Essays on Measuring Credit and Property Prices Gaps

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Chapter 1: Credit and House Prices Cycles

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Table of Contents

Introduction

Motivation

- The study of housing prices and excessive credit has become more important in understanding financial market stability
- We also observed increasing use of monetary policies, significant growth in macro balance sheet size, including real estate values and total credit lending to household
- We study the dynamic relationship between housing prices and household credit in this paper

Contribution

1. Relationship between housing prices and household credit

- Apply Unobserved Component Model (Clark 1987) to extract information about trends and cycles

  ⇒ Jointly examine the two variables and their interaction both in the long-run and short-run

- Specify cycles to be VAR process (cross-cycle) rather than univariate AR process

  ⇒ Test if past movement of one cycle has predictive power over another cycle

Contribution

2. Technical contribution to the optimization process:

- Novel numerical optimization / parameters constraint method to ensure the cyclical components are in feasible stationary region

3. Overcome "curse of dimensionality" using Bayesian method:

- Common problem in estimating complex unobserved component state space model
- We use random walk Metropolis-Hasting method to estimate posterior distribution of parameters of interest

Literature Review

1. Dynamics of credit changes:

- Kiyotaki & Moore (1997), Myerson (2012), Guerrieri & Uhlig (2016), Boissay et al (2016).

2. Dynamics of house prices changes:

- Hong & Stein (1999), Glaeser et al (2008) (2017), Kishor, Kumari, & Song (2015)

Literature Review

3. House price cycles generates credit cycles:

- Bernanke & Gertler (1989), Bernanke et al (1999); Kiyotaki & Moore (1997) “
- Empirical Evidence: Fitzpatrick and McQuinn (2007), Berlinghieri (2010), Gimeno and Martinez-Carrascal (2010), Anundsen and Jansen (2013), for evidence from Ireland, USA, Spain and Norway, respectively

4. Credit cycles genereates house price cycles:

- Agnello & Schuknecht (2011), Kermani (2012), Justiniano et al (2019), Schularick et al (2012) (2016)

⇒ However, the debate on which cycle causes changes on the other is still open

Data

Bank of International Settlement (BIS)

- Household Credit to GDP: Total Credit to non-financial sector (household)
- House Price Index: Residential property prices: selected series (real value). Index = 100 at full sample average for each country

- 2 countries: US & UK
- Time frame: 1990:Q1 - 2019:Q3

Model

Unobserved Component Model

$$100 * ln\frac{Credit}{GDP} = y_t = \tau_{yt} + c_{yt} \tag{1}$$

$$100 * lnHPI = h_t = \tau_{ht} + c_{ht} \tag{2}$$

- Trends: τ_{yt} & τ_{ht}

$$\begin{aligned} \tau_{yt} &= \mu_{yt-1} + \tau_{yt-1} + \eta_{yt}, & \eta_{yt} &\sim iidN(0, \sigma^2_{\eta y}) \\ \mu_{yt} &= \mu_{yt-1} + \eta_{\mu yt}, & \eta_{\mu yt} &\sim iidN(0, 0.01) \\ \tau_{ht} &= \mu_{ht-1} + \tau_{ht-1} + \eta_{ht}, & \eta_{ht} &\sim iidN(0, \sigma^2_{\eta h}) \\ \mu_{ht} &= \mu_{ht-1} + \eta_{\mu ht}, & \eta_{\mu ht} &\sim iidN(0, 0.01) \end{aligned}$$

Model

Unobserved Component Model

- Cycles: c_{yt} & c_{ht}

$$c_{yt} = \phi_y^1 c_{yt-1} + \phi_y^2 c_{yt-2} + \phi_y^{x1} c_{ht-1} + \phi_y^{x2} c_{ht-1} + \varepsilon_{yt} \tag{3}$$

$$\varepsilon_{yt} \sim iidN(0, \sigma^2_{\varepsilon y}) \tag{4}$$

$$c_{ht} = \phi_h^1 c_{ht-1} + \phi_h^2 c_{ht-2} + \phi_h^{x1} c_{yt-1} + \phi_h^{x2} c_{yt-1} + \varepsilon_{ht} \tag{5}$$

$$\varepsilon_{ht} \sim iidN(0, \sigma^2_{\varepsilon h}) \tag{6}$$

Model

State Space Representation

- Transition equation:

$$\beta_t = F\beta_{t-1} + \tilde{v}_t \tag{7}$$

- Where the transitory components are:

$$\begin{bmatrix} \tau_{yt} \\ c_{yt} \\ c_{yt-1} \\ \tau_{ht} \\ c_{ht} \\ c_{ht-1} \\ \mu_{yt} \\ \mu_{ht} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & \phi_y^1 & \phi_y^2 & 0 & \phi_y^{x1} & \phi_y^{x2} & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & \phi_h^{x1} & \phi_h^{x2} & 0 & \phi_h^1 & \phi_h^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \tau_{yt-1} \\ c_{yt-1} \\ c_{yt-2} \\ \tau_{ht-1} \\ c_{ht-1} \\ c_{ht-2} \\ \mu_{yt-1} \\ \mu_{ht-1} \end{bmatrix} + \begin{bmatrix} \eta_{yt} \\ \varepsilon_{yt} \\ 0 \\ \eta_{ht} \\ \varepsilon_{ht} \\ 0 \\ \eta_{\mu yt} \\ \eta_{\mu ht} \end{bmatrix}$$

Model

Covariance Matrix

$$Q = \begin{bmatrix} \sigma^2_{\eta y} & 0 & 0 & \sigma_{\eta y \eta h} & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon y} & 0 & 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \sigma_{\eta y \eta h} & 0 & 0 & \sigma^2_{\eta h} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & \sigma^2_{\varepsilon h} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix} \tag{8}$$

Model

Optimization process

- Kalman filter with adjusted Likelihood function:

$$
\begin{aligned}
l(\theta) = -0.5\sum_{t=1}^{T} ln[(2\pi)^2|f_{t|t-1}|] - 0.5\sum_{t=1}^{T}\eta'_{t|t-1}f^{-1}_{t|t-1}\eta_{t|t-1} \\
-w1\sum_{t=1}^{T}(c^2_{yt}) - w2\sum_{t=1}^{T}(c^2_{ht})
\end{aligned}
$$

Empirical Results

Extended Models Regression Results: United States

	VAR2		VAR2 1-cross lag		VAR2 2-cross lags	
Parameters	Median	[10%, 90%]	Median	[10%, 90%]	Median	[10%, 90%]
ϕ_y^1	1.4826	[1.4216, 1.5446]	1.2074	[1.1374, 1.2785]	1.2004	[1.1227, 1.2753]
ϕ_y^2	-0.4887	[-0.5500, -0.4280]	-0.2483	[-0.3152, -0.1825]	-0.2554	[-0.3209, -0.1884]
ϕ_y^{x1}			**0.0318**	**[0.0228, 0.0407]**	0.0380	[0.0003, 0.0732]
ϕ_y^{x2}					-0.0088	[-0.0451, 0.0297]
ϕ_h^1	1.8594	[1.8276, 1.8915]	1.8038	[1.7700, 1.8363]	1.7999	[1.7658, 1.8345]
ϕ_h^2	-0.8728	[-0.9047, -0.8408]	-0.8261	[-0.8605, -0.7903]	-0.8316	[-0.8687, -0.7942]
ϕ_h^{x1}			**0.0104**	**[0.0007, 0.0204]**	0.3305	[0.2535, 0.4066]
ϕ_h^{x2}					-0.2882	[-0.3584, -0.2163]
σ_{ny}	0.0942	[0.0558, 0.1285]	0.2954	[0.2312, 0.3414]	0.0853	[0.0530, 0.1136]
σ_{ey}	0.8282	[0.7616, 0.9059]	0.8631	[0.8287, 0.9012]	0.7278	[0.6672, 0.7955]
σ_{nh}	0.0193	[0.0150, 0.0265]	0.1390	[0.1222, 0.1618]	0.0190	[0.0147, 0.0258]
σ_{eh}	0.8360	[0.7713, 0.9111]	0.8988	[0.8641, 0.9355]	0.8001	[0.7321, 0.8735]
ρ_{nynh}	0.0082	[-0.3118, 0.3230]	0.0082	[-0.3117, 0.3226]	0.0167	[-0.2998, 0.3328]
ρ_{eyeh}	0.1000	[-0.0181, 0.2185]	0.1537	[0.0399, 0.2619]	0.1642	[0.0460, 0.2764]
llv	197.7900	[195.5700, 201.0700]	204.9400	[202.4200, 208.4500]	187.7900	[184.8500, 192.1700]

Note:

US Bayesian method random walk Metropolis-Hasting posterior distribution estimates

Empirical Results

Extended Models Regression Results: United Kingdom

	VAR2		VAR2 1-cross lag		VAR2 2-cross lags	
Parameters	Median	[10%, 90%]	Median	[10%, 90%]	Median	[10%, 90%]
ϕ_y^1	1.9827	[1.9770, 1.9898]	1.4238	[1.3585, 1.4892]	1.4354	[1.3627, 1.5080]
ϕ_y^2	-1.0056	[-1.0126, -0.9985]	-0.4698	[-0.5305, -0.4090]	-0.4946	[-0.5599, -0.4301]
ϕ_y^{x1}			**0.0238**	**[0.0154, 0.0319]**	0.0023	[-0.0208, 0.0257]
ϕ_y^{x2}					0.0165	[-0.0075, 0.0399]
ϕ_h^1	1.4119	[1.3987, 1.4238]	1.3173	[1.2647, 1.3701]	1.2844	[1.2233, 1.3458]
ϕ_h^2	-0.4323	[-0.4464, -0.4227]	-0.3315	[-0.3885, -0.2746]	-0.3041	[-0.3686, -0.2409]
ϕ_h^{x1}			**-0.0173**	**[-0.0464, 0.0062]**	0.4847	[0.2707, 0.6894]
ϕ_h^{x2}					-0.4960	[-0.6698, -0.3198]
σ_{ny}	0.1055	[0.0896, 0.1254]	0.2714	[0.2150, 0.3155]	0.0737	[0.0463, 0.0987]
σ_{ey}	0.8113	[0.7957, 0.8259]	0.8021	[0.7699, 0.8376]	0.6336	[0.5803, 0.6925]
σ_{nh}	0.0062	[0.0055, 0.0072]	0.0789	[0.0742, 0.0845]	0.0062	[0.0055, 0.0071]
σ_{eh}	1.8647	[1.8332, 1.8845]	1.2242	[1.1886, 1.2613]	1.5020	[1.4080, 1.6063]
ρ_{nynh}	0.0589	[0.0418, 0.0808]	0.0189	[-0.3049, 0.3393]	0.0150	[-0.3101, 0.3306]
ρ_{eyeh}	0.3373	[0.2938, 0.3485]	0.2536	[0.1713, 0.3337]	0.2533	[0.1582, 0.3426]
llv	607.7600	[605.0700, 610.0600]	578.6200	[576.1600, 582.1500]	559.5500	[556.6400, 563.6200]

Note:

UK Bayesian method random walk Metropolis-Hasting posterior distribution estimates

VAR(2) - 1 Cross-lag Model Estimate - UK and US

		UK VAR2 1-cross lag		US VAR2 1-cross lag	
Description	Para.	Median	[10%, 90%]	Median	[10%, 90%]
Credit to household 1st AR parameter	ϕ_y^1	1.4238	[1.3585, 1.4892]	1.2074	[1.1374, 1.2785]
Credit to household 2nd AR parameter	ϕ_y^2	-0.4698	[-0.5305, -0.4090]	-0.2483	[-0.3152, -0.1825]
Credit to household 1st cross cycle AR parameter	ϕ_y^{x1}	**0.0238**	**[0.0154, 0.0319]**	**0.0318**	**[0.0228, 0.0407]**
Credit to household 2nd cross cycle AR parameter	ϕ_y^{x2}				
Housing Price Index 1st AR parameter	ϕ_h^1	1.3173	[1.2647, 1.3701]	1.8038	[1.7700, 1.8363]
Housing Price Index 2nd AR parameter	ϕ_h^2	-0.3315	[-0.3885, -0.2746]	-0.8261	[-0.8605, -0.7903]
Housing Price Index 1st cross cycle AR parameter	ϕ_h^{x1}	**-0.0173**	**[-0.0464, 0.0062]**	**0.0104**	**[0.0007, 0.0204]**
Housing Price Index 2nd cross cycle AR parameter	ϕ_h^{x2}				
S.D. of permanent shocks to Credit to household	σ_{ny}	0.2714	[0.2150, 0.3155]	0.2954	[0.2312, 0.3414]
S.D. of transitory shocks to Credit to household	σ_{ey}	0.8021	[0.7699, 0.8376]	0.8631	[0.8287, 0.9012]
S.D. of permanent shocks to Housing Price Index	σ_{nh}	0.0789	[0.0742, 0.0845]	0.1390	[0.1222, 0.1618]
S.D. of transitory shocks to Housing Price Index	σ_{eh}	1.2242	[1.1886, 1.2613]	0.8988	[0.8641, 0.9355]
Correlation: Permanent credit to household/Permanent HPI	ρ_{nynh}	0.0189	[-0.3049, 0.3393]	0.0082	[-0.3117, 0.3226]
Correlation: Transitory credit to household/Transitory HPI	ρ_{eyeh}	0.2536	[0.1713, 0.3337]	0.1537	[0.0399, 0.2619]
Log-likelihood value	llv	578.6200	[576.1600, 582.1500]	204.9400	[202.4200, 208.4500]

Note:

UK - US Bayesian method random walk Metropolis-Hasting posterior distribution estimates

VAR(2) - 1 Cross-lag Model Estimate Summary

- The sum of AR parameters of the cyclical components in all three models is smaller, although close to one
- The standard deviation of the shocks in the cycles σ_{ei} is much higher than the standard deviation of the shocks to the trend σ_{ni} of both credit and housing prices
- Variations in the housing price cyclical components σ_{eh} of the UK are bigger than in the US
- The correlation of the shocks to the cyclical components among the two variables ρ_{eyeh} suggests that cyclical variation among housing price and household credit is strongly positively correlated

Cross-country Comparison of Causal Coefficients

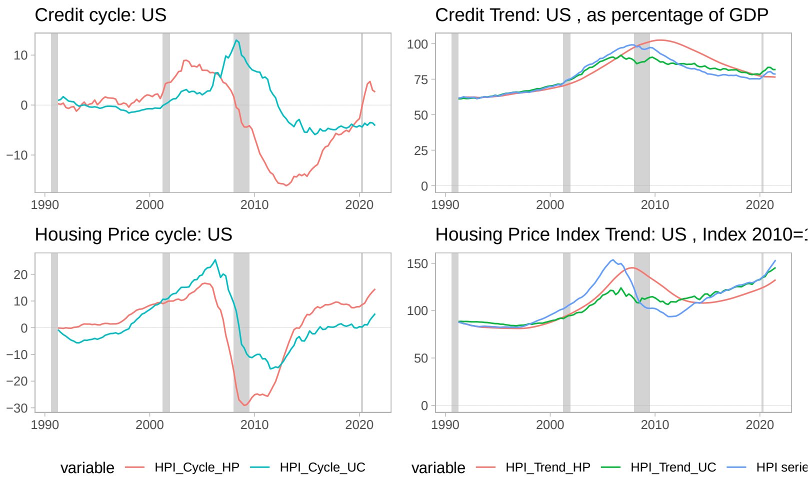
	ϕ_y^{x1} HPI on Credit		ϕ_h^{x1} Credit on HPI	
Country	Median	[10%, 90%]	Median	[10%, 90%]
Australia	0.0157	[-0.0093, 0.0412]	0.0521	[0.0014, 0.1060]
Belgium	0.0279	[0.0013, 0.0559]	-0.0656	[-0.0980, -0.0339]
Canada	0.0191	[0.0032, 0.0332]	-0.0152	[-0.0343, 0.0025]
Finland	0.0080	[0.0017, 0.0156]	0.0085	[0.0021, 0.0156]
France	0.0298	[0.0185, 0.0411]	-0.0643	[-0.1098, -0.0241]
Germany	0.0728	[0.0500, 0.0917]	-0.0061	[-0.0282, 0.0052]
Hong Kong	-0.0031	[-0.0079, 0.0019]	-0.0629	[-0.0836, -0.0453]
Italy	0.1001	[0.0895, 0.1063]	-0.0027	[-0.0072, 0.0014]
Japan	-0.0088	[-0.0326, 0.0174]	0.1659	[0.1202, 0.2173]
Netherlands	0.0058	[-0.0039, 0.0166]	-0.0043	[-0.0156, 0.0070]
New Zealand	0.0078	[-0.0035, 0.0199]	-0.0139	[-0.0249, -0.0036]
Norway	0.0109	[0.0097, 0.0116]	0.0059	[0.0047, 0.0066]
South Korea	0.0106	[-0.0033, 0.0308]	0.0027	[-0.0251, 0.0369]
Spain	0.0144	[0.0003, 0.0331]	0.0051	[-0.0023, 0.0146]
Sweden	0.0159	[0.0071, 0.0252]	0.0400	[0.0218, 0.0617]
United Kingdom	0.0238	[0.0154, 0.0319]	-0.0173	[-0.0464, 0.0062]
United States	0.0318	[0.0228, 0.0407]	0.0104	[0.0007, 0.0204]

Cross-country Comparison of Causal Coefficients Summary

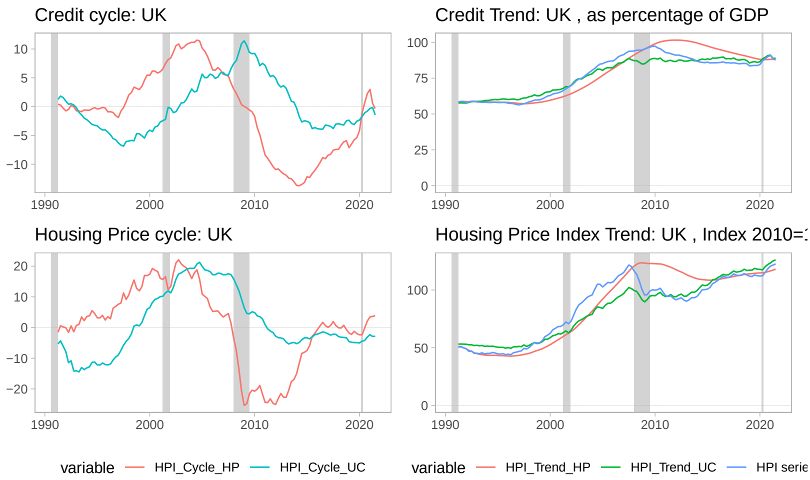
- In 11 out of 17 countries, the HPI on Credit causal coefficient ϕ_y^{x1} are positive and significant
- Only 6 countries have positive and significant Credit on HPI causal coefficient ϕ_y^{x1}. Three of which have smaller magnitudes than their ϕ_y^{x1} counterpart

$\rightarrow$ Overall, we found evidence that past transitory shocks to house price credit will cause a positive deviation in future transitory household credit. However, the effect in the opposite direction is much smaller and sometimes insignificant

Unobserved Component Graphs: United States



Unobserved Component Graphs: United Kingdom



Conclusion

- Extracting temporary and permanent components information gave insights on the dynamics of the two series housing and credit
- Evidence showing that past movement of a cycle has predictive power over the other cycle

Chapter 2: Measuring Credit Gaps

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Table of Contents

Introduction

Motivation

- No unanimity on how to measure excessive credit. Bank for International Settlements uses HP filter to create a credit gap measurement that performs well in predicting future financial crises. However, there are other competing gap measurements.
- Nelson (2008) that the deviation of a non-stationary variable from its long-run trend should predict future changes of opposite sign in the variable. We utilize this idea and forecast combination method to propose a synthesized credit gap measurement.

Contribution

Since different trend-cycle decomposition methods of credit-to-GDP ratio provide us different credit gap measures, we handle the model uncertainty by assigning weights on these different credit gap measures based on its relative out-of-sample predictive power based on Bates and Granger (1969) forecast combination method.

- Our proposed credit gap measure dominates the alternate credit gaps in terms of its relative out-of-sample predictive power.

Methodology

Data

The measure of credit is total credit to the private non-financial sector, as published in the BIS database, capturing total borrowing from all domestic and foreign sources.

- Quarterly data from 1983:Q1-2020:Q2

Model

All these trend-cycle decomposition methods are based on the premise that a non-stationary series is the sum of a trend and a stationary cyclical component:

$$y_t = \tau_t + c_t \tag{9}$$

Trend-cycle decomposition models

HP filter

$$min_\tau(\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t-1} - \tau_t) - (\tau_t - \tau_{t-1})]^2) \qquad (10)$$

- λ will be set at 1600, 3000, 400000 in our models

Unobserved-Component model: Clark(1987)

$$\tau_t = \tau_{t-1} + \eta_t, \eta_t \tilde{}\, iid(0, \sigma_\eta^2) \qquad (11)$$

$$c_t = \Phi(L)c_t + u_t, u_t \tilde{}\, iid(0, \sigma_u^2)$$

Trend-cycle decomposition models

Beveridge-Nelson

$$y_t = y_0 + \mu t + \Psi(1) \sum_{k=1}^{t} u_t + \breve{u}_t - \breve{u}_0 \qquad (12)$$

Hamilton filter (2018)

$$y_{t+h} = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + v_{t+h} \qquad (13)$$

Forecasting model:

$$\Delta y_t = \alpha + \beta(L)\Delta y_{t-1} + \gamma(L)GAP_{t-1} + v_t \tag{14}$$

Baseline Model AR(1):

$$\Delta y_t = \alpha + \beta(L)\Delta y_{t-1} + v_t \tag{15}$$

Forecast combination

$$w_m = \frac{\widehat{\overline{\sigma}}_m^2}{\widehat{\overline{\sigma}}_1^2 + \widehat{\overline{\sigma}}_2^2 + ...\widehat{\overline{\sigma}}_M^2} \tag{16}$$

- where $\widehat{\overline{\sigma}}_m^2$ is inverted out-of-sample forecast error variance of forecast M based on the cyclical component M.

Empirical Results

We perform these estimations recursively to preserve the 1-sided nature of the credit gap.

Our first estimation sample runs from 1983:Q1-1988:Q4 and saves the last estimate of the cycle. We keep adding one more observation to the estimation sample and keep saving the last observation of the cycle for different methods.

- This approach provides us with a 1-sided estimate of the credit gap from different methods.

Empirical Results:

Forecasting Performance of Credit Gap Models (U.S.)

Horizon	HP	RU	BIS	Hamilton	Linear	Quadratic	BN	UC	Average	Bates-Granger
1	0.993	0.987	1.012	0.994	1.028	1.005	1.010	0.985	0.962	**0.959**
2	0.974	0.963	1.016	0.980	1.058	1.014	0.975	0.961	0.924	**0.917**
3	0.966	0.953	1.023	1.011	1.055	1.036	0.965	0.937	0.906	**0.896**
4	0.982	0.966	1.022	1.029	1.055	1.045	1.033	0.910	0.922	**0.910**
1 - 4	0.964	0.945	1.030	1.005	1.081	1.041	0.978	0.913	0.882	**0.872**

The table shows the ratio of RMSEPs of different models in comparison to the benchmark AR(1) model. The first set of forecasts is for 1994:Q1-1994:Q4; the final set is for 2019:Q3-2020:Q2. Q=1-4 denotes averages over next 4-quarters. HP is Hodrick-Prescott, RU is Ravn-Uhlig, BIS is based on Borio and Lowe (2002), BN is Beveridge-Nelson, UC is Unobserved Component Model.

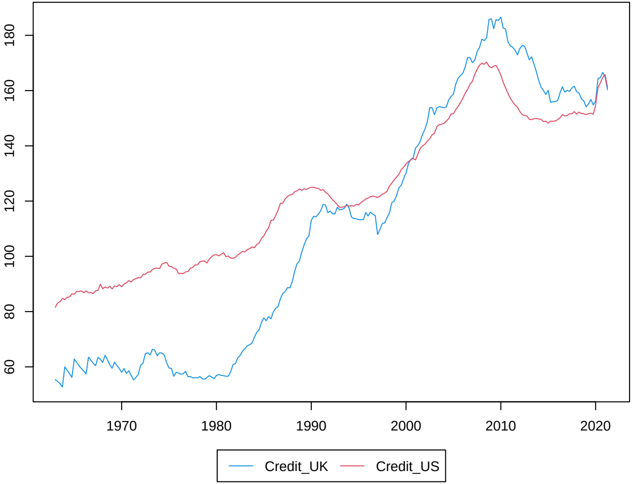
Empirical Results:

Forecasting Performance of Credit Gap Models (U.K.)

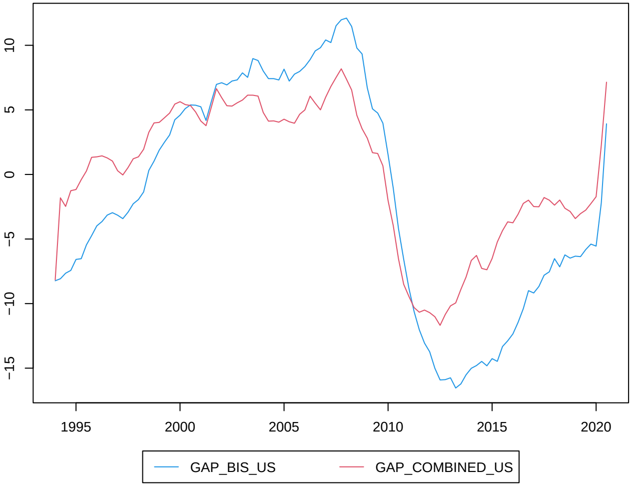
Horizon	HP	RU	BIS	Hamilton	Linear	Quadratic	BN	UC	Average	Bates-Granger
1	1.001	0.990	1.001	0.992	1.010	0.979	1.028	1.009	**0.977**	0.979
2	0.979	0.970	1.007	0.969	1.016	0.962	1.028	0.999	0.962	**0.957**
3	0.979	0.971	1.018	0.969	1.055	0.966	1.009	0.989	0.959	**0.955**
4	0.990	0.987	1.028	1.005	1.055	0.981	1.019	0.981	0.972	**0.967**
1 - 4	0.972	0.952	1.034	0.960	1.081	0.929	1.054	0.985	0.918	**0.910**

The table shows the ratio of RMSEPs of different models in comparison to the benchmark AR(1) model. The first set of forecasts is for 1994:Q1-1994:Q4; the final set is for 2019:Q3-2020:Q2. Q=1-4 denotes averages over next 4-quarters. HP is Hodrick-Prescott, RU is Ravn-Uhlig, BIS is based on Borio and Lowe (2002), BN is Beveridge-Nelson, UC is Unobserved Component Model.

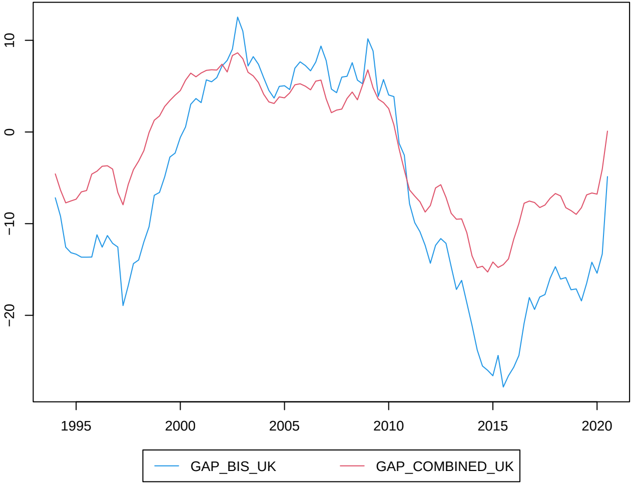
Credit-to-GDP Ratios



Credit Gap Comparison (U.S.)



Credit Gap Comparison (U.K.)



Conclusion

Our results show that this method of combining credit gaps yield us a credit gap measure that dominates credit gaps from different trend-cycle decomposition methods in terms of superior out-of-sample forecasting of changes in credit-to-GDP ratio.

Chapter 3: Identifying Unsustainable Credit Gaps

Chapter 3: Identifying Unsustainable Credit Gaps

Table of Contents

Motivation

- To overcome model uncertainty in using credit gap as an early warning indicator (EWI) of systemic financial crises, we propose using model averaging of different credit gap measurements. The method is based on Bayesian Model Average - Raftery (1995)

Motivation

- Area under the curve of operating characteristic (AUROC or AUC) has been widely used as a criterion to determine the performance of a EWI. But it has recently received some criticism.
- Borio and Drehmann (2009) and Beltran et al (2021) proposed a policy loss function constraining the relevance of the curve measurement to just a portion where Type II error rate is less than $1/3$ or at least $2/3$ of the crises are predicted.
- Detken (2014) proposed using partial standardized area under the curve (psAUC) as an alternative measurement of the performance of an EWI.

Contribution

- Compare different credit gap measurements' performance as EWIs using a new criterion - partial standarized AUC (psAUC) contraining Type II error $< 1/3$.
- Overcome model uncertainty by implementing model averaging. We incoporated psAUC values in the model selection and weighting process, instead of AUC values.
- For ease of policy implication, we propose a single credit gap measurement from weighted averaging other popularly studied credit gap measurements. The gap has superior performance in model fit and out-of-sample prediction.

Literature Review

Beltran (2021) - measured and the performance of BIS Basel credit gap, along with other decomposition methods and optimized the smoothing parameters ρ in those filters to minimize policy loss function.

$$L_{\theta,\rho} = \alpha \, TypeI(\theta) + (1-\alpha)\, TypeII(\theta) | TPR \geq 2/3$$

- θ is the optimized threshold that minizes loss function.

Galán (2019) proposed rolling sample of 15 and 20 years when creating one sided cycle.

Drehmann (2021) created Hamilton filter in a panel setting with fixed coefficients on independent variables across countries.

Data

Sample data periods:

- 1970:Q4 - 2017:Q4 quarterly data across 43 countries.
  - We omit periods for countries with shorter credit measurements.

Systemic crisis data:

- European Systemic Risk Board crisis data set (Lo Duca et al. 2017)
- Laeven and Valencia (2018)

Credit/GDP ratio data:

- Bank of International Settlement (BIS)
  - Latest credit data is available until 2021:Q3

Emprical Model

Credit gaps creation

$$100 * \frac{Credit}{GDP} = y_t = \tau_{yt} + c_{yt} \tag{17}$$

- We created 90 candidate one-sided credit gap measurements based on the literature.
    - Once a country has more than 15 years of credit measurement available, we start storing its one-sided credit gap values onward.

Early Warning Indicator - Logistic regression:

$$pre.crisis_{ti} \sim credit.gap_{tij} \tag{18}$$

- i is country indicator. j is credit gap filter type
- where $pre.crisis_{it} = 1$ or 0
- The pre-crisis indicator is set to 1 when t is between 5-12 quarters before a systemic crisis.
- We discard measurements between 1-4 quarters before a crisis, periods during a crisis and post-crisis periods identified in Lo Duca et al. (2017) and Laeven and Valencia (2018).
    - The indicator is set to 0 at other periods.
    - pre-crisis periods of imported crises identified in the dataset are also set to 0. However, we still discard measurements of periods during and post-crisis for imported crises.

AUROC

Each logistic regression with a different gap measurement yields a Area Under Curve (AUC) of receiver operating characteristic value. There is an underlying assumption that the higher the AUC value is the better overall performance of a credit gap is as an EWI.

- However, the AUC value received some criticism regarding the area on its lower left corner, where the predictive power of the threshold (TPR) is low.

$$AUC = \int_0^1 TPRd(FPR)$$

A ROC curve in the EWI setting represents True Positive Rate (TPR) and False Positive Rate (FPR) of different credit gap thresholds indicating a pre-crisis period.

partial standardised AUROC (psAUROC)

To overcome the issue of unnecessary information included in the full AUC. An approach to estimate partial AUC was proposed by Detken et al (2014) in the early warning literature.

- psAUC can reveal useful additional information as long as the partial area does not become too restricted

pAUROC (or pAUC)

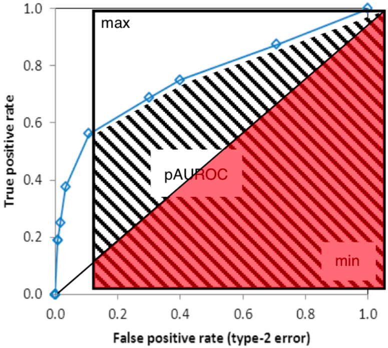
Beltran (2021) constrainted the policy loss function to TPR $\geq 2/3$ or Type II error rate $< 1/3$. They then estimated the policy loss function value at different points on the ROC curve by assigning different policy preferences α.

$\Rightarrow$ In this paper, we propose to restrict the consideration of the ROC curve to TPR $\geq 2/3$, then estimate the psAUC of the restricted ROC curve region instead.

$$pAUROC = \int_{\frac{2}{3}}^{1} TNR \, d(TPR) \tag{19}$$

- TNR = 1- FPR
- FPR = Type I error rate, FNR = Type II error rate

standardize psAUROC - Detken (2014)



$$psAUROC = \frac{1}{2}\left[1 + \frac{pAUROC - min}{max - min}\right] \tag{20}$$

Variable selection

Comparing performance of individual credit gaps

Using partial area under the curve (psAUC) values

Test for gaps combination performance

Using Markov Chain Monte Carlo Model Comparison (MC^3) developed by Madigan and York (1995). The method assigns posterior probability for different credit gaps being selected in most likely models/combinations. Babecky (2014) used this MC^3 method to identify potential variables in EWI models.

$$Model_k : pre.crisis_{ti} \sim \sum_j \beta_j * credit.gap_{tij}$$

Variable selection

We selected 29 credit gap measurements based on these 2 criteria.

Variable selection (top 23 gaps ranked by psAUC)

Cycles	BIC	AIC	AUC	psAUC	c.Threshold	Type.I	Type.II	Policy.Loss.Function
null	0.0000	0.0000	0.5000	**0.5000**		1.0000	0.0000	1.0000
c.bn6.r20	-108.0679	-114.4506	0.7048	**0.6379**	0.6581	0.3962	0.3019	0.2481
c.hamilton28.panel	-149.8518	-156.2346	0.7107	**0.6359**	9.7674	0.3912	0.3066	0.2470
c.hamilton13.panelr20	-150.2442	-156.6269	0.7036	**0.6333**	5.9895	0.4261	0.2547	0.2464
c.hamilton24.panel	-134.4093	-140.7920	0.6991	**0.6322**	7.1794	0.4383	0.2689	0.2644
c.hamilton20.panelr20	-151.5617	-157.9445	0.7048	**0.6313**	7.9350	0.4321	0.3066	0.2807
c.ma	-120.8108	-127.1936	0.6922	**0.6313**	5.7813	0.3989	0.3160	0.2590
c.hamilton20.panelr15	-135.3713	-141.7540	0.6985	**0.6312**	7.5244	0.4616	0.2689	0.2854
c.hamilton13.panelr15	-126.2968	-132.6796	0.6924	**0.6311**	6.5289	0.4297	0.2830	0.2647
c.hamilton28.panelr20	-164.6015	-170.9842	0.7158	**0.6302**	10.8558	0.3948	0.2925	0.2414
c.hamilton24.panelr20	-155.8638	-162.2466	0.7096	**0.6301**	9.1672	0.4251	0.2830	0.2608
c.hamilton24.panelr15	-143.2235	-149.6062	0.7033	**0.6299**	10.4963	0.3984	0.3160	0.2586
c.hamilton20.panel	-126.8625	-133.2452	0.6907	**0.6288**	5.6212	0.4686	0.2830	0.2997
c.hamilton28.panelr15	-154.4533	-160.8361	0.7091	**0.6270**	11.5510	0.3854	0.2972	0.2369
c.hamilton13.panel	-133.9347	-140.3175	0.6922	**0.6250**	4.9769	0.4285	0.2877	0.2664
c.bn2.r20	-109.3128	-115.6955	0.6963	**0.6218**	0.2776	0.4080	0.3255	0.2724
c.linear	-135.4069	-141.7896	0.6879	**0.6204**	3.9989	0.4616	0.2925	0.2986
c.bn2	-135.9914	-142.3741	0.6842	**0.6165**	0.1864	0.4530	0.3113	0.3021
c.bn6	-132.7915	-139.1742	0.6835	**0.6113**	0.4710	0.4371	0.2830	0.2712
c.bn6.r15	-54.9953	-61.3781	0.6756	**0.6070**	0.5680	0.4179	0.3255	0.2806
c.bn2.r15	-83.9469	-90.3297	0.6749	**0.6047**	0.1349	0.4761	0.3302	0.3357
c.poly4.r20	3.5738	-2.8090	0.5772	**0.6011**	0.1651	0.4980	0.3302	0.3570
BIS Basel gap	-121.5910	-127.9738	0.6733	**0.5960**	3.0578	0.4441	0.3255	0.3032
c.bn4	-169.1186	-175.5014	0.6892	**0.5943**	1.2840	0.3837	0.3255	0.2532
c.bn4.r15	-89.6147	-95.9975	0.6669	**0.5929**	0.4435	0.4792	0.2925	0.3152
c.bn5.r20	-99.7674	-106.1501	0.6744	**0.5928**	0.5016	0.4234	0.3302	0.2883

Model Averaging

Bayesian Model Averging

The Bayesian Model Average method is formalized in Raftery (1995) to account for model uncertainty.

Model posterior probability

Model k posterior probability (weight):

$$P(M_k|D) = \frac{P(D|M_k)P(M_k)}{\sum_{l=1}^{K} P(D|M_l)P(M_l)} \approx \frac{exp(-\frac{1}{2}BIC_k)}{\sum_{l=1}^{K} exp(-\frac{1}{2}BIC_l)} \quad (21)$$

- Where $P(M_k)$ is model prior probability and can be ignored if all models are assumed equal prior weights.
- $P(D|M_k)$ is marginal likehood. And $P(D|M_k) \propto exp(-\frac{1}{2}BIC_k)$
- In which $BIC_k = 2log(Bayesfactor_{sk}) = \chi^2_{sk} - df_k log(n)$. s indicates the saturated model.

Model posterior probability

- $BIC_k = 2log(Bayesfactor_{sk}) = \chi^2_{sk} - df_k log(n)$
- χ^2_{sk} is the deviance of model K from the the saturated model
    - $\chi^2_{sk} = 2(ll(Ms) - ll(Mk))$
    - $ll(Mk)$ is the log-likelihood of model Mk given data D

Alternate deviance measurement

We propose using psAUC instead of log-likelihood in the measurement of deviance. Hence, an alternative BIC value can be estimated at:

$$
\begin{aligned}
BIC_{alt,k} &= 2log(Bayesfactor_{alt,sk}) && (22)\\
&= 2(1000 * (psAUC_s - psAUC_k)) - df_k log(n) && (23)
\end{aligned}
$$

- We scaled the psAUC value by 1000 since $0 < psAUC < 1$. Also, by design, $psAUC_s = 1$.

Posterior distribution of coefficients of interest:

β_j is the coefficient of credit gap j (c_j) in a logistic regression model k against pre-crisis indicator. When considering a particular β_1 :

$$p(\beta_1|D, \beta_1 \neq 0) = \sum\nolimits_{A_1} p(\beta_1|D, M_k)p'(M_k|D)$$

- where $p'(M_k|D) = p(M_k|D)/pr[\beta_1 \neq 0|D]$
- and $pr[\beta_1 \neq 0|D] = \sum\limits_{A_1} p(M_k|D)$
  - this is the probability that β_1 is in the averaged model
  - $A_1 = \{M_k : k = 1, ..., K; \beta_1 \neq 0\}$, is the set of models that includes β_1

Approximation of point estimate:

$$\hat{\beta}_1 = E[\beta_1 | D, \beta_1 \neq 0] = \sum_{A_1} \hat{\beta}_1(k) p'(M_k | D) \tag{24}$$

$SD^2[\beta_1|D, \beta_1 \neq 0] =$
$[\sum_{A_1}[se_1^2(k)+] + \hat{\beta}_1(k)]p'(M_k|D) - E[\beta_1|D, \beta_1 \neq 0]^2$

- Where $\hat{\beta}_1(k)$ and $se_1^2(k)$ are respectively the MLE and standard error of β_1 under the model M_k. (Leamer 1978, p.118; Raftery 1993a)

Weighted credit gap creation

Motivation

GLM binomial estimation:

$$\widehat{pre.crisis}_{ti} = \widehat{probability}_{ti} = \frac{1}{1 + exp(-(a + \sum_j \hat{\beta}_j c_{tij}))}$$

- With $\hat{\beta}_j = E[\beta_j | D, \beta_j \neq 0] = \sum_{A_j} \hat{\beta}_j(k) p'(M_k | D)$

$\Rightarrow$ We propose a single weighted credit gap $\hat{c}_{ti}$ that satisfies:

$$\frac{1}{1 + exp(-(a + \hat{\beta}\hat{c}_{ti}))} = \frac{1}{1 + exp(-(a + \sum_j \hat{\beta}_j c_{tij}))}$$

OR

$$\sum_j \hat{\beta}_j c_{tij} = \hat{\beta}\hat{c}_{ti} \tag{25}$$

Weighted averaged credit gap - creation

$$\sum_j \hat{\beta}_j c_{tij} = \hat{\beta}\hat{c}_{ti}$$

We then propose $\hat{\beta} = \sum_j \hat{\beta}_j$

Therefore,

$$\hat{c}_{ti} = \frac{\sum_j (\hat{\beta}_j c_{tij})}{\sum_j \hat{\beta}_j} = \sum_j w_j c_{tij} \tag{26}$$

The weight of each candidate credit gap j is $w_j = \frac{\hat{\beta}_j}{\sum_j \hat{\beta}_j}$

One-sided crisis weighted averaged credit gap

- The weight of each candidate credit gap j is $w_j = \frac{\hat{\beta}_j}{\sum_j \hat{\beta}_j}$
- We save the weights w_j at every incremental period t of available data to create a one-sided weight vector w_{tj}.

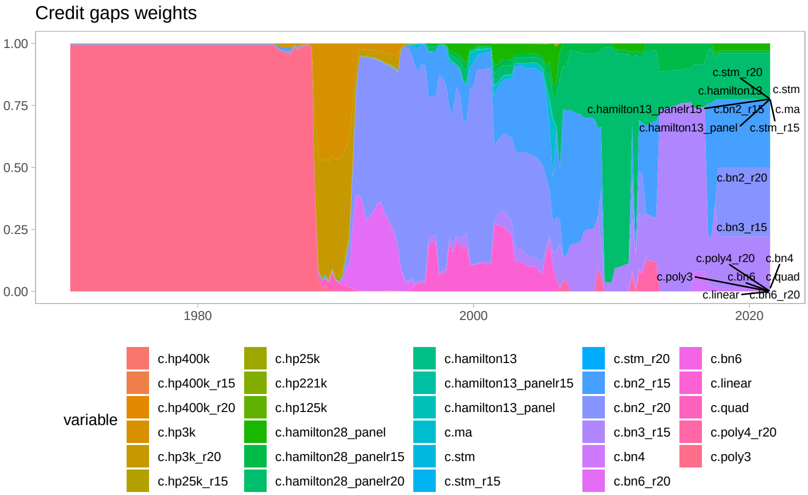
$\Rightarrow$ To create one-sided crisis weighted averaged credit gap for each country i ($\hat{c}_{ti}$), we compute:

$$\hat{c}_{ti,one-sided} = \sum_j w_{tj} * c_{tij} \tag{27}$$

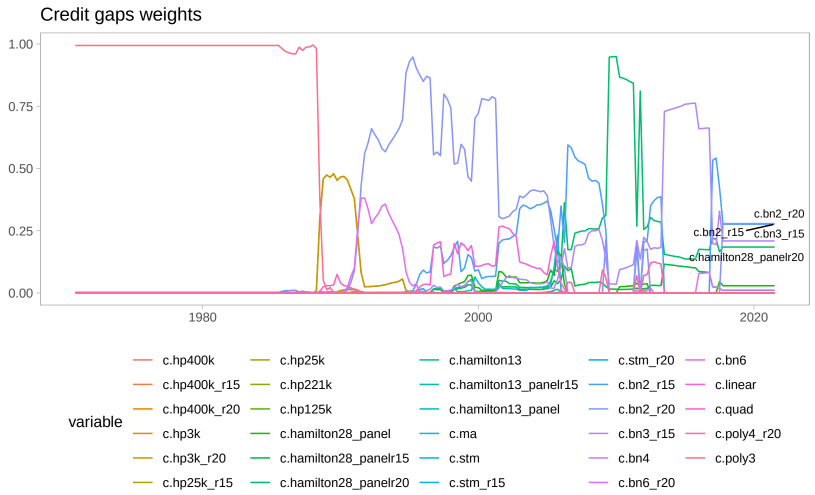
Empirical Results

Weights stacked graph

Weights are restricted to be positive to ensure stability



Weights series graph



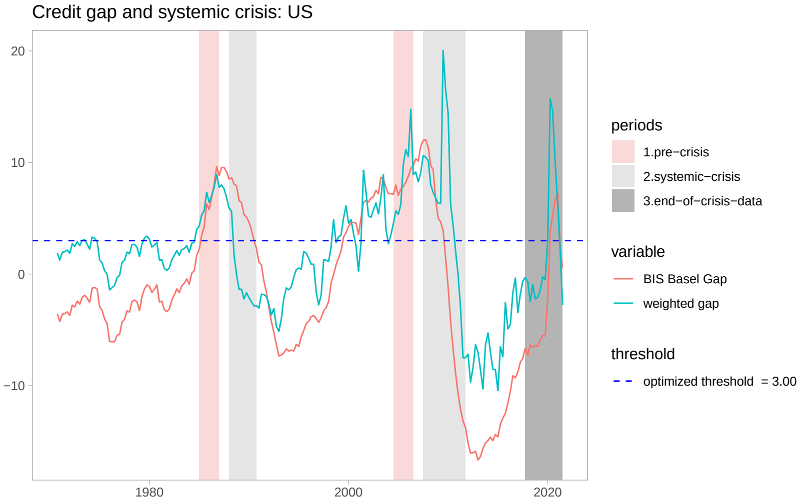
Comparing performance of weighted gap - Full Sample

Cycles	BIC	AIC	AUC	psAUC	c.Threshold	Type.I	Type.II	Policy.Loss.Function
null	0.0000	0.0000	0.5000	**0.5000**		1.0000	0.0000	1.0000
1.sided weighted.cycle	**-127.5308**	**-133.9135**	**0.7182**	**0.6454**	**2.8892**	**0.3532**	**0.3255**	**0.2307**
c.bn6.r20	-108.0679	-114.4506	0.7048	**0.6379**	0.6581	0.3962	0.3019	0.2481
c.hamilton28.panel	-149.8518	-156.2346	0.7107	**0.6359**	9.7674	0.3912	0.3066	0.2470
c.ma	-120.8108	-127.1936	0.6922	**0.6313**	5.7813	0.3989	0.3160	0.2590
c.hamilton13.panelr15	-126.2968	-132.6796	0.6924	**0.6311**	6.5289	0.4297	0.2830	0.2647
c.hamilton28.panelr20	-164.6015	-170.9842	0.7158	**0.6302**	10.8558	0.3948	0.2925	0.2414
c.hamilton28.panelr15	-154.4533	-160.8361	0.7091	**0.6270**	11.5510	0.3854	0.2972	0.2369
c.hamilton13.panel	-133.9347	-140.3175	0.6922	**0.6250**	4.9769	0.4285	0.2877	0.2664
c.bn2.r20	-109.3128	-115.6955	0.6963	**0.6218**	0.2776	0.4080	0.3255	0.2724
c.linear	-135.4069	-141.7896	0.6879	**0.6204**	3.9989	0.4616	0.2925	0.2986
c.bn6	-132.7915	-139.1742	0.6835	**0.6113**	0.4710	0.4371	0.2830	0.2712
c.bn2.r15	-83.9469	-90.3297	0.6749	**0.6047**	0.1349	0.4761	0.3302	0.3357
c.poly4.r20	3.5738	-2.8090	0.5772	**0.6011**	0.1651	0.4980	0.3302	0.3570
BIS Basel gap	**-121.5910**	**-127.9738**	**0.6733**	**0.5960**	**3.0578**	**0.4441**	**0.3255**	**0.3032**
c.bn4	-169.1186	-175.5014	0.6892	**0.5943**	1.2840	0.3837	0.3255	0.2532
c.stm.r15	-79.5531	-85.9358	0.6575	**0.5924**	2.0027	0.4778	0.3160	0.3281
c.hp125k	-92.2897	-98.6725	0.6562	**0.5924**	2.5216	0.4547	0.3302	0.3158
c.hp221k	-106.8842	-113.2670	0.6656	**0.5921**	2.6641	0.4561	0.3160	0.3079
c.hp400k.r15	-67.1228	-73.5055	0.6472	**0.5912**	2.6223	0.4592	0.3255	0.3168
c.stm	-89.2228	-95.6055	0.6523	**0.5903**	2.2064	0.4684	0.3302	0.3284
c.bn3.r15	-144.4817	-150.8645	0.6687	**0.5882**	0.1862	0.4780	0.3302	0.3375
c.hp400k.r20	-88.8450	-95.2277	0.6545	**0.5871**	2.8130	0.4494	0.3302	0.3110
c.stm.r20	-87.2179	-93.6006	0.6482	**0.5859**	1.9362	0.4826	0.3302	0.3419
c.hp25k.r15	-55.8805	-62.2632	0.6275	**0.5812**	1.1403	0.5032	0.3066	0.3473
c.hp25k	-56.0388	-62.4215	0.6274	**0.5782**	1.2839	0.4970	0.3160	0.3469

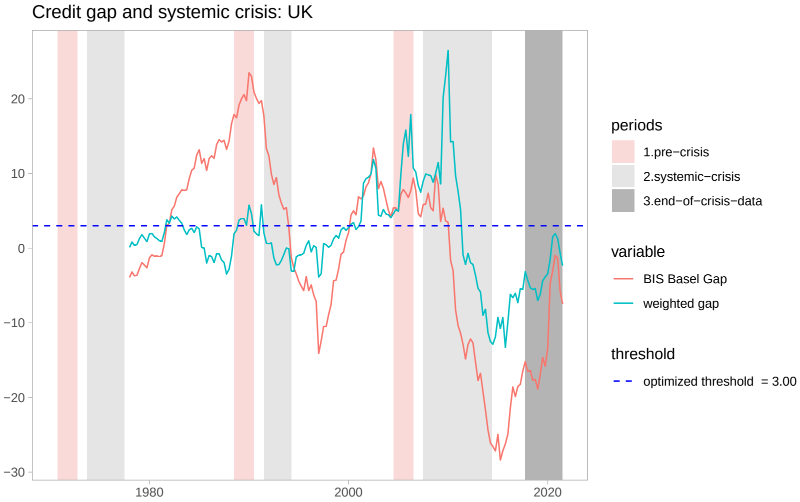
Comparing performance of weighted gap as an EWI - EME

Cycles	BIC	AIC	AUC	psAUC	c.Threshold	Type.I	Type.II	Policy.Loss.Function
null	0.0000	0.0000	0.5000	**0.5000**		1.0000	0.0000	1.0000
c.bn3.r15	-46.2774	-51.3507	0.7365	**0.6308**	0.6244	0.3059	0.3333	0.2047
c.poly3	5.3862	0.3129	0.5737	**0.6046**	1.8089	0.5280	0.3056	0.3721
c.bn2.r15	-13.2062	-18.2795	0.6879	**0.5879**	0.2952	0.3566	0.3333	0.2383
c.poly4.r20	7.0732	1.9999	0.5040	**0.5816**	-0.9609	0.5962	0.3333	0.4665
1.sided weighted.cycle	**6.2094**	**1.1361**	**0.5325**	**0.5811**	**-1.0639**	**0.6827**	**0.1111**	**0.4784**
c.linear	-9.3676	-14.4409	0.5787	**0.5774**	-0.9783	0.6294	0.2222	0.4455
c.bn2.r20	-16.6411	-21.7144	0.6760	**0.5751**	0.1470	0.4510	0.3056	0.2968
c.hamilton13	6.5749	1.5016	0.5468	**0.5710**	3.6354	0.6206	0.3056	0.4785
c.ma	-11.6401	-16.7133	0.5572	**0.5457**	-0.2250	0.7220	0.1667	0.5491
c.hamilton28.panel	-7.8687	-12.9420	0.5392	**0.5384**	-1.7750	0.6958	0.2778	0.5613
c.quad	6.1997	1.1264	0.4654	**0.5334**	-6.4882	0.7456	0.1944	0.5938
c.hamilton13.panelr15	-1.6660	-6.7393	0.5087	**0.5274**	-1.1064	0.7002	0.3333	0.6014
c.hp25k.r15	3.6420	-1.4313	0.5018	**0.5265**	-3.5672	0.7850	0.1111	0.6285
c.hp25k	3.9466	-1.1267	0.4975	**0.5247**	-3.7339	0.7893	0.1111	0.6354
c.hp3k	3.3678	-1.7054	0.5276	**0.5235**	-1.1119	0.7019	0.3333	0.6038
c.hp3k.r20	3.3703	-1.7030	0.5276	**0.5235**	-1.1125	0.7028	0.3333	0.6050
c.hamilton13.panel	-1.6294	-6.7027	0.5166	**0.5222**	-2.9398	0.7500	0.2778	0.6397
BIS Basel gap	**-0.7015**	**-5.7748**	**0.4928**	**0.5217**	**-5.3969**	**0.7920**	**0.1389**	**0.6465**
c.hamilton28.panelr20	-4.9986	-10.0719	0.5123	**0.5213**	-1.5578	0.6932	0.3333	0.5916
c.hamilton28.panelr15	-3.3914	-8.4647	0.4987	**0.5162**	-1.8326	0.7220	0.3333	0.6324
c.hp400k.r15	5.0603	-0.0129	0.4777	**0.5147**	-5.7358	0.8121	0.1111	0.6718
c.stm.r15	4.7567	-0.3166	0.4780	**0.5129**	-5.6472	0.8191	0.0833	0.6778
c.hp221k	1.5902	-3.4831	0.4787	**0.5123**	-5.6416	0.8121	0.1111	0.6718
c.stm.r20	3.1397	-1.9336	0.4768	**0.5095**	-5.3727	0.8226	0.0833	0.6835
c.hp125k	3.0774	-1.9958	0.4740	**0.5094**	-5.8918	0.8226	0.0833	0.6835

Plot weighted gap against BIS gap



Plot weighted gap against BIS gap



Thank You

I look forward to your questions and comments