Appendix: Essays on Measuring Credit and Property Prices Gaps

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Appendix

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

Model

State Space Representation

- Transition equation:

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

- Where the transitory components are:

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

Chapter 2: Measuring Credit Gaps

Table of Contents

Introduction

- Motivation
- Contribution

Methodology

- Data
- Empirical Model
- Results

Conclusion

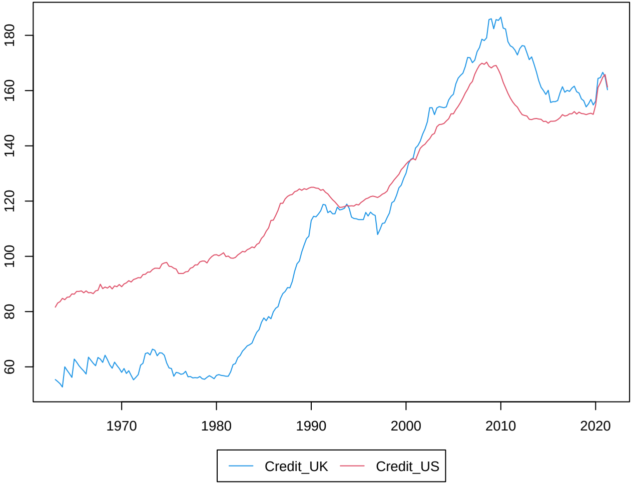
Empirical Results

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.

Credit-to-GDP Ratios



Chapter 3: Identifying Unsustainable Credit Gaps

Table of Contents

Introduction

- Motivation
- Contribution
- Literature Review

Methodology

- Data
- Empirical Model
  - Model Selection
  - Model Averaging
  - Weighted gap creation

Results

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.

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

- 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.

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.

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

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

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 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:

$$BIC_{alt,k} = 2log(Bayesfactor_{alt,sk}) \tag{3}$$
$$= 2(1000 * (psAUC_s - psAUC_k)) - df_k log(n) \tag{4}$$

- 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 $pr[\beta_1 \neq 0|D] = \sum_{A_1} p(M_k|D)$
    - 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:

$$\hat{\beta}_1 = E[\beta_1|D, \beta_1 \neq 0] = \sum_{A_1} \hat{\beta}_1(k) p'(M_k|D) \tag{5}$$

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

- 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)