How do financial vulnerabilities and bank resilience affect medium-term macroeconomic tail risk?[◇]

David Aikman[*] — Bank of England

Jonathan Bridges[†] — Bank of England

Sinem Hacıoğlu Hoke[‡] — Bank of England, DAFM

Cian O'Neill[§] — Bank of England

Akash Raja[¶] — Bank of England, LSE

May 24, 2019

Preliminary, do not quote without authors' permission

Abstract

How can macroeconomic tails 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 3 to 5 years. We find that such downside risks can be partially mitigated, however, by increasing the capitalisation of the banking system. We estimate that GDP-at-Risk over the medium term deteriorated by around 2.5% in the run-up to the crisis on average across the countries in our sample. Using our estimates, we argue that a countercyclical capital buffer of 2.5% (5%) would have been sufficient to mitigate up to one-quarter (one-half) of this increase in medium term macroeconomic tail risk.

Keywords: Financial stability, GDP-at-Risk, Macroprudential policy, Quantile regressions.

JEL Classification: G01, G18, G21

[*]Threadneedle Street, London EC2R 8AH, UK. E-mail: david.aikman@bankofengland.co.uk

[†]Threadneedle Street, London, EC2R 8AH, UK. E-mail: jonathan.bridges@bankofengland.co.uk

[‡]Threadneedle Street, London EC2R 8AH, UK. Data Analytics for Finance and Macro (KCL). E-mail: sinem.hacioglu@bankofengland.co.uk

[§]Threadneedle Street, London EC2R 8AH, UK. E-mail: Cian.O'Neill@bankofengland.co.uk

[¶]Threadneedle Street, London, EC2R 8AH, UK. E-mail address: akash.raja@bankofengland.co.uk

◇ We are grateful to Alex Brazier, Steve Cecchetti, Anil Kashyap, John Muellbauer, Hélène Rey and seminar participants at the Bank of England, ECB and ESRB for useful comments and discussions. The views expressed in this paper are those of the authors and do not reflect those of the Bank of England or any of its Committees.

1 Introduction

The distribution of GDP growth has a fat left-hand tail. The macroeconomic fallout following the global financial crisis was a stark reminder of the enormous costs – both economic and social – of landing in that left-hand tail. It has rightly prompted a renewed focus on the drivers of economic tail risks, the danger posed by financial instability and how that danger can best be mitigated.

Much of the output lost in the Great Recession can be explained by the amplifying effects of large debt and asset price imbalances, intermediated by a fragile financial system (Bernanke (2018), Gertler and Gilchrist (2018), Aikman et al. (2019)). System resilience had not kept pace with growing macrofinancial vulnerabilities. The lesson was clear: vulnerabilities must be monitored, early warnings given and action taken to counter the associated tail risks. Financial Policy Committees have now been set up in over 40 countries around the world (Edge and Liang (2017)) to pursue these tasks – these Committees represent the institutional memory of the global financial crisis. Their remit is macroprudential: "prudential" in its focus on building resilience against tail events and "macro" in its focus on the implication of system-wide vulnerabilities for the real economy at large (Crockett (2000), Borio (2003)).

Operationalising a macroprudential framework requires a programme of research on two key relationships. First, the impact of vulnerabilities observable today on the future GDP distribution, particularly the left-hand tail. This relationship must be established at a sufficiently medium-term horizon to facilitate a macroprudential response, before it is too late. Second, an understanding is required of how macroprudential tools can mitigate tail risks in the economy – for example, by building financial system resilience – and what, if any, costs such interventions might have to other parts of the GDP distribution. This second step is crucial if policymakers are to calibrate appropriate responses, as vulnerabilities ebb and flow through the financial cycle.

This paper makes novel contributions to our understanding of both of these two key relationships. First, by providing a multivariate narrative for the drivers of advanced economy GDP tail risks, with an explicit focus on the policy relevant, medium-term horizon. Second, by establishing the role of bank capital – an indicator of financial system resilience that can be directly influenced by regulatory authorities – in mitigating those tail risks. To do so, we develop a cross-country panel dataset for 16 advanced economies over the period 1980Q4-2017Q4. For each country, we collect time series for five vulnerability measures. These span credit growth, house prices and current account imbalances, a fast-moving financial conditions measure and a measure of banking sector capital relative to total assets. The latter is a novel addition to a cross-country panel of this kind and facilitates new insights. We construct this capital series by aggregating individual bank balance sheet information for each of our 16 countries over four decades.

We formalise the link between our vulnerability measures and the projected GDP distribution by constructing local projections (following Jordà (2005)) in a panel quantile regression setting. This approach affords a rich dimensionality to our results. It permits us to jointly estimate the dynamic relationship between each of our five vulnerability indicators and the shape of the GDP distribution at various horizons. Within the estimated GDP distribution, our macroprudential focus is on the left-hand tail, which we measure at the 5^{th} percentile. We therefore add to the fast-developing literature on so-called "GDP-at-risk".[1] GDP-at-risk is defined as the worst forecasted outturn for real GDP growth at a given horizon up to given probability, say 5%, and provides a useful summary statistic around which to anchor macroprudential analysis.[2]. For financial stability, a systematic, repeatable framework for risk assessment is particularly valuable, given the rarity of tail events, the propensity for crisis memory to fade and the potential for inaction bias (see Knight (2006) and IMF-FSB-BIS (2016)). It is therefore not surprising that macroprudential authorities around the world are exploring GDP-at-risk as a potential organising framework.[3]

Our primary contribution is to establish the link between financial system resilience – as measured by banking system capitalisation – and GDP tail risks in the medium term. We document that 73% of the worst GDP catastrophes in our dataset follow periods of below-average bank capitalisation. Consistent with that, our quantile regressions

[1]See Cecchetti (2006) and De Nicolò and Lucchetta (2012) for early expositions of this approach. See Adrian et al. (2016) and Adrian et al. (2018) for more recent contributions to this literature.

[2]There are parallels to the inflation forecast targeting regime, which helped to embed a systematic framework for monetary stability 20 years ago, e.g. Svensson (1997)

[3]See for example IMF (2017), Aikman et al. (2018), ECB (2018), Duprey and Ueberfeldt (2018) and Bank of Japan (2018)

demonstrate that higher levels of bank capital significantly improves GDP-at-risk in the medium-term. To our knowledge, this is the first paper to establish this link. Our findings support 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 estimates suggest an economically significant role for bank capital in shaping macroeconomic tail risks. For example, we estimate that by the eve of the financial crisis, the diminution in UK banking sector resilience relative to average was sufficient to account for a $\frac{3}{4}$ of a percentage point deterioration in 5% GDP-at-Risk each year over the three year horizon 2007-2010. Our estimates therefore provide some insight into the potential benefits of building bank capital 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 (2010)). We illustrate that had this CCyB tool been in place pre-crisis and had it followed a strategy whereby it reached 2.5% (5%) by the eve of the crisis, it could have been sufficient to offset around one-quarter (one-half) of the deterioration in GDP tail risks that had occurred on average across the countries in our sample between 2002 and 2007.

We also find tentative evidence, however, that raising bank capital has some cost to the central GDP outlook in the near-term. Our estimates can therefore define an illustrative policy possibility frontier, which traces out the reduction in medium-term tail risks and the cost to near-term median growth associated with different increments to bank capital. Such a framework could help to provide the underpinnings for macroprudential cost-benefit analysis.

Our second main contribution is to embed these novel bank capital estimates within a rich, multivariate framework which jointly estimates the impact of various vulnerability indicators on GDP-at-risk. In a departure from the existing literature, our focus is on the role these vulnerabilities have in shaping *medium-term* macroeconomic tail risks, which can provide a meaningful early warning to policymakers. In this setting, we find that rapid growth in credit and house prices and a wide current account deficit all provide important indicators of deteriorating GDP-at-risk over the next three years. In contrast, financial conditions measures – which have received the bulk of the attention in this literature to date – do not contribute meaningfully to tail risks at this horizon, once our other vulnerabilities and macroeconomic controls have been taken into account. Instead, tightening financial conditions provide the best *near-term* signal that existing vulnerabilities could crystallise over the next year, posing significant downside news for the GDP distribution over that shorter horizon.

Taking our estimates together, we are illustrate the significant variation in medium-term tails risks in advanced economies over the past four decades, decomposing the contribution from each of our vulnerability indicators. For example, in the UK and US, we pick up the sharp deterioration in GDP-at-risk in the late 1980s as credit, house price and current account vulnerabilities grew and interest rates were hiked sharply. The early 1990s recession ensued, followed by a period of relatively benign tail risks. A long slide in tail risks then began through the 2000s, with credit, house price and current account vulnerabilities re-emerging, accompanied by falling bank capital resilience.

While this retrospective analysis is encouraging, we offer this result with an important health-warning: we find that including the crisis episode and its aftermath is key to uncovering the impact of credit growth and bank capital on tail risk in our sample. When calculated in pseudo real time, our coefficients on these two vulnerabilities are not stable prior to the inclusion of the crisis observations. While disappointing, this is unsurprising. We argue that these results reflect the distinct nature of the global financial crisis, an event that has few precursors in our data sample. Empirical models such as this are always subject to the 'rear-view mirror' critique of inductive reasoning. Nevertheless, we argue that with this experience now in-sample, our metrics are better suited to spotting build-ups in tail risk in future – to paraphrase Carmen Reinhart and Kenneth Rogoff, helping at least to guard against the call that 'next time is different'.

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.

2 Related Literature

Our paper relates to three main strands of the literature.

First, and most directly, it is closely related to recent work by Adrian et al. (2016), Adrian et al. (2018) and Aikman et al. (2018) that have applied quantile regression techniques to estimate the distribution of GDP growth conditional on financial and economic conditions.[4] This literature in turn builds on Cecchetti (2006) and Cecchetti and Li (2008), which introduced the application of this technique to study the impact of housing and equity price booms on tail risks.[5]

Adrian *et al.* (2019) find that downside risks to US economic activity at the 4-quarter ahead horizon depend strongly on measures of financial conditions, while upper quantiles tend to be stable over time. Adrian *et al.* (2018) extends this analysis to consider the relationship between financial conditions and growth at horizons up to 12 quarters across a panel of 11 advanced and 11 emerging economies separately. They confirm the strong relationship between financial conditions and growth in the near term, but find that this relationship reverses over the medium term, with looser conditions predicting an increase in tail risk at this horizon. They also find that credit booms (captured via a binary variable that takes the value of 1 when the change in credit-to-GDP over 8 quarters and the FCI are each in the upper terciles of their historical distributions) are associated with deterioration in the projected 5^{th} quantile of growth in the medium term.

Our contribution relative to this body of work is to explore a wider set of indicators of downside risk to growth in a multivariate framework, including the effect of measures of banking system resilience. Moreover, to highlight the potential utility of this technique to inform macroprudential authorities' risk assessments, we focus to a greater extent than in the above papers on tail risks over the medium term, which we define to mean 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

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

[5] Chavleishvili and Manganelli (2019) present a methodology for analysing the relationships between quantiles of endogenous variables in a quantile vector autoregression framework.

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 Jorda *et al.* (2013) find that, conditional on a crisis, real GDP is almost 1% lower after five years following this shock. This echoes and extends findings from earlier and subsequent research by numerous authors.[6] 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. (2016)) and theories of implicit government guarantees (Farhi and Tirole (2009)).

One contribution of our paper is to 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 nonlinear 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 (2015) 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 in this regard is Jorda *et al.* (2019), which examines the relationship between bank capital ratios and the probability and severity of crises using a large t cross-country data set. They find no relationship between measures of bank capital and the probability of crises; but 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

[6]For research on the relationship between credit growth and financial crisis risk, see Gavin and Hausmann (1995); McKinnon and Pill (1996); Honohan (1997); Eichengreen and Arteta (2000); Bordo *et al.* (2001); Borio and Lowe (2002a) and (2002b); Borio and Lowe (2004); Borio and Drehmann (2009); Drehmann et al. (2011); Mendoza and Terrones (2011); Baron and Xiong (2017); and Bridges *et al.* (2017)

that we find higher capital ratios improves tail growth outcomes over the medium term. Our finding is consistent too with micro-econometric evidence that banks that entered the last crisis with higher capital ratios contracted their lending by less (see 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)). Given the limited usage of macroprudential tools over the majority of our sample, we are not able to identify the impact of specific macroprudential shocks. For illustration, however, 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

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.

For each country, we collect time series for five vulnerability measures: the 3-year percentage point change in the private non-financial sector credit-to-GDP ratio; 3-year real house price growth; the current account deficit as a percentage of GDP; realised volatility over one quarter in equity prices (we also report results replacing this with a financial conditions index); and, as a measure of the resilience of the financial system, banking system tangible common equity (TCE) to total asset ratios. The TCE ratio is a widely-used measure of banks' resilience (see Demirguc-Kunt *et al.* (2013) and Basel Committee on Banking Supervision (2009).[7] All variables are standardised using country-level means and standard deviations.

Table B.I documents data sources for each variable, Table B.II reports summary statistics on our dataset, and Figure 1 plots the median and interquartile range of real GDP growth, changes in credit-to-GDP and the TCE ratio across our panel of countries.

We construct a novel cross-country dataset for the TCE ratio. To do this, we first collect individual bank balance sheet data on firms' group level tangible common equity (defined as common equity minus preference shares and intangible assets) and total assets. This information is obtained from Thomson Reuters Worldscope. The tangible common equity (TCE) ratio for bank i is the ratio of its tangible common equity to tangible assets.

For each country, we collect individual bank data. 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 the Appendix A.1. 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.

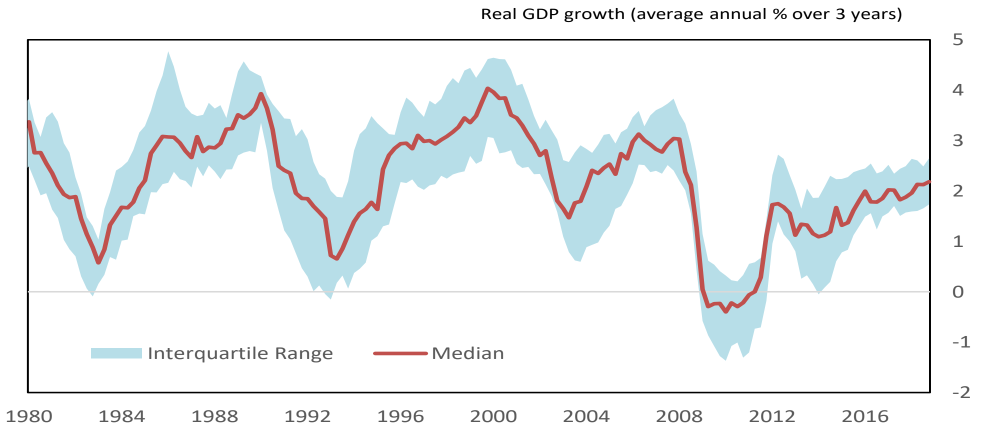
To estimate the impact of country-specific financial conditions, we have included two alternative variables. Firstly, we use equity price volatility as a proxy for financial conditions in our baseline specification to make use of its longer data availability. This series can be extended back to 1980 with the other variables in our specification. The volatility series is measured as the monthly standard deviation of returns in each country's equity price index. For example, in the UK it measures the standard deviation of returns in the FTSE All-share index.

For robustness we also show results using an FCI with a sample beginning in 1991. The FCI and volatility series are generally well correlated - for example, for the US the correlation is 0.92, while for the UK it is 0.72. Our financial conditions index (FCI) follows the framework of Koop and Korobilis (2014) which is also utilised by Adrian

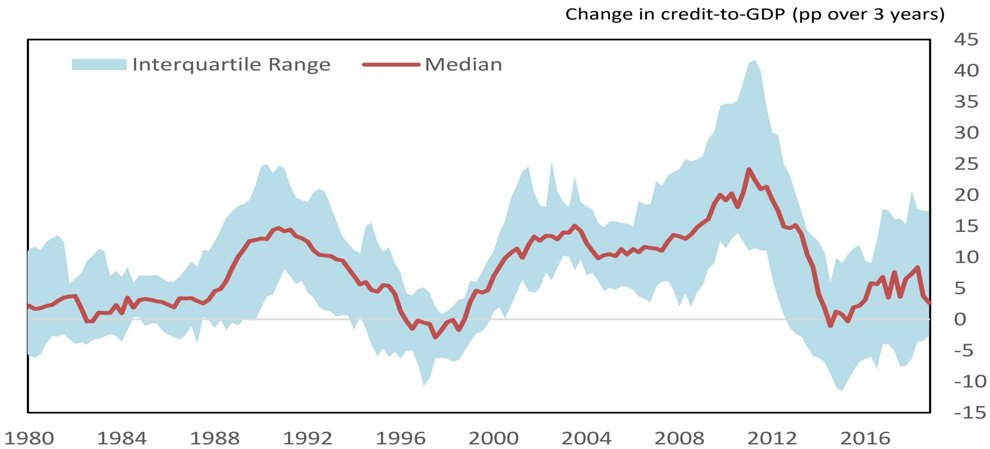
[7] The TCE measure we use is strongly correlated with other measures of banking system leverage. It has a correlation of 0.75 with the Financial Policy Committee's leverage indicator for the United Kingdom, for instance.

Figure 1: Median and Interquartile range of selected indicators across sample of countries

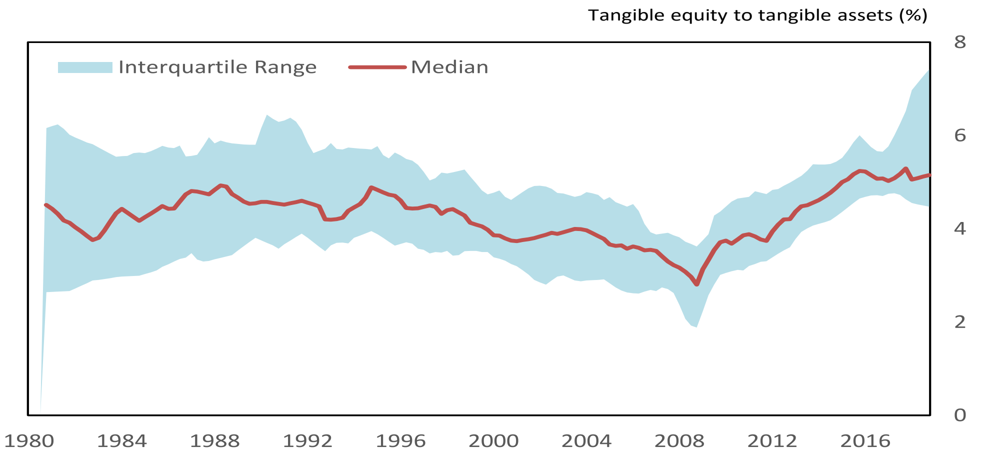
(a) Real GDP Growth



(b) 3 year change in Credit-to-GDP



(c) Capital Ratio



et al. (2018). Our index differs in that it does not include house prices and credit growth variables.[8] These two variables are introduced to the specification separately to isolate their impact. 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.

3.2 An initial look at the data

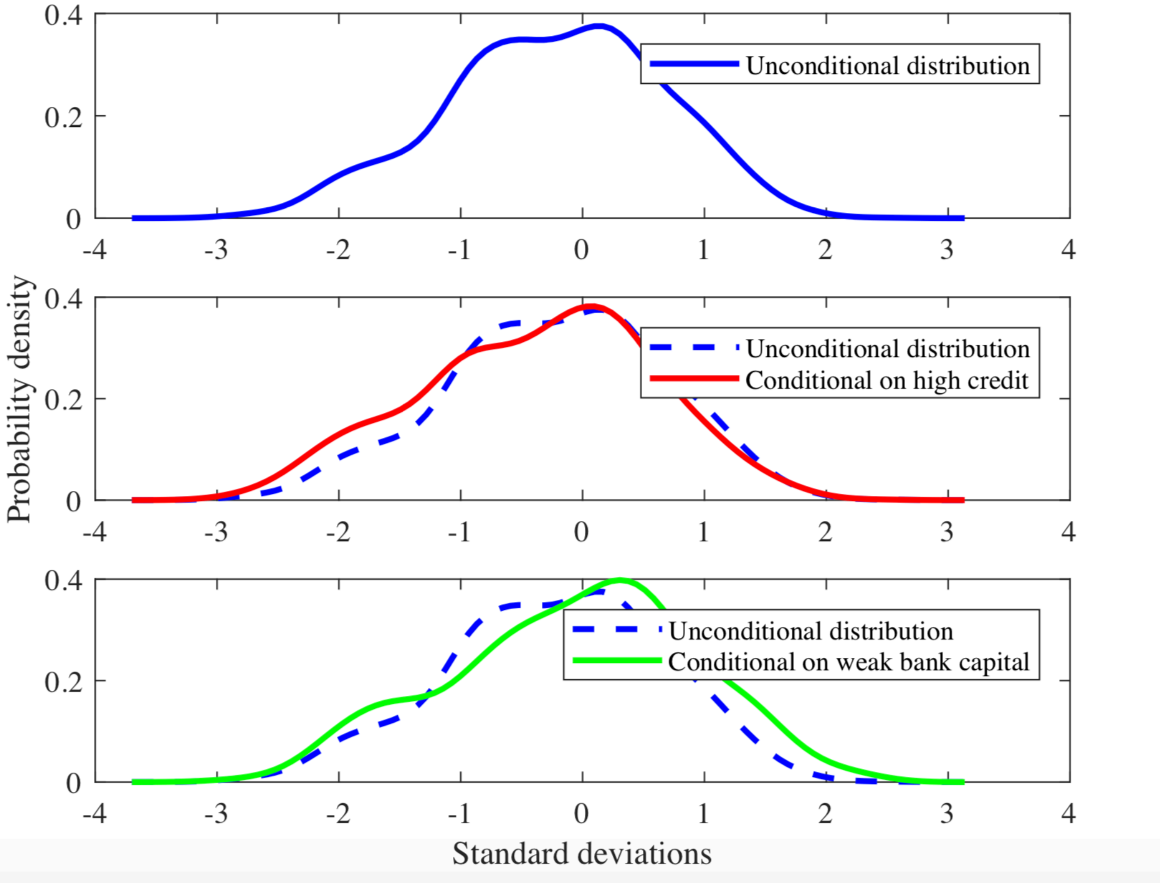
In this section, we examine the behaviour of our vulnerability measures in the lead-up to tail realisations of real GDP growth.

The top panel in Figure 2 plots the unconditional distribution of 3-year growth rates in real GDP pooled across all 16 countries in our dataset. 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 is highly non-normal (a fact confirmed by the Jarque-Berra test): it 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, the "2.5% GDP-at-Risk", is -2.09 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 2 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. Visual inspection of these distributions reveals that probability mass has shifted to the left-hand tail: the 2.5% GDP-at-Risk deteriorates from -2.09 to -2.26 standard deviations from the mean. The bottom panel in Figure 2 repeats the 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% GDP-at-Risk to deteriorate from -2.09 to -2.15.

[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.

Figure 2: Probability densities 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. Figure (a) plots the unconditional distribution of real GDP growth, standardised using country-specific means and standard deviations. Figure (b) plots the distribution conditional on 3-year real credit growth exceeding its sample mean 12 quarters earlier. Figure (c) 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 32.76 (vs critical value of 5.97); for the distributions conditional on high credit and weak bank capital, the test statistics are 23.92 and 23.03 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 (calculated using full sample information), 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.[9] Segmenting each of our 16 countries' 37-year time series in this way generates a total of 294 distinct GDP episodes. We sort these episodes by their severity and truncate the sorted data at n equals 30 – approximately the bottom decile of the distribution of real GDP growth. This procedure picks out the 30 worst GDP episodes in our sample with GDP declines that range from -1.8 to -3.2 standard deviation moves. 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.

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, 19 of the 30 (63%) 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 remarkably close to the finding in Dell-Arriccia *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 basis, 68% of the most severe GDP declines were preceded by 3-year real house price growth being above its country-specific mean, and an impressive 73% 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 50% 'hit rates' in each case – around what would be expected in a random draw.

[9] 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.

Table 1: Vulnerability measures and GDP catastrophes

	No. of GDP catastrophes preceded by:	*Memo: No. of financial crises preceded by:*
Credit booms	63% (19 of 30)	*63% (22 of 35)*
House price booms	68% (19 of 28)	*59% (20 of 34)*
Current account deficits	50% (15 of 30)	*57% (20 of 35)*
Volatility spikes	50% (15 of 30)	*65% (22 of 34)*
Weak bank capital	73% (16 of 22)	*76% (25 of 33)*

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 Baron-Werner-Xiong's (2019) 'combined list'. n=30 corresponds to the bottom decile of the distribution of 3-year real GDP growth rates (full sample n=294).

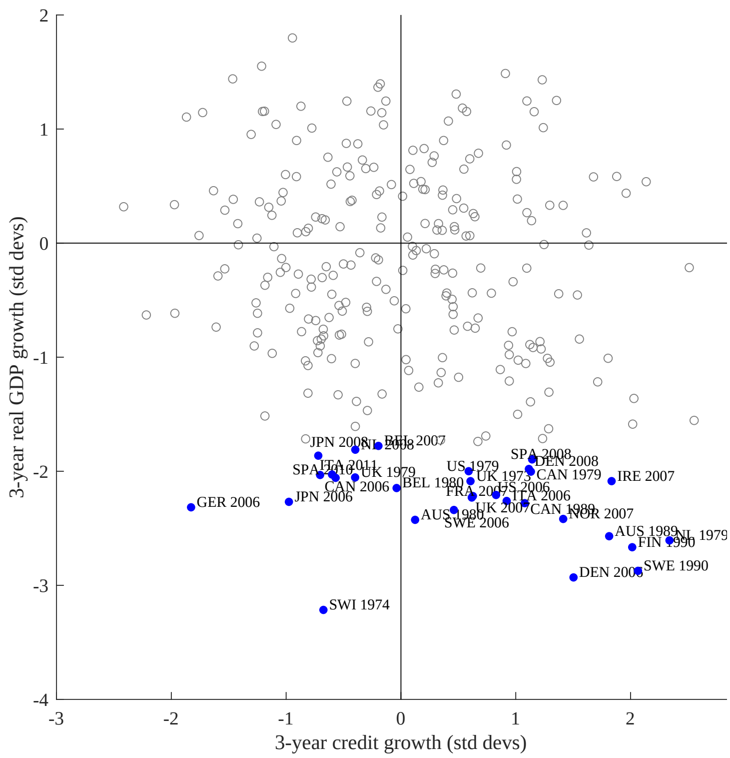
Figure 3 presents this information in scatter plot format. The blue filled dots in each panel are the 30 most severe real GDP contractions in our sample; the grey unfilled dots are the remaining 264 observations generated by our procedure. The upper panel plots this against the 3-year growth in credit-to-GDP 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 blue 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.

Nevertheless, particularly large vulnerability build-ups may provide an even stronger signal of substantial GDP tail risks ahead. Table 2 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

Figure 3: 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

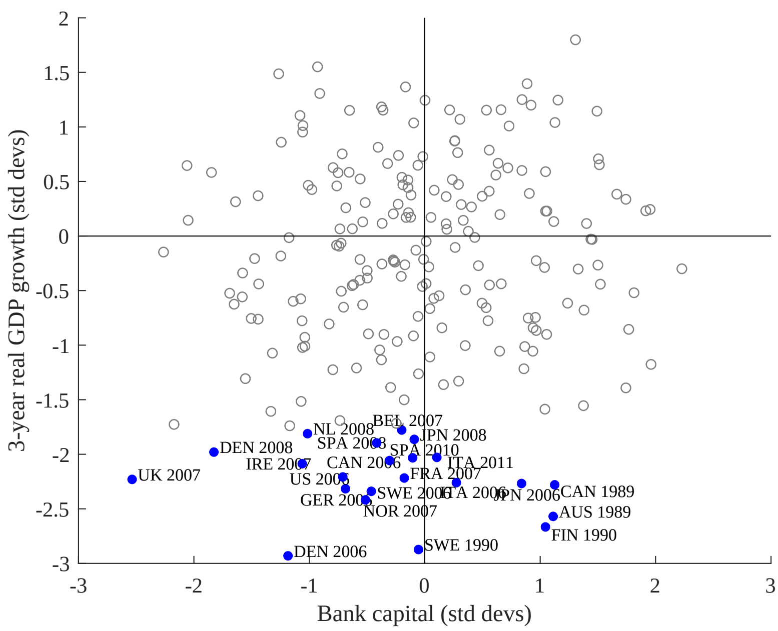


Table 2: Vulnerability measures and GDP catastrophes, extended statistics

Weakest real GDP outcomes preceded by:		$n = 30$ (baseline)	$n = 15$	$n = 100$
Credit booms	$> \mu$	63% (19 of 30)	80% (12 of 15)	59% (57 of 97)
	$> \mu + \sigma$	37% (11 of 30)	47% (7 of 15)	31% (30 of 97)
	$> \mu + 2\sigma$	10% (3 of 30)	20% (3 of 15)	6% (6 of 97)
House price booms	$> \mu$	68% (19 of 28)	71% (10 of 14)	60% (53 of 93)
	$> \mu + \sigma$	36% (10 of 28)	57% (8 of 14)	26% (24 of 93)
	$> \mu + 2\sigma$	7% (2 of 28)	14% (2 of 14)	3% (3 of 93)
Current account deficits	$< \mu$	50% (15 of 30)	53% (8 of 15)	60% (60 of 100)
	$< \mu + \sigma$	27% (8 of 30)	27% (4 of 15)	20% (20 of 100)
	$< \mu + 2\sigma$	7% (2 of 30)	0% (0 of 15)	2% (2 of 100)
Volatility spikes	$> \mu$	50% (15 of 30)	33% (5 of 15)	45% (42 of 94)
	$> \mu + \sigma$	7% (2 of 30)	7% (1 of 15)	13% (12 of 94)
	$> \mu + 2\sigma$	3% (1 of 30)	0% (0 of 15)	6% (6 of 94)
Weak bank capital	$< \mu$	73% (16 of 22)	58% (7 of 12)	60% (43 of 72)
	$< \mu + \sigma$	23% (5 of 22)	17% (2 of 12)	24% (17 of 72)
	$< \mu + 2\sigma$	5% (1 of 22)	8% (1 of 12)	3% (2 of 72)

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.

performance, with 37% of GDP catastrophes preceded by a one-standard deviation credit boom and 10% preceded by a two-standard deviation boom.

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, Werner and Xiong (2018)) 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 25 of the 33 crises in our dataset (76%) preceded by weakly capitalised banking systems.

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 influences 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.[10]

The first stage involves using a standard within estimator to estimate the fixed effects.

[10] There are other ways of treating fixed effects in quantile regression setting, e.g. Galvao (2011).

We estimate the following linear pooled panel quantile model:

$$(Y_{i,t+h} - Y_{i,t})/(h/4) = \alpha_i^{(h)} + \gamma^{(h)} X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t+h}$ denotes the *log* level of real GDP of country i at time $t+h$ for horizons $h = 1, 2, \ldots, 20$ quarters. The left-hand-side of Eq. 1 is the average annualised growth rate of real GDP over h horizons, $y_{i,t+h}$ where $y_{i,t+h} = (Y_{i,t+h} - Y_{i,t})/(h/4)$. This means that our coefficient units are comparable across horizons. Fixed effects are denoted by $\alpha_i^{(h)}$ and X_{it} contains our vulnerability metrics and control variables for country i measured at time t. The vulnerability indicators are the 3-year growth rate of 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.

Canay (2011) shows that the fixed effects can be estimated as $\hat{\alpha}_i^{(h)} = E_t(y_{i,t+h} - \gamma^{(h)} X_{i,t})$ in the first stage. 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 $\beta_\tau^{(h)}$,

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

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

Our assumption that the quantiles of GDP growth are a linear function of the covariates in our X matrix warrants some discussion. One implication is that variations in bank capital requirements and hence capital ratios can offset any undesirable increases in GDP-at-Risk – there is, in other words, perfect substitutability between shifts in credit growth, house prices, current account deficits and financial conditions on the one hand, and bank capital on the other, in terms of their impact on tail risks to growth. In practice, this is unlikely to be the case, most clearly in cases where the build-up in vulnerability is being financed largely outside the banking system

The model is estimated from 1 to 20 quarters ahead using local projections a là Jordà (2005) to understand how the left tail of GDP growth develops over a forecast horizon that is relevant for macroprudential policy, and to investigate any 'term structure' in GDP-at-risk. For inference, we follow the block bootstrapping method of Kapetanios (2008), also see 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 although changing the block size to 4 or 12 blocks does not alter our results.

5 Results

The methodology outlined above affords a rich dimensionality to our results. It permits us to jointly estimate the impact of each of our five vulnerability indicators on the shape of the GDP distribution at various horizons, controlling for the impact of changes in central bank policy rates, inflation and lagged GDP growth.

To analyse results from our baseline multivariate quantile regression, we first focus on the relationship between our vulnerability indicators and the 5^{th} quantile of GDP growth (henceforth referred to as the 5% GDP at Risk). This is the severity of recession we would not expect to be exceeded in more than 5% of cases, given the prevailing level of vulnerabilities and state of the macroeconomy.

Figure 4 plots local projections (Jordà (2005)) of the estimated change in the 5% 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.[11] The coefficients are reported in common annualised GDP growth units. So the coefficient of -0.3pp at the 12 quarter horizon for credit growth in Figure 4a means that a one standard deviation increase in credit growth is associated with an average annual deterioration of -0.3pp in the 5% level of 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

[11] We invert the sign of the current account balance and equity volatility such that our priors are such that an increase in each variable in the regression brings about an deterioration in GDP-at-Risk over the medium term.

the next three years.

We proceed by discussing these results in three stages. First, we focus on the impact of innovations in vulnerabilities on the 5% level of GDP-at-Risk over the medium term, which we take as a three year horizon ($h = 12$).[12] This arguably is the relevant policy horizon for implementing macroprudential policy responses to address the impact of building vulnerabilities.[13] Next, we assess how the information content of vulnerability indicators differs for the 5% level of GDP-at-Risk when we focus on the near-term horizon. Finally, we discuss our results across the full GDP growth distribution at various horizons, expanding our attention beyond the 5% GDP-at-Risk measure.

5.1 Indicators of downside risks to growth over the medium term

5.1.1 Baseline results

Figure 5 summarises the impact of each of our vulnerability indicators and macro controls on the 5% level of GDP-at-Risk at the three-year horizon.

Credit, house prices and current account deficits: Our first finding is 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 Jorda *et al.* (2013) for key contributions to this literature; see Aikman *et al.* (2018) for a summary of the wider literature.

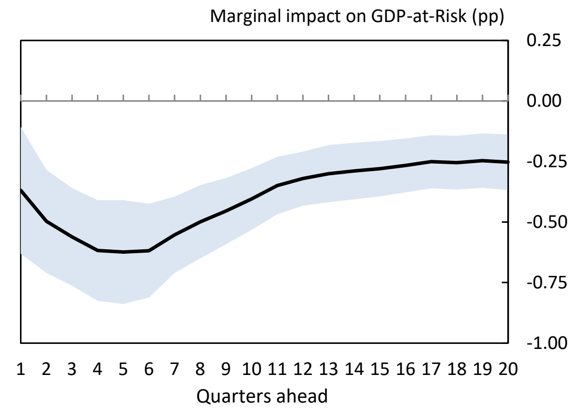
The estimated impacts of each of these three vulnerabilities on 5% GDP-at-Risk are both statistically and economically significant. For example, a one standard deviation increase in the 3-year change of credit-to-GDP is associated with 0.3pp weaker GDP-at-Risk per annum over the next 3 years. To give a sense of scale, the average three-

[12]Given that the local projections presented in Figure 4 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.

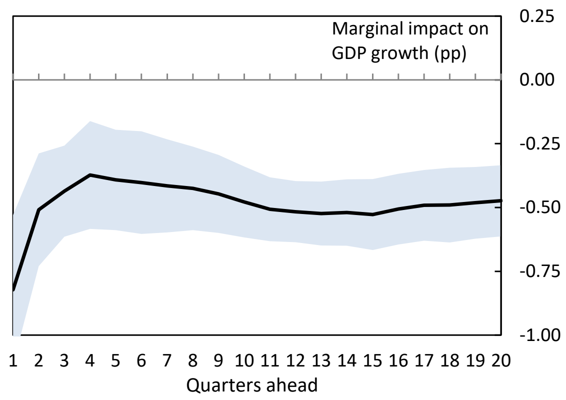
[13]For instance, unless in exceptional circumstances, the countercyclical capital buffer has an implementation lag of one year. Moreover, macroprudential authorities may also prefer to vary their countercyclical tools in a gradual manner – see for example Bank of England (2016)

Figure 4: Baseline results: local projections showing impact of each variable on 5^{th} percentile of GDP growth at horizons from one quarter to five years ahead

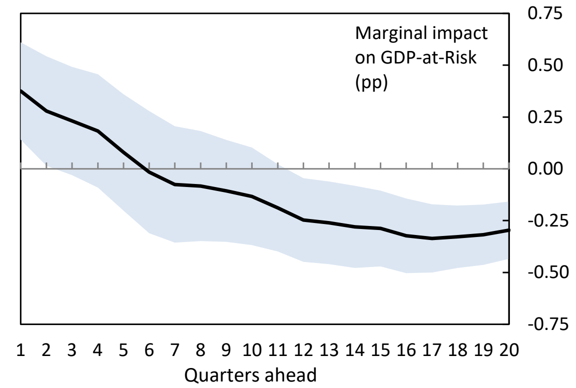
(a) Credit-to-GDP (3 year pp change)



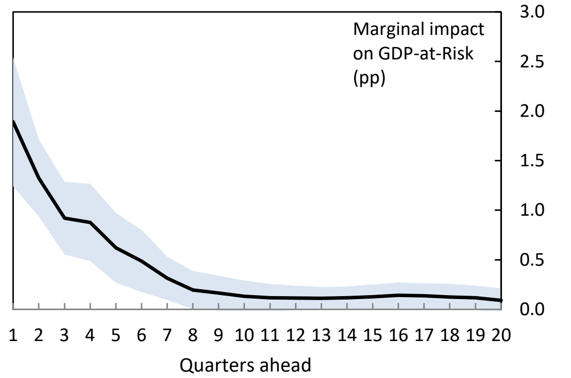
(b) Current account deficit



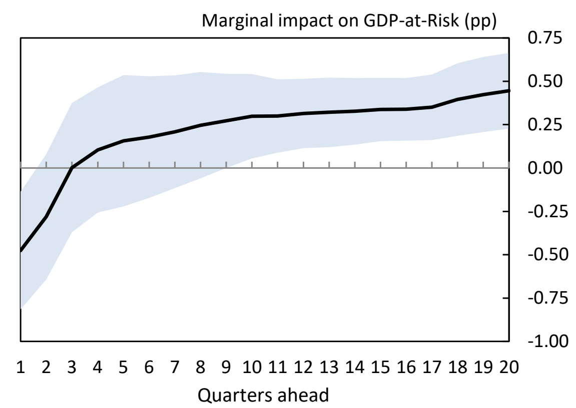
(c) Real house price growth (3 year)



(d) Volatility



(e) Capital ratio



Note: 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.

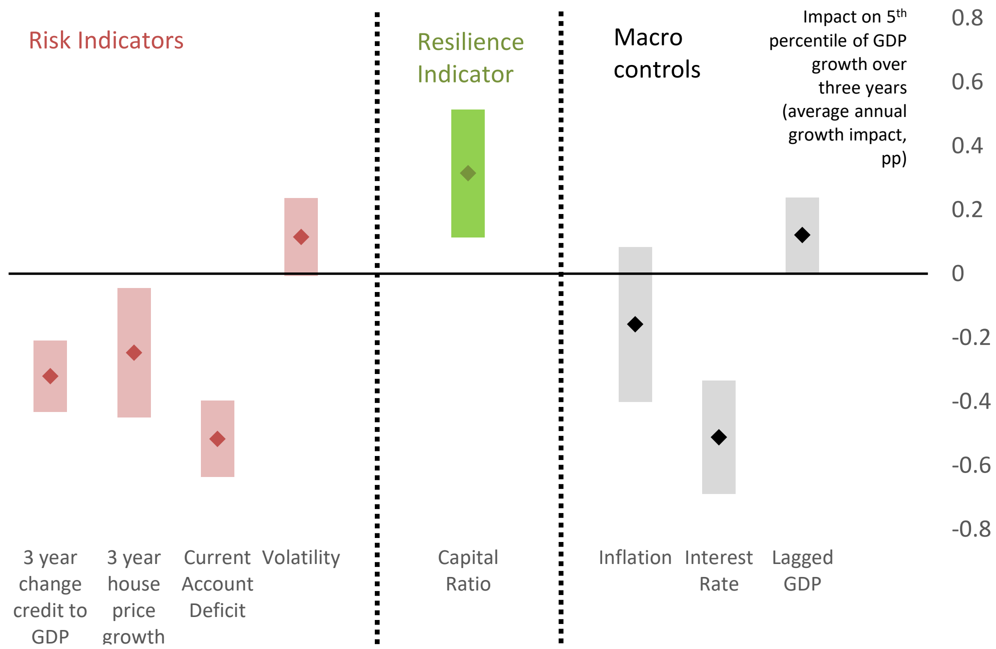
year increase in the credit to GDP ratio in the United Kingdom over our 1980-2017 sample period was 7 percentage points, with a standard deviation of 12 percentage points. Between 2004 and 2007, the credit to GDP ratio rose by 23 percentage points, 1.3 standard deviations above the mean growth rate. Our credit coefficient suggests that this will have accounted for a 0.4 percentage points per year deterioration in the left tail of the GDP growth distribution between 2008 and 2010, cumulating to around a 1.2% increase in the severity of the UK's medium-term GDP-at-Risk.

The estimated medium-term coefficient on real house price growth is similar in magnitude (-0.25pp per year), 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 1 standard deviation increase in the deficit increasing the severity of GDP-at-Risk in the medium term by 0.5 percentage points per year. This is consistent with potential amplification mechanisms associated with a heavy reliance on foreign funding. For example, to the extent that foreign flows prove relatively flighty, a large deficit may be associated with greater amplification of asset price and funding cost adjustments in the event of an adverse shock.

As a cross-check on these results, the annex reports results from an alternative specification of these regressions where the impact of vulnerability indicators is estimated individually (again conditional on macroeconomic controls). 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 (see Figure B.I).

Volatility and financial conditions: By contrast, we find no significant relationship between our financial market volatility measure and macroeconomic tail risks over the medium term. This is 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. Our point estimate suggests that a reduction in volatility is associated with a small decrease in the severity of the of GDP-at-Risk three years ahead. But this effect is not statistically different from zero.

FIGURE 5: Impact of each variable on 5^{th} percentile of GDP growth at 3-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 12 quarters. GDP growth is measured as the average annual growth rate over 3 years. Confidence intervals represent plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping.

As a cross-check on this finding Table 3, the reports results from a regression where we replace our volatility measure with an index of financial conditions from Eguren-Martin and Sokol (2019). This index is available only over a shorter sample period, so our estimation in this case begins in 1991. Reassuringly, our baseline results do not materially change in this variant, and in particular we continue to find only a small relationship between financial conditions and medium-term GDP-at-risk.

These findings contrast with those reported in Adrian et al (2018), whereby loose financial conditions create an intertemporal trade-off in that they reduce tail risks in the near term at the cost of a modest increase in GDP-at-Risk in the medium-term. We hypothesize that this might reflect the macroeconomic controls and vulnerability measures that these estimates are conditioned on. We observe very similar results to Adrian et al (2018) when our regression specification is stripped down to include just the financial conditions index and lags of GDP growth. But the medium-term impact on

GDP-at-Risk cannot be distinguished from zero when we add our various controls, with the change in the policy rate having a noticeable impact. [14]

Moreover, 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.

Bank capital: Turning to the impact of financial system resilience, we find that higher levels of banking system capital significantly improves GDP-at-risk in the medium-term. This is a novel finding, consistent with the notion that credit crunch amplification mechanisms are a key driver of severe macroeconomic tail events and that higher banking sector capitalisation can forestall these adverse dynamics. Our estimated coefficient suggests an 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. As an illustration, the United Kingdom's TCE ratio averages 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 each year over the three year horizon 2008-2010.

One potential concern is that our bank capital measure is based on annual bank reports and has been interpolated to a quarterly frequency in order to match the frequency of other series in our panel. In Table 3, we report results where we reestimate our baseline model using an annual version of our dataset, with no interpolation of the capital data.

[14] 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.

Reassuringly, this results in a near-identical 0.3 percentage point coefficient on capital at the three-year horizon (and the coefficient remains statistically significant). Another possible concern is that our results may be heavily dependent on one outlying country in our sample, perhaps one with idiosyncratic structural features of its banking system. To test this, we have confirmed that the range of coefficients obtained on capital when dropping one country at a time from our advanced economy sample remains stable and statistically significant.

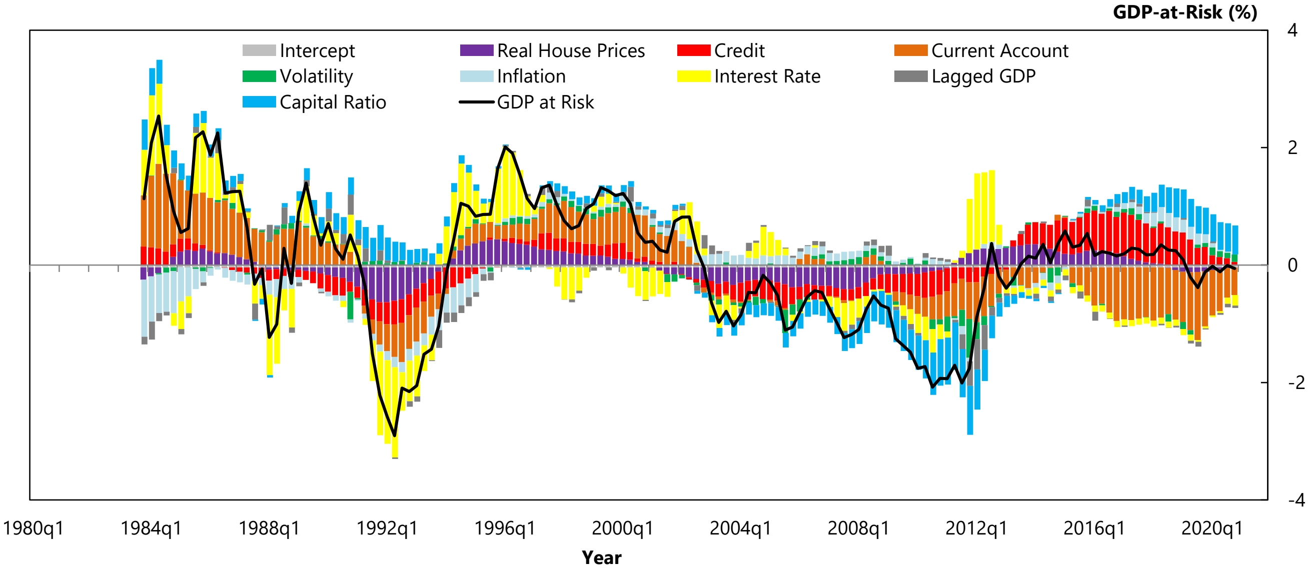
In Figure 6, we use our baseline regression results as a lens through which to view the drivers of tail risks to growth in the United Kingdom and United States over our sample. The upper panel shows the time series of predicted UK GDP at Risk at the 5% level, while the lower panel shows the estimated series for the United States. To interpret these charts correctly, note that the black solid line shows the level of tail risk at each point in time as predicted by our model 3-years earlier. So the reading for 2008Q1, for instance, is the 5th quantile of the distribution of average annual GDP growth over the period 2005Q1-2008Q1, as predicted in 2005Q1. Some care is required when interpreting the decompositions given that we are not identifying the impact of orthogonal exogenous shocks via this exercise, given the impacts of our five vulnerabilities are estimated jointly.

Our model suggests that, retrospectively speaking given that the coefficients are estimated using full sample information and we are using final estimates of all variables, 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.

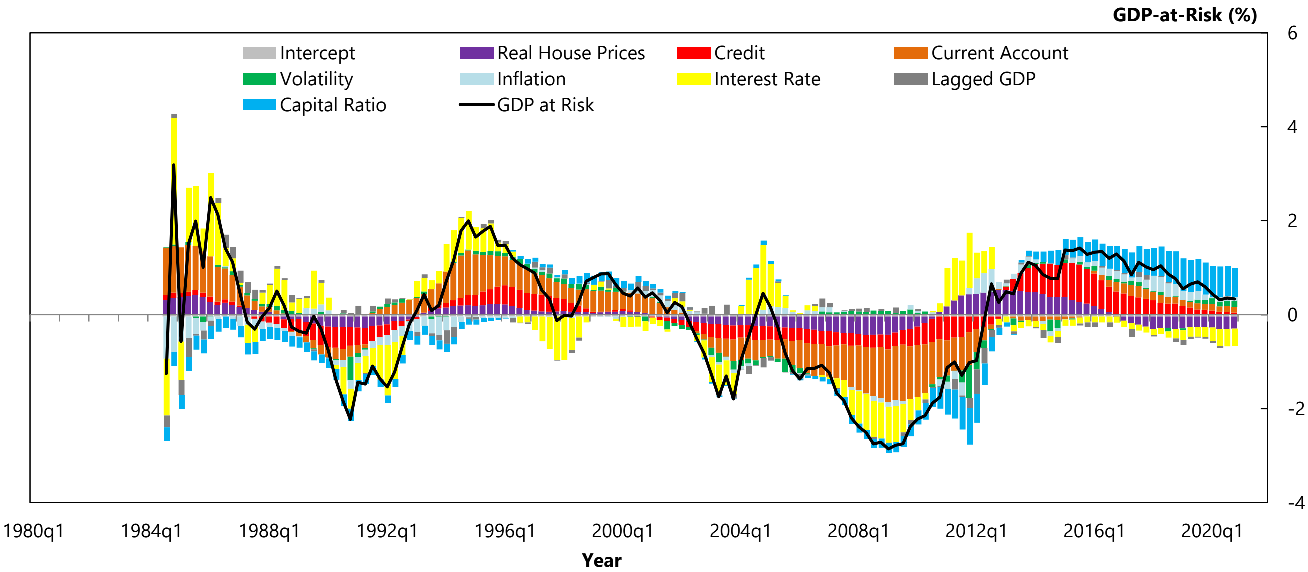
This benign period continued up until the late 1990s/early 2000s, when rapid growth in credit and house prices resumed, this time accompanied by weaker bank capital adequacy – factors which, when combined, created a large and persistent increase in growth tail risks by the mid-2000s. By 2006Q2, over two years and before the failure of Lehman heralded the worst of the global financial crisis, our model predicts that GDP-at-Risk over the

Figure 6: Decomposition of 5% 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$^{\text{th}}$ percentile of GDP growth at each point in time as predicted by our model 3-years earlier. The bars shows the contribution of each indicator to that total.

subsequent 3 years had 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 – this alone is estimated to have reduced tail risks to growth by as much as 1.3 percentage points per year. [15] Offsetting these positive developments, 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' bubble.

We do, however, capture an unprecedented build-up in GDP-at-Risk from the mid-2000s onwards, driven by rapid growth in credit and house prices, and notably the widening in the current account deficit.[16] 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. In the post-crisis period, our model estimates 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.

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

[16]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)).

Table 3: Estimated impact on 5th percentile of GDP growth after 12 quarters

	Baseline (1)	2	3	4
Credit-to-GDP (3yr change)	-0.32	-0.30	-0.39	-0.27
	(-0.21, -0.43)	(-0.15, -0.46)	(-0.21, -0.58)	(0.01, -0.54)
Real House Prices (3yr growth)	-0.25	0.03	0.11	-0.17
	(-0.04, -0.45)	(0.21, -0.16)	(0.41, -0.19)	(0.22, -0.56)
Current account (% of GDP)	-0.52	-0.63	-0.38	-0.52
	(-0.4, -0.64)	(-0.46, -0.8)	(-0.18, -0.57)	(-0.32, -0.72)
Volatility (SDs from Mean)	0.11			0.02
	(0.24, -0.01)			(0.22, -0.19)
FCI		0.09		
		(0.25, -0.08)		
Global Factor			-0.46	
			(-0.01, -0.91)	
Capital Ratio (quarterly)	0.31	0.57	0.59	
	(0.51, 0.11)	(0.73, 0.4)	(0.93, 0.24)	
Capital Ratio (annual)				0.31
				(0.58, 0.04)

Note: The table shows estimates of the average annual impact of a one standard deviation change in each variable on the 5th percentile of GDP growth over the following 12 quarters. Four separate specifications are used; our baseline, (2) our baseline with the FCI replacing equity volatility, (3) our baseline with a global factor (see Miranda-Agrippino and Rey (2018)) replacing equity volatility, and (4) our baseline but with all variables in annual space.

5.1.2 Inclusion of a global risk factor

In this sub-section, we consider how fluctuations in the global financial cycle influence downside risks to growth for the countries in our sample – 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.[17]

The financial cycle measure we focus on is the global factor proposed in Miranda-Agrippino and Rey (2018) – which is extracted from a large panel of risky asset prices across various geographical areas and is available from 1990 to 2012. The impact of including this additional covariate in our regressions is reported in Table 3. 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 this factor (i.e. a loosening in global financial conditions) is estimated to increase the severity of a downturn by -0.46 percentage points per annum over this horizon. The coefficients on the other variables in our regression are broadly unaffected by the inclusion of this factor, apart from house price growth which loses significance. 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.

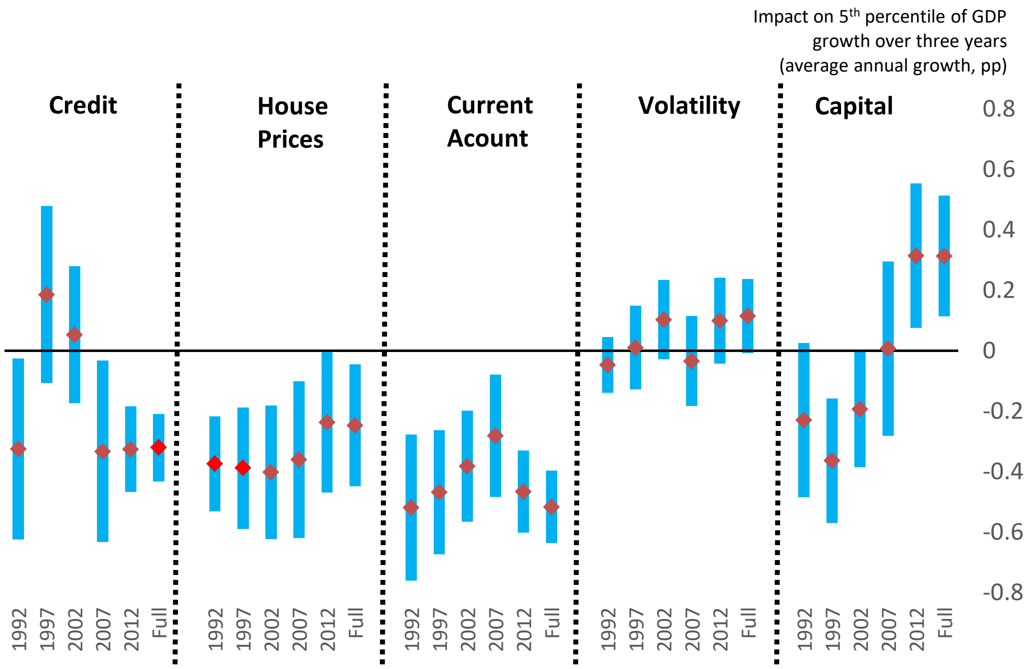
5.1.3 Challenges in measuring GDP-at-Risk in real time

So far, we have analysed how indicators of vulnerabilities in the financial system influence downside risks to GDP growth using full sample estimates of coefficients in our quantile regressions and full sample estimates of means and standard deviations when standardising indicators. This provides a retrospective view of the ebbs and flows in GDP-at-Risk, given what we know now about how our vulnerability indicators have behaved over the sample, including their co-movement with economic growth. In this sub-section, we examine how our results change if we base our period t assessment on information (i.e. regression coefficients, means and standard deviations) available only up to t.

Figure 7 presents the quantile betas for 5% GDP-at-Risk 3-years ahead estimated using different sub-samples of our dataset. In particular, the far-left bar for each variable

[17] 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.* (2018) report a similar finding.

FIGURE 7: Real time impact of each variable on 5th percentile of GDP growth at 3-year horizon



Note: The figure shows how the 12 quarter coefficients in our baseline model change if we restrict the vulnerabilities sample at each of the points on the x-axis.

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

Overall, while the pseudo real time coefficient estimates for house prices, current account deficits and volatility are relatively stable over these sub-samples, the estimated impacts of credit growth and bank capital vary significantly, both in terms of magnitude and sign. In particular, a researcher estimating this regression in the early-2000s would have found roughly zero impact from credit growth for tail risks to GDP and, even more strikingly, a *negative* relationship between banking system capitalisation and GDP-at-Risk (i.e. more bank capital increases recession severity).

We offer two considerations for interpreting these results. First, the instability of our estimated coefficients emphasises the challenges involved in uncovering the impact of vulnerability metrics such as these on extreme tails of the distribution of growth, using what remains a relatively small sample of data.[18] As such, caution is required when using results from such exercises to inform real-time risk assessment.[19] 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.

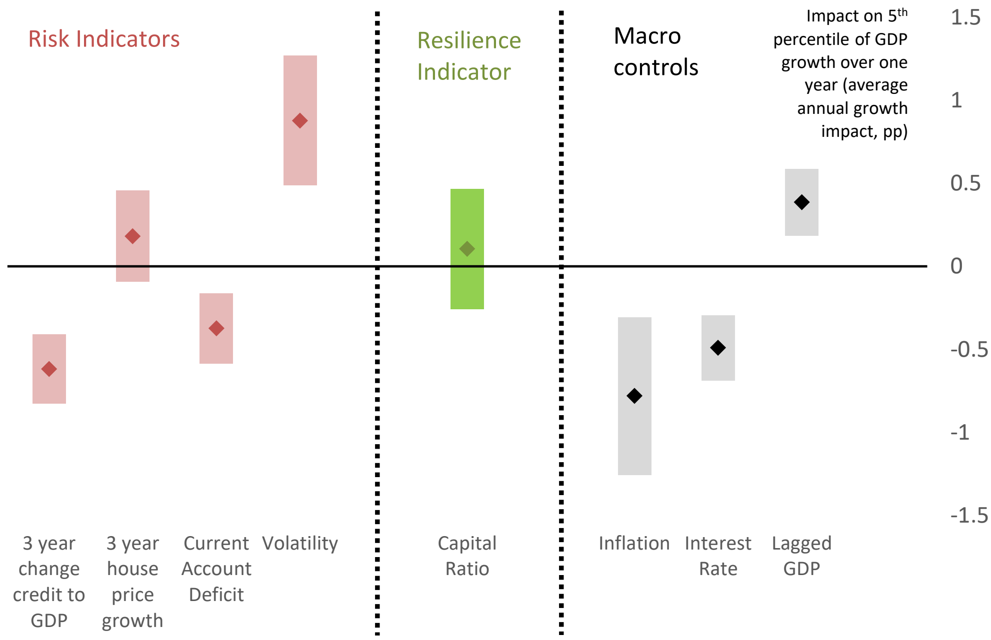
5.2 Near-term risks and the term-structure of GDP-at-Risk

While the main focus of our analysis is on downside risks to growth over the medium term, in this section we describe briefly the factors our quantile regressions emphasise 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

[18]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'.

[19]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).

Figure 8: Impact of each variable on 5$^{\text{th}}$ 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$^{\text{th}}$ percentile of real GDP growth after 4 quarters. GDP growth is measured as the average annual growth rate. Confidence intervals represent plus and minus 1 standard deviation. Standard errors are generated using block bootstrapping.

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 easing is warranted.

Unsurprisingly, the key determinant of GDP at Risk at the 4 quarter horizon in our baseline regression is equity market volatility, as shown in Figure 8. A one standard deviation increase in volatility is associated with a full percentage point weakening in predicted growth one year ahead at the 5$^{\text{th}}$ 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. The change in policy interest rates is also found to contribute significantly to near-term downside risk. These results are consistent with Adrian *et al.* (2017), which finds a significant link between financial conditions and tail risks to economic activity at this horizon. It is consistent too with the vast literature that emphasises credit spreads and other financial indicators as good predictors of recession risk (see e.g.

Gilchrist and Zachrajsek (2012)).

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 increases 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 be informative about tail risks at a 2 quarter horizon, but this effect cannot be distinguished from zero 4-quarters ahead. The impact of capitalisation in the banking system capital also cannot be distinguished from zero at this horizon.

Figure 9 illustrates the contributions of these variables to one-year ahead, 5% 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 6), fluctuations in risk in the near-term are dominated by swings in volatility, a proxy for risk-appetite and financial conditions more broadly.

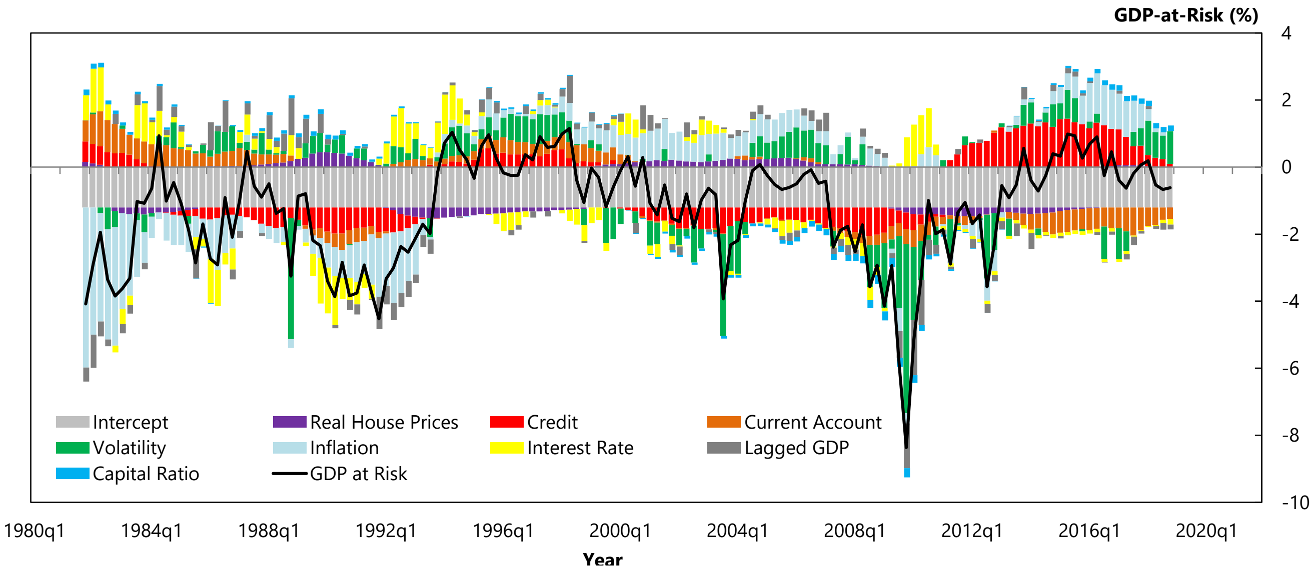
5.3 Characterising the full predicted GDP growth density at various horizons

We complete the presentation of our quantile regression results by discussing how our estimates of the tail of the predicted distribution of GDP growth compares with other quantiles of the distribution. We focus on the 50$^{\text{th}}$ quantile (the median) and the 95$^{\text{th}}$ quantile.

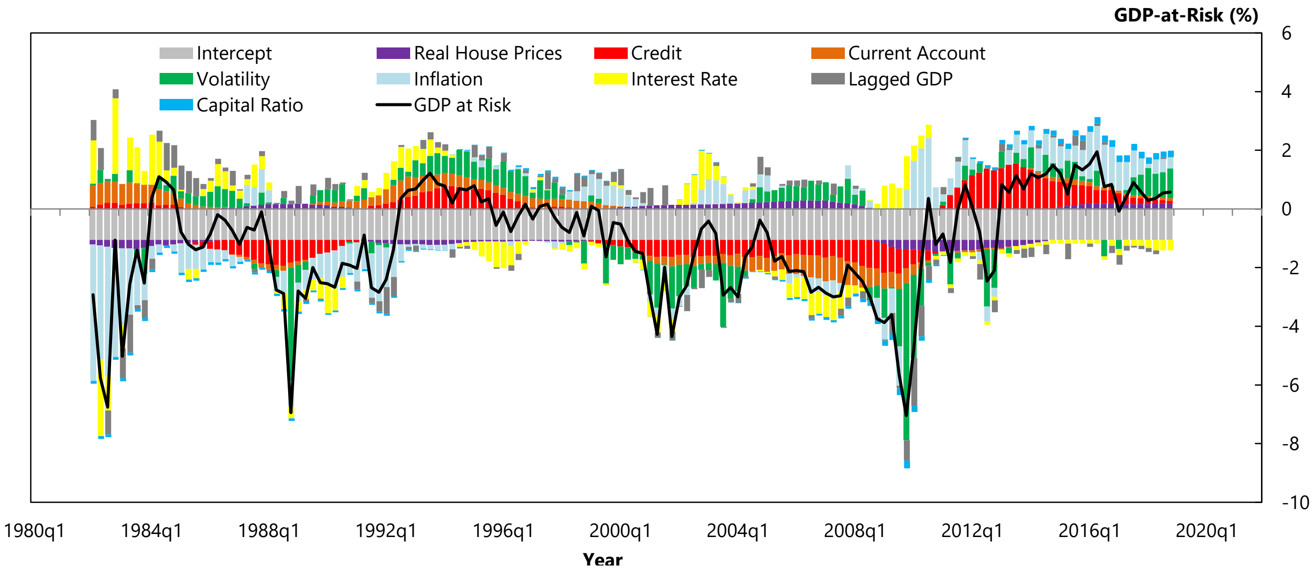
Figure 10 presents coefficient estimates for the 5$^{\text{th}}$, 50$^{\text{th}}$ and 95$^{\text{th}}$ quantiles at the 3-year ahead and 1-year ahead horizons. Our main finding here, which may at first be surprising, is that the impact of our vulnerability measures on growth is, by and large, estimated 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$^{\text{th}}$ quantile than at the median or 95$^{\text{th}}$. 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

FIGURE 9: Decomposition of 5% GDP-at-Risk at 1 year horizon

(A) UK – 1 year ahead



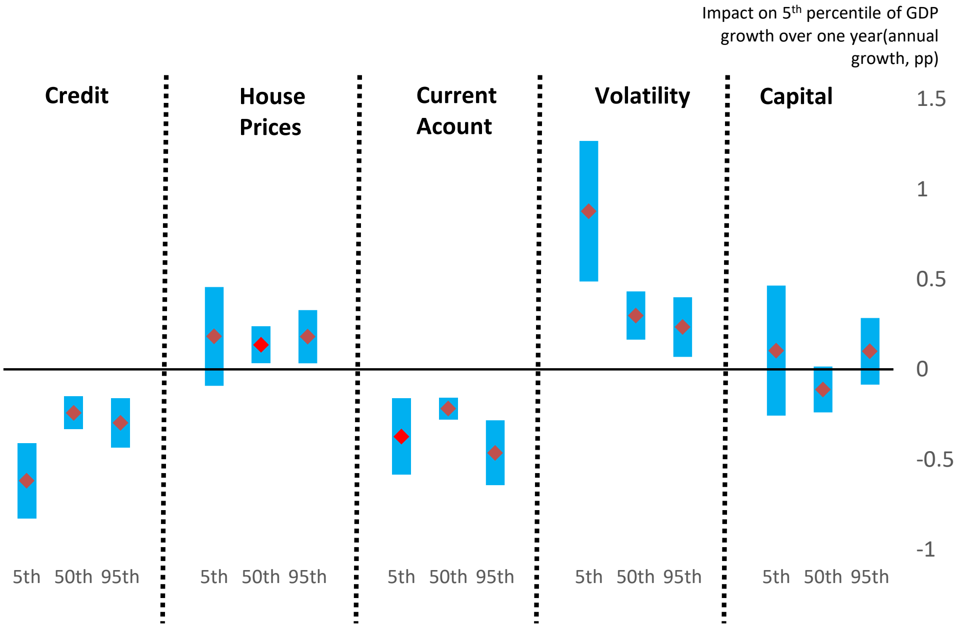
(B) USA – 1 year ahead



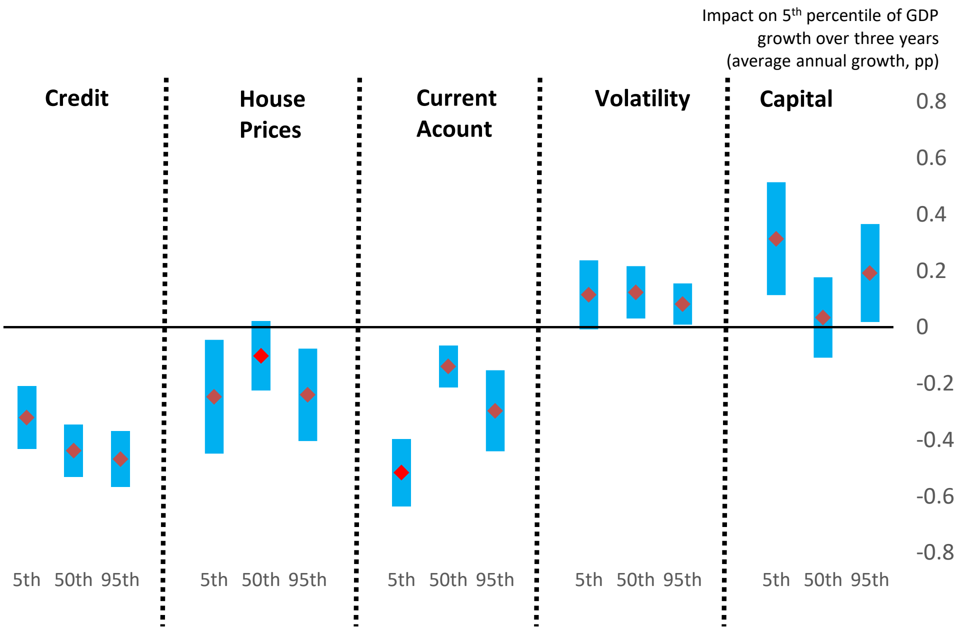
Note: The black solid line shows the 5$^{\text{th}}$ percentile of GDP growth at each point in time as predicted by our model 1 year earlier. The bars shows the contribution of each indicator to that total

Figure 10: Impact of each variable on 5th, 50th and 95th percentiles of GDP growth

(a) 1 year ahead



(b) 3 years ahead



Note: 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. 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.

distribution.

One other finding of note is that higher capital ratios tend to be associated with a weaker central outlook for growth (e.g. 50^{th} quantile) over a 1-2 year horizon, 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 (costly) 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' absorb the shock mitigating the impact on bank credit supply and medium-term macroeconomic tail risks. We will explore this trade-off further in the next section.

To illustrate the economic significance of these estimates, Figures 11a and 11b presents time series estimates of predicted quantiles of UK GDP growth both in the near term (1-year ahead) and in the medium term (3-years ahead). The dotted lines shows the actual outturn of real GDP growth at each frequency. Barring one observation (the annual growth rate in 2009Q1), the outturns of GDP growth fall within the central 90% 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 0.8 percentage points), while as we have seen, the left-hand tail (5^{th} quantile) varies substantially (its standard deviation is 1.6 percentage points). This is consistent with Adrian et al.'s (2019) results. 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 still increases in the run up to stress events).

Finally, Figures 11c and 11d plot predicted densities of UK growth for 2008 Q3 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^{th}, 95^{th} percentiles, and every decile in between) at both horizons. Relative to a baseline predicted density from earlier in the great moderation era (1997Q3), 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 11d). 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 information 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. Such a flexible empirical framework can provide insights into a wide array of policy questions. 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.

The countercyclical capital buffer and medium-term tail risks

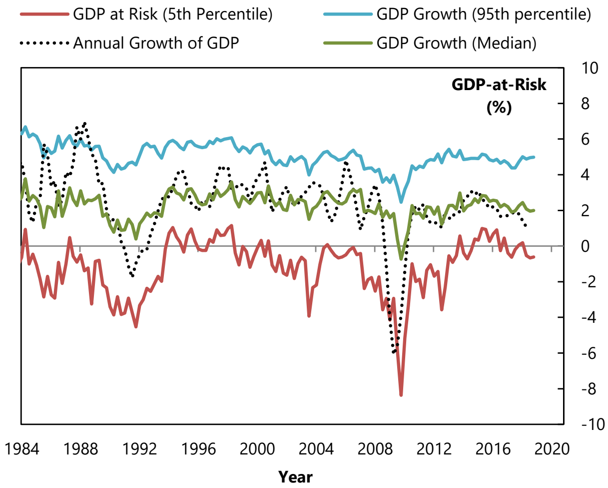
Our estimates provide some insight into the potential benefits of building banking sector capital resilience in response to growing financial vulnerabilities. The countercyclical capital buffer (CCyB) is a macroprudential tool designed for this purpose, introduced under the Basel III regulation which followed the global financial crisis (Basel Committee on Banking Supervision (2010)). 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.[20]

How much difference might raising the CCyB above its neutral setting make to GDP-

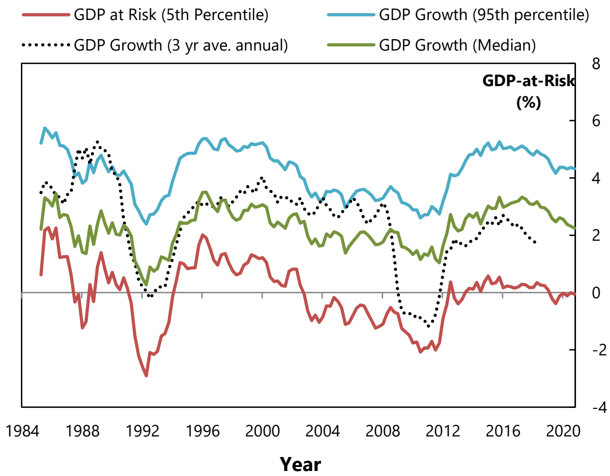
[20] See IMF's Annual Macroprudential Policy Survey (2018) and Quarles (2019) for a discussion of recent international CCyB experience .

Figure 11: Predicted GDP growth density

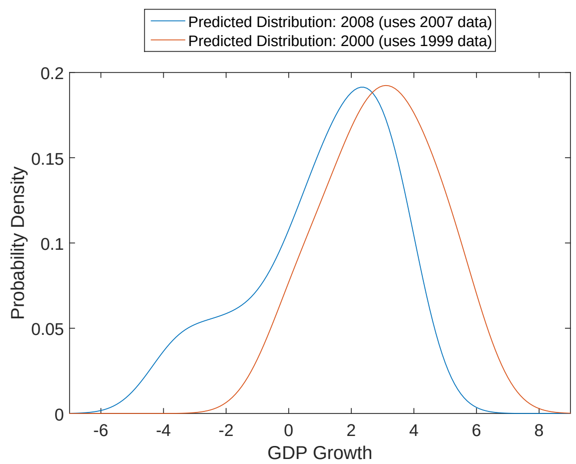
(A) One year ahead and actual outurn



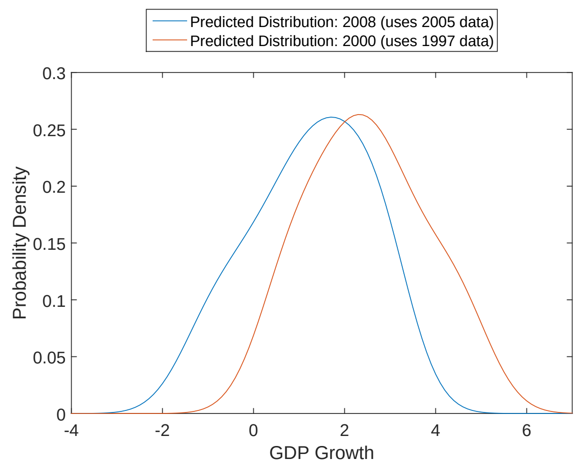
(B) Three years ahead and actual outurn



(C) Predicted density (1 year ahead)



(D) Predicted density (3 years ahead)



Note: The top panel shows the predicted 5^{th}, 50^{th} and 95^{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) at-risk?[21] As an illustration, we set out a counterfactual in which the CCyB was in active use during the run-up to the financial crisis. In Table 4, 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. We imagine a stylised CCyB strategy, the first where the CCyB reaches 2.5% by the eve of the crisis, the second where it reaches 5%.[22] We consider two examples – the first where the annual increment to the CCyB was 0.5pp, reaching a peak of 2.5% by the eve of the crisis; the second where the annual increment was 1pp each year, reaching a peak of 5%.[23]

The first three columns of Table 4 show our 5% GDP-at-risk estimates three years ahead for each country in our panel. We report this estimate in 2002 and in 2007 respectively. For 13 of the 16 countries in our sample, tail risks deteriorated during this period, with an average worsening of 0.8pp in average annual GDP-at-risk three years out. Next, we document the estimated impact on GDP-at-risk by end-2007 that our imagined CCyB paths over the preceding five years may have had.[24] 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 CCyB path reaching 2.5% by end-2007 is estimated to induce an average annual improvement

[21] Some countries have a positive neutral setting of the CCyB, in order to facilitate a gradualist strategy for raising the buffer and to maximise the chance of having a buffer available to cut in the event of an adverse shock – see for example Bank of England (2016).

[22] Given the one year implementation lag following an increase in the CCyB, this counterfactual experiment would mean the fifth and final CCyB increase was announced in 2006Q4 and would have taken effect in 2007Q4, a few quarters before the failure of Lehman Brothers and the worst of the financial crisis.

[23] There is no upper limit to the CCyB, though international reciprocation of the measure is only mandated up to a level of 2.5%. A range of 2.5 to 5% is chosen for illustrative purposes only. It is, however, broadly consistent with the findings of Aikman et al (2019), which considers how high the CCyB might have had to be set in the US ahead of the financial crisis, in order to materially reduce the size of the credit crunch which followed. The authors estimate that a CCyB range of 3.1% to 4.7% might have been required. 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.

[24] Clearly we must be cautious in interpreting such a counterfactual, given the CCyB framework was not in place during our sample period and so 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 results are based is defined relative to total (unweighted) assets. For the purposes of this illustration, we simply assume that both the average risk weight and the domestic lending conversion factor are 50% for every country in our panel. We therefore assume that a 1pp change in the CCyB rate translates into approximately a 1/4 pp change in our TCE ratio measure.

Table 4: Illustration of the potential offsetting effect of raising the CCyB in response to growing GDP-at-risk from 2002 to 2007

	Estimated 5% GDP-at-risk avg 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 Q4	2007 Q4	Change 2002 to 2007	CCyB set at 2.5% by end-2007	CCyB set at 5% by end-2007	CCyB set at 2.5% by end-2007	CCyB set at 5% by end-2007
AUS	-0.4	-2.3	**-1.9**	0.3	0.5	14%	28%
BEL	0.1	-0.9	**-1.0**	0.3	0.6	27%	53%
CAN	0.4	-0.5	**-0.9**	0.4	0.9	50%	99%
DNK	-0.3	-1.9	**-1.7**	0.1	0.3	8%	17%
FIN	1.0	-0.6	**-1.6**	0.2	0.4	11%	21%
FRA	0.0	-1.0	**-1.0**	0.3	0.6	29%	58%
GER	-0.4	0.7	**1.1**	0.3	0.5	-	-
IRE	-0.3	-2.1	**-1.9**	0.1	0.2	7%	13%
ITA	-0.5	-1.3	**-0.7**	0.3	0.6	39%	78%
NLD	-1.1	0.3	**1.4**	0.2	0.5	-	-
NOR	0.3	-0.5	**-0.8**	0.2	0.3	21%	42%
SPAIN	-1.0	-2.1	**-1.1**	0.3	0.5	23%	46%
SWE	-0.3	-0.1	**0.1**	0.3	0.6	-	-
SWI	0.4	-0.5	**-1.0**	0.1	0.2	11%	22%
UK	-1.1	-1.9	**-0.8**	0.2	0.4	27%	55%
USA	-1.2	-1.7	**-0.5**	0.2	0.3	32%	64%
Average	-0.3	-1.0	**-0.8**	0.2	0.5	23%	46%

Note: assumes an average risk weight of 50% and a 50% domestic CCyB pass-through rate (also abstracts from reciprocation of any foreign CCyBs). A 1pp domestic CCyB increase is therefore assumed to be associated with a 0.25pp in the TCE to total assets ratio. This should be treated as an indicative proxy.

in GDP-at-risk of 0.2pps over 2008-2010. That effect increases to 0.5pps under the more aggressive CCyB path. To put that effect into context, the final columns of Table 4 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 a quarter and a half of the build-up in tail risks respectively.

A tentative cost-benefit analysis of raising capital

Macroprudential interventions – such as raising countercyclical 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 also to affect different moments 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 introduce sand in the wheels of financial intermediation which, in the near-term at least, may dampen the central path for activity. A framework for cost-benefit analysis is therefore needed to weigh up these competing effects and calibrate the appropriate policy intervention.

Our empirical framework can support such cost benefit analysis given its flexibility in estimating the impact of vulnerabilities across the GDP distribution and at different horizons. For example, as an illustration, suppose we proxy benefits with the impact on 5% GDP-at-Risk at the three-year horizon. And we proxy costs with the estimated impact on the 50th percentile of the GDP distribution at the one-year horizon.[25] 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, as our five vulnerabilities (and our macroeconomic controls) have ebbed and flowed.

Figure 12a 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

[25] 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.[26] 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 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 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, though they have settled at a somewhat worse level than in the 1980s and 1990s.

We can use our estimates to illustrate the potential policy trade-offs involved with raising bank capital at specific points in this history. As summarised in Figure 10 , we find that increases in bank capital are associated with a mild negative effect on the one-year ahead median outlook for growth.[27] On the other hand – as discussed in Section 5.1

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

[27] Our point estimate is that a 1 percentage point increase in the TCE ratio is associated with a 0.1 percentage point decline in the median forecast for growth over the subsequent 4 quarters. For comparison, the BIS-FSB's Macroeconomic Assessment Group estimated that a 1 percentage point increase in risk-weighted capital requirements (corresponding to around a 0.5 percentage point increase in our TCE

– we also find that increases in bank capital substantially reduce tail risks in the medium term. The implication is that an increase in bank capital moves us to the south-east in Figure 12a. Such a policy might appeal most at stages where the economy is located in the northwest quadrant of our diagram: when the central outlook is strong, but tail risks are high. The 2000s stand out as a prime example of such a period in Figure 12a, where the balance between near-term strength and medium-term vulnerabilities was skewed relative to the other decades in our sample.

Figure 12b therefore takes 2004 as an example and traces out a policy possibility frontier at that time. This frontier (in blue) is derived from increasing the capital ratio by 1-3pp 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. This illustration provides some indication of the policy choices available for a macroprudential authority and presents the associated trade-off in a simplified two-dimensional space. It is a starting point. 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.

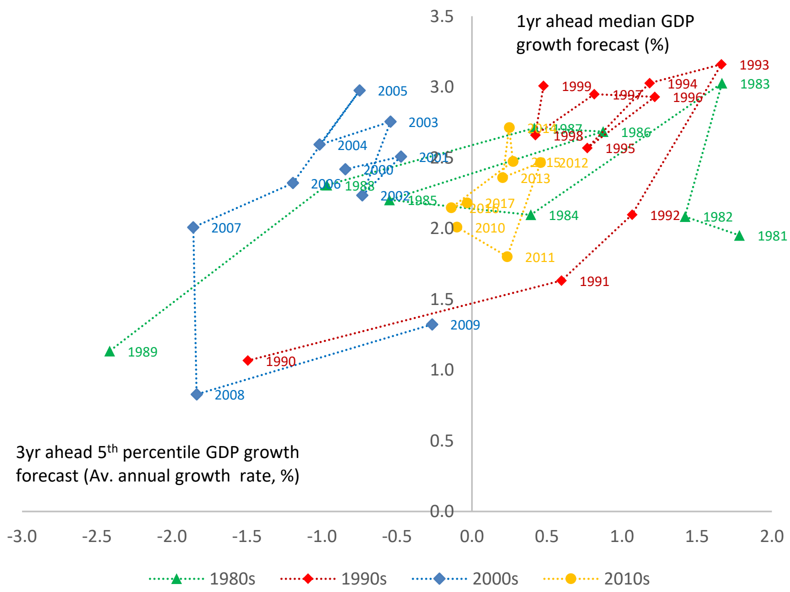
7 Conclusion

In this paper, we have developed a rich empirical framework within which to 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). The provision

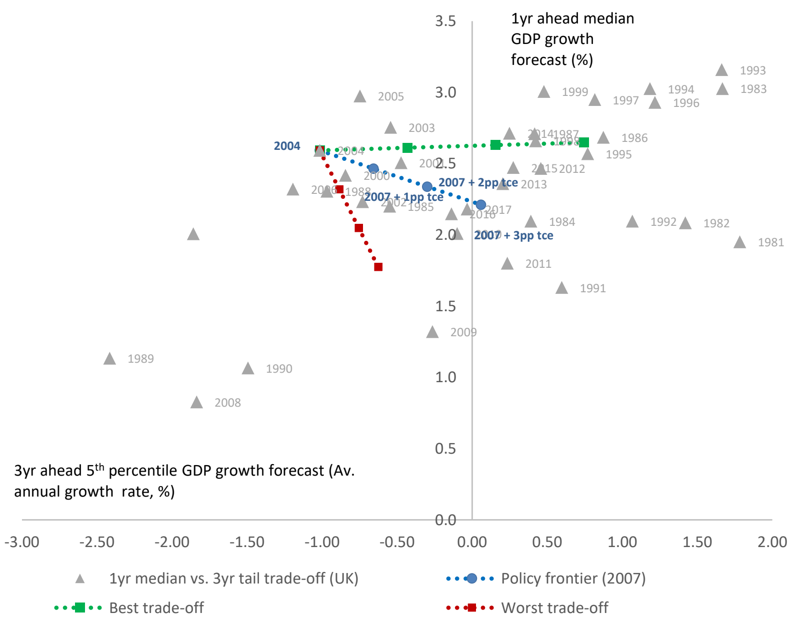
ratio measure) would reduce the level of GDP by around 0.2% relative to baseline.

Figure 12: An indicative quantification of the possibility frontier of GaR (medium-term) and median (near-term) outturns for different policy settings

(a) Outturns



(b) Impact of changing capital



Note: The x-axis of Figure 12 plots – for the UK – the three year ahead 5% GDP-at-Risk estimate from the labelled year, based on our baseline results. The y-axis plots the estimated one-year ahead median outlook, based on the estimates presented in Figure 10a. 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 10). 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 10a).

of sufficient early warning when this tail fattens is crucial for the successful operationalisation of the macroprudential frameworks that have been established worldwide, as a legacy of the global financial crisis.

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 two-thirds 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.

Our joint estimation of these vulnerabilities allows us to retrospectively trace out the evolution of tail risks over the past four decades and coherently "add-up" the contributions from different factors. For example, we illustrate that all three vulnerabilities contributed towards a marked rise in GDP-at-risk in the UK and US in both the late 1980s and through the 2000s. We show in contrast that increases in equity volatility – or a tightening in a broader index of financial conditions – does not have a significant role to play in providing an early warning signal for the medium term, once our other measures have been taken into account. Instead, moves in financial conditions play a role as a near-term indicator, alerting that tail risks over the coming year have changed. This illustrates the importance of a risk assessment framework that considers different indicators for different purposes. It is the slower-moving vulnerabilities that can provide the signal to respond countercyclically and ahead of time, while faster-moving financial indicators can put policymakers on alert that the resilience they have previously built might soon need to be used.

Most importantly, this paper provides a framework within which financial system resilience is linked explicitly to downside risks to economic growth. We demonstrate that an increase in bank capital can improve GDP-at-risk in the medium-term. This is a crucial step if policymakers are to calibrate appropriate responses to the ebb and flow of the financial cycle. Indeed, we demonstrate that had countercyclical capital tools – such as the newly established countercyclical capital buffer (CCyB) – been in place in the run-up to the crisis and been actively used, they could have had a material effect in ameliorating the ballooning tail risks that came from rising vulnerabilities. This would likely not have been a free lunch, however. We also find tentative evidence that raising capital in the near-term may have some costs to the most likely GDP growth outturn over the next year. A macroprudential trade-off therefore emerges, whereby buying insurance against GDP tail risks in the medium term likely comes with some premium on near-term growth. We are able to illustrate the nature of this trade-off with our empirical results.

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

References

(2012): "The global financial crisis: Explaining cross-country differences in the output impact," *Journal of International Money and Finance*, 31(1), 42 – 59.

Adrian, T., N. Boyarchenko, and D. Giannone (2016): "Vulnerable growth," Staff Reports 794, Federal Reserve Bank of New York.

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

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

Aikman, D., J. Bridges, A. Kashyap, and C. Siegert (2019): "Would Macroprudential Regulation Have Prevented the Last Crisis?," *Journal of Economic Perspectives*, 33(1), 107–130.

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

Bernanke, B. (2018): "The Real Effects of the Financial Crisis," Brookings papers on economic activity, The Brookings Institution.

Borio, C. (2003): "Towards a Macroprudential Framework for Financial Supervision and Regulation?," *CESifo Economic Studies*, 49(2), 181–215.

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

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

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

Catao, L. A., and G. M. Milesi-Ferretti (2014): "External liabilities and crises," *Journal of International Economics*, 94(1), 18–32.

Cecchetti, S., M. R. King, and J. Yetman (2011): "Weathering the financial crisis: good policy or good luck?," BIS Working Papers 351, Bank for International Settlements.

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

Cerutti, E. M., S. Claessens, and L. Laeven (2015): "The Use and Effectiveness of Macroprudential Policies; New Evidence," IMF Working Papers 15/61, International Monetary Fund.

Crockett, A. D. (2000): "Marrying the micro- and macro-prudential dimensions of financial stability," Speech, BIS.

Dagher, J., G. Dell'Ariccia, L. Laeven, L. Ratnovski, and H. Tong (2016): "Benefits and Costs of Bank Capital," IMF Staff Discussion Notes 16/04, International Monetary Fund.

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

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

den Heuvel, S. J. V. (2008): "The welfare cost of bank capital requirements," *Journal of Monetary Economics*, 55(2), 298 – 320.

Duprey, T., and A. Ueberfeldt (2018): "How to Manage Macroeconomic and Financial Stability Risks: A New Framework," *Bank of Canada Staff Analytical Note*, 11.

ECB (2018): "Financial Stability Review, May 2018," Report, ECB.

Edge, R. M., and N. Liang (2017): "New Financial Stability Governance Structures and Central Banks," Working paper, Hutchins Center.

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

Gersbach, H., and J.-C. Rochet (2017): "Capital regulation and credit fluctuations," *Journal of Monetary Economics*, 90, 113 – 124.

Gertler, M., and S. Gilchrist (2018): "What Happened: Financial Factors in the Great Recession," *Journal of Economic Perspectives*, 32(3), 3–30.

IMF (2017): "Global Financial Stability Report October 2017: Is Growth at Risk?," Report, International Monetary Fund.

IMF-FSB-BIS (2016): "Elements of Effective Macroprudential Policies - Lessons from International Experience," Report, IMF-FSB-BIS.

Jordà, O., B. Richter, M. Schularick, and T. Alan M (2017): "Bank Capital Redux: Solvency, Liquidity, and Crisis," Working Paper 23287, National Bureau of Economic Research.

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

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

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

Knight, M. D. (2006): "Marrying the micro- and macroprudential dimensions of financial stability: six years on," Speech, Bank for International Settlements.

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

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

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

Meh, C. A., and K. Moran (2010): "The role of bank capital in the propagation of shocks," *Journal of Economic Dynamics and Control*, 34(3), 555 – 576.

Mian, A., and A. Sufi (2010): "Household Leverage and the Recession of 2007–09," *IMF Economic Review*, 58(1), 74–117.

Miles, D., J. Yang, and G. Marcheggiano (2013): "Optimal Bank Capital," *Economic Journal*, 123(567), 1–37.

Repullo, R. (2013): "Cyclical adjustment of capital requirements: A simple framework," *Journal of Financial Intermediation*, 22(4), 608 – 626.

Repullo, R., and J. Suarez (2012): "The Procyclical Effects of Bank Capital Regulation," *The Review of Financial Studies*, 26(2), 452–490.

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

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

Svensson, L. E. O. (1997): "Inflation forecast targeting: Implementing and monitoring inflation targets," *European Economic Review*, 41(6), 1111–1146.

A Data Appendix

A.1 Capital ratios

We self-construct an annual cross-country measure of the tangible common equity (TCE) ratio as follows: 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.

B Annex

Table B.I: Data sources

Variable	Data Source	Frequency	Notes
Real GDP	OECD	Quarterly	
Credit-to-GDP	BIS	Quarterly	3 year change in ratio
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

Table B.II: Summary statistics by country

		N	Mean	Std Dev.	Min	25th pctile	75th pctile	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 growth)	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 growth)	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 growth)	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 growth)	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 growth)	149	-0.2	1.0	-4.0	-0.5	0.0	2.0

Summary statistics by country

		N	Mean	Std Dev.	Min	25th pctile	75th pctile	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 growth)	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 growth)	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 growth)	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 growth)	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 growth)	149	-0.3	1.2	-5.0	-0.8	0.3	3.0

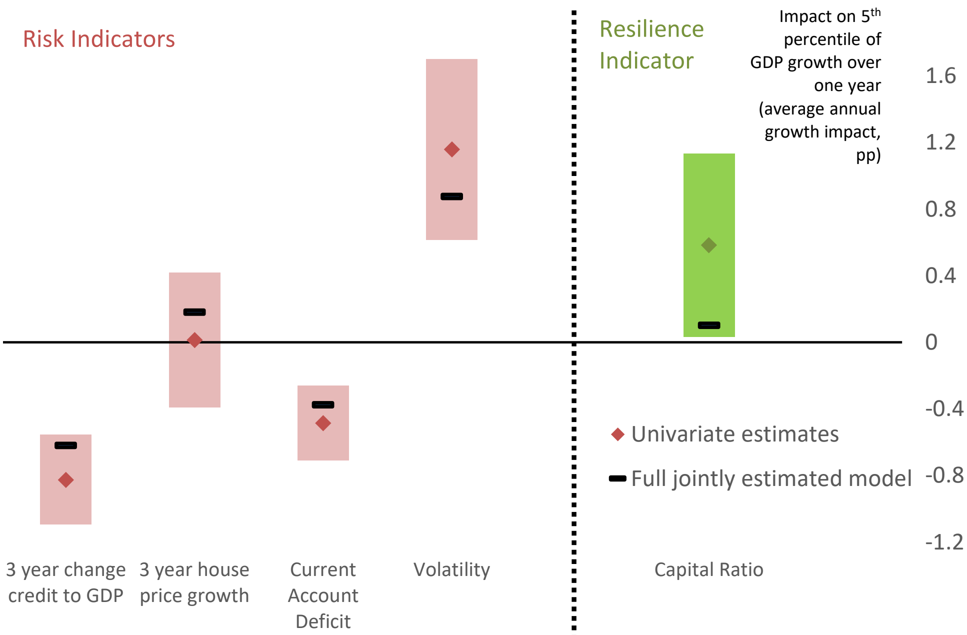
Summary statistics by country

		N	Mean	Std Dev.	Min	25th pctile	75th pctile	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 growth)	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 growth)	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 growth)	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 growth)	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 growth)	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 growth)	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 growth)	2384	-0.3	2.0	-32.0	-1.0	0.5	30.0

Figure B.I: Baseline results and univariate model

(A) 3 years ahead

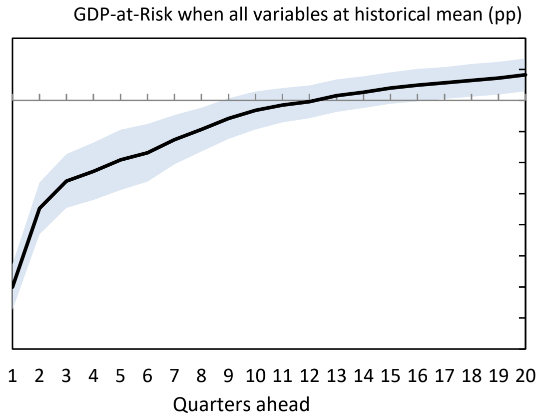
(B) 1 year ahead



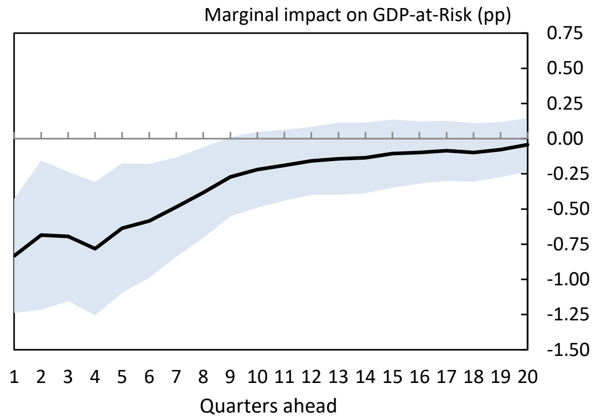
Note: Figure shows the impact of a one standard deviation change in each indicator at time t on the $^{\text{th}}$ percentile of real GDP growth after 4 or 12 quarters. GDP growth is measured as the average annual growth rate at each horizon. Confidence intervals represent plus and minus 1 standard deviation.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

Figure B.II: Baseline results - 5$^{\text{th}}$ percentile: intercept and controls

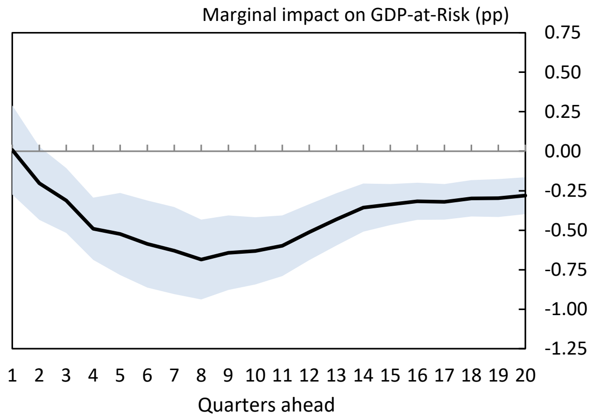
(A) Intercept



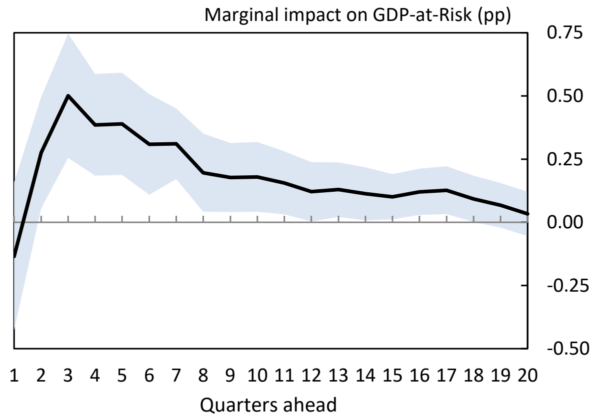
(B) Inflation



(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 4. 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 amd minus 1 standard deviation. Standard errors are genrated using block bootstraping.