Measuring Credit and Property Price Gaps

Nam Nguyen

UWM

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Credit and House Prices Cycles

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Introduction

Motivation

The study of housing prices has become more important in understanding financial market stability. We also observed increasing use of monetary policies, growth in macro balance sheet, credit.

Contribution

Relationship between housing prices and household credit

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

  $\Rightarrow$ Focus on the dynamics between transitory cycle components

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

  $\Rightarrow$ Test if past movement of one cycle has predictive power over another cycle

Literature Review

1. Credit cycles generation:

- 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)

3. House price cycles generates credit cycles:

- Bernanke & Gertler (1989), Kiyotaki & Moore (1997), Mian & Sufi (2018)
- 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.

Literature Review

4. Credit cycles genereates house price cycles:

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

5. Macro prudential DSGE model

- Quint & Rabanal (2018), Paries et al (2018).

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)

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

Model

Unobserved Component Model

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

$$100 * lnHPI = h_t = \tau_{ht} + c_{ht} \quad (2)$$

- Trends: τ_{yt} & τ_{ht}

$$\tau_{yt} = \tau_{yt-1} + \eta_{yt}, \qquad \eta_{yt} \sim iidN(0, \sigma^2_{\eta y})$$

$$\tau_{ht} = \tau_{ht-1} + \eta_{ht}, \qquad \eta_{ht} \sim iidN(0, \sigma^2_{\eta h})$$

Model

Unobserved Component Model

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

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

$$\varepsilon_{yt} \sim iidN(0, \sigma_{\varepsilon y}^2)$$

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

$$\varepsilon_{ht} \sim iidN(0, \sigma_{\varepsilon h}^2)$$

Model

State Space Representation

- Transition equation:

$$\beta_t = F\beta_{t-1} + \tilde{v}_t \tag{3}$$

- Where the transitory components are:

$$\begin{bmatrix} \tau_{yt} \\ c_{yt} \\ c_{yt-1} \\ \tau_{ht} \\ c_{ht} \\ c_{ht-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_y^1 & \phi_y^2 & 0 & \phi_y^{x1} & \phi_y^{x2} \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \phi_h^{x1} & \phi_h^{x2} & 0 & \phi_h^1 & \phi_h^2 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{yt-1} \\ c_{yt-1} \\ c_{yt-2} \\ \tau_{ht-1} \\ c_{ht-1} \\ c_{ht-2} \end{bmatrix} + \begin{bmatrix} \eta_{yt} \\ \varepsilon_{yt} \\ 0 \\ \eta_{ht} \\ \varepsilon_{ht} \\ 0 \end{bmatrix} \tag{4}$$

Model

Unobserved Component Model

$$Q = \begin{bmatrix} \sigma^2_{\eta y} & 0 & 0 & \sigma_{\eta y \eta h} & 0 & 0 \\ 0 & \sigma^2_{\varepsilon y} & 0 & 0 & \sigma_{\varepsilon y \varepsilon h} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \sigma_{\eta y \eta h} & 0 & 0 & \sigma^2_{\eta h} & 0 & 0 \\ 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & \sigma^2_{\varepsilon h} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{5}$$

Empirical Results

Results Regression Table: United States

Parameters	VAR(2)		VAR(2) 1st-cross-lag		VAR(2) 2-cross-lags	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
ϕ_y^1	1.8497	0.0645	1.3050	0.1048	1.5502	0.0622
ϕ_y^2	-0.8917	0.0639	-0.5099	0.0696	-0.5754	0.0642
ϕ_y^{x1}			0.0332	0.0027	0.0141	0.0083
ϕ_y^{x2}					0.0037	0.0114
ϕ_h^1	1.7847	0.0345	2.0529	0.0421	1.8338	0.0658
ϕ_h^2	-0.8034	0.0345	-1.2469	0.0731	-0.9358	0.0611
ϕ_h^{x1}			1.0795	0.2918	1.7429	0.4406
ϕ_h^{x2}					-1.6544	0.4175
σ_{ny}	0.4793	0.0244	0.4718	0.0241	0.4195	0.0206
σ_{ey}	0.0281	0.0154	0.0256	0.0136	0.0375	0.0132
σ_{nh}	0.4549	0.0440	0.4742	0.0383	0.4937	0.0367
σ_{eh}	0.2566	0.0323	0.0876	0.0756	0.0966	0.0478
σ_{eyeh}	-1.0000	0.0001	1.0000	8.5939×10^{-5}	1.0000	2.5743×10^{-6}
σ_{nynh}	0.3974	0.0721				
Log-likelihood value	-339.7258		-346.9160		-332.0706	

Weights of likelihood function: $w1 = 0.6$, $w2 = 0.4$, $w3 = 0.004$, $w4 = 0.003$

$l(\theta) = -w1\sum_{t=1}^{T} ln[(2\pi)^2|f_{t|t-1}|] - w2\sum_{t=1}^{T} \eta'_{t|t-1} f^{-1}_{t|t-1}\eta_{t|t-1} - w3 * \sum_{t=1}^{T}(c^2_{yt}) - w4 * \sum_{t=1}^{T}(c^2_{ht})$

Empirical Results

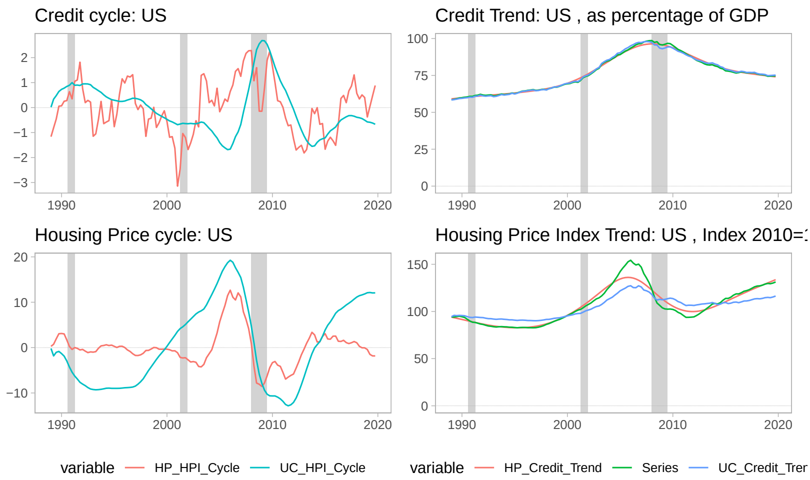
Results Regression Table: United Kingdom

Parameters	VAR(2)		VAR(2) 1st-cross-lag		VAR(2) 2-cross-lags	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
ϕ_y^1	1.9725	0.0234	1.8820	0.0005	1.8895	0.0002
ϕ_y^2	−0.9827	0.0263	−0.8160	0.0022	−0.8743	0.0026
ϕ_y^{x1}			−0.0240	0.0004	0.1756	0.0008
ϕ_y^{x2}					−0.1964	0.0035
ϕ_h^1	1.5048	0.1019	1.5748	0.0056	1.5742	0.0643
ϕ_h^2	−0.5608	0.1252	−0.7094	0.0077	−0.7364	0.0586
ϕ_h^{x1}			0.3783	0.0171	0.7214	0.0492
ϕ_h^{x2}					−0.5959	0.0442
σ_{ny}	0.7063	0.0600	0.7017	0.0353	0.6040	0.0374
σ_{ey}	0.0004	0.0104	0.1127	0.0052	0.0160	0.0063
σ_{nh}	1.8676	0.1617	1.6429	0.1023	1.9038	0.1115
σ_{eh}	0.6568	0.2583	0.6323	0.0193	0.1289	0.0269
σ_{eyeh}	0.6888	13.1231	1.0000	7.0580×10^{-6}	0.9998	0.0061
σ_{nynh}	0.5680	0.1125				
Log-likelihood value	−454.6450		−464.0793		−456.5685	

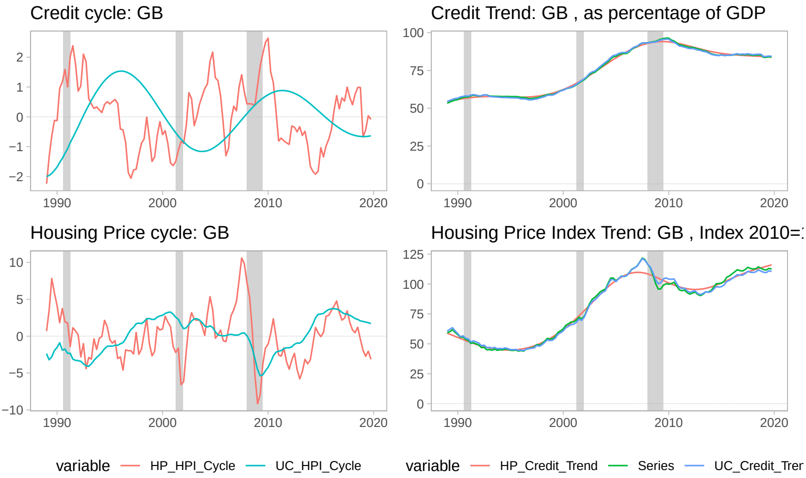
Weights of likelihood function: w1 = 0.8, w2 = 0.2, w3 = 0.003, w4 = 0.004

$l(\theta) = -w1\sum_{t=1}^{T} ln[(2\pi)^2|f_{t|t-1}|] - w2\sum_{t=1}^{T}\eta'_{t|t-1}f^{-1}_{t|t-1}\eta_{t|t-1} - w3 * \sum_{t=1}^{T}(c^2_{yt}) - w4 * \sum_{t=1}^{T}(c^2_{ht})$

Results Regression Graphs: United States VAR(2)

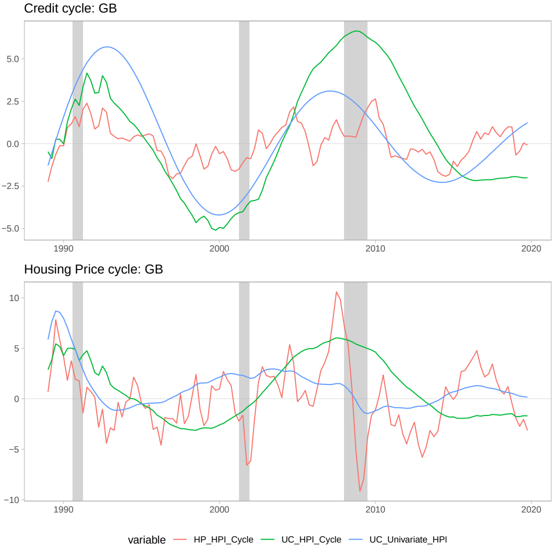


Results Regression Graphs: United Kingdom VAR(2)



Comparison with other decomposition methods: US

Comparison with other decomposition methods: UK



Conclusion

Dynamics of temporary components in housing and credit

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

Measuring Credit Gaps

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Introduction

Motivation

There is 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 in alternative settings.

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 that has a high predictive power.

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:

$$y_t = \tau_t + c_t \tag{6}$$

Trend-cycle decomposition models

HP filter

$$min_{\tau}(\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t-1} - \tau_t) - (\tau_t - \tau_{t-1})]^2) \tag{7}$$

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

Unobserved-Component model: Clark(1987)

$$\tau_t = \tau_{t-1} + \eta_t, \eta_t \tilde{\ } iid(0, \sigma_\eta^2) \tag{8}$$

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

Trend-cycle decomposition models

Beveridge-Nelson

$$y_t = y_0 + \mu t + \Psi(1) \sum_{k=1}^{t} u_t + \breve{u}_t - \breve{u}_0 \tag{9}$$

Hamilton filter (2018)

$$y_{t+h} = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + ... + \beta_p y_{t-p} + v_{t+h} \tag{10}$$

Forecasting model:

$$\Delta y_t = \alpha + \beta(L)\Delta y_{t-1} + \gamma(L)GAP_{t-1} + v_t \tag{11}$$

Forecast combination

$$w_m = \frac{\widehat{\overline{\sigma}}^2_m}{\widehat{\overline{\sigma}}^2_1 + \widehat{\overline{\sigma}}^2_2 + \ldots \widehat{\overline{\sigma}}^2_M} \tag{12}$$

- where $\widehat{\overline{\sigma}}^2_m$ 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 RMSEs 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.

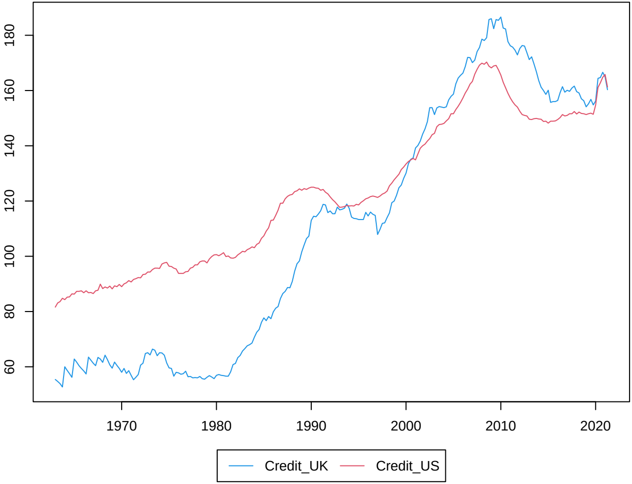
Empirical Results:

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

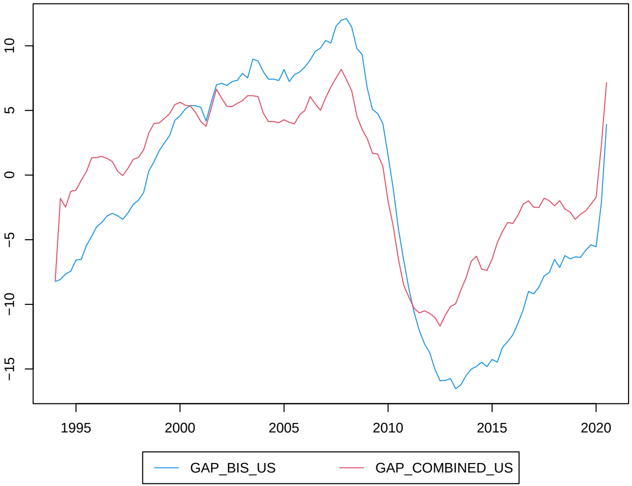
Horizon	HP	RU	BIS	Hamilton	Linear	Quadratic	BN	UC	Average	Bates-Granger
1	1.001	0.990	1.001	0.992	1.010	0.979	1.028	1.009	0.977	**0.979**
2	0.979	0.970	1.007	0.969	1.016	0.962	1.028	0.999	0.962	**0.957**
3	0.979	0.971	1.018	0.969	1.055	0.966	1.009	0.989	0.959	**0.955**
4	0.990	0.987	1.028	1.005	1.055	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 RMSEs 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.

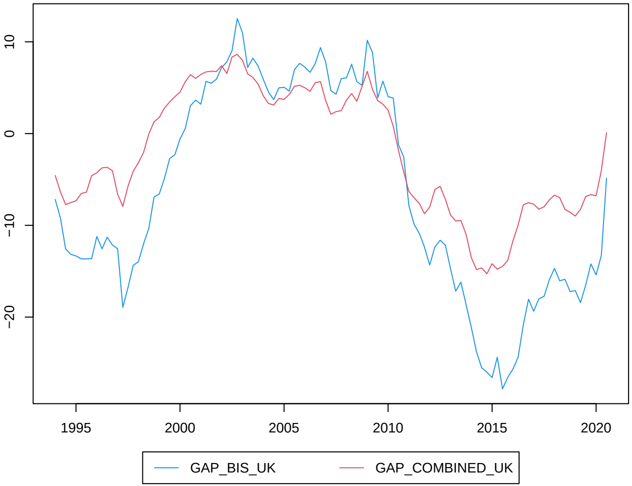
Credit-to-GDP Ratios



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.

Thank You

I look forward to your questions and comments