Essays on Measuring Credit and Property Prices Gaps

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Chapter 3: Identifying Unsustainable Credit Gaps

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)

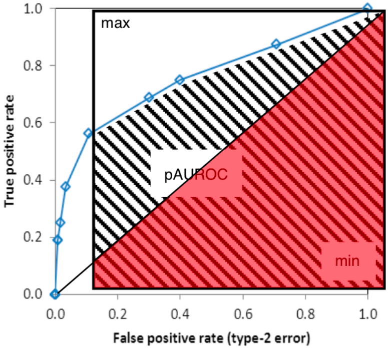
Motivation from Literature

- 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.

standardize psAUROC - Detken (2014)



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

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 gap decompositions

$$100 * \frac{Credit}{GDP} = y_t = \tau_{yt} + c_{yt} \tag{2}$$

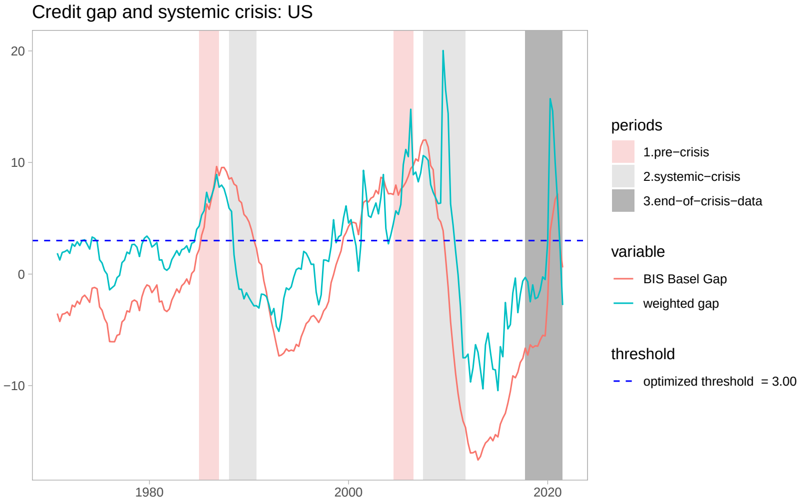
- We created 90 candidate one-sided credit gap measurements based on the literature.
  - Once a country has more than 15 years of credit measurement available, we start storing its one-sided credit gap values onward.

Early Warning Indicator - Logistic regression:

$$pre.crisis_{ti} \sim credit.gap_{tij} \quad (3)$$

- 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.

Plot of Credit gap, Threshold and Crisis periods



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.

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):

$$P(M_k|D) = \frac{P(D|M_k)P(M_k)}{\sum_{l=1}^{K} P(D|M_l)P(M_l)} \approx \frac{exp(-\frac{1}{2}BIC_k)}{\sum_{l=1}^{K} exp(-\frac{1}{2}BIC_l)} \quad (4)$$

- 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.

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

$$\sum_j \hat{\beta}_j c_{tij} = \hat{\beta}\hat{c}_{ti} \tag{5}$$

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,

$$\hat{c}_{ti} = \frac{\sum_j (\hat{\beta}_j c_{tij})}{\sum_j \hat{\beta}_j} = \sum_j w_j c_{tij} \tag{6}$$

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}.

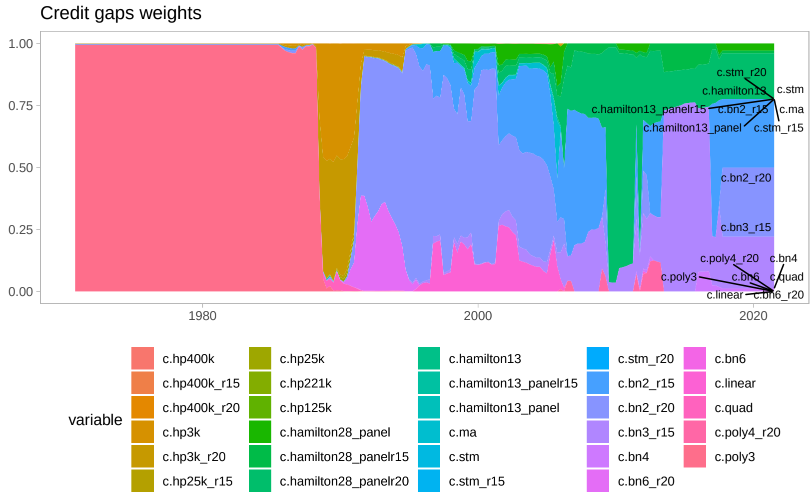
$\Rightarrow$ To create one-sided crisis weighted averaged credit gap for each country i ($\hat{c}_{ti}$), we compute:

$$\hat{c}_{ti,one-sided} = \sum_j w_{tj} * c_{tij} \tag{7}$$

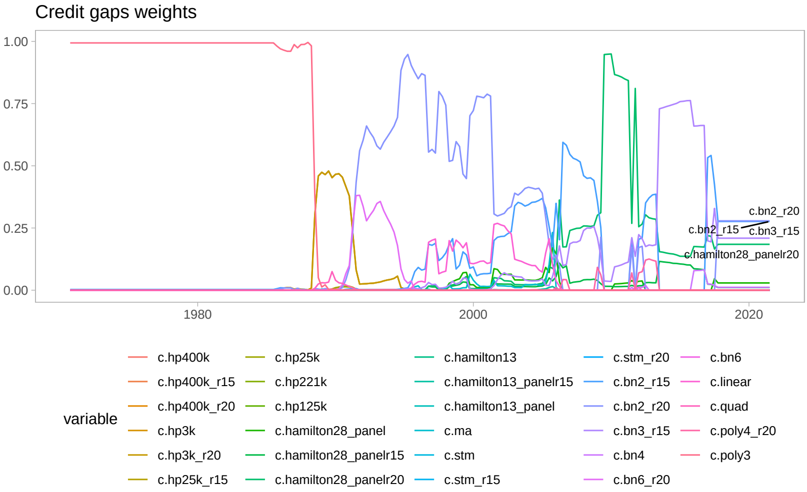
Empirical Results

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**	NA	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 - Full Sample

Out-of-sample prediction

Cycle	BIC	AUC	psAUC	c.Threshold	Type I	Type II	Policy Loss Function
c.null	0.0000	0.4767	**0.4907**	0.0000	1.0000	0.0000	1.0000
NA	(1.8172)	(0.0128)	**(0.0049)**	NA	NA	NA	NA
1.sided weighted.cycle	**-80.9638**	**0.7134**	**0.6404**	**2.9939**	**0.3707**	**0.3208**	**0.2411**
NA	**(5.0654)**	**(0.0033)**	**(0.0037)**	**(0.6513)**	**(0.0282)**	**(0.0092)**	**(0.0164)**
c.hamilton28.panel	-121.3928	0.7078	**0.6318**	9.6472	0.4043	0.3071	0.2583
NA	(3.0642)	(0.0018)	**(0.0027)**	(1.1148)	(0.0119)	(0.0165)	(0.0070)
c.hamilton13.panel	-123.8627	0.6894	**0.6220**	5.1997	0.4206	0.3132	0.2757
NA	(4.9205)	(0.0021)	**(0.0034)**	(0.6877)	(0.0194)	(0.0199)	(0.0092)
c.hamilton28.panelr15	-132.7462	0.7052	**0.6217**	11.6613	0.3874	0.3127	0.2486
NA	(5.5529)	(0.0041)	**(0.0053)**	(0.5448)	(0.0245)	(0.0135)	(0.0141)
c.linear	-106.5647	0.6846	**0.6158**	4.0160	0.4621	0.3113	0.3108
NA	(4.8347)	(0.0017)	**(0.0028)**	(1.5341)	(0.0110)	(0.0156)	(0.0080)
c.bn2.r20	-76.7863	0.6908	**0.6137**	0.2458	0.4327	0.3208	0.2907
NA	(2.1205)	(0.0043)	**(0.0066)**	(0.2248)	(0.0239)	(0.0116)	(0.0149)
c.bn6.r20	-86.4636	0.6757	**0.5987**	0.2144	0.4713	0.3231	0.3286
NA	(2.8925)	(0.0160)	**(0.0205)**	(1.1466)	(0.0471)	(0.0114)	(0.0445)
c.bn6	-101.2737	0.6693	**0.5935**	0.3956	0.4611	0.3250	0.3203
NA	(4.0553)	(0.0130)	**(0.0176)**	(0.6125)	(0.0472)	(0.0061)	(0.0459)
BIS Basel gap	**-110.9026**	**0.6707**	**0.5932**	**3.3012**	**0.4490**	**0.3250**	**0.3073**
NA	**(4.6247)**	**(0.0018)**	**(0.0025)**	**(0.7148)**	**(0.0080)**	**(0.0052)**	**(0.0059)**

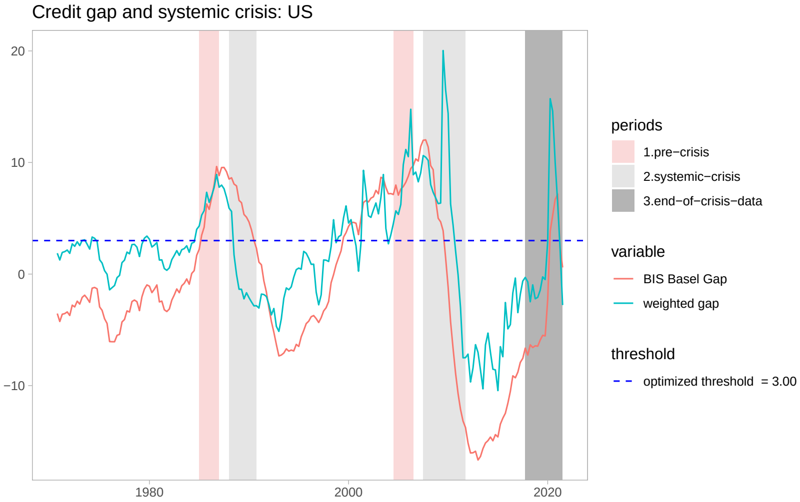
Note:

3-fold cross-validation results. Standard deviations are reported in parentheses.

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**	NA	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



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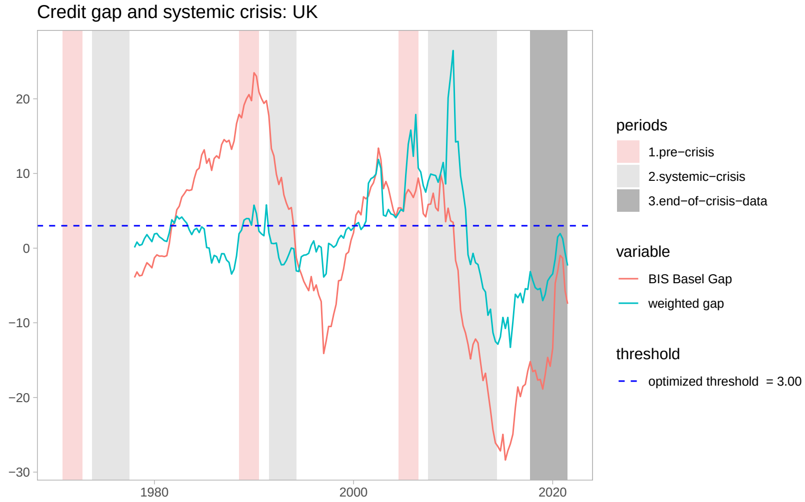

Out-of-sample Prediction for Individual Countriess

We extrapolated our one-sided weight vector from 2017:Q4 to 2021:Q3, and analyzed the weighted gap as an EWI. Our model identified 9 countries that are experiencing pre-crisis periods:

- Canada, France, Hong Kong (SAR), Japan, South Korea, Saudi Arabia, Switzerland, Sweden, and Thailand

Thank You

I look forward to your questions and comments