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

David Aikman
Bank of England

(with Jon Bridges, Sinem Hacıoğlu Hoke, Cian O'Neill and Akash Raja)

Central Bank of Ireland Workshop, 19 Dec 2019

[0] The views expressed are those of the authors and do not necessarily reflect the views of the Bank of England or its policy committees.

Motivation

The creation of bodies charged with macroprudential remits and powers has been a key response to the crisis

- Edge and Liang (2019) nd that 47 of the 58 countries they survey have nancial stability committees of one sort or another, although most do not have power to take pre-emptive actions

The initial task of these macropru authorities was fairly clear: repair the financial system by boosting the capital and liquidity position of the banking system

If we're serious about implementing countercyclical macropru, we now need a framework to anchor/discipline such decisions, akin to the role played by the inflation target/forecast in monetary policy decision-making

I think forecasts of GDP-at-Risk are worth considering as a possible anchor

What do we do?

We investigate the empirical relationship between various financial vulnerability indicators and tail risks to GDP in a quantile regression framework

The vulnerability indicators we look at include banking sector leverage ratios, credit to the non-financial sector, external imbalances and property prices

We focus on the information content of these indicators for tail risks over a policy-relevant medium-term horizon (3-5 years)

Where do we fit in?

Our work relates most directly with recent work by Adrian, Grinberg, Liang, Malik (IMF WP, 2018) & Adrian, Boyarchenko, Giannone (AER, 2019). Builds on earlier work by Cecchetti (2006) and Cecchetti and Li (2008)

- Both papers focus on the relationship between nancial conditions and near term tail risks to GDP growth

Also links to studies of the impact of bank capital on resilience Jorda, Richter, Schularick and Taylor (2017) & Carlson, Shan and Warusawitharana (2013).

Where do we fit in?

Our work relates most directly with recent work by Adrian, Grinberg, Liang, Malik (IMF WP, 2018) & Adrian, Boyarchenko, Giannone (AER, 2019). Builds on earlier work by Cecchetti (2006) and Cecchetti and Li (2008)

- Both papers focus on the relationship between nancial conditions and near term tail risks to GDP growth

Also links to studies of the impact of bank capital on resilience Jorda, Richter, Schularick and Taylor (2017) & Carlson, Shan and Warusawitharana (2013).

We contribute to the literature in two ways:

- First, we condition estimates of GDP-at-Risk on metrics of the resilience of the banking system (bank leverage)
- Second, we jointly estimate the impact of various vulnerability indicators, allowing us to `add up' their contribution in a relevant common currency

Data

Cross country panel of 16 advanced economy countries over 1980Q4 – 2017Q4

- Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands , Norway, Spain, Sweden, Switzerland, UK, USA

Data

Cross country panel of 16 advanced economy countries over 1980Q4 – 2017Q4

- Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands , Norway, Spain, Sweden, Switzerland, UK, USA

We collect data on five vulnerability measures as explanatory variables

- 3 year change in credit-to-GDP
- 3 year real house price growth
- Current account de cit
- Realised equity price volatility
- Banking system capital

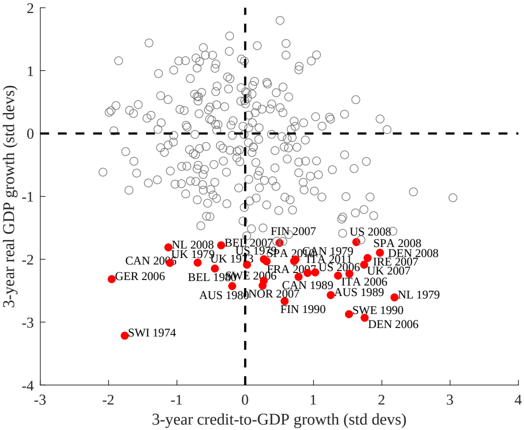
Bank capital

Our bank capital metric is constructed by aggregating individual bank data into country-level measures

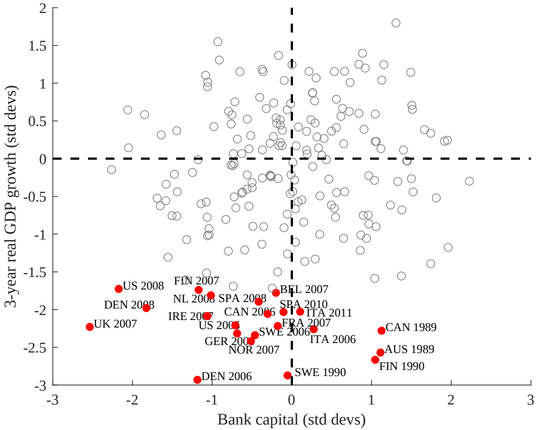
We focus on the tangible common equity ratio defined as tangible common equity to tangible assets

These data are available at annual frequency. We linearly interpolate these data to create a quarterly series for our baseline results (results robust to using annual specification)

Credit growth prior to the largest declines in output in our sample



Bank capital prior to the largest declines in output in our sample



Methodology

We estimate the following linear pooled panel quantile model

$$Y_{i;t+h} \quad Y_{i;t} = {}^{h}_{i;} + {}^{h}X_{i;t} + {}_{i;t}$$

where $Y_{i;t+h}$ denotes the log level of real GDP of country i at time $t+h$ for horizons $h = 1; 2; : : : ; 20$ quarters

The model is estimated from 1 to 20 quarters ahead using Jorda (2005)'s local projection method

The quantile regressions are estimated on a panel of advanced economy countries

The estimation requires the treatment of country-specific fixed effects to avoid estimation bias by following Canay (2011)

Baseline Specification

Dependent Variable	Risk	Resilience	Macro Controls
Real GDP growth	Credit to GDP changes Real house price growth Current Account Financial market Volatility	Capital Ratio	Inflation Policy Rate Lagged GDP

Baseline Specification

Dependent Variable	Risk	Resilience	Macro Controls
Real GDP growth	Credit to GDP changes Real house price growth Current Account Financial market Volatility	Capital Ratio	Inflation Policy Rate Lagged GDP

At each quarter, GDP growth is measured as $\frac{Y_{i;t+h} \quad Y_{i;t}}{h=4}$

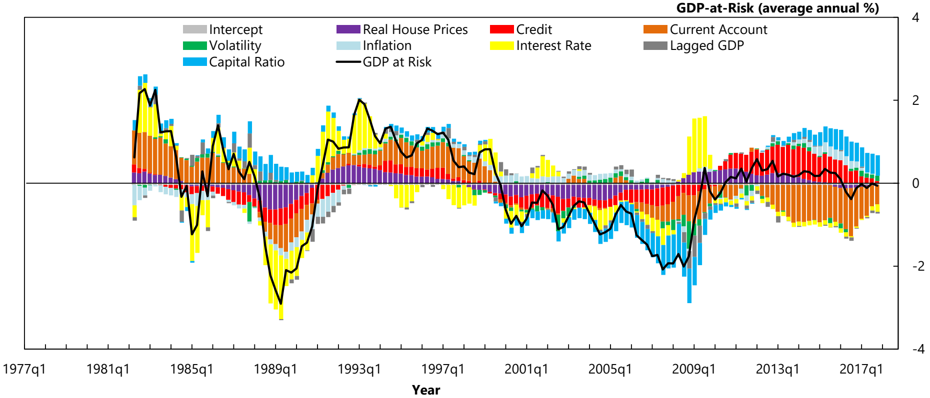
Estimation sampe: 1980Q4 – 2017Q4

5th percentile betas at $h = 12$

Credit growth, house price growth and current account deficits associated with worse GDP at Risk

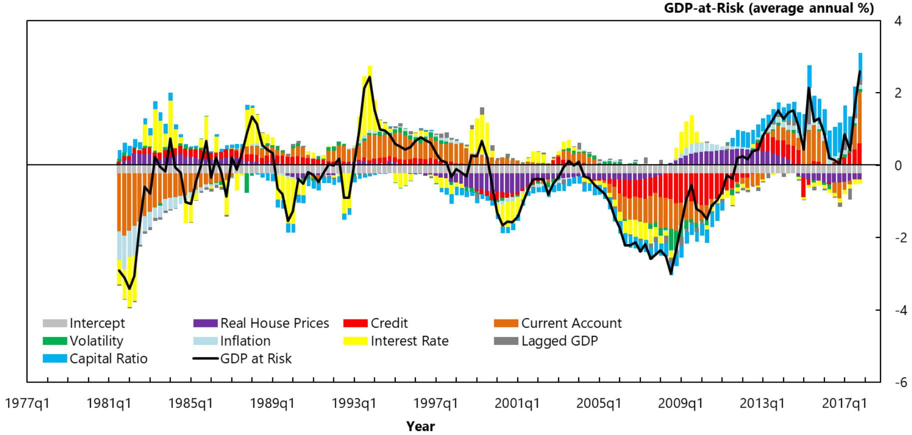
Higher bank capital associated with improved GDP at Risk

Decomposing 5% UK GDP-at-Risk (12 quarters ahead)



At a given quarter, the forecast is conditioned on data available three years earllier, eg 2009Q1 point is conditioned on financial vulnerability indicators as of 2006Q1

Decomposing 5% Irish GDP-at-Risk (12 quarters ahead)



At a given quarter, the forecast is conditioned on data available three years earllier, eg 2009Q1 point is conditioned on financial vulnerability indicators as of 2006Q1

Some robustness checks

Replacing volatility with a Financial Conditions Index (cuts sample to 1991)

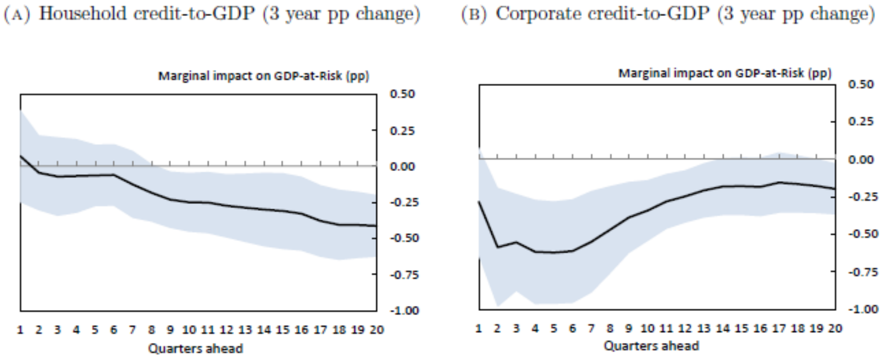
Adding a global factor of risky asset prices (Miranda-Agrippino and Rey (2018))

Using annual observations of data

Splitting credit into household and corporate

Running specification using 1 year instead of 3 year growth rates of credit and house prices

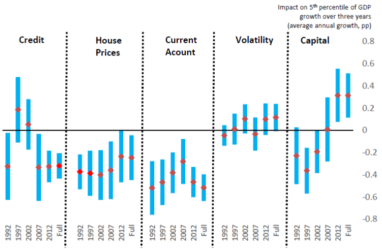
Impact of household vs corporate credit



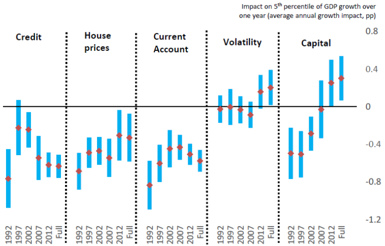
Innovations in household and corporate have a different time signature on GDP-at-Risk

5th percentile betas at h = 12 in sub-samples

(A) Full model



(B) Single variable model



Credit and bank capital coefficients are unstable in truncated samples

What difference might the CCyB have made pre-crisis?

Illustrative exercise, taking into account cross-country differences in risk build-ups and mappings from CCyB to capital measure used in the analysis

We find that a CCyB of 5% would have offset 40% of the build up in tail risk pre-crisis

Table 1: Impact of raising the CCyB

	Estimated change in GDP-at-Risk between 2002 and 2007	Estimated impact of: CCyB = 5%
UK	-1.1pp	0.3pp (29%)
US	-1.7pp	0.7pp (42%)
Cross-country average	-1.5pp	0.6pp (42%)

Concluding remarks

- Credit booms, house price booms and wide current account deficits pose material downside risks to growth at horizons of 3-5 years
- Such downside risks can be partially mitigated by increasing the capitalisation of the banking system
  - a 5% CCyB pre-crisis would have mitigated around 40% of the increase in GDP-at-Risk
- Capital only has a discernible impact in samples that include the GFC!

Concluding remarks (cont.)

In work in progress (with Kristina Bluwstein and Sudipto Karmakar), we are developing a ‘semi-structural’ simulation model with which to explore interactions between bank capitalisation, debt-deleveraging and the effective lower bound in a GDP-at-Risk setting

Preliminary findings suggest

- a high debt, weak capital economy with substantial monetary policy space has risks equivalent to a low debt, strong capital economy close to the ELB
- the frequency of credit crunch episodes increases substantially in a low-for-lon environment

Simulation results (cont.)

We choose regime thresholds such that in steady state the economy has:

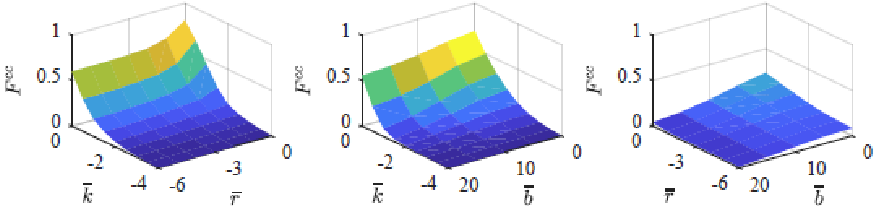
- 3% points of monetary policy headroom
- 2% points of `usable' capital bu ers (6% points of RWAs). UK banks' aggregate leverage ratio was 5.4% as of end-2017
- 10% points of credit growth before it becomes vulnerable to develeraging

Table 2: Simulation results

	E(y)	VaR^5(y)
Baseline	-0.95	-6.34
Weakly-capitalised banks (1pp usable capital)	-1.13	-7.14
High debt (5pp credit growth prior to deleveraging risk)	-1.56	-8.79
Weakly-capitalised banks and high debt	-1.86	-9.79
High r* (6pp easing capacity) plus low capital/high debt	-1.15	-6.33
Memo: Linear model	0.00	-1.20

The baseline 5th percentile of output is > 6% below trend. Risks are similar in a high debt/low capital economy with greater monetary easing capacity

Interactions between constraints



Thank you!

Aikman, Bluwstein and Karmakar (2019))

What we do

We build a semi-structural model of the drivers of GDP-at-Risk

This is a complement to the hitherto mainly empirical work – allows us ask 'what if' questions (eg impact on GDP-at-Risk of being in a low for long environment) and assess alternative policy strategies

We focus on 3 'macro-critical' constraints:

- a credit crunch in bank credit supply when bank equity capital is depleted
- deleveraging by overly-indebted borrowers when credit-to-GDP is elevated
- an e ective lower bound on interest rates
- The model also captures the possibility of disruptions in the supply of market-based nance leading to shocks to credit spreads

The model

The model is an augmented version of the standard New Keynesian model to allow for 3 nonlinear constraints

Aggregate demand, inflation and interest rates are determined by IS and Phillips curves and a Taylor rule:

$$y_t = {}^{y} y_{t \quad 1} \quad \tilde{}^{r} (r_t \quad {}_{t \quad 1} + s_t) + \tilde{} \quad {}^{y}_{t}$$

$${}_t = \quad {}_{t \quad 1} + {}^{y} y_{t \quad 1} + {}^{s} s_{t \quad 1} + {}_t$$

$$r_t = \max[\bar{r}; (1 \quad {}^{r})(\quad {}_t + {}^{y} y_t) + {}^{r} r_{t \quad 1} + {}^{r}_{t}]$$

The shocks in these equations are all independent and normally distributed

The model (cont.)

The financial side of our model consists of equations for credit demand, the supply of finance and the evolution of banks' capital ratios:

$$b_t = y_t + \ {}^{b} b_{t\ \ 1} \quad {}^{r}(r_t \quad {}_{t\ \ 1} + s_t) + \ {}^{b}_{t}$$

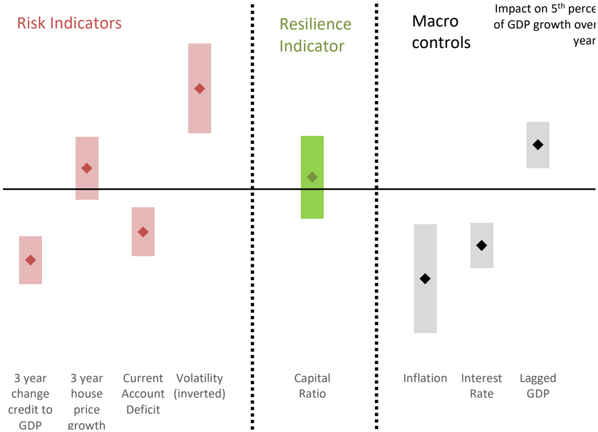
$$s_t = f\,{}^{s} s_{t\ \ 1} + f\,{}^{b} b_t \quad f\,{}^{\tilde{k}b} k_{t\ \ 1} + \ {}^{s}_{t}$$

$$k_t = \ {}^{k} k_{t\ \ 1} \quad {}^{r}\Delta r_t + \ {}^{s}(r_{t\ \ 1} + s_{t\ \ 1}) + \ {}^{k}_{t}$$

The variable ${}^{k}_{t}$ captures banks' credit losses, which we posit are decreasing in the level of output:

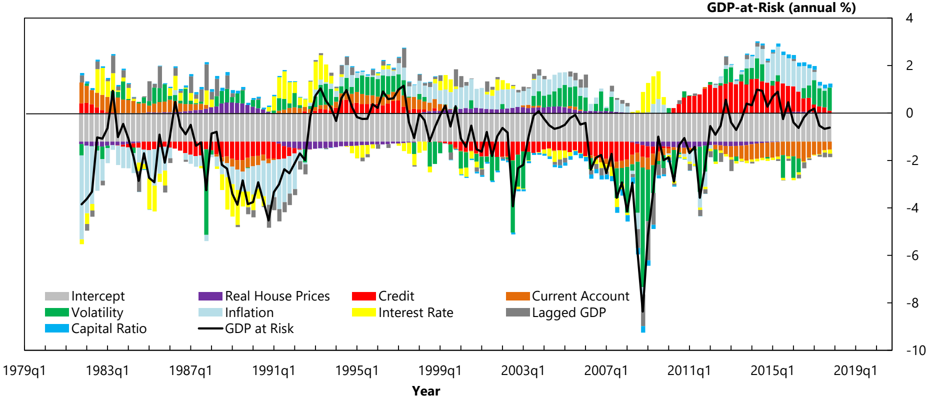
$${}^{k}_{t} = \ {}^{y} y_{t\ \ 1} + \ {}^{k}\ {}^{k}_{t\ \ 1} + u^{k}_{t}$$

Indicators of downside risks over short term



Equity market volatility is a key determinant
Credit growth and current account also important
Bank capital and house price growth have no impact

Decomposing GDP at Risk (4 quarters ahead)



At a given point, the forecast uses data up to one year earllier, e.g. 2009Q1 point uses data until 2008Q1