modest growth 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 as much as 1.3 percentage points per year (or nearly 4 percentage points cumulatively).[23] Offsetting these positive developments to some extent, however, has been the increasing current account deficit.

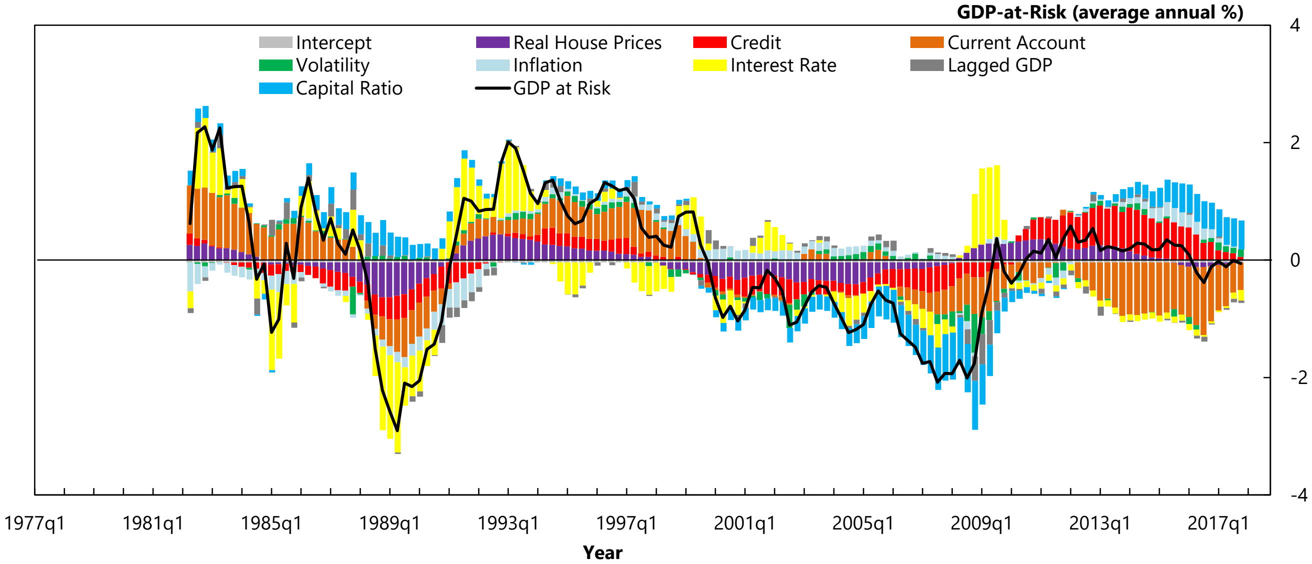
Our estimate of GDP-at-Risk for the United States shares a remarkably similar time path. Risks to growth are estimated to have built significantly in the mid-to-late 1980s, driven by rapid growth in credit and house prices, against the backdrop of a weakly capitalised banking system. These risks were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

[23] That is, if we compare current levels of banking system capital to the level at the trough of the crisis.

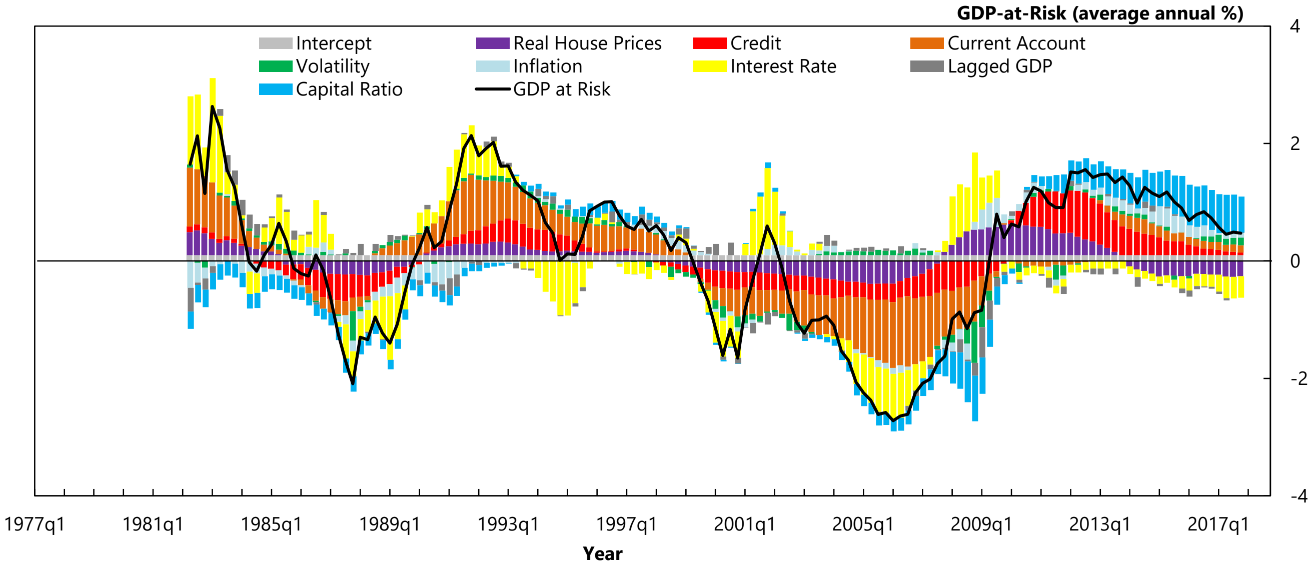
bubble.

FIGURE 5: Decomposition of GDP-at-Risk at 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. It is 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 through multiplying by 3.

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 widening in the current account deficit.[24] Many contemporaneous accounts emphasised risks 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 2006Q2, our model predicts that US GDP-at-Risk over the subsequent 3 years had reached −2.7% per year (or about 8 percentage points 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.

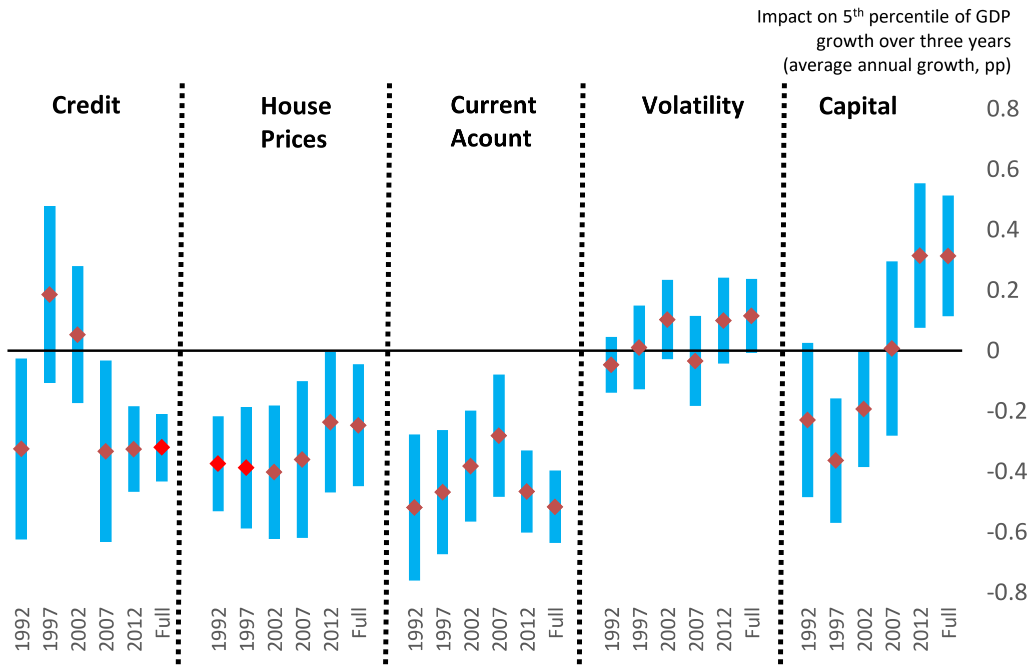
5.1.2 Measuring GDP-at-Risk over sub-samples

Figure 6 presents coefficients for GDP-at-Risk 3-years ahead estimated using different sub-samples of our dataset. In particular, the far-left bar for each variable reports the 3-year ahead coefficient estimate (plus confidence interval) for the truncated sample period of vulnerabilities observed from 1980Q4 to 1992Q1 (that is, including their impact on GDP realisations up to 1995Q1); subsequent bars then expand the sample with an incremental 5 years of data. Figure 6a presents results using sub-samples of our full baseline model, while Figure 6b presents results using a simpler models only including each vulnerability indicator in turn (plus controls).

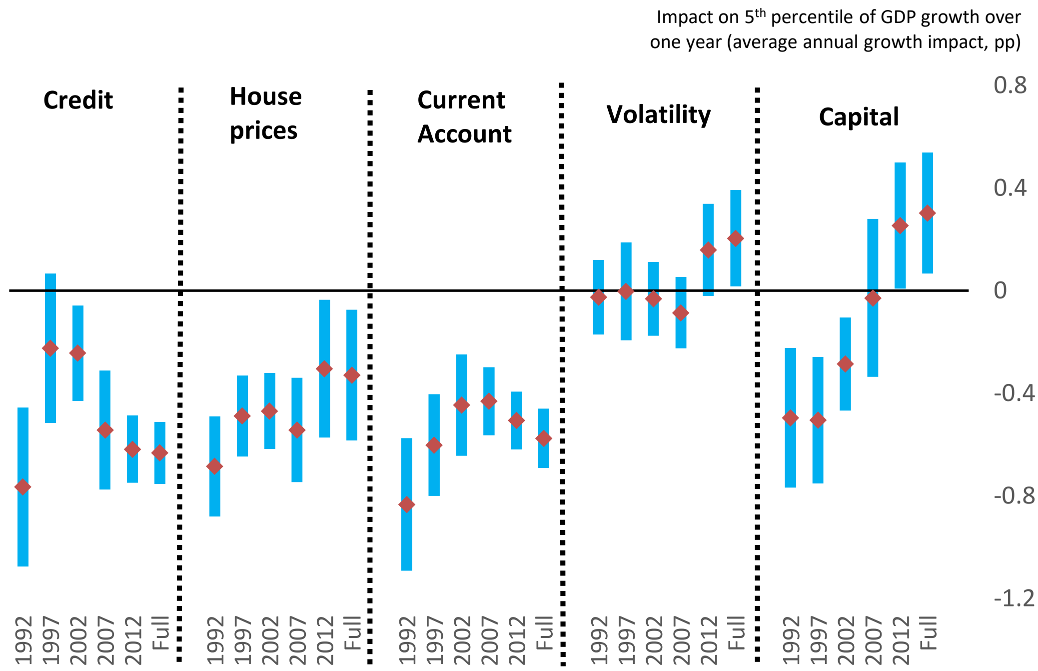
[24] In contrast to the United Kingdom, our measure of banking system capital does not contribute to the increase in US GDP-at-Risk over this period. Commercial bank leverage, which our metric captures, was relatively stable over this period, with the increase in leverage concentrated in the large dealer institutions (Duffie (2019)).

Figure 6: Impact of each variable on 5th 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 which incldues each variable individually (plus macro controls) (B) change if we restrict the vulnerabilities sample at each of the points on the x-axis.

Overall, while the coefficient estimates for house prices, credit growth (Figure 6b) 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). That we do not find a positive relationship between these variables 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 of vulnerability metrics on extreme tails of the distribution of growth, using what remains a relatively small sample of data.[25] As such, caution is required when using results from such exercises to inform real-time risk assessment.[26] Second, it is plausible that having seen genuinely extreme observations in indicators and growth before and after the global financial crisis, the 5$^{\text{th}}$ percentile coefficients in this regression will be less responsive to new data henceforth.

5.2 Near-term risks to GDP growth

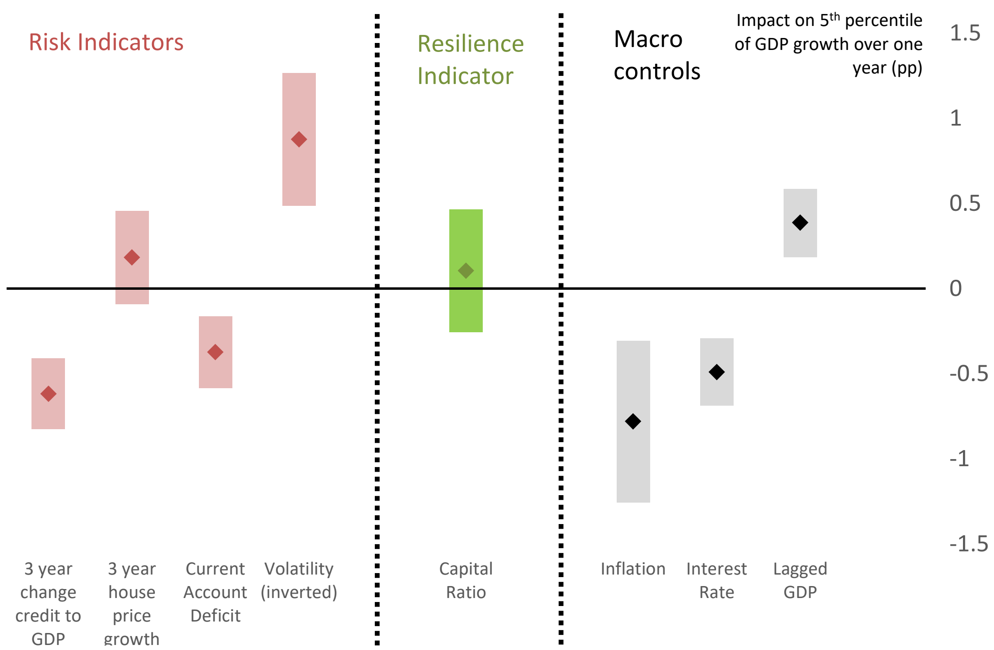
While the main focus of our analysis is on downside risks to growth over the medium-term, we briefly describe the factors our analysis highlights as key determinants of risk in the near-term. Our motivation in doing so is principally to permit comparison with the large literature on this topic. But we note that our results may also be informative for macroprudential policymakers in considering whether to release buffers that have been built up previously, and for monetary policymakers in contemplating whether monetary

[25]This is reminiscent of Mendoza and Terrones' observation in their 2012 analysis of credit booms, which updated an earlier analysis from 2008. 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'.

[26]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, 2012). This concern has also been emphasized in the literature on the credit-to-GDP gap (e.g., Edge and Meisenzahl, 2011).

easing is warranted.

FIGURE 7: Impact of each variable on 5^{th} percentile of GDP growth at 1-year horizon

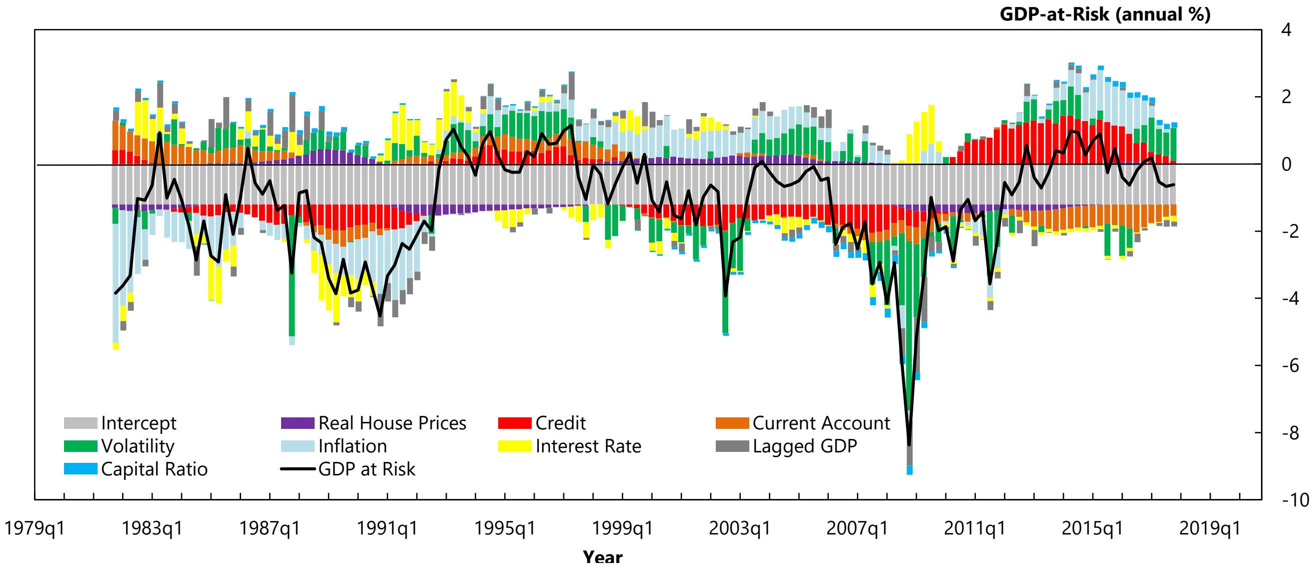


Note: Figure shows the impact of a one standard deviation change in each indicator at time t on the 5^{th} percentile of real GDP growth after 4 quarters. GDP growth impact is measured as the annual growth rate impact after one year. Confidence intervals represent ± 1 standard deviation. Standard errors are generated using block bootstrapping.

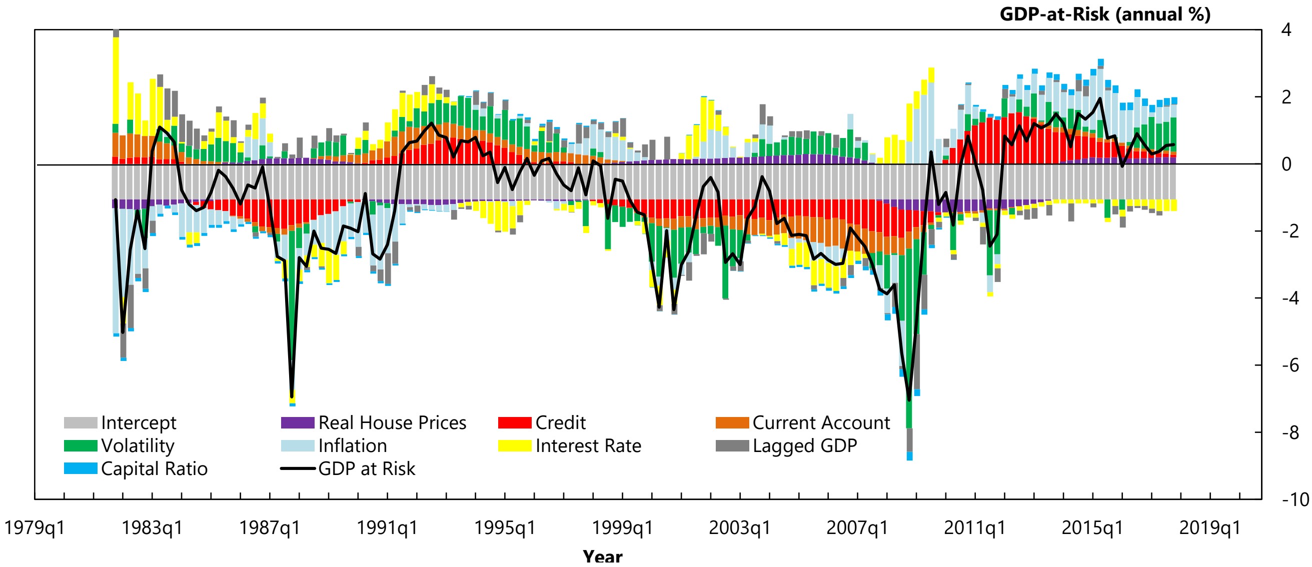
Unsurprisingly, the key determinant of GDP-at-Risk at the four-quarter horizon in our baseline regression is equity market volatility, as shown in Figure 7. This contrasts starkly to our medium-term analysis where volatility does not play a meaningful role in shaping tail risks. Our volatility measure is highly correlated with financial conditions more broadly, as discussed in Section 3.1. A one standard deviation increase in volatility is associated with a full percentage point weakening in predicted growth one year ahead at the 5^{th} percentile. To put this in context, volatility spiked by 2.2 standard deviations in the first quarter of 2008. We obtain similar results when our volatility measure is replaced with the shorter-sample financial conditions index described in Section 3. An increase in policy interest rates is also found to contribute significantly to near-term downside risk. These results are consistent with Adrian et al. (2019), which finds a significant link between financial conditions and tail risks to economic activity at this shorter horizon. It is consistent too with the vast literature that emphasises credit spreads and other financial indicators as good predictors of recession risk (e.g. Gilchrist and Zakrajšek (2012)).

Figure 8: Decomposition of 5% GDP-at-Risk at 1 year horizon

(a) UK – 1 year ahead



(b) USA – 1 year ahead



Note: The black solid line shows the 5^{th} percentile of GDP growth 1 year after each point in time, as predicted by our model. It is using coefficients estimated from the full sample. The bars shows the contribution of each indicator to that total.

Other significant contributors to downside risks to growth a year ahead include rapid credit growth (a one standard deviation increase in the 3-year credit-to-GDP ratio worsens the severity of tail risks by 0.6 percentage points), and current account deficits, (a one standard deviation increase in the deficit heightens GDP-at-Risk by 0.4 percentage points over the coming year).

Falls in house price growth are found to signal greater tail risks at a 2 quarter horizon, but this effect cannot be distinguished from zero 4-quarters ahead. The impact of banking sector capitalisation also cannot be distinguished from zero at this horizon. In each case, this lack of a significant effect in driving near-term GDP tail risks contrasts to an important role in the medium-term.

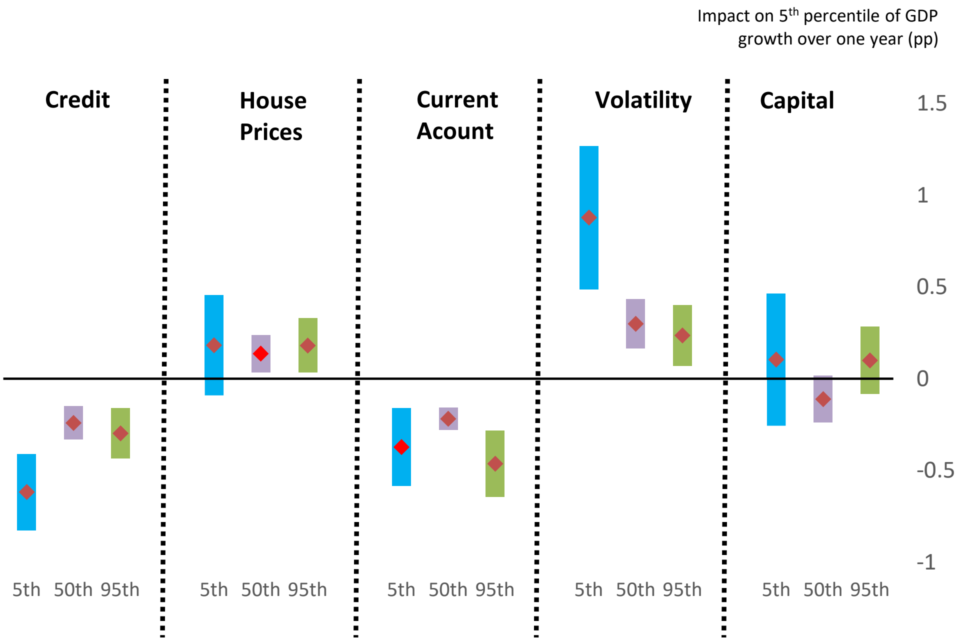
Figure 8 illustrates the contributions of the vulnerability indicators to one-year ahead GDP-at-Risk for the United Kingdom and United States over our sample period. Relative to the equivalent predicted tail 3-years ahead (shown in Figure 5), fluctuations in risk in the near-term are dominated by swings in volatility, a proxy for risk-appetite and financial conditions more broadly.

5.3 Characterising the full predicted GDP growth distribution

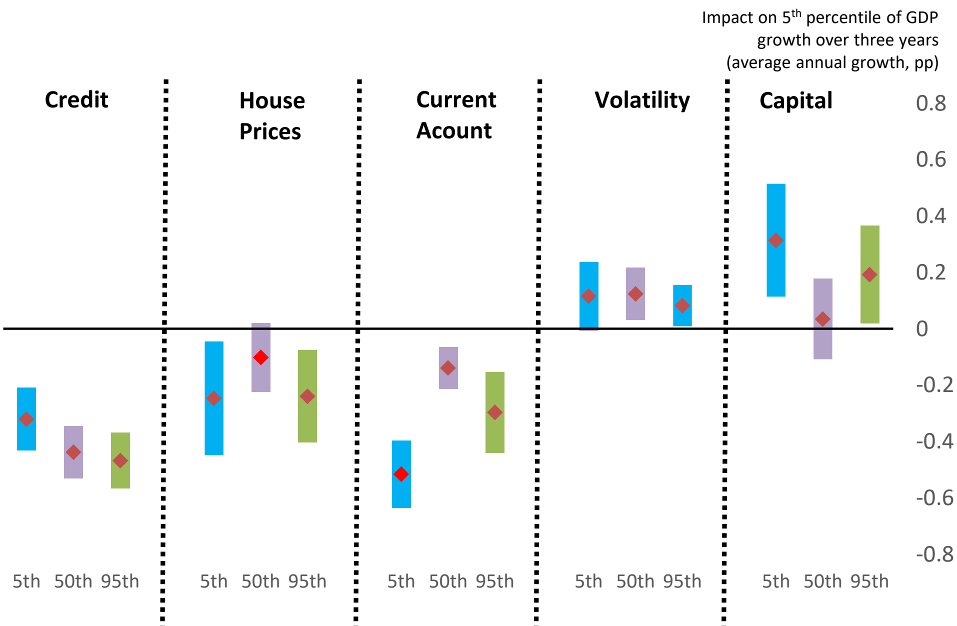
Our last set of results compares estimates of the tail of the predicted distribution of GDP growth with other parts of the distribution. We focus on comparisons with the 50^{th} quantile (the median) and the 95^{th} quantile. Figure 9 presents coefficient estimates for the 5^{th}, 50^{th} and 95^{th} quantiles at the 3-year ahead and 1-year ahead horizons. 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 quantiles. This masks, however, important differences in the magnitude of the estimated coefficients in some cases. This is particularly so at the 1-year horizon where innovations in credit growth and volatility have significantly larger impacts at the 5^{th} quantile than at the median or 95^{th}. These differences in coefficient estimates are less pronounced 3-years ahead, though 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.

FIGURE 9: Impact of each variable on 5th, 50th and 95th percentiles of GDP growth

(A) 1 year ahead



(B) 3 years ahead



Note: This figure shows the impact of a one standard deviation change in each indicator at time t on a particular percentile of real GDP growth after 4 or 12 quarters. Impact on GDP growth is measured as the average annual growth rate impact at each horizon at the labelled percentile. Confidence intervals represent plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

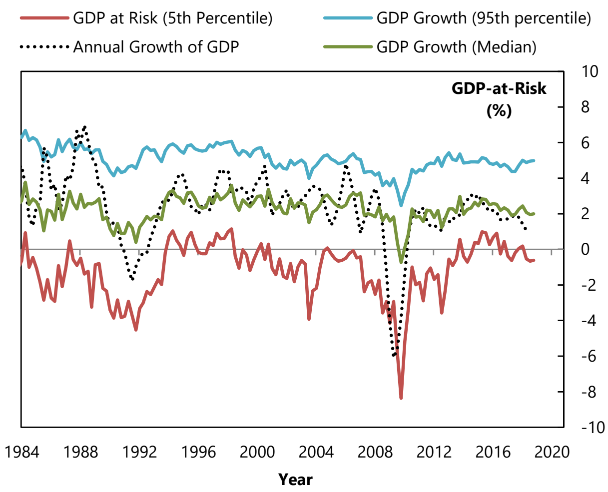
Another noteworthy finding is that higher capital ratios tend to be associated with a slightly weaker central outlook for growth (e.g. 50^{th} quantile) over a 1-2 year horizon, albeit at borderline levels of statistical significance, but are associated with less severe tail risks 3-to-5 years ahead. This, we argue, is consistent with theories that emphasise the role of bank capital as a loss-absorbing buffer. Absent a large shock, higher bank capital means marginally tighter bank credit availability for households and bank-dependent corporate borrowers, and hence slower growth in the near-term. But in the event of a low probability shock that causes material losses for banks, larger capital cushions help banks to absorb the shock, mitigating the impact on bank credit supply and macroeconomic activity over the medium term. We will explore this trade-off further in the next section.

To illustrate the economic significance of these estimates, Figures 10a and 10b presents time series estimates of predicted quantiles of UK GDP growth both 1 year ahead and 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 Figures 5 and 8. For example, the point labelled 2008 gives our forecast for 2008 GDP made either one year ahead (in 2007) in Figure 10a or three years ahead (in 2005) Figure 10b.

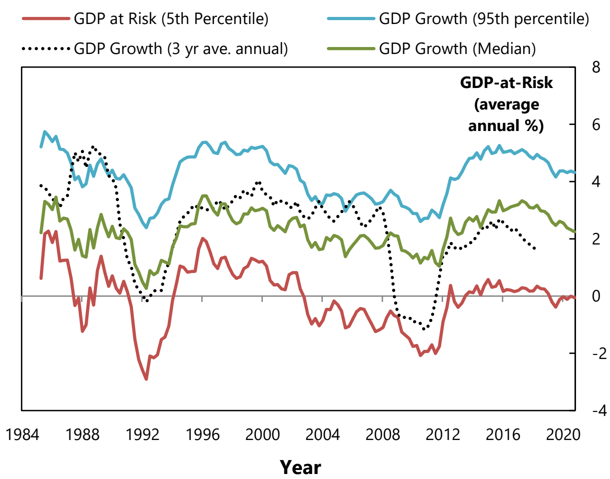
Barring one observation (the annual growth rate in 2009Q1), the outturns of GDP growth do not fall outside the lower 5% region of the predicted density at both horizons considered. We find that the shape of the predicted distribution of growth in the near term fluctuates significantly in response to changes in our indicators. In particular, the right-hand tail (95^{th} quantile) of the distribution is relatively stable (its standard deviation is 0.8pps), while as we have seen, the left-hand tail (5^{th} quantile) varies substantially (its standard deviation is 1.6pps). This is consistent with the results of Adrian et al. (2019). By contrast, innovations in vulnerability indicators act more like 'location shifters' for the entire predicted density of GDP growth 3-years ahead, with both 95^{th} and 5^{th} quantiles varying significantly (although the distance between these points of the distribution does increase in the run up to stress events).

FIGURE 10: Predicted GDP growth density

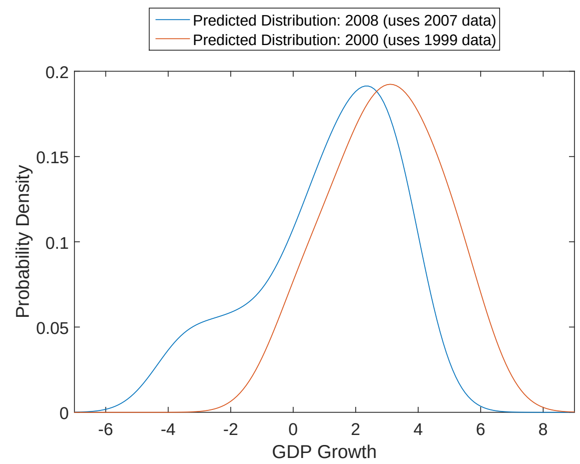
(A) Forecast from one year previously vs. actual outturn



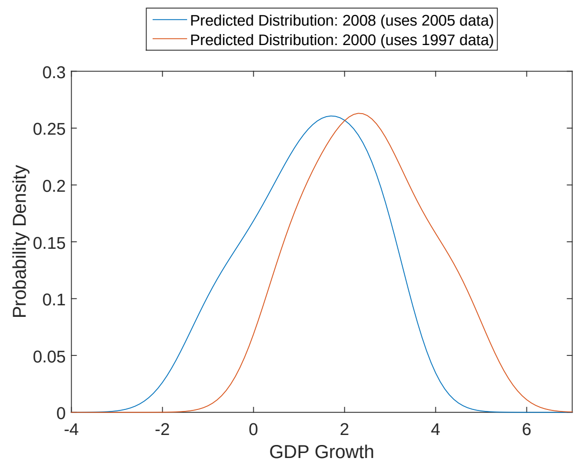
(B) Forecast from 3 years previously vs. actual outturn



(C) Predicted density (1 year ahead)



(D) Predicted density (3 years ahead)



Note: The top panel shows the predicted 5$^{\text{th}}$, 50$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of GDP growth using data either 4 quarters (A) or 12 quarters (B) ahead of each point in time as well as the realised observation at each point. The bottom panel shows the full predicted distribution of GDP growth in 2008 and 2000, using data from 2007 and 1999 (C) or 2005 and 1997 (D).

Finally, Figures 10c and 10d plot predicted densities of UK growth for 2008 Q3 as of 1-year and 3-years beforehand. These are obtained by applying a kernel density estimator to our full-sample quantile regression coefficients (estimated at the 5$^{\text{th}}$ percentile, 95$^{\text{th}}$ percentile, and every decile in between) at both horizons. Relative to a baseline predicted density for the year 2000 (shown for comparison), a researcher armed with this model in 2005Q3 would have predicted a marked leftward shift in the entire distribution and a fattening in the left-hand tail, well in advance of the crisis that was to follow (Figure 10d). By the eve of the crisis - in 2007Q3 - the fattening in that left-hand tail one year ahead would have become stark. 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.

6 Policy discussion

As we have set out, our results permit us to jointly estimate the impact of five vulnerability indicators on the shape of the GDP distribution at various horizons. The fact that we include bank capital in our framework may be of particular interest to macroprudential policymakers, given that they can influence this measure directly through regulatory requirements. In this section, we set out two policy illustrations related to our results on bank capital. The first focuses on our finding that higher bank capital ratios can reduce GDP tail risks in the medium term. The second illustrates a potential cost-benefit analysis framework for macroprudential intervention, given our tentative finding that higher capital ratios detract somewhat from the near-term median growth outlook, as well improving tail risks further out.

6.1 Policy Illustrations

The countercyclical capital buffer and medium-term tail risks

Our estimates provide some insight into the potential benefits of building banking sector capital resilience in response to growing financial vulnerabilities. The countercyclical capital buffer (CCyB) is a macroprudential tool designed for this purpose, introduced under the Basel III regulation which followed the global financial crisis (Basel Committee on Banking Supervision (2010a)). A framework for this tool has been established in over 70 countries and the CCyB has now been set at a positive level in 13 countries worldwide.[27]

How much difference might raising the CCyB above its neutral setting make to GDP-at-Risk? In Table 2, we consider the potential offsetting effect that raising the CCyB might have had on the deteriorating outlook for GDP-at-Risk from 2002 to 2007 across our advanced economy sample.

Clearly we must be cautious in interpreting such a counterfactual experiment, given the CCyB framework was not in place during our sample period and the link between bank capital and the GDP distribution may not be stable over different regulatory regimes. Moreover, we do not have a clean mapping from our bank capital measure to the CCyB. In particular, the CCyB rate is defined relative to risk-weighted assets and applies only to domestic exposures, whereas the TCE ratio on which our estimates are based is defined relative to total (unweighted) assets. In order to approximate this mapping, we draw on risk weights data from Bank for International Settlements (2018) and domestic exposures data based on the BIS Consolidated Banking Statistics database. See Appendix B for further details on this.

For illustrative purposes, we consider two stylised CCyB strategies: in the first, the CCyB reaches 2.5% by the eve of the crisis, while in the second, it reaches 5%.

The first two columns of Table 2 show our GDP-at-Risk estimates over the next three years, for each country in our panel, as of 2002 and 2007 respectively. The third column shows how that estimate of tail risks changed between 2002 and 2007. For 13 of the 16 countries in our sample, tail risks deteriorated during this period, with an average deterioration of 1.5 percentage points in average annual GDP-at-Risk three years out (or 4.5 percentage points cumulatively).

The remaining columns of Table 2 document the estimated impact of our counterfactual CCyB strategies on GDP-at-Risk by end-2007. Given our finding that raising bank capital improves GDP-at-Risk in the medium term, both our counterfactual CCyB paths result in reduced tail risk. On average across our sample of countries, a counterfactual CCyB of 2.5% by mid-2007 is estimated to improve GDP-at-Risk by 0.34 percentage points each year over the period 2008-2010 (a cumulative improvement of 0.9 percentage

[27]See International Monetary Fund (2018) and Quarles (2019) for a discussion of recent international CCyB experience.

Table 2: Illustration of the potential offsetting effect of raising the CCyB in response to growing GDP-at-Risk from 2002 to 2007

	Estimated GDP-at-Risk (av. annual GDP growth over next three years)			**Estimated impact of CCyB on GDP-at-Risk**		**Proportion of deterioration in GDP-at-Risk from 2002 to 2007 offset by CCyB**	
	2002 Q2	2007 Q2	Change 2002 to 2007	CCyB set at 2.5% by mid-2007	CCyB set at 5% by mid-2007	CCyB set at 2.5% by mid-2007	CCyB set at 5% by mid-2007
Australia	0.3	-1.7	**-2.0**	0.5	1.0	25%	50%
Belgium	0.4	-0.4	**-0.9**	0.3	0.5	29%	57%
Canada	1.4	0.0	**-1.4**	0.5	1.0	36%	72%
Denmark	0.0	-2.0	**-2.1**	0.2	0.4	9%	18%
Finland	1.4	-0.8	**-2.2**	0.3	0.7	15%	30%
France	0.4	-0.9	**-1.3**	0.3	0.5	21%	41%
Germany	-0.3	0.5	0.7	-	-	-	-
Ireland	-0.1	-1.9	**-1.7**	0.2	0.3	10%	19%
Italy	-0.2	-1.3	**-1.1**	0.7	1.5	65%	131%
Netherlands	-1.0	0.1	1.1	-	-	-	-
Norway	0.9	-0.3	**-1.2**	0.2	0.5	19%	39%
Spain	-0.7	-2.2	**-1.4**	0.3	0.7	24%	47%
Sweden	-0.1	0.1	0.2	-	-	-	-
Switzerland	0.9	0.1	**-0.8**	0.1	0.1	8%	16%
UK	-0.6	-1.7	**-1.1**	0.2	0.3	15%	29%
USA	-0.4	-2.1	**-1.7**	0.4	0.7	21%	42%
Average (simple)	-0.3	-1.2	**-1.5**	0.3	0.6	21%	42%
Average (PPP weights)	-0.2	-1.7	**-1.5**	0.3	0.3	19%	38%

Note: Columns 1 and 2 show our medium-term GDP-at-risk estimates for each country in 2002 and 2007 respectively. Column 3 shows the change between those dates – for 13 of 16 countries, GDP-at-risk deteriorated. Columns 4 and 5 show the improvement to GDP-at-risk from counterfactual CCyB strategies, which set the tool at 2.5% and 5% respectively by 2007. See Appendix B for an explanation of how our estimates for the impact of the TCE ratio on GDP-at-risk are converted into units comparable to the CCyB tool. All numbers in columns 1-5 are shown as the average annual GDP-at-risk estimate/impact over three years (or three times each number in cumulative space). Averages calculated across the 13 (of 16) countries for which medium-term GDP-at-risk deteriorated between 2002 and 2007. PPP weights are based on data in 2007.

points). That effect doubles to a 1.8 percentage point cumulative improvement under the more activist CCyB path, where the tool is raised to 5% pre-crisis.

To put that effect into context, the final columns of Table 2 document the share of the total deterioration in tail risks over 2002 to 2007 that each of these CCyB strategies could have acted to offset. For the 13 countries where GDP-at-Risk had deteriorated during the 2000s, we estimate that the 2.5% and 5% counterfactual CCyB paths could have offset around 20% and 40% of the build-up in tail risks respectively. These results should be interpreted with caution, not least because the exercise is subject to the Lucas Critique. Moreover, these beneficial impacts are biased downwards to the extent that raising the CCyB may also be expected to reduce credit and house price growth, at the margin at least. That said, they are illustrative of the scale of activism that might be required to reduce build-ups in tail risk during large credit booms.

A tentative cost-benefit analysis of raising capital

Macroprudential interventions – such as raising capital – are likely to be associated with some macroeconomic costs, as well as benefits. These costs and benefits are likely to accrue over different time horizons and affect different parts of the GDP distribution. For example, a typical macroprudential intervention may seek to improve tail risks to the macroeconomy in the medium term, by either bolstering financial system resilience to adverse shocks or by leaning on the build-up of vulnerabilities that might otherwise amplify such shocks. Such interventions, however, may dampen economic activity in the near term.

Our empirical results can be used to support such cost benefit analysis of policy actions. For example, suppose we proxy policy benefits with the impact on GDP-at-Risk at the three-year horizon. And we proxy costs with the estimated impact on the 50$^{\text{th}}$ percentile of the GDP distribution at the one-year horizon.[28] Our results allow us to map out directly how measures of medium-term risk and the near-term central outlook have evolved in our sample in response to fluctuations in our five vulnerabilities.

Figure 11a plots this locus for the United Kingdom over the past 37 years. A movement to the north-east represents an unambiguous improvement: a better outlook for

[28] Aikman et al. (2018) sets out a stylised framework of this kind; see also Duprey and Ueberfeldt (2018).

both median growth in the near-term and for tail risks to growth over the medium-term. In contrast, a movement to the north-west is the macroprudential equivalent of a trade-off inducing shock in models used for monetary policy analysis: stronger near-term prospects for the central case, but at the cost of larger future GDP-at-Risk.

The evolution of these two measures provides an intuitive account of macro-financial risks in the UK economy over the past four decades. Following the 1980-81 recession, the central outlook for growth recovered with relatively mild tail risks through the early to mid-1980s. By the late 1980s, however, tail risks had begun to build materially as vulnerabilities grew during the Lawson boom and interest rates rose sharply. By 1989 – as financial conditions tightened ahead of the early 1990s recession – the outlook for the central case deteriorated sharply, while medium-term tail risks remained severe. The 1990-91 recession followed.

As the economy emerged from that recession, prospects recovered substantially: from 1993 to the turn of the millennium, a relatively benign combination of a strong near-term outlook and relatively low medium-term tail risks prevailed. Entering the 2000s, there was not much news on the near-term central outlook.[29] There was, however, an increase in tail risks during this period, as credit and real estate vulnerabilities grew and capital ratios declined. By 2007 the near-term central outlook also worsened materially and medium-term tail risks increased further. The financial crisis ensued, with a significant realisation of tail risks and a lurch down in the near-term central outlook in 2008 and 2009. Post-crisis, the central outlook has recovered and stabilised, albeit at a somewhat lower level than in previous decades. Over the same period, medium-term tail risks have also declined relative to the 2000s.

We can use our estimates to illustrate the policy trade-offs involved with raising bank capital at specific points in this history. Our results suggest that an increase in bank capital moves us towards the south-east in Figure 11a. Such a policy might be beneficial at times when the economy is located in the northwest quadrant of our diagram: the central outlook is strong, but tail risks are high. The 2000s stand out as a prime example of such a period in Figure 11a, where the balance between near-term strength and medium-term

[29] Then-Governor of the Bank of England, Mervyn King, coined this the ''NICE" decade, given that it was characterised by Non-Inflationary Consistent Expansion.

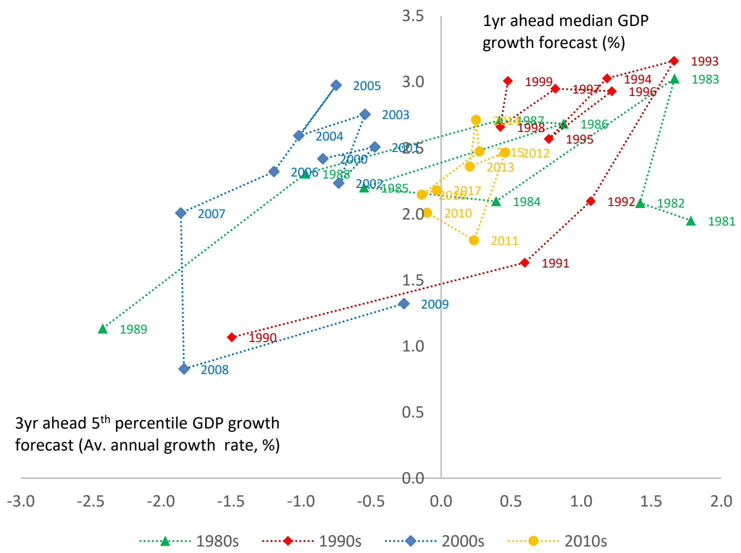
vulnerabilities was skewed relative to the other decades in our sample.

Figure 11b therefore takes 2004 as an example and traces out a policy possibility frontier at that time. As in the previous section, all the necessary caveats around counterfactual policy exercises of this kind continue to apply: the regulatory regime has since changed and our estimates are subject to the Lucas Critique. We illustrate a policy frontier for 2004 in blue, derived by increasing the TCE capital ratio by 1 to 3 percentage points relative to its 2004 level and using our central estimates of the impact of capital on the GDP distribution to map out the consequences. The red and green lines illustrate our uncertainty about the nature of this trade-off, by taking bank capital coefficient estimates on both the near-term median and medium-term tail GDP growth that are one standard deviation away from our point estimates. In 2004, our estimates suggests the median outlook for growth in 2005 was 2.5%, but that GDP-at-risk over each of the next three years averaged -1.1%. Our frontier suggests, for example, that a 2pp increase in the TCE ratio in this circumstance would have reduced the central outlook for growth in 2005 to 2.25%, but would have had the benefit of shrinking GDP-at-risk to -0.4% over the 2005 to 2008 period.

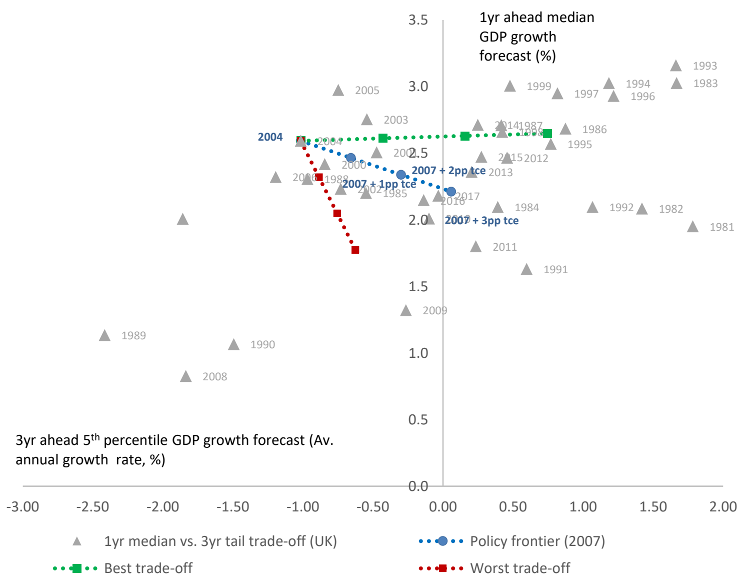
Tracing out these policy possibilities provides some indication of the policy choices available for a macroprudential authority and presents the associated trade-off in a simplified two-dimensional space. To build on this cost benefit analysis framework, it will be necessary for future research to more thoroughly map out (both with reduced-form empirics and structural accompaniments) the impact of the full range of macroprudential tools on the GDP distribution through time and their potential to interact. Accompanying this deeper understanding of the possibility frontier for macroprudential policy, it will also be necessary to consider the appropriate level of GDP-at-Risk aversion for society when managing the trade-off between the near term outlook and tail risks in the medium term.

Figure 11: An indicative quantification of the possibility frontier for medium-term GDP-at-risk and near-term median growth, under different policy settings for bank capital

(a) UK estimates for medium-term GDP-at-risk and near-term median growth 1981-2017



(b) Illustration of policy frontier in 2004 under different bank capital settings



Note: The x-axis plots the three year ahead GDP-at-Risk estimate from the labelled year, based on our baseline results for the UK. The y-axis plots the estimated one-year ahead median outlook, based on the estimates presented in Figure 9a. In the bottom panel of this chart, we illustrate the estimated impact on these two measures of raising capital from a starting point of 2004. The blue line is based on our point estimates for the impact of higher capital (presented in Figure 9). The best (worst) trade-off line is based on a +1 (-1) standard error capital coefficient for both the medium term GDP-at-Risk and near-term median growth coefficients (also presented in Figure 9a).

7 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 GDP 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 three to five 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 increase GDP-at-risk in the medium-term. We also find significant roles for both rapid house price growth and, particularly, 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 our credit growth vulnerability 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 tool 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.

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A Robustness checks and additional material

A.1 Further analysis of vulnerability measures and GDP catastrophes

Table 1 presents the proportion of GDP catastrophes preceded by heightened vulnerabilities, as measured by an indicator being above its country specific mean. However, particularly large vulnerability build-ups may provide an even stronger signal of substantial GDP tail risks ahead. Table A.I explores this hypothesis, by showing the 'hit rates' of larger moves in each of our vulnerability indicators in predicting GDP catastrophes. For example, we repeat the exercise from Table 1 under more stringent definitions of a credit boom that requires credit growth to have been at least one and two standard deviations above its country-specific mean. Under a null hypotheses that these vulnerability indicators are unrelated to subsequent GDP collapses and are themselves normally distributed, we might expect these hit rates to fall to around 16% and 2.5% for vulnerabilities defined at the 1 and 2 standard deviation levels respectively. All of our vulnerabilities exceed these null 'hit rates' and credit booms appear to have the strongest performance at a one standard deviation level, with 37% of GDP catastrophes preceded by a one-standard deviation credit boom.

A.2 Local projections of intercept and control variables in baseline model

Figure 3 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.

A.3 Alternative specifications of baseline model

As outlined in Section 5.1, Table A.II, reports results where we re-estimate our baseline model with the FCI (replacing the equity volatility); with the global factor of Miranda-

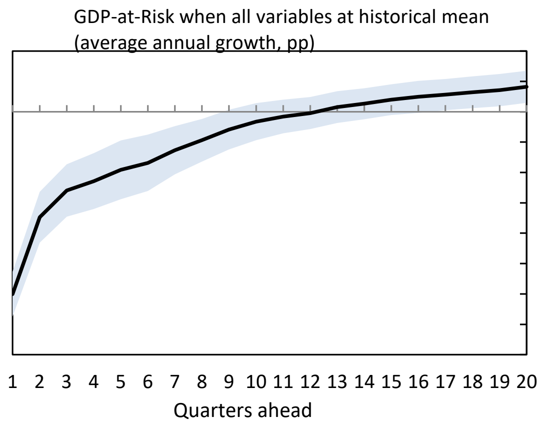
Table A.I: Vulnerability measures and GDP catastrophes, extended statistics

Weakest real GDP outcomes preceded by:		$n = 30$ (baseline)	$n = 15$	$n = 100$
Credit booms	$> \mu$	73% (22 of 30)	80% (12 of 15)	63% (61 of 97)
	$> \mu + \sigma$	37% (11 of 30)	47% (7 of 15)	27% (26 of 97)
	$> \mu + 2\sigma$	3% (1 of 30)	7% (1 of 15)	4% (4 of 97)
House price booms	$> \mu$	71% (20 of 28)	79% (11 of 14)	61% (57 of 93)
	$> \mu + \sigma$	36% (10 of 28)	64% (9 of 14)	25% (23 of 93)
	$> \mu + 2\sigma$	7% (2 of 28)	14% (2 of 14)	3% (3 of 93)
Current account deficits	$< \mu$	53% (16 of 30)	60% (9 of 15)	60% (60 of 100)
	$< \mu + \sigma$	30% (9 of 30)	33% (5 of 15)	20% (20 of 100)
	$< \mu + 2\sigma$	7% (2 of 30)	7% (1 of 15)	2% (2 of 100)
Volatility spikes	$> \mu$	47% (14 of 30)	27% (4 of 15)	41% (39 of 94)
	$> \mu + \sigma$	10% (3 of 30)	7% (1 of 15)	11% (10 of 94)
	$> \mu + 2\sigma$	7% (2 of 30)	0% (0 of 15)	6% (6 of 94)
Weak bank capital	$< \mu$	77% (17 of 22)	67% (8 of 12)	61% (43 of 71)
	$< \mu + \sigma$	32% (7 of 22)	17% (2 of 12)	27% (19 of 71)
	$< \mu + 2\sigma$	9% (2 of 22)	8% (1 of 12)	3% (2 of 71)

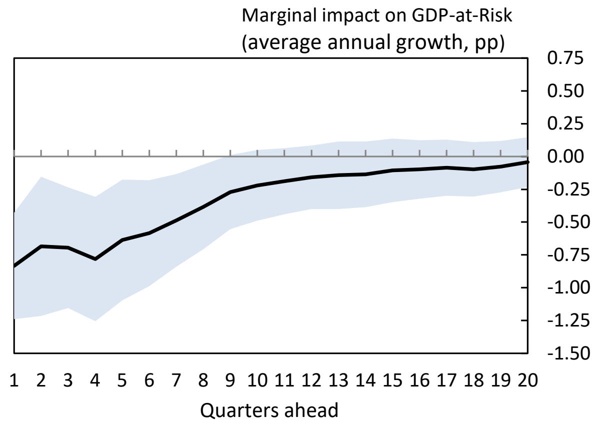
Note: This table presents summary statistics of the correlation between the largest drops in GDP growth and the vulnerability indicators in our dataset. It extends Table 1 by considering differently scaled booms and different samples of GDP falls.

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

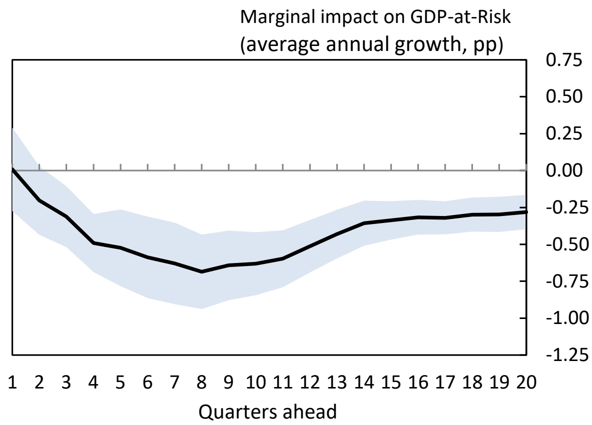
(A) Intercept



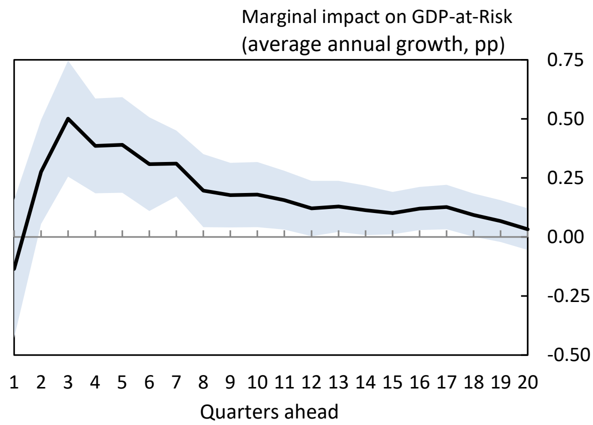
(B) Inflation



(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 3. Charts show the impact of a one standard deviation change in the 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 plus amd minus 1 standard deviation. Standard errors are genrated using block bootstraping.

Agrippino and Rey (2015) (replacing equity volatility) and with all variables in annual space.

In Figure 3 we plot local projections showing the impact of a one standard deviation change in each indicator on GDP-at-Risk in our baseline model. Figure A.II repeats this

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

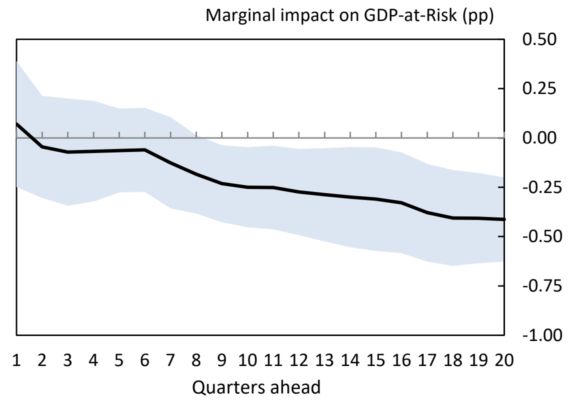
	Baseline (1)	2	3	4
Credit-to-GDP (3yr change)	-0.32 (-0.21, -0.43)	-0.30 (-0.15, -0.46)	-0.35 (-0.23, -0.46)	-0.27 (0.01, -0.54)
Real House Prices (3yr growth)	-0.25 (-0.04, -0.45)	0.03 (0.21, -0.16)	-0.15 (0.03, -0.33)	-0.17 (0.22, -0.56)
Current account (% of GDP)	-0.52 (-0.4, -0.64)	-0.63 (-0.46,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

Note: this table shows estimates of the average annual impact of a one standard deviation change 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.

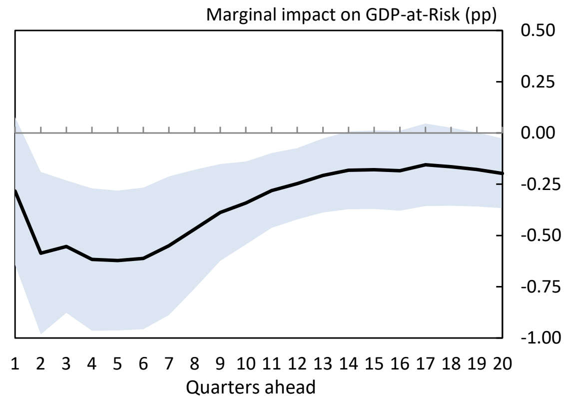
estimation, but splits total credit into its household and corporate credit components. The top row of Figure A.II presents the impact of a one standard deviation change in household or corporate credit-to-GDP on GDP-at-Risk and shows that after 20 quarters the impact of an increase in household credit 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 3, although the coefficient on the current account is generally smaller.

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

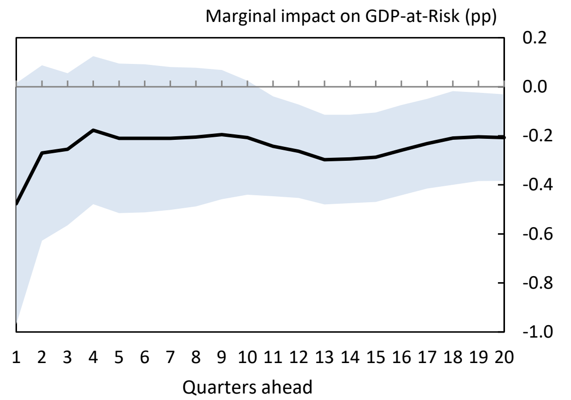
(a) Household credit-to-GDP (3 year pp change)



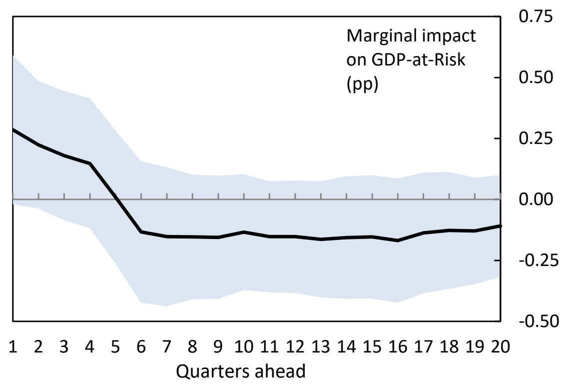
(b) Corporate credit-to-GDP (3 year pp change)



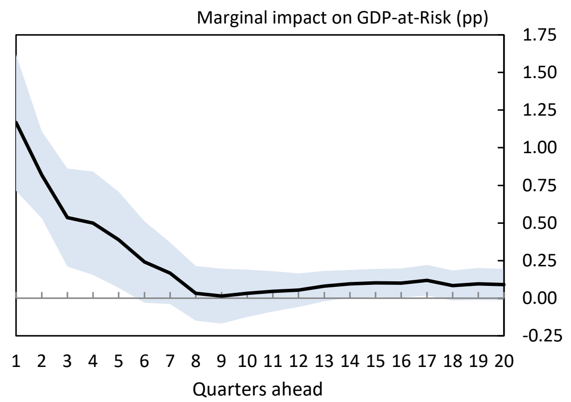
(c) Current account deficit



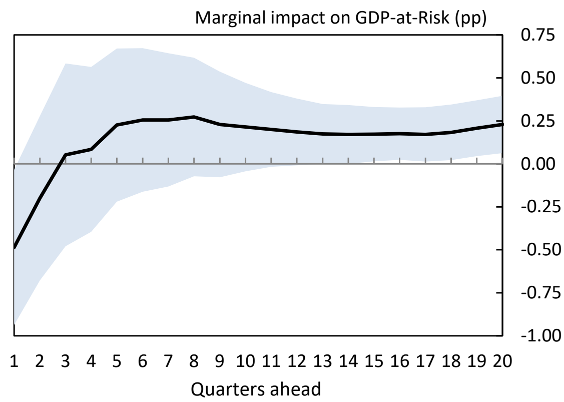
(d) Real house price growth (3 year)



(e) Volatility



(f) Capital ratio



Note: these charts show the impact of a one standard deviation 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 plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping following Kapetanios (2008).

As a cross-check on the baseline results in Figure 4, Figure A.III reports results from an alternative specification of quantile regressions where the impact of vulnerability indicators is estimated individually.[30] 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.

B Further information on policy illustrations

In Section 6 and Table 2 we consider the potential offsetting effect that raising the CCyB might have had on the deteriorating outlook for GDP-at-Risk from 2002 to 2007 across our advanced economy sample. Here we provide additional details on how the results were measured.

We do not have a clean mapping from our bank capital measure to the CCyB. In particular, the CCyB rate is defined relative to risk-weighted assets and applies only to domestic exposures, whereas the TCE ratio on which our estimates are based is defined relative to total (unweighted) assets. In order to approximate this mapping, we draw on risk weights data from Bank for International Settlements (2018) and domestic exposures data based on the BIS Consolidated Banking Statistics database. Given this counterfactual experiment concerns the build-up of vulnerabilities pre-crisis, we use country-level average risk weights in 2006 (or 2008 if 2006 not available) as reported in Bank for International Settlements (2018). This covers 11 of the 16 countries in our sample – for countries where data are not available, we take the average risk weight across all other countries in our sample. For the USA, we use data from the New York Fed Quarterly Trends for Consolidated US Banking Organizations. The average risk weight over all countries in the sample is 50%.

Domestic conversion factors for the CCyB are calculated using the BIS "Consolidated Banking Statistics" database. For each country, we calculate the ratio of domestic relative to total global bank exposures to the non-bank, non-financial private sector. We use the earliest data available (typically 2013-2014). The average domestic conversion factor in

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

the sample is 64%. Taken together, these data suggest that a 1 percentage point change in the CCyB rate in our counterfactual would have translated into approximately a 1/3 percentage point change on average in our TCE ratio measure.

For the USA, we also account for the fact that the CCyB applies only to large banks (subject to the Advanced Approaches capital framework), which reduces the effective pass-through rate of the tool to the system as a whole. Based on the Federal Reserve Boards' Large Commercial Banks statistical release, we estimate that these banks account for 57% of total US banking sector assets and have a domestic pass-through rate of 82%, such that the effective pass-through rate is $0.57 \times 0.82 = 47\%$.

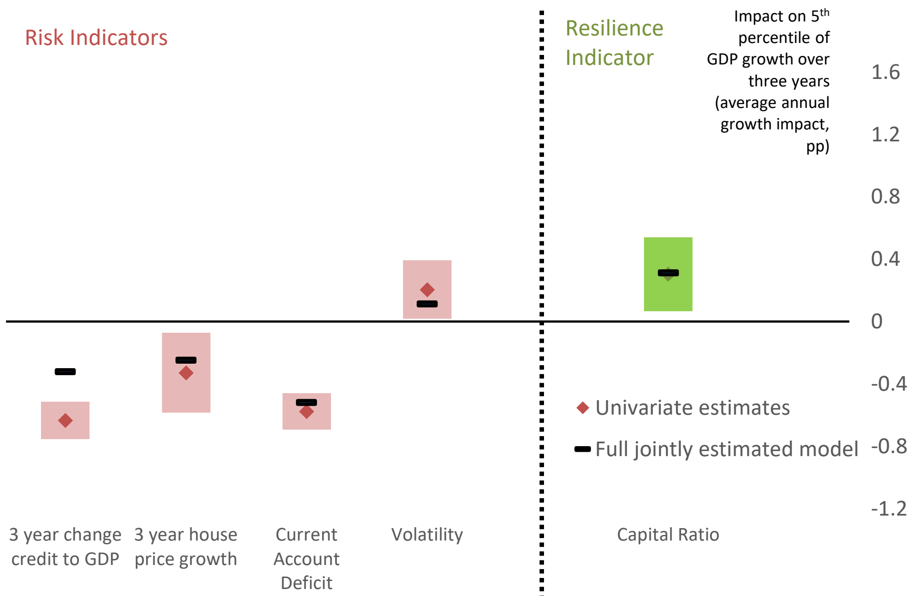
For illustrative purposes, we consider two stylised CCyB strategies: in the first, the CCyB reaches 2.5% by the eve of the crisis, while in the second, it reaches 5%. These magnitudes are broadly consistent with the findings of Aikman et al. (2019), who argue that a US CCyB between 3.1% and 4.7% might have been required to mitigate the credit crunch during the crisis. These estimates are based on the size of eventual capital injections from the Troubled Asset Relief Program (TARP) in October 2008, the degree of private sector capital raising and the extent of the reduction in real economy lending that accompanied it.

The final four columns of Table 2 document the estimated impact on GDP-at-Risk by end-2007 of our counterfactual CCyB strategies. Given our finding that raising bank capital improves GDP-at-Risk in the medium term, both our counterfactual CCyB paths result in reduced tail risk. On average across our sample of countries, a counterfactual CCyB of 2.5% by mid-2007 is estimated to improve GDP-at-Risk by 0.34 percentage points each year over the period 2008-2010 (a cumulative improvement of 0.9 percentage points). That effect doubles to a 1.8 percentage point cumulative improvement under the more activist CCyB path, where the tool is raised to 5% pre-crisis.

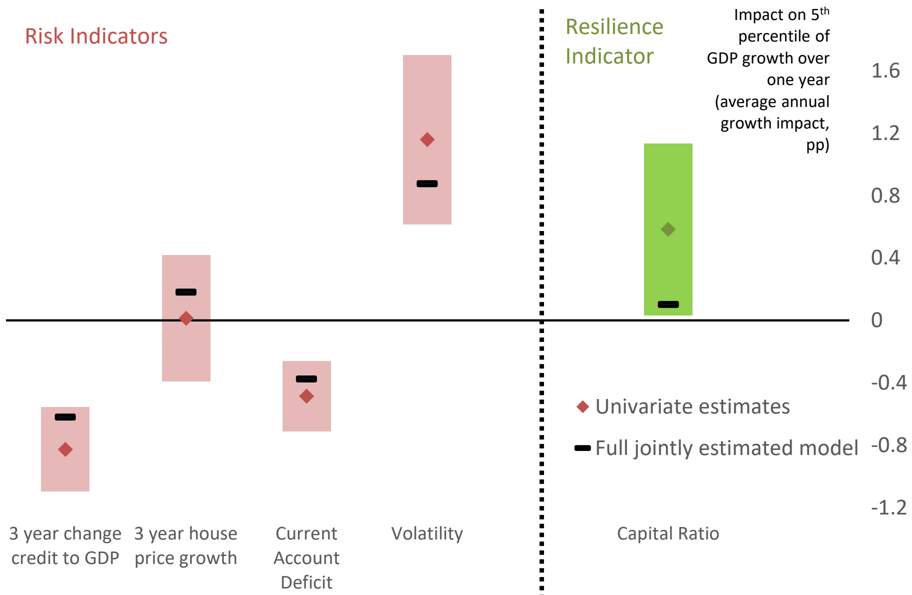
We apply our estimated coefficient that a one standard deviation change in the TCE ratio improves medium-term GDP-at-risk by 0.3pp per annum (see Figure 5) uniformly across our panel. However, the reduction in GDP-at-risk associated with a unit change in the CCyB varies across countries, given country-level variation in: i) the standard deviation in the TCE ratio; ii) the average risks weight; and iii) the domestic conversion factor.

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

(a) 3 years ahead



(b) 1 year ahead



Note: Figure shows the impact of a one standard deviation change in each indicator at time t on the 5^{th} percentile of real GDP growth after 4 or 12 quarters. GDP growth is measured as the average annual growth rate at each horizon. Confidence intervals represent plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping. 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 4).

C Data Appendix

C.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, using Thomson Reuters Worldscope, annual data on total assets, equity and intangible assets for each banking group operating in that year. 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.

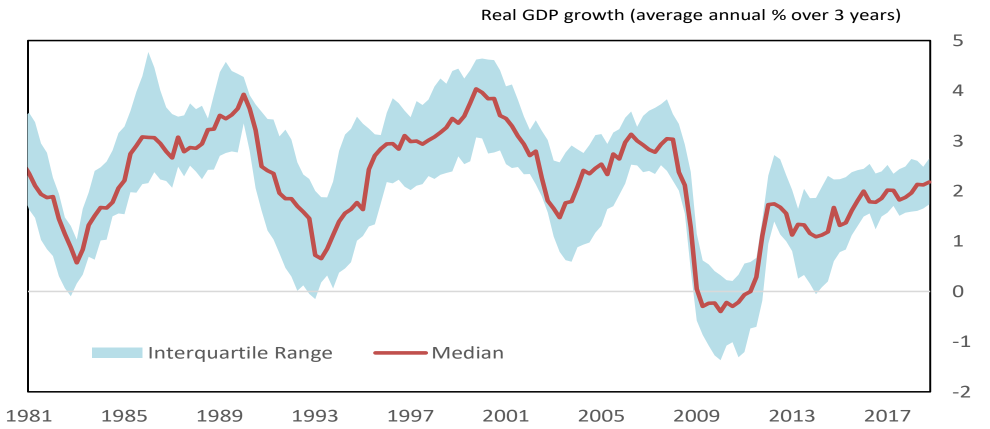
Table C.I documents data sources for each variable, Table C.II reports summary statistics on our dataset, and Figure C.I plots the median and interquartile range of real GDP growth, changes in credit-to-GDP and the TCE ratio across our panel of countries. Table C.III reports summary statistics on the 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.

Table C.I: Data sources

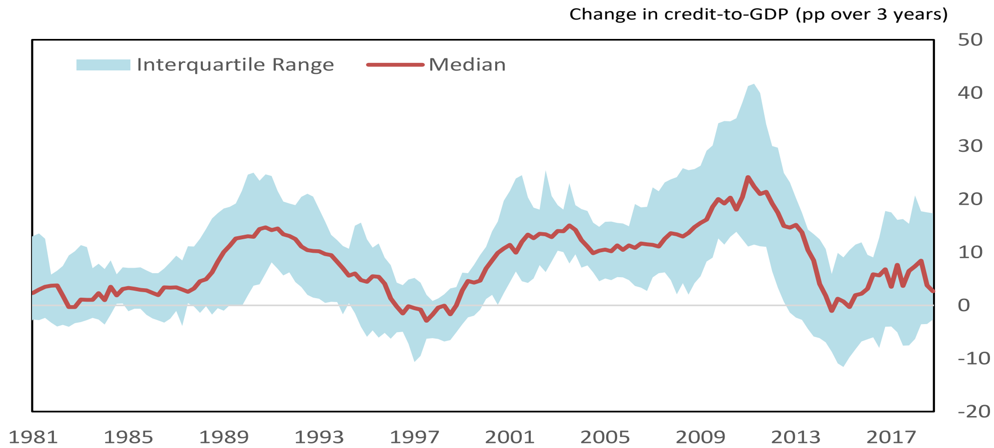
Variable	Data Source	Frequency	Notes
Real GDP	OECD	Quarterly	
Credit-to-GDP	BIS	Quarterly	3 year change in ratio of private non-financial credit to GDP
House prices	OECD	Quarterly	3 year growth in real house prices
Current Account	OECD	Quarterly	Per cent of GDP
Volatility	Datastream	Daily	Quarterly standard 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 C.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

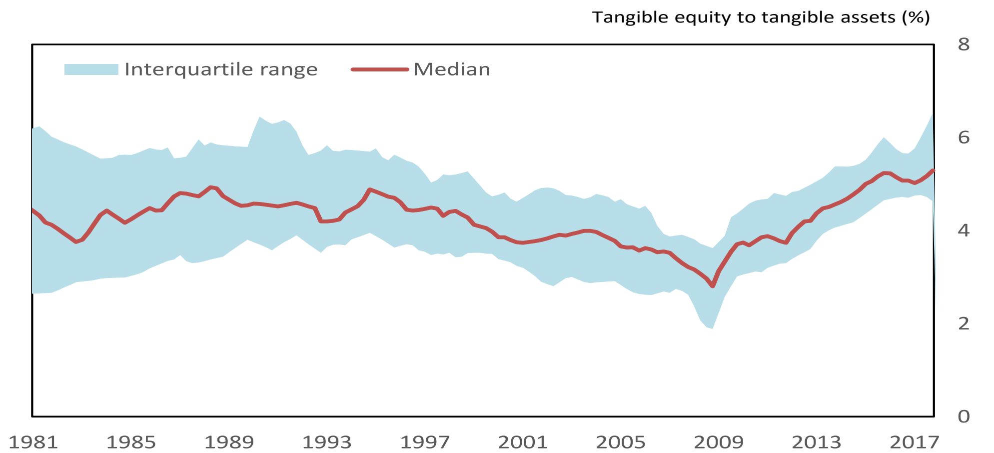


Table C.II: Summary statistics by country

		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 C.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 3.1 and C.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.