House Prices and Credit Cycles

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Abstract

Our study is based on the idea that house prices and credit to household are jointly determined and they affect each other both in the short-run and in the long-run. We decompose the movements of the two variables of interest into permanent (long-run) and transitory (short-run) components using an unobserved components vector autoregressive model. Our dynamic model shows findings to support the hypothesis that a short-run positive shock to household credit is associated with an increase in house prices above its long-run trend. Additionally, by utilizing additional information generated by the unobserved component model, our multivariate model performs better than univariate models do in capturing the dynamics of the household credit and house prices over the last two decades, especially during the period of the recent financial crisis. We were also able to estimate the predictive ability that cyclical components of a variable have on their counterparts by employing cross-correlation coefficients in the VAR model.

1 INTRODUCTION

The Great Recession caused researchers to shift their focus on the narrative of credit, housing market and financial stability. However, the debate on whether house prices have been the main driving source of the credit cycle, or financial conditions (credit) are the main determinants of house price cycle is still open. One strand of literature has argued that increase in credit supply played a major role in the boom and the subsequent bust in the housing market in the U.S. Another strand of literature has argued that credit supply itself can't explain the big swings in house prices and have attributed beliefs and other unobserved characteristics as a major source of house price variations. At the same time, some researchers have argued that credit booms are preceded and sometimes driven by housing booms. The increase in collateral and relaxation of banks' funding constraint leads to an increase in the willingness of the banking sector to provide funding not only to the residential sector, but also commercial real estate as well as overall funding to the businesses. Most of the work in the literature has considered the relationship between house prices and credit separately, that is, if house prices are affected by credit or changes in house prices affect credit. It is perfectly reasonable to assume that house prices and credit have a dynamic relationship and the causality does not necessarily run from one variable to another. The novel contribution of this study is to develop a model to jointly examine the two variables of interest: household credit and house prices and their interaction. In particular, we pay attention to the long-run and short-run movements in credit and house prices and model their joint dynamics. **In doing so, we use data from two countries: the US and the UK**. The methodology that I use in this paper to extract transitory and permanent information from non-stationary time series is a decomposition method called Unobserved Components model pioneered by (Beveridge & Nelson, 1981). The implementation details of the methodology is inspired by (Morley, 2007) and (Huang & Kishor, 2019). This method allows the permanent component to be shown as a random walk and the transitory component to be a stationary process with mean zero. The stationary transitory component configuration is important to infer meaningful structural linkage between the two variables of interest: household credit and house prices; as non-stationary transitory components do not offer meaningful inferences. This brings up the paper's second novel contribution to the literature. By explicitly configuring cross correlation coefficients on the cyclical components of the two variables, we will be able to examine the predictive ability of the cycles. This would produce a much desired inference for macro-prudential policy implication to stabilize the macroeconomy.

Using sample data from the US and the UK, We find interesting and meaningful results from the estimated multivariated correlated unobserved component model. The maximum-likelihood estimates of our correlated multivariate UC model suggest that there is a strong positive correlation between the transitory shock to household credit and the transitory shock to the house prices index. This suggests that a temporary increase in household credit is associated with an increase in house prices above its long-run level. These results support the narrative evidence on the strong relationship between household credit and house prices. More importantly, we also find evidence that lags of household credit cycle has predictive ability in forecasting the magnitude of house prices gap above its long-run level by examining the cross correlation coefficient on the cyclical components. We also find that the trend-cycle decomposition of the two variables of interest captures the recent boom and bust behavior and compares favorably to a univariate trend-cycle decomposition benchmark. In particular, we find that the house prices and household credit were significantly higher than its long-term trend before the financial crisis and then there was an overreaction during the crisis leading the house price and credit cycle to a negative territory implying that house prices and credit were below their long-run trend. The magnitude of the model's cyclical components for both house price and credit during this time of crisis is significantly higher than that of other univariate decomposition models' such as the HP filter and the VAR unobserved component model.

Finally, our sample data show that the correlation between house price and credit is much higher in the UK than in the US as shown in Table 1. This help testing the robustness of our model. **The plan of the paper is as followed, in section 2 we will introduce the summary of data and their description. In section 3, we will lay out the details of the decomposition methodology using unobserved component model with vector auto-regression (VAR). In section 4, we will go over results of the model regression and our interpretation. In section 5, we will test the robustness of the model by comparing the results against some traditional methods of analyzing time series data. And lastly, in section 6, we will give our conclusion remark for the model.**

2 LITERATURE REVIEW

There has been an increasing interest in the study of the interaction between credit, speculation and house prices (Mian & Sufi, 2011, 2018), (Kishor, 2020), (Guerrieri & Uhlig, 2016) and (Davis & Van Nieuwerburgh, 2015) have detailed literature reviews on the dynamics between housing market and credit conditions. We will list the four literatures branches that study the dynamics of the credit cycles, housing prices cycles and then the key connection between boom-bust episodes in housing markets and boom-bust episodes in credit markets. There are two approaches to this interaction:(i) The house price cycles generates the credit cycles. (ii) The credit cycles generates the house price cycles.

One strand of the literature focuses on how credit cycles are generated. (Kiyotaki & Moore, 1997) modeled the fluctuation of credit condition due to credit limit and asset prices. The model shows how exogenous shocks can create cyclical fluctuation in credit, asset prices and real output. (Myerson, 2012) proposed a model of credit cycles generated by moral hazard in dynamic interactions among different generations of financial agents. (Guerrieri & Uhlig, 2016) used a catastrophe model for credit, in which multiple equilibria are possible due to adverse selection: as credit increases, the composition of borrowers worsens at this can generate a crash in credit market. (Boissay, Collard, & Smets, 2016) studied the topic of endogenous boom and bust in credit market using a dynamic stochastic general equilibrium (DSGE) model, in which moral hazard and asymmetric information may endogenously lead to sudden freezes and crises in the credit market. As for classifying periods of booms and bursts in credit condition, (Alessi & Detken, 2018) used a random forest model to identify unsustainable credit growth periods.

The second branch of the literature focuses on dynamics of house prices changes. We first look at the generation of momentum in house price changes. Asset prices valuation tend to vary when information about their performance is available. (Barberis, Shleifer, & Vishny, 2005) pointed out that securities with good performance records receive extremely high valuations, and those valuation will return to the mean on average. (Hong & Stein, 1999) suggested a model with information diffuses gradually across the population, and if agents implement simple univariate strategies, their attempts at arbitrage will lead to overreaction at long horizons. (Capozza, Hendershott, & Mack, 2004) analyzed dynamic properties of markets exhibiting serial correlation and mean reversion. These properties allows for prices to overshoot equilibrium (cycles) and diverge permanently from equilibirum. (Glaeser, Gyourko, & Saiz, 2008) incorporated housing supply elasticity into the analysis of housing prices momentum and shows that the price run-ups of the 1980s were almost exclusively experienced in cities with more inelastic housing supply. (Head, Lloyd-Ellis, & Sun, 2014) showed that variation in the time it takes to sell houses induces transaction prices to exhibit serially correlated growth. (Glaeser & Nathanson, 2017) modeled the leads house prices expectation approximation to display missing features in rational models: momentum at short run horizon, mean reversion in long run horizon and excess longer-term volatility relative to fundamentals. (Kishor, Kumari, & Song, 2015) studied the U.S. housing market by using a combination of Unobserved Component model and GARCH model to study the time-varying importance of permanent and transitory housing components in the U.S. housing prices. (Katharina Knoll, Schularick, & Steger, 2017) constructed a house price index for 14 economies in over 140 years. They argue that real house prices have largely followed a “hockey stick” pattern: fairly consistent for a long period of time, then followed by a pronounced increase towards the second half of the century with substantial cross-country variation. Furthermore, they say that most of the price increase can be attributed to the increase in the price of land, and that house prices have risen faster than income in recent decades. (K. Knoll, 2016) argued that rise in house prices coincides with a rise the the price-rent ratio, a fundamental that shows intrinsic value of housing.

Another branch of literature is the one that studies the hypothesis that house price cycles generates the credit cycles. The dynamics of houses price on household credit can be viewed through the lens of the borrower balance sheet. (Bernanke & Gertler, 1989) developed a neoclassical model of the business cycle in which the condition of borrowers’ balance sheets is a source of output dynamics. The mechanism is that higher borrower net worth reduces the agency costs of financing real capital investments. The financial acceleration effects implies that stronger balance sheets due to higher asset prices will lead to lower cost of borrowing to invest. Which suggests that a boom in housing prices will lead to a boom in credit. (Kiyotaki & Moore, 1997) further incorporated this positive feedback through asset prices, and the associated intertemporal multiplier process that affect borrowing capacity and output into their paper. An increase in home equity due to increase in house prices will allow borrower to borrow more to finance either personal consumption or more speculation housing investment. (Mian & Sufi, 2018) showed that the crash in the housing market and following credit crunch showed the importance of housing prices for household balance sheet as well as banking sector balance sheet.

There are papers that have studied the hypothesis that credit cycles generates house price cycles. (Agnello & Schuknecht, 2011), (Agnello, Castro, & Sousa, 2018) examined different variables that are likely to create a bubble in housing markets. First is the effect of credit constraint on house prices. (Stein, 1995) is the first paper to explore the effects of down-payment requirements on house price volatility. The paper highlighted the self-reinforcing effect that runs from house prices to down payments and housing demand, back to house prices. If house prices decline, the value of households' collateral declines, depressing housing demand and hence pushing house prices further down. This multiplier effect can generate multiple equilibria and accounts for the house price boom-bust episodes. The self-reinforcing effect has the same spirit of the transmission mechanism put forth by (Kiyotaki & Moore, 1997). In a recent related paper, (Ortalo-Magne & Rady, 2006) showed that income volatility of young households or relaxation of their credit constraints can explain excess volatility of house prices through identifying a powerful driver of the housing market: the ability of young households to afford the down payment on a starter home.

Another research branch has also explored the effect of financial innovation, or financial liberalization on house prices. (Kermani, 2012) proposed a model to emphasize the importance of financial liberalization and its reversal to explain the housing boom and bust. (He, Wright, & Zhu, 2015) also proposed a model where housing collateralizes loans and house price boom and bust can be generated by financial innovation because the liquidity premium on housing is non-monotone in the loan-to-equity ratio. (Huo & Ríos-Rull, 2016) had a model with heterogenous households, housing and credit constraints, and also show that financial shocks can generate large drops in housing prices. (Favilukis, Kohn, Ludvigson, & Van Nieuwerburgh, 2012) studied the impact of systemic changes in housing finance: changes in housing collateral requirements and the change in borrowing costs (the spread of mortgage rates over risk-free security) on how these factors affect risk premiums in housing markets, and how those risk premiums in turn affect home prices.(Favilukis, Ludvigson, & Van Nieuwerburgh, 2017) developed a quantitative general equilibirum model with housing and collateral constraints to explore what drives fluctuations in house prices to rent ratio. They propose that a relaxation of financing constraints leads to a large boom in house prices. And the boom in house prices is entirely the result of a decline in the housing risk premium. (Mian & Sufi, 2018) showed that speculation is a critical channel through which credit supply expansion affects the housing cycle.

After the financial crisis, there has also been an explosion of interest on the effect of credit expansion on house prices. (Justiniano, Primiceri, & Tambalotti, 2019) argued that loosening of the collateral requirements alone cannot explain the recent housing boom in the US, but there must have been an expansion in the credit supply. The authors argued that house prices rose from 2000 to 2007 without an expansion of leverage. The cause that lead to the housing boom before recession was because of an increase in credit supply or available funds rather than an increase in leverage. The rates of mortgages to real estate remained constant. This contradict with the popular view that attributes the housing boom to looser borrowing constraints associated with lower collateral requirements, which would shift the demand for credit. In short, the increase in supply of credit was the cause of housing boom. Beyond 2007, the paper argues that there was an increase in collateralizing houses relative to available funds, or that available funds for lending decreased, leading to a rise in mortgage rates and a collapse of house prices. More interestingly, Jorda, Schularick and Taylor have studied the interplay between credit cycles, house price cycles and economic performance in a series of papers. (Schularick & Taylor, 2012) created a new data sets for 14 developed countries over 140 years and showed how credit growth is a powerful predictor of financial crises. (Jordà, Schularick, & Taylor, 2016) claimed that mortgage lending booms were loosely related to financial crisis before WWII, but have become a more important predictor of financial fragility after. The share of mortgages on banks' balance sheets doubled in the later half of twentieth century, driven by a rise of mortgage lending to households. Household debt to asset ratios have risen substantially in many countries in the study. Financial stability risks have been linked to real estate lending booms.(Jordà, Schularick, & Taylor, 2015) claim that there has been an increase in the mentality of "bets on the house" in the past century. Mortgage credit has risen dramatically as a share of banks' balance sheets from about one third at the beginning of the last century, to about two thirds nowadays. They use a novel IV local projection methods to demonstrate that loose monetary conditions lead to booms in real estate and house prices' bubbles. These in turn leads to higher risk of financial crises. Mortgage booms and house price bubbles have been closely associated with a higher likelihood of a financial crisis.(Jordà, Schularick, & Taylor, 2017) claimed that a century-long and stable ratio of credit to GDP gave way to rapid financialization and surging leverage in the last forty years. This coincide with a shifts in foundational macroeconomic relationships. More financialized economies exhibit more tail risk, as well as tighter real-real and real-financial correlations, including of course the credit and real estate correlation. The paper also show that both real house prices and mortgages in 17 sample countries display a "hockey stick" in their patterns. Meaning they both stay stable for a long period of time before ticking up drastically at the end of the sample. It can be shown that house price growth and mortgage growth generally co-move. (Favara & Imbs, 2015) showed an expansion in mortgage credit has significant effects on house prices using a spatial IV-strategy with the US branching deregulation between 1994 and 2005 as an instrument for credit. The treated banks credit expansion lead to increases in housing demand. (Di Maggio & Kermani, 2017) showed that a credit expansion can generate a boom and bust in house prices and real activity. The paper use the exploitation of the same federal deregulation in preemption of local laws against predatory lending in 2004 to gauge the effect of the supply of credit on the real economy.

However, the debate on whether house prices have been the main driving source of the credit cycle, or financial conditions (credit) are the main driving force of house price cycle is still open. In this paper, **I will use** a dynamic model in order to be able explain the relationship between these two variables in both short-term and long-term.

3 DATA DESCRIPTION

Our sample periods include quarterly data from January 1989 to January 2020. The sample periods were chosen based on the nature of the change in regulation of credit and housing markets beginning early 1990s. The main source of the data comes from the Bank of International Settlement (BIS). The housing price index is based on base index of 2010 as 100. The credit to household data is measured as percentage of GDP. We will take natural log of this series and use the log-transformed series in the model estimation.

Despite their importance, comparable cross-country data on residential property prices are hard to gather. The complicated nature of property transactions and property types further, lack of standardization and short time span of data available complicate the compilation of a housing price index. To address this data gap, the BIS published a data set on residential property price statistics across the globe.[1] Combining with actual transaction prices and sources from appraisal and advertised prices, a comparable index of house prices of quarterly frequency is created for each country.

Even though there are other sources with the data regarding credit to household such as the International Financial Statistics from IMF or the Federal Reserve Economic Data. We decide to use the credit to household data from the BIS for better compatibility and adjustments in breaks of data collecting methodological frameworks.[2] To achieve as long a period as possible for time series data on credit, the construction of the series combined data from institutional sector financial accounts, balance sheets of domestic banks and international banking institution.

In this study, we selected the US and UK as two representative countries to use because of the longevity and continuity of the time series data available.

Table 1 shows the description of the data used in this paper. House prices data tends to fluctuate with greater magnitude than credit series. And the housing prices in the UK increases at a faster rate than the US. Table 2 shows the correlation of the series with its lag values of 1 and 2 quarters. The house prices series in the UK is more closely correlated with its household credit series than in the US.

[1] Housing price indices are available for 55 countries. https://www.bis.org/publ/qtrpdf/r_qt1409h.htm

[2] The BIS has constructed long series on credit to the private non-financial sector for 44 economies, both advanced and emerging. Credit is provided by domestic banks, all other sectors of the economy and nonresidents. https://www.bis.org/statistics/totcredit/credpriv_doc.pdf

Table 1: Descriptive statistics

Country	Index	Mean	Max	Min	Frequency	Periods
UK	Δy_t	0.3802	2.6989	-1.7626	Quarterly	1989:Q1-2020:Q1
	Δh_t	0.5926	7.2322	-6.7250	Quarterly	1989:Q1-2020:Q1
US	Δy_t	0.1989	3.5088	-1.9427	Quarterly	1989:Q1-2020:Q1
	Δh_t	0.3004	3.4809	-6.7164	Quarterly	1989:Q1-2020:Q1

Δy_t is growth rate of credit to household series, Δh_t is growth rate of house prices index series. The measurements are in percentage.

Table 2: Correlation matrix

Country		y_t	y_{t-1}	y_{t-2}	h_t	h_{t-1}	h_{t-2}
UK	y_t	1	0.9991	0.9969		0.9442	0.9491
	h_t	0.9391	0.9314	0.9225	1	0.9975	0.9925
US	y_t	1	0.9983	0.9947		0.7232	0.7415
	h_t	0.7041	0.6891	0.6730	1	0.9951	0.9817

y_t is credit to household series, h_t is housing price index series. Both are log transformed.

4 EMPIRICAL MODEL

4.1 Model Specification

Our model is a multivariate extension of the model used in (Morley, 2007). We will use a bivariate unobserved component model to model the dynamics in credit to household as ratio to GDP (y_t) and house prices index (h_t). **In our model, the credit and house prices series are log-transformed and are each sum of a trend and a cycle components.**

We begin with the notations of two series: (Credit) as Credit to household as ratio to GDP and (HPI) as Housing Price Index.

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

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

Where τ_{yt} is the trend component of the credit series. c_{yt} is the cycle component of the credit series. Likewise, τ_{ht} and c_{ht} are trend and cycle components of the house prices series.
The trend components of the model follows a random walk process:

$$\tau_{yt} = \tau_{yt-1} + \eta_{yt}, \qquad \eta_{yt} \sim iidN(0, \sigma^2_{\eta y}) \tag{3}$$

$$\tau_{ht} = \tau_{ht-1} + \eta_{ht}, \qquad \eta_{ht} \sim iidN(0, \sigma^2_{\eta h}) \tag{4}$$

The cycle components of the model is a VAR(2) process:.

$$c_{yt} = \phi_y^1 c_{yt-1} + \phi_y^2 c_{yt-2} + \phi_y^{x1} c_{ht-1} + \phi_y^{x2} c_{ht-2} + \varepsilon_{yt}, \qquad \varepsilon_{yt} \sim iidN(0, \sigma^2_{\varepsilon y}) \tag{5}$$
$$c_{ht} = \phi_h^1 c_{ht-1} + \phi_h^2 c_{ht-2} + \phi_h^{x1} c_{yt-1} + \phi_h^{x2} c_{yt-2} + \varepsilon_{ht}, \qquad \varepsilon_{ht} \sim iidN(0, \sigma^2_{\varepsilon h}) \tag{6}$$

Each series is decomposed into a stochasted trend component ($\tau_{jt}, j = y,h$) and a cyclical component ($c_{jt}, j = y,h$) implying an $I(1)$ process for all the variables. The non-stationarity of these variables is confirmed by the unit root tests where we do not reject the null of unit root for all the variables.[3] In contrast to (Morley, 2007), we do not impose a common trend restriction. The two variables have their own trend and cycle components and these components are allowed to have a certain degree of correlation.

Secondly, we specify the dynamics of trend and cycle components. The cyclical component in each series is assumed to follow an AR(2) process, and in additional configurations, lags of the other series. This assumption captures the autocorrelation structures and provices rich dynamics in the data series to enable us to identify all the parameters under the state-space model framework.[4] The trend components are assumed to follow a random walk process, and as mentioned above, we do not impose a common trend among the two variables.

Thirdly, we assume the shocks to the trend and cyclical components follow a white noise process, but allow for non-zero cross-correlation across series. The shocks to the trend components ($\eta_{jt}, j = y,h$) have a long-run effect on the trend because the trend is assumed to follow a random walk process. The shocks to the cyclical component ($\varepsilon_{jt}, j = y,h$) have a short-run effect on the cycles because the cycles follow a stationary autoregressive process with two lags. The shocks to each trend component are allowed to be correlated across each other, so are the shocks to the cyclical components. However, we impose the zero correlation between the shocks to the trend component and the shocks to the cycle component within and between series. That is to say, we assume that the shocks that generate a long-run effect are different from the shocks that generate a short-run effect. This assumption isolates the temporary shocks from permanent shocks.

The above dynamic equations can be represented in a state space form where the measurement equation is:

$$\tilde{y}_t = A + H\beta_t \tag{7}$$

[3]The detailed results are not reported here for brevity. They are available upon request

[4]The cyclical dynamics in theory can also be modeled as VAR processes. The presence of cross-correlation among shocks and cross-cycle coefficients in our framework captures the cross-variable dynamics.

$$\begin{bmatrix} y_t \\ h_t \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \tau_{yt} \\ c_{yt} \\ c_{yt-1} \\ \tau_{ht} \\ c_{ht} \\ c_{ht-1} \end{bmatrix}$$

And the transition equations are:

$$\beta_t = F\beta_{t-1} + \tilde{v}_t \tag{8}$$

Where the transitory components are:

$$\begin{bmatrix} \tau_{yt} \\ c_{yt} \\ c_{yt-1} \\ \tau_{ht} \\ c_{ht} \\ c_{ht-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \phi_y^1 & \phi_y^2 & 0 & \phi_y^{x1} & \phi_y^{x2} \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \phi_h^{x1} & \phi_h^{x2} & 0 & \phi_h^1 & \phi_h^2 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{yt-1} \\ c_{yt-1} \\ c_{yt-2} \\ \tau_{ht-1} \\ c_{ht-1} \\ c_{ht-2} \end{bmatrix} + \begin{bmatrix} \eta_{yt} \\ \varepsilon_{yt} \\ 0 \\ \eta_{ht} \\ \varepsilon_{ht} \\ 0 \end{bmatrix} \tag{9}$$

The covariance matrix for $\tilde{v}_t$, denoted Q, is:

$$Q = \begin{bmatrix} \sigma^2_{\eta y} & 0 & 0 & \sigma_{\eta y \eta h} & 0 & 0 \\ 0 & \sigma^2_{\varepsilon y} & 0 & 0 & \sigma_{\varepsilon y \varepsilon h} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \sigma_{\eta y \eta h} & 0 & 0 & \sigma^2_{\eta h} & 0 & 0 \\ 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & \sigma^2_{\varepsilon h} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{10}$$

Regarding variance and covariance estimates, it should be pointed out that, in the variance-covariance matrix of the shocks the the trend and cycle, $\sigma_{\eta y \eta h}$ is the covariance of the shocks to the trend of credit to household as percentage of GDP and house prices index, whereas $\sigma_{\varepsilon y \varepsilon h}$ is the covariance of the shocks to the cycles component of the two variables. The estimates of correlation coefficients, instead of covariances, will be reported in Table 4 and Table 5. We estimate the model using the classical maximum likelihood via the Kalman Filter.[5]

4.2 Parameters constraints

A minor novel contribution of the paper is the introduction of a technique to constraint model parameters in feasible stationary regions by imposing penalties on magnitudes of stationary components, configuring a feasible estimation procedure for the Unobserved Component model has been a difficult challenge of using the model.

[5] See (Kim & Nelson, 1999) and (Durbin & Koopman, 2012) for the details of the estimation procedure.

The estimation of the unobserved component model uses a nonlinear log-likelihood function maximization in (Morley, 2007). Estimating this function requires a stationary constraint using numerical optimization, this method is prone to produce corner solutions that are not meaningful.

I did not put stationary constraints directly on the autoregressive parameters. Since such constraints on a VAR(2) system is complex to set up. However, to achieve feasible stationary transitory measurement, I implemented an additional term on the objective function:

$$l(\theta) = -w1\sum_{t=1}^{T} ln[(2\pi)^2|f_{t|t-1}|] - w2\sum_{t=1}^{T} \eta'_{t|t-1} f^{-1}_{t|t-1} \eta_{t|t-1} - w3 * \sum_{t=1}^{T}(c^2_{yt}) + w4 * \sum_{t=1}^{T}(c^2_{ht}) \quad (11)$$

The last two terms in the objective function acts as a penalty against too much transitory deviation from zero. Without this penalty, the trend would be linear or all the movements in the measured series would be matched by transitory movements.

Regarding constraints on covariance matrix, I applied the same constraints as in (Morley, 2007) to imply for positive-definite covariance matrix.

Table 3: Parameters description

Description	Parameter
Log-likelihood value	llv
Credit to household	
Credit to household 1st AR parameter	ϕ_y^1
Credit to household 2nd AR parameter	ϕ_y^2
Credit to household 1st cross cycle AR parameter	ϕ_y^{x1}
Credit to household 2nd cross cycle AR parameter	ϕ_y^{x2}
S.D. of permanent shocks to Credit to household	σ_{ny}
S.D. of permanent shocks to Credit to household	σ_{ey}
Housing Price Index	
Housing Price Index 1st AR parameter	ϕ_h^1
Housing Price Index 2nd AR parameter	ϕ_h^2
Housing Price Index 1st cross cycle AR parameter	ϕ_h^{x1}
Housing Price Index 2nd cross cycle AR parameter	ϕ_h^{x2}
S.D. of permanent shocks to Housing Price Index	σ_{nh}
S.D. of permanent shocks to Housing Price Index	σ_{eh}
Cross-series correlations	
Correlation: Permanent credit to household/Permanent Housing Price Index	σ_{nynh}
Correlation: Transitory credit to household/Transitory Housing Price Index	σ_{nynh}

5 EMPIRICAL RESULTS

In this following section, I will apply the unobserved components model to data from 2 countries: US and UK.

Choosing **the initial values** from an estimated VAR(2) regression on HP filtered cycle and trend series. The following likelihood function weights are selected in a manner that they make the decomposed series most stable.

Table 4: United Kingdom regression results

Parameters	VAR(2)		VAR(2) 1-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 = 0.6, w2 = 0.4, w3 = 0.004, w4 = 0.003

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

Table 5: United States regression results

Parameters	VAR(2)		VAR(2) 1-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 = 0.8, w2 = 0.2, w3 = 0.003, w4 = 0.004

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

The tables 4 and 5 shows maximum-likelihood estimates of all three Unobserved Component VAR(2) models. The first model is a parsimonious UC VAR(2) model with no cross-cycle correlation terms (ϕ_y^x and ϕ_h^x are set to be zero). The next two models introduces one and two cross-cycle coefficients on the lags of cyclical component respectively.

The model selection criteria is to choose models with highest log-likelihood value. The parsimony UC VAR(2) models with no cross-cycle terms and the one with 2 cross-cycle terms model have the highest likehood values. Therefore, discussion regarding estimation results will focus mostly on these two. Additionally, because of identification problem, I will omit the cross correlation of trend component σ_{nynh} in the estimation results for cross-cycle correlation models.

5.1 Dynamic relationship between Credit to household and Housing Price

The results of VAR(2) model regression suggests that permanent shocks dominate transitory shocks in term of variation in both household credit and housing price variables. The standard deviation of the shocks in cycle of credit is 0.0004 in the UK and 0.0281 in the US, much smaller than standard deviation of the shocks to trend of credit in the UK of 0.7063 and in the US of 0.4793. The same applies for housing price, the standard deviation of the shocks in cycle of housing price is 0.6568 in the UK and 0.2566 in the US, smaller than standard deviation of the shocks to trend of housing price in the UK of 1.8676 and in the US of 0.4549. This result also indicates that variations in the trend components of the UK is bigger than the US, while variations in the cycle components of the UK is smaller than the US. In regard of the estimated parameters, the sum of AR parameters of the cyclical components in all 3 models are smaller although close to one. This implies that shocks to the cycle are persistent but will eventually dissipate.

The correlation analysis of the shocks to the cyclical components among the two variables suggests that cyclical variation among housing price and credit household is strongly positively correlated. Although we ran into the problem of identification or perfect collinearity with a cross-series correlation of 1 in a few estimated models. The overall results suggest that transitory shock to housing credit is closely positively correlated to transitory shock in housing price. The estimated correlation result in VAR(2) 2-cross cycle lags model is 0.9998 for the UK at 95% significant level. This implies that a transitory increase in household credit will lead to an appreciation in housing price above its long-run trend.

The correlation analysis of the shocks to the trends among the two variables reveals that there is also a long-term underlying correlation between shocks to the trend components of household credit and housing price. However, this correlation is much smaller compared to the correlation of the transitory components. The long-term components correlation estimated value is 0.568 in the UK and 0.3974 in the US. Overall, the results from the above analyses suggest that the short-run and long-run dynamics of the two variables are very different. Therefore, there is a benefit in decomposing the series into trend and cyclical components.

5.2 Trend-cycle decomposition

The following graphs shows the UC forecast series against the actual data series.

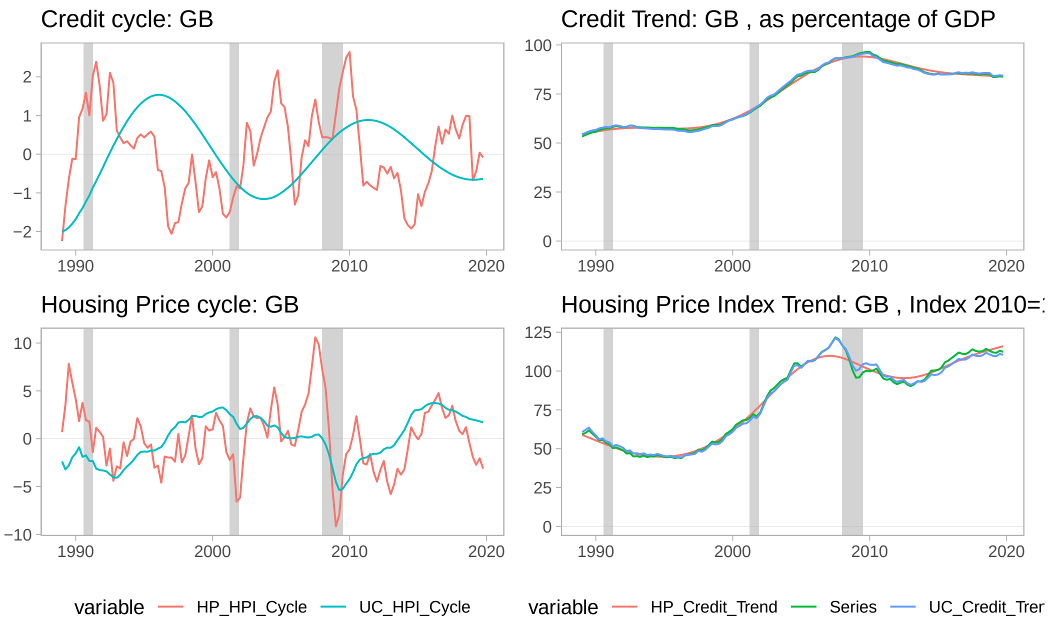

Figure 1: VAR(2) UK

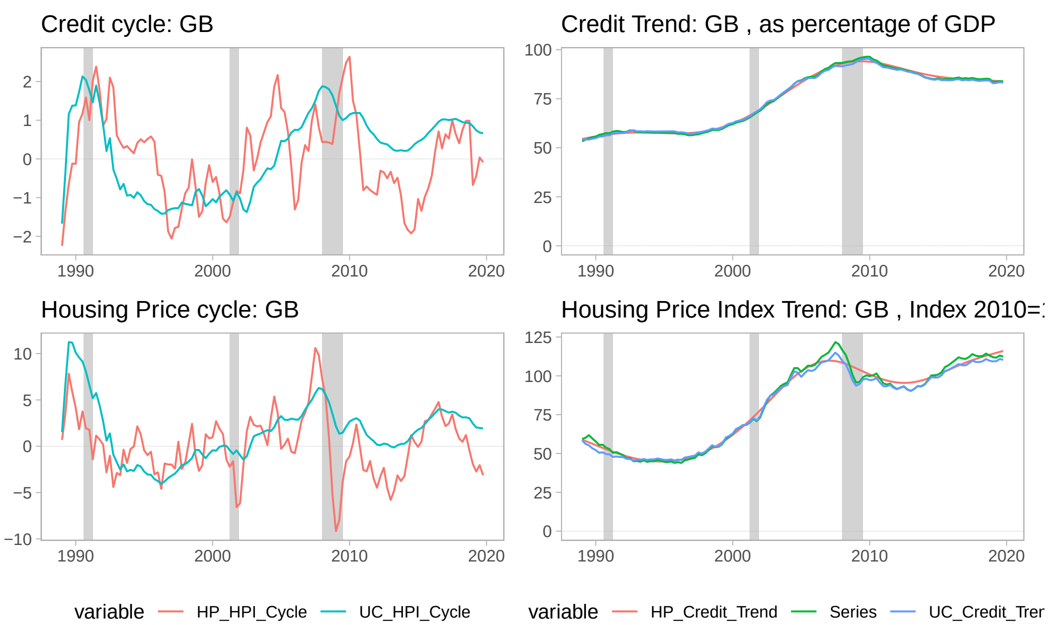

Figure 2: VAR(2) Cross-cycle 1st lag only UK

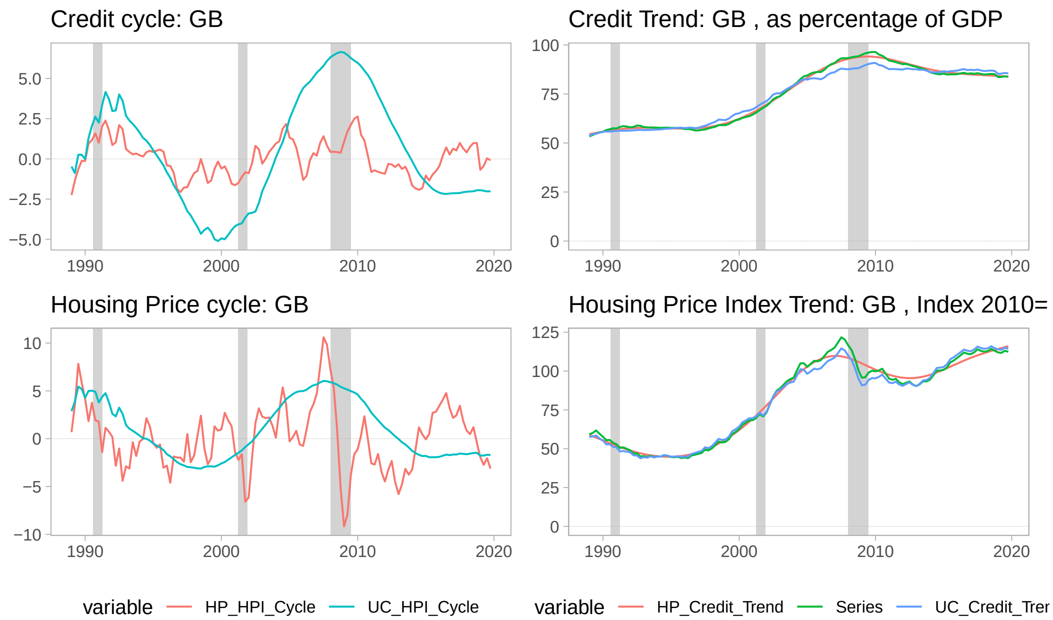

Figure 3: VAR(2) Cross-cycle 2 lags UK

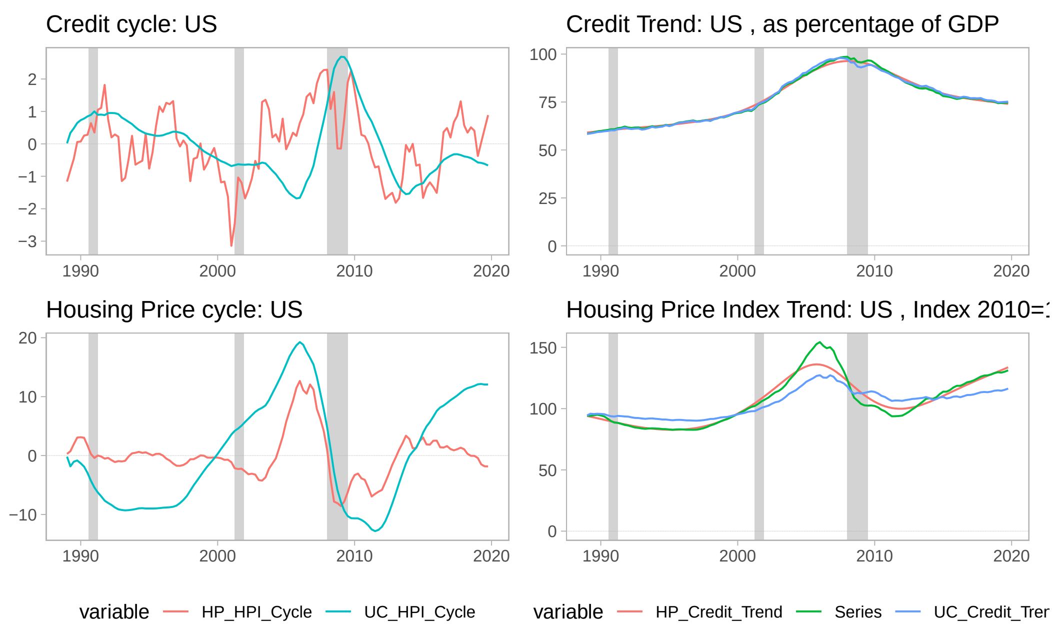

Figure 4: VAR(2) US

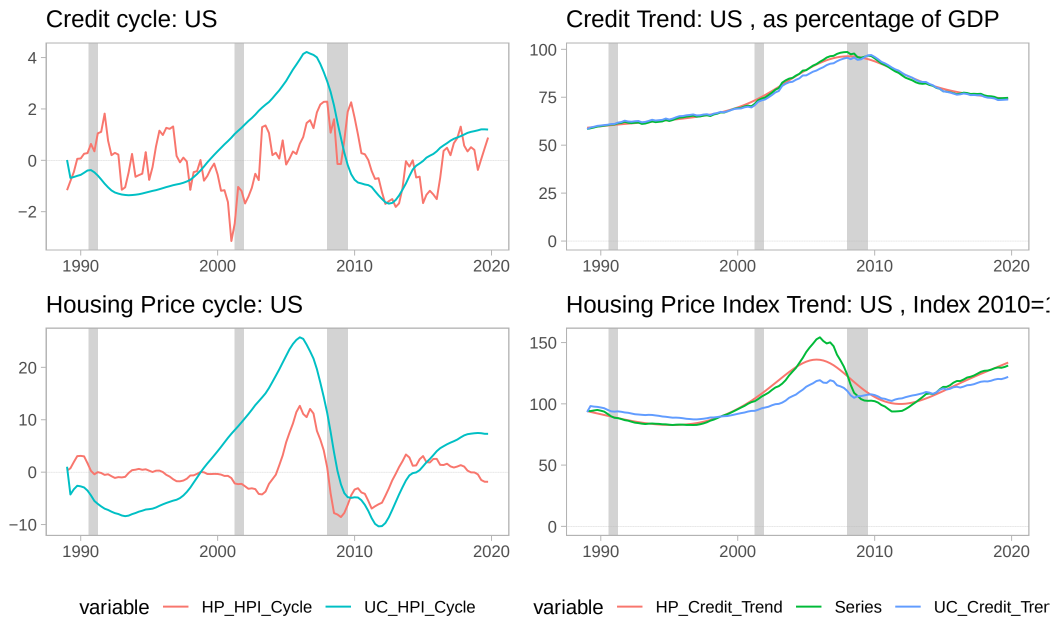

Figure 5: VAR(2) Cross-cycle 1st lag only US

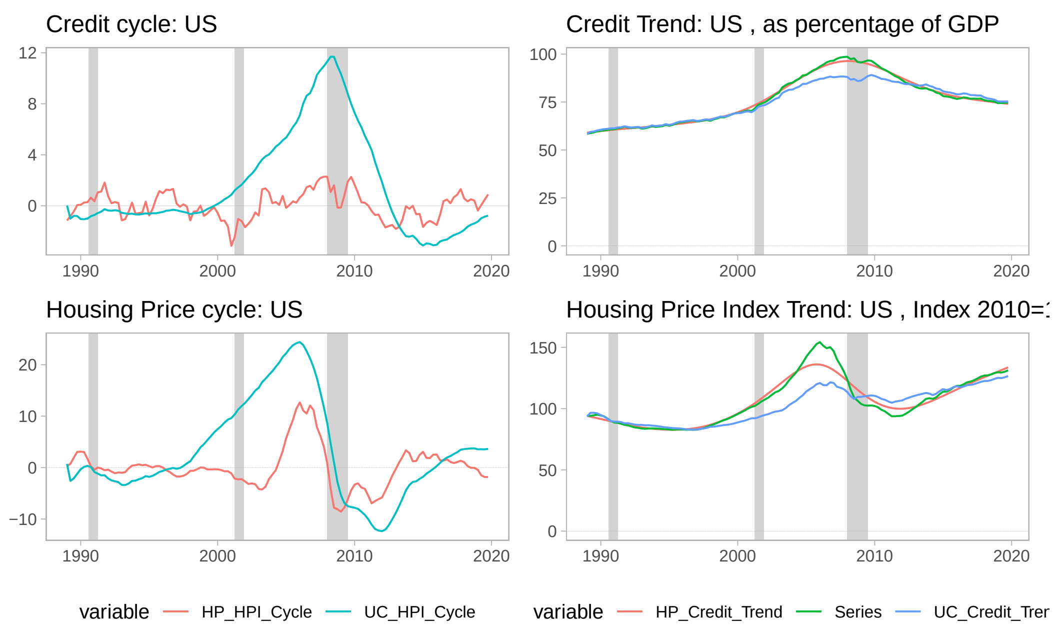

Figure 6: VAR(2) Cross-cycle 2 lags

In this subsection, we decompose trend and cycle of household credit and housing price using the correlated unobserved component model. The stochastic trend in the multivariate UC model captures the long-run evolution in household credit, housing price, and the effect of the recent global financial crisis. In the long run, there is an increasing trend in the housing price index. The household credit trend is also increasing but since the series is credit to household as a ratio to GDP, the rate at which household credit trend increases is smaller than that of the housing price index. There is a downward movement of the trend components in both credit and housing price after the financial crisis. However, the housing price index trends made a quicker recovery than household credit did.

The cyclical components of the model capture the evolution of household credit, housing price, and their dynamic relationship. In Figures 1-6, we can see that there is an increase in credit transitory component before the financial crisis of 2008-2009 happened, and there is a negative shock to the transitory component of housing price after the recession is captured in the model as well.

It is also important to point out that our models capture a significant bigger gap in transitory shock in both credit and house price than a Hodrick-Prescott (HP) filter would. Our model utilizes additional information from decomposed long-run and short-run variables, which were extracted from a nonstochastic time series. Another approach in dealing with nonstochastic time series is to first-differencing the series, which loses a lot of important information from a limited sample. Thus when dealing with a time series of low frequency and long-term assets such as housing price, it is worthwhile to consider using the unobserved component model rather than simply applying an HP filter since it reveals more lower frequency information. The graphs indicate that the magnitude of transitory shocks the models capture is higher and the frequency of the movement of the cycles is lower than that of other decomposition methods (HP filter). The graphs also imply that the models detect a bigger credit gap in the UK (Figure 3), and also bigger gaps in household credit and house price in the US (Figure 4-6).

5.3 Predictive ability of cyclical components

A novel contribution of this paper is to introduce the cross-cycle parameter ϕ_h^{xt} and ϕ_y^{xt} in which it measures the effect of a change in last periods' credit transitory component on the current housing price transitory component and vice versa. From Table 4 and 5, in both cross-cycle regressions in the UK and US, we can observe that there is a significant positive effect of last period credit cycle deviation on current housing cycle component (ϕ_h^{x1}). While the coefficients of transitory housing index deviation on household credit (ϕ_y^{x1}) are much smaller. This holds true for 2-crosscycle lags model also. This showed evidence that transitory shocks to household credit will cause a positive deviation in transitory housing price. However, transitory shocks to housing price have significantly smaller impact on household credit.

6 Comparison with other decomposition methods

In this section, we check the robustness of our results by comparing the estimated trend-cycle from our approach with univariate trend-cycle decomposition using different methods. In addition to the estimation of the correlation between shocks to the permanent and transitory component, the use of multivariate model in theory should also provide us a superior measurement of trend and cycle components as compared to the univariate models. To test this hypothesis, we also perform trend-cycle decomposition using the univariate models (Figure 7 and 8). The univariate models include a HP filter model and a univariate VAR(2) UC model. The HP filter method uses an algorithm to smooth the original data series to estimate the trend component and the difference between them, which is the cyclical component. The parameter value λ is set at 1600 as suggested by Hodrick and Prescott for the quarterly data. The univariate UC model only uses a single series of either credit to household or house prices index to decompose a stochastic trend component and a cyclical component with the same specification as in the multivariate UC model.

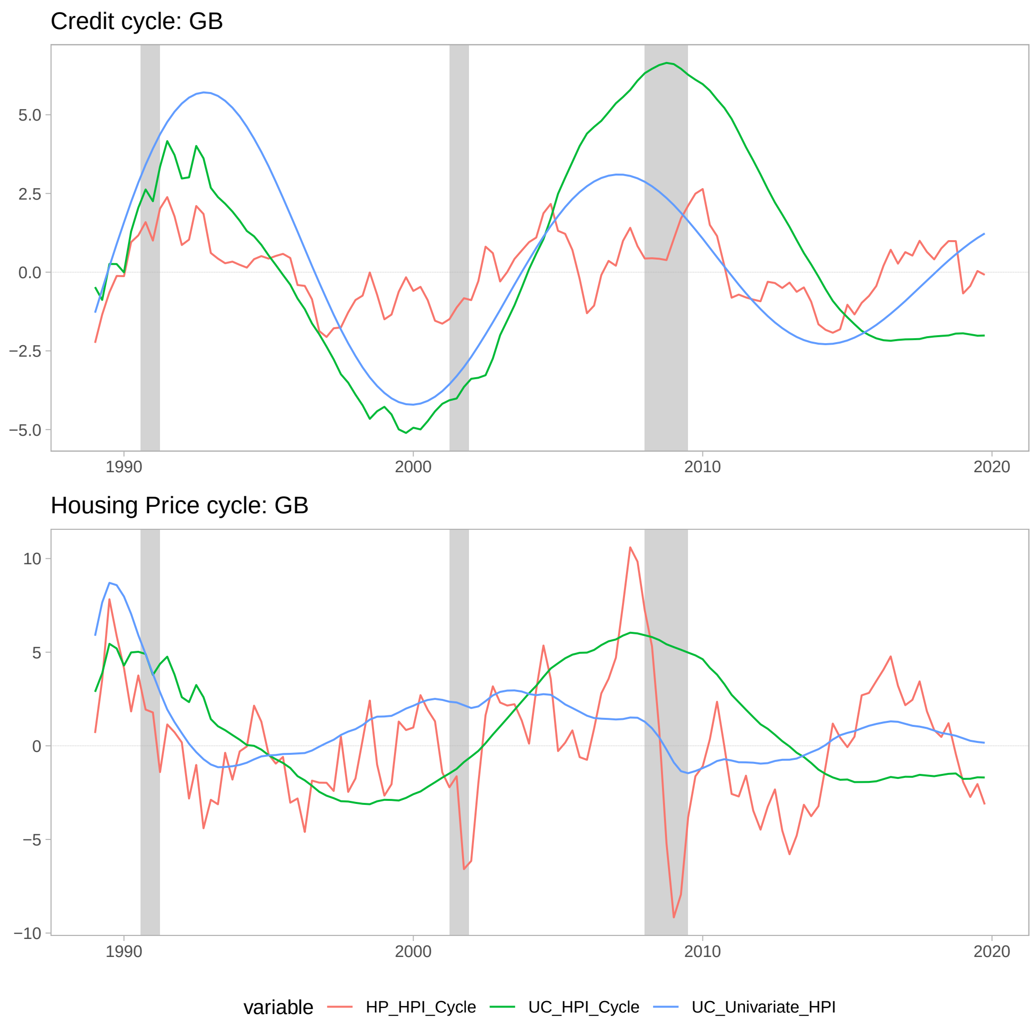

Figure 7: Comparing Multivariate UC cycles with alternate decompositions: UK

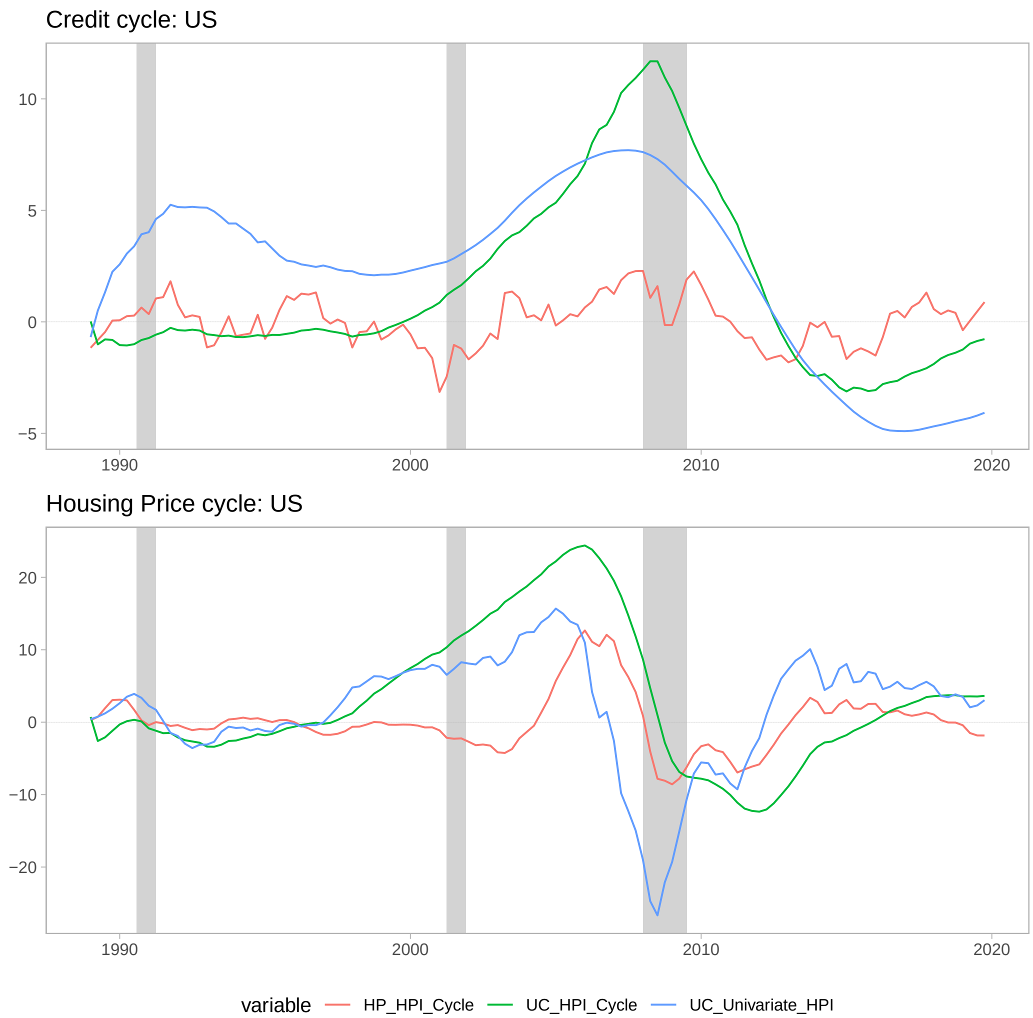

Figure 8: Comparing Multivariate UC cycles with alternate decompositions: US

The results from Figure 7 and Figure 8 suggest that the estimate of trend and cycles obtained from the multivariate UC model is capable of capturing the dynamics of the two variables during the sample period. The two univariate models, without assuming a linear trend, fail to generate realistic trend and cycle series by ignoring the relationship between the two variables of interest. The HP cycle seems to do very well at remaining stationary, but by doing so, it missed out in capturing the boom of house prices in the US leading to the Great Recession of 2009. The cycle from the univariate UC model, is close to the multivariate counter part but failed to fully indicate the magnitude of boom and bust in house prices in the UK before and after the crisis. Overall, it is clear from the analysis above that there is valuable pay-off in utilising information from extracting permanent and transitory components of credit to household and house prices index in order to study the dynamics of the two variables.

7 Conclusion

Our study is based on the idea that house prices and credit are jointly determined and they affect each other both in the short-run and in the long-run. We decompose the movements of the two variables of interest into a permanent and transitory component. The correlations among the cyclical components support the idea that the rise of household credit is associated with an increase in house prices above it long-run trend. Our multivariate model captures the dynamics features of the household credit and house prices series and performs better than univariate benchmarks in capturing the boom and bust during the last two decades. Additionally, employing cross correlation effects on the transitory components of the two series allows me to test the predictive ability of the cyclical components and found evidence to support that a household credit gap can positively predict a house prices gap. These findings suggests macroprudential policy implications since house prices are increasingly becoming a more important topic.

Further development for this paper should include studying on policy implications of credit and house price gaps with high magnitudes, introducing more robust optimal constraints on parameters to ensure stability and model robustness rather than an ad-hoc approach of selecting weights. Additional examination of the multicollinearity and identification issues also need to be addressed.

APPENDIX

Model estimation - Initial values selection

The priors for autoregressive parameters in matrix F are taken from VAR regression of the HP filter cycle decomposition of the series.

For $\beta_{0|0}$, I set $\tau_{0|0}$ as the value HP filtered trend component and omit the first observation from the regression. $c_{0|0}$ cycle components are also set to be equal to their HP filter counterpart. Variance $var(\tau_{0|0}) = 100 + 50 * random$; while other measures of the starting covariance are set to be their unconditional values.

Starting standard deviation and correlation values are randomized within reasonable range.

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