Credit and House Prices Cycles

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Abstract

In this paper, I examine the idea that house prices and credit to households are jointly determined, affecting each other in the short and long run. I 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. The dynamic model shows findings to support the hypothesis that a short-run positive shock to house prices is associated with an increase in household credit above its long-run trend. Furthermore, by utilizing additional information generated by the unobserved component model, our multivariate model performs better than univariate models in capturing the dynamics of household credit and house prices over the last three decades, especially during the recent financial crisis. I also estimated the predictive ability of cyclical components of a variable on their counterparts from other variables 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 the 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 US. Another strand of literature has argued that credit supply itself cannot explain the big swings in house prices and has 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 constraints leads to an increase in the willingness of the banking sector to provide funding not only to the residential sector but also to 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, I pay attention to the long-run and short-run movements in credit and house prices and model their joint dynamics. In doing so, I use data from the US and the UK. The methodology 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 are inspired by Morley (2007) and Huang & Kishor (2019). This method allows the permanent component to be shown as a random walk with a local growth rate component and the transitory component to be a stationary process with a mean zero. The stationary transitory component configuration is essential 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. Discovering causality in the structure of a dynamical system from observed time series is a traditional and important problem. By explicitly configuring cross-correlation coefficients on the cyclical components of the two variables, I will be able to examine the predictive ability of the cycles. This would produce a much desired inference for macro-prudential policy implications to stabilize the macroeconomy.

Using sample data from the US and the UK, I find interesting and meaningful results from the estimated multivariate correlated unobserved component model. The maximum-likelihood estimates of my proposed 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 their long-run level. These results support the narrative evidence of the strong relationship between household credit and house prices. More importantly, I also find evidence that lags of the household credit cycle have the 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. I 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, I find that the house prices and household credit were significantly higher than their long-term trend before the financial crisis. Then there was an overreaction during the crisis leading the house price and credit cycle to 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, my 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 tests the robustness of my model. The plan of the paper is as follows. In section 2, I will discuss the relevant literature branches. In section 3, I will introduce the summary of data and their description. In section 4, I will describe the decomposition methodology using unobserved component model with vector auto-regression (VAR). Specifically, in subsection 4.2, I introduced my contribution to the numerical optimization process in the literature. In section 5, I will go over the model regression results and my interpretation. I will also show cross-countries evidence when using the data from other developed countries. In section 6, I will test the robustness of the model by comparing the results against some traditional methods of analyzing time series data. And lastly, in section 7, I will give my 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); Mian & Sufi (2018) , Kishor (2020) , Guerrieri & Uhlig (2016), and Davis & Van Nieuwerburgh (2015) have detailed literature reviews on the dynamics between the housing market and credit conditions. I list the four literature branches that study the dynamics of the credit cycles, housing price cycles, and then the critical 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 generate the house price cycles.

One strand of the literature focuses on how credit cycles are generated. Kiyotaki & Moore (1997) modeled the fluctuation of credit conditions due to credit limits 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, this can generate a crash in the credit market. Boissay, Collard, & Smets (2016) studied the topic of endogenous boom and bust in the 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 conditions, Alessi & Detken (2018) used a random forest model to identify unsustainable credit growth periods.

The second branch of the literature focuses on the dynamics of house price changes. I first look at the generation of momentum in house price changes. Asset prices and valuations 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 valuations 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 allow prices to overshoot equilibrium (cycles) and permanently diverge from equilibrium. Glaeser, Gyourko, & Saiz (2008) incorporated housing supply elasticity into the analysis of housing prices momentum and showed 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 the long-run horizon, and excess longer-term volatility relative to fundamentals. Kishor, Kumari, & Song (2015) studied the US housing market by using a combination of the Unobserved Component model and GARCH model to study the time-varying importance of permanent and transitory housing components in the US 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 an extended period, 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 a rise in house prices coincides with a rise in the price-rent ratio, a fundamental that shows the intrinsic value of housing.

Another branch of literature is the one that studies the hypothesis that house price cycles generate 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 imply that stronger balance sheets due to higher asset prices will lead to a lower cost of borrowing to invest, suggesting that a housing price boom 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 affects borrowing capacity and output into their paper. An increase in home equity due to an increase in house prices will allow borrowers 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 sheets and banking sector balance sheets.

Some papers have studied the hypothesis that credit cycles generate house price cycles. Agnello & Schuknecht (2011) , Agnello, Castro, & Sousa (2018) examined different variables likely to create a bubble in housing markets. First is the effect of credit constraints 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 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 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 as the transmission mechanism 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 could explain excess volatility of house prices by 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 showed 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 equilibrium model with housing and collateral constraints to explore what drives fluctuations in house prices to rent ratio. They propose that relaxation of financing constraints leads to a significant boom in house prices. Furthermore, 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 in the effect of credit expansion on house prices. Justiniano, Primiceri, & Tambalotti (2019) argued that loosening 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 of the housing boom before the recession was an increase in credit supply or available funds rather than an increase in leverage. The rates of mortgages to real estate remained constant. This contradicts 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 the supply of credit was the cause of the 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, in a series of papers, Jorda, Schularick, and Taylor have studied the interplay between credit, house price, and economic performance. Schularick & Taylor (2012) created 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 crises before WWII but have become a more important predictor of financial fragility. The share of mortgages on banks' balance sheets doubled in the later half of the twentieth century, driven by household mortgage lending. Household debt to asset ratios have risen substantially in the study's many countries. Financial stability risks have been linked to real estate lending booms. Jordà, Schularick, & Taylor (2015) claims 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 method to demonstrate that loose monetary conditions lead to booms in real estate and house price bubbles. These, in turn, lead to a 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 coincides with a shift in foundational macroeconomic relationships. More financialized economies exhibit more tail risk and tighter real-real and real-financial correlations, including the credit and real estate correlation. The paper also shows that real house prices and mortgages in 17 sample countries display a "hockey stick" pattern. They both stay stable for a long 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 led to increases in housing demand. Di Maggio & Kermani (2017) showed that a credit expansion could generate a boom and bust in house prices and real activity. The paper uses the exploitation of the same federal deregulation in preemption of local laws against predatory lending in 2004 to gauge the effectiveness 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 the house price cycle is still open. In this paper, I will use a dynamic model to explain the relationship between these two variables in both the short-term and long-term.

3 Data Description

The sample periods include quarterly data from 1990:Q4 to 2021:Q3. The sample periods were chosen based on the nature of the change in the regulation of credit and housing markets beginning early 1990s. Also, many developed countries started recording their housing price index at the same time.[1] The main source of the data comes from the Bank of International Settlement (BIS). The real housing price index is based on the base index of 2010 as 100. The credit to household data is measured as a percentage of GDP. I 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, lack of standardization, and short time span of data available further 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.[2] 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 households, such as the International Financial Statistics from IMF or the Federal Reserve Economic Data, I decided to use the credit to household data from the BIS for better compatibility and adjustments for breaks

[1]The 17 countries with both credit and house price data available: Australia, Belgium, Canada, Finland, France, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, South Korea, Spain, Sweden, United Kingdom, United States

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

methodology in data collection.[3] 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 institutions.

In this study, I selected the US and UK as two representative countries to use because of the longevity and reliability of the time series data available.[4] Table 1 describes the data used in this paper. House price data tends to fluctuate with greater magnitude than credit series. Furthermore, the housing prices in the UK increase at a faster rate than in the US. Table 2 shows the correlation of the series with its lag values of 1 and 2 quarters. The house price series in the UK is more closely correlated with its household credit series than in the US.

Table 1: Descriptive statistics

Country	Index	Mean	Max	Min	Frequency	Periods
UK	Δy_t	0.3802	2.6989	-1.7626	Quarterly	1990:Q4-2021:Q3
	Δh_t	0.5926	7.2322	-6.7250	Quarterly	1990:Q4-2021:Q3
US	Δy_t	0.1989	3.5088	-1.9427	Quarterly	1990:Q4-2021:Q3
	Δh_t	0.3004	3.4809	-6.7164	Quarterly	1990:Q4-2021:Q3

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.

[3] 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 non-residents. https://www.bis.org/statistics/totcredit/credpriv_doc.pdf

[4] For other countries' analysis, I summarized results in subsection 5.4.

Table 2: Correlation matrix

Country		y_t	y_{t-1}	y_{t-2}	h_t	h_{t-1}	h_{t-2}
UK	y_t	1.0000	0.9991	0.9969		0.9442	0.9491
	h_t	0.9391	0.9314	0.9225	1.0000	0.9975	0.9925
US	y_t	1.0000	0.9983	0.9947		0.7232	0.7415
	h_t	0.7041	0.6891	0.6730	1.0000	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

My proposed model is a multivariate extension of the model used in (Morley, 2007). I use a bivariate unobserved component model to model the dynamics in credit to households as ratio to GDP (y_t) and house prices index (h_t). In my model, the credit and house prices series are log-transformed and are each sum of a trend and cycle components.

I begin with the notations of two series: (Credit) as credit to households 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 have a random walk component and a time-varying local growth rate component μ_t. This approach follows the structural time series model specification discussed in Beltran, Jahan-Parvar, & Paine (2021) and Campagnoli, Petrone, & Petris (2009):

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

$$\mu_{yt} = \mu_{yt-1} + \eta_{\mu yt}, \qquad \eta_{\mu yt} \sim iidN(0, 0.01) \tag{4}$$

$$\tau_{ht} = \mu_{ht-1} + \tau_{ht-1} + \eta_{ht}, \qquad \eta_{ht} \sim iidN(0, \sigma^2_{\eta h}) \tag{5}$$

$$\mu_{ht} = \mu_{ht-1} + \eta_{\mu ht}, \qquad \eta_{\mu ht} \sim iidN(0, 0.01) \tag{6}$$

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

$$c_{yt} = \phi_y^1 c_{yt-1} + \phi_y^2 c_{yt-2} + \phi_y^{x1} c_{ht-1} + \phi_y^{x2} c_{ht-2} + \varepsilon_{yt}, \qquad \varepsilon_{yt} \sim iidN(0, \sigma^2_{\varepsilon y}) \tag{7}$$

$$c_{ht} = \phi_h^1 c_{ht-1} + \phi_h^2 c_{ht-2} + \phi_h^{x1} c_{yt-1} + \phi_h^{x2} c_{yt-2} + \varepsilon_{ht}, \qquad \varepsilon_{ht} \sim iidN(0, \sigma^2_{\varepsilon h}) \tag{8}$$

Each series is decomposed into a stochastic trend with a local growth rate 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 I do not reject the null hypothesis of unit root for all the variables.[5] In contrast to (Morley, 2007), I 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, I 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 provides rich dynamics in the data series to enable us to identify all the parameters under the state-space model framework.[6] The trend components are assumed to follow a random walk process with a time-varying local growth rate component. As mentioned above, I do not impose a common trend between the two variables.

Thirdly, I assume the shocks to the trend and cyclical components follow a white noise process

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

[6] 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.

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, and so are the shocks to the cyclical components. However, I impose the zero correlation between the shocks to the trend components and the shocks to the cycle components within and between series. That is to say, I assume that the shocks that generate a long-run effect differ from those 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:

$$\tilde{y}_t = A + H\beta_t \tag{9}$$

Where the measurement components are:

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

And the transition equations are:

$$\beta_t = F\beta_{t-1} + \tilde{v}_t \tag{10}$$

Where the transitory components are:

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

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

$$
Q = \begin{bmatrix} \sigma^2_{\eta y} & 0 & 0 & \sigma_{\eta y \eta h} & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon y} & 0 & 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \sigma_{\eta y \eta h} & 0 & 0 & \sigma^2_{\eta h} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\varepsilon y \varepsilon h} & 0 & 0 & \sigma^2_{\varepsilon h} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.01 \end{bmatrix} \tag{11}
$$

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 - 6. Additionally, the variance of the local growth rate $\sigma^2_{\mu it}$ is fixed at 0.01 as I followed the steps in Campagnoli et al. (2009) and

Beltran et al. (2021) of handling long cycle quarterly data and also for simplifying the computation problem.

The model estimation methodology I used is based on the classical maximum likelihood via the Kalman Filter.[7] Additionally, my novel contribution to the literature on estimating trend-cycle component models is to overcome the common "curse of dimensionality" problem in estimating a complex unobserved component model, which resulted in perfect multicollinearity and problematic estimation results. To solve this problem, I implemented a Bayesian inference technique called random-walk Metropolis-Hastings sampler and referred to its implementation in Blake & Mumtaz (2017) to obtain draws from the posterior distribution. I use the last 1 million draws from the 1.5 million (Markov chain Monte Carlo) MCMC iterations to analyze the posterior distribution. The Bayesian method is a full information-based approach that uses all moments of the observations. The details of the implementation steps of the model estimation using the random-walk Metropolis-Hastings sampler are shown in appendix 9.

4.2 Parameters Constraints

Another minor novel contribution of the paper is introducing 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.

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 additional terms on the objective log-likelihood function:

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

$$l(\theta) = -0.5\sum_{t=1}^{T} ln[(2\pi)^2|f_{t|t-1}|] - 0.5\sum_{t=1}^{T} \eta'_{t|t-1} f_{t|t-1}^{-1} \eta_{t|t-1} - w_1 * \sum_{t=1}^{T}(c_{yt}^2) - w_2 * \sum_{t=1}^{T}(c_{ht}^2) \quad (12)$$

The last two terms in the objective function act as a penalty against too much transitory deviation from zero. Without this penalty, the trend would be linear, or transitory movements would match all the movements in the measured series. This paper will impose the additional penalty terms' weight w_i at 0.0005.

Regarding constraints on the covariance matrix, I applied the same constraints as in (Morley, 2007) to imply the 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 transitory 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 transitory shocks to Housing Price Index	σ_{eh}
Cross-series correlations	
Correlation: Permanent credit to household/Permanent Housing Price Index	ρ_{nynh}
Correlation: Transitory credit to household/Transitory Housing Price Index	ρ_{eyeh}

5 Empirical Results

In this section, I will apply the unobserved components state-space model to data from 2 countries: the US and UK. Since I use a Bayesian inference technique, instead of reporting the estimated expected mean and standard deviation as in the frequentist approach, I will report the estimate of the parameters using the median of the posterior distribution and its 10th and 90th percentile value. An estimate of a parameter with a negative 10th percentile and positive 90th percentile values would mean that we do not have evidence to reject the null hypothesis of said parameter equals zero.

Table 4: UK Regression Results - All three models

	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 Metropolis-Hasting random walk posterior distribution estimates

Table 5: US Regression Results - All three models

	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 Metropolis-Hasting random walk posterior distribution estimates

Table 6: VAR(2) 1 cross-lag : UK and US regression results

		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 regression results

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, log-likelihood value, suggests that the best fit model is VAR(2) with 2 cross lags. But because this paper focuses on the estimate of the causal cross cycle correlation parameter, I select the second model - VAR(2) with only 1 cross lag in the cycle component as the one to limit the scope of analysis on.

5.1 Dynamic Relationship between Credit to Household and Housing Price

From Table 6, the VAR(2) - 1 cross lag model regression results suggest that transitory shocks dominate permanent shocks in terms of variation in both household credit and housing price variables. The standard deviation of the shocks in the cycle of credit σ_{ey} is 0.8021 in the UK and 0.8631 in the US, much higher than the standard deviation of the shocks to the trend of credit σ_{ny} in the UK of 0.2714 and the US of 0.2954. The same applies to housing prices, the standard deviation of the shocks in the cycle of housing price σ_{eh} is 1.2242 in the UK and 0.8988 in the US, higher than the standard deviation of the shocks to the trend of housing price σ_{nh} in the UK of 0.0789 and the US of 0.1390. This result also indicates that variations in the housing price cyclical components of the UK are bigger than in the US. In contrast, variations in other components of the UK do not differ from the US. Regarding the estimated parameters, the sum of AR parameters of the cyclical components in all three models is 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 household credit is strongly positively correlated. The estimate ρ_{eyeh} at 0.2536 for the UK and 0.1537 for the US suggest that transitory shock to housing credit is closely positively correlated to transitory shock in housing price. This implies that a transitory increase in household credit is correlated with an appreciation in housing prices above their long-run trend.

The correlation analysis of the shocks to the trends ρ_{nynh} among the two variables reveals no significant correlation between shocks to the trend components of household credit and housing price. The median estimate for the permanent component's correlation is much smaller than the correlation of the transitory components.

Lastly, I analyze the correlation value of the time-varying local growth rate components μ_{it} from both household credit and housing price index trends as specified in equations 2.3-2.6. After estimating the unobserved components, as in figures 2.2 and 2.5, we can calculate the correlation values between those two local growth rate components. The correlation value $\rho_{\mu yh}$ for the UK at 0.5603 is significantly higher than that for the US at -0.0574. This result supports the hypothesis that the underlying trend components of household credit and housing price index in the UK are more correlated than in the US.

Overall, the above analyses' results suggest that the two variables' short-run and long-run dynamics 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 show the UC forecast series against the actual data series. As discussed in the previous subsection, I focus our analysis on the VAR(2) 1 cross-lag model in Figures 2.2 and 2.5.

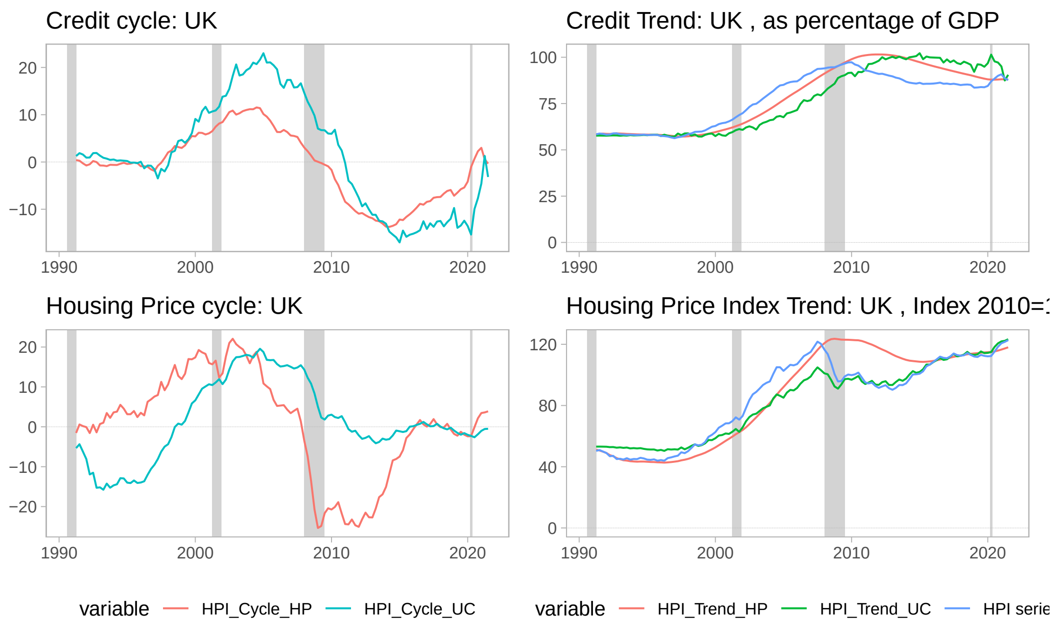

Figure 1: UK VAR(2)

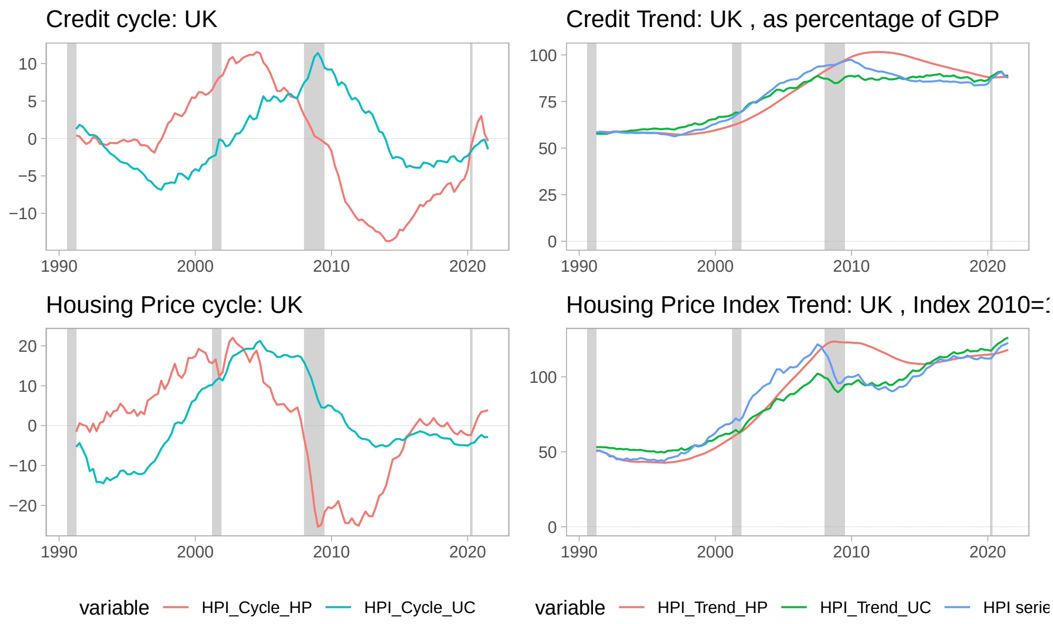

Figure 2: UK VAR(2) 1 cross-lag

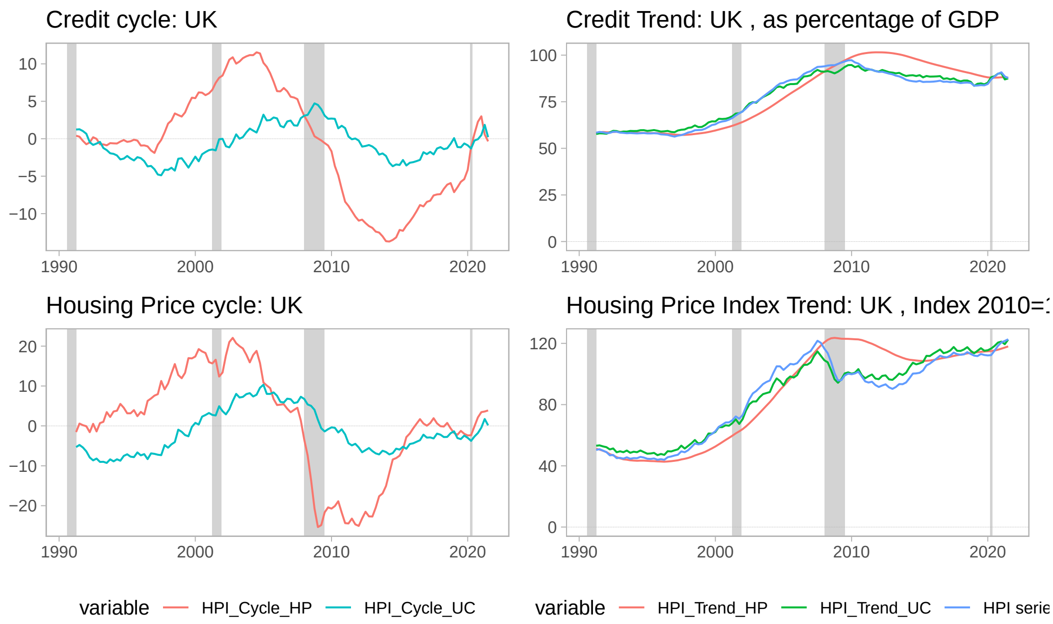

Figure 3: UK VAR(2) 2 cross-lags

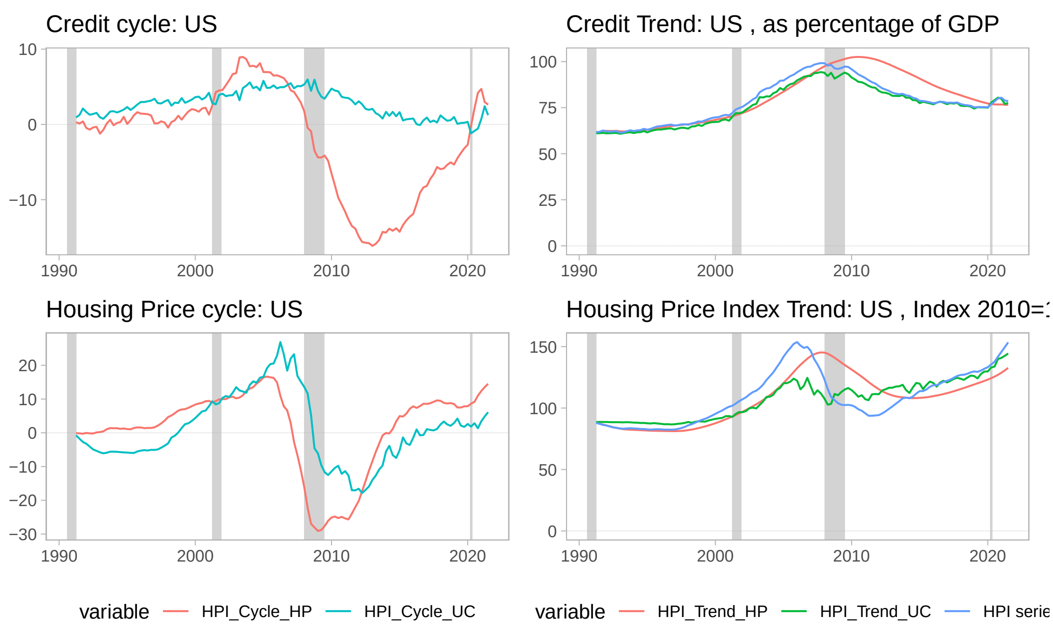

Figure 4: US VAR(2)

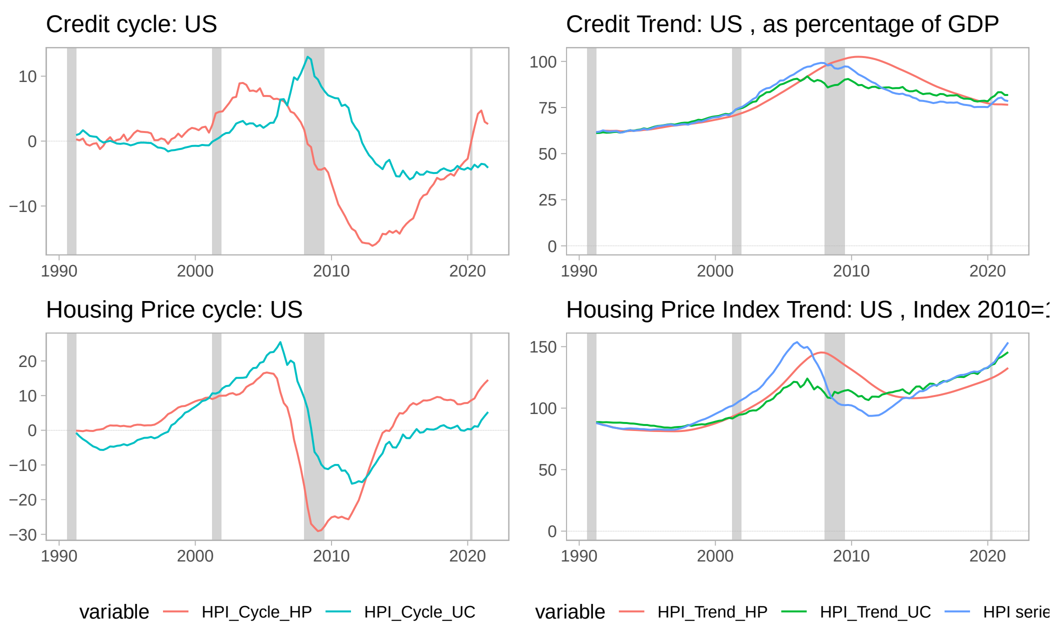

Figure 5: US VAR(2) 1 cross-lag

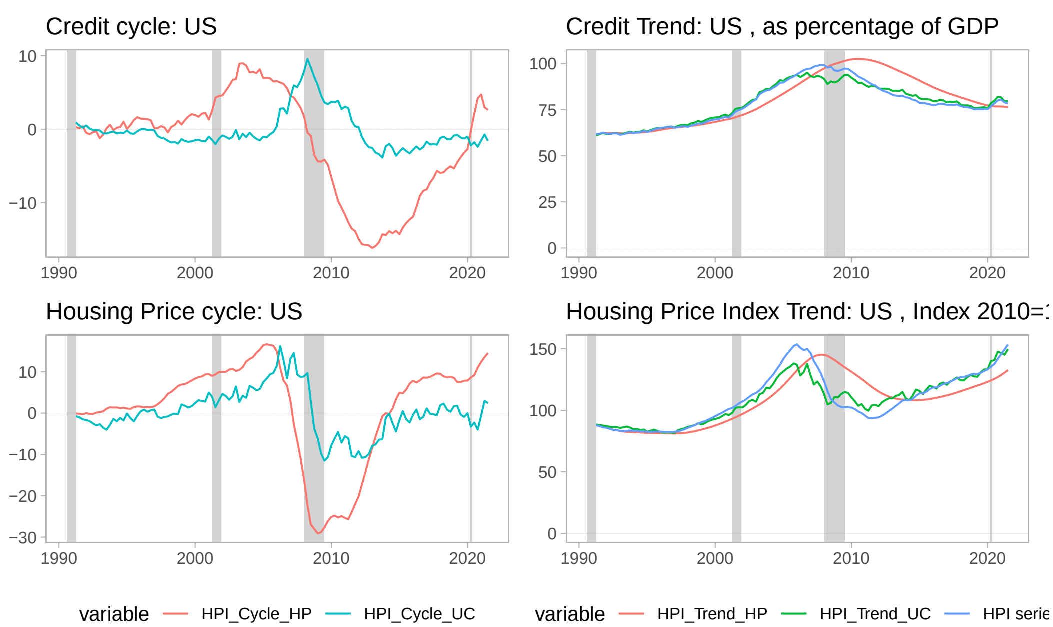

Figure 6: US VAR(2) 2 cross-lags

In this subsection, I decompose the 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 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 households as a ratio to GDP, the rate at which the household credit trend increases is lower than that of the housing price index. There was a downward movement of the trend components in both credit and housing prices after the crisis. However, the housing price index trends made a quicker recovery than household credit.

The cyclical components of the model capture the evolution of household credit, housing price, and their dynamic relationship. In Figures 2.1-2.6, we can see an increase in the credit transitory component before the 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. Specifically, in Figures 2.2 and 2.5, the VAR(2) model with 1 cross-lag coefficients identified the timing of temporary gaps increase in both credit and housing price before the crisis more accurately than the one-sided HP filter could.

It is also important to point out that our models capture a significantly bigger positive gap in transitory shock in both credit and house price than a Hodrick-Prescott (HP) filter would for the US in Figure 2.5. 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 much important information from a limited sample. Thus when dealing with a time series of low frequency and long-term assets such as housing prices, it is worthwhile to consider using the unobserved component model rather than simply applying an HP filter or first-differencing since it reveals more lower frequency information. The graphs indicate that the magnitude of transitory shocks the models capture is higher, and the movement frequency of the cycles is lower than that of other decomposition methods (HP filter).

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 previous periods' credit transitory component on the current housing price transitory component and vice versa. From Table 6, in both cross-cycle regressions in the UK and US, we can observe that there is a significant positive effect of last period house price cycle deviation on current household credit cycle component (ϕ_y^{x1}). While the coefficients of transitory household credit deviation on housing price index (ϕ_h^{x1}) are smaller, and even statistically insignificant in the case of the US. This holds true for the 2-crosscycle lags model also on the other regression results Tables 4 and 5; when we take the sum of the 2-crosscycle lags coefficients, they show similar results. This showed evidence that past transitory shocks to house price credit will cause a positive deviation in future transitory household credit. On the contrary, the effect in the opposite direction is much smaller.

5.4 Cross Countries Analysis

In this subsection, I will further discuss estimates of the causal coefficient ϕ_y^{xt} and ϕ_h^{xt} in cross-country settings. The window for sample data I selected starting from 1990:Q4 - 2021:Q3 coincides with the period when many developed countries started recording their housing price index. This created an opportunity for us to compare the estimates of the causal coefficient parameters. Specifically, I estimated our VAR(2) 1 cross-lag model using data from 17 developed countries, as shown in Table 7.

The overall result shows that there is cross-countries evidence to further support the hypothesis established in the previous subsection 5.3 that past transitory shocks to house price credit will cause a positive deviation in future transitory household credit; or that the ϕ_y^{x1} coefficient parameter estimates are positive and statistically significant.

Out of the 17 countries in our sample, 11 countries in Europe and North America, except for the Netherlands, have a positive and significant estimate for ϕ_y^{x1} (HPI on Credit causal coefficient). On the other hand, East Asian countries such as Japan, South Korea, and Hong Kong (SAR), along

Table 7: VAR(2) 1 cross-lag : Cross countries estimates

	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]

Note:

Cross Countries causal coefficients

with Australia, and New Zealand, have insignificant estimates for ϕ_y^{x1}.

As for the other parameter, ϕ_h^{x1} (Credit on HPI causal coefficient), only six countries have positive and significant estimates: Australia, Finland, Japan, Norway, Sweden, and the US. Furthermore, three of those positive estimates are also smaller in magnitude compared to their counterpart ϕ_y^{x1}, except for Australia, Japan, and Sweden. Interestingly, there are also countries with negative and significant estimates for ϕ_h^{x1}, which are Belgium, France, Hong Kong, and New Zealand. Their negative values implied that a positive increase in transitory household credit would have a negative effect on future transitory household prices. Overall, from all 17 available countries' estimates, I found no strong evidence to support ϕ_h^{x1} (Credit on HPI causal effect) to be significant.

The two outliers in this analysis are Japan and Italy. Italy has a much higher ϕ_y^{x1} (HPI on Credit causal coefficient) than other countries, this could be a result of the country experiencing a boom in house prices before the global crisis. And after its bust in 2009, house prices have not been able to recover since, see graphs in Figure 21. In contrast, Japan has a much higher ϕ_h^{x1} (Credit on HPI causal coefficient) than other countries. This could be due to Japan's economy's unique characteristics in which it has been experiencing three consecutive lost decades of stagnation trying to recover after the Japan Banking crisis in early 1990. Its household credit and house price index have declined ever since early 1990. However, there are signs of recovery in recent years for Japan, see graphs in Figure 22.

6 Comparison with other Decomposition Methods

In this section, I check the robustness of the model results by comparing the estimated trend-cycle from my multivariate approach with univariate trend-cycle decomposition using different methods. In addition to estimating the correlation between shocks to the permanent and transitory component, the use of a multivariate model, in theory, should also provide us with a superior measurement of trend and cycle components compared to the univariate models. To test this hypothesis, I also perform trend-cycle decomposition using the univariate models (Figure 7 and 8). The univariate models include an 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 125,000 as suggested by Hodrick and Prescott and Ravn & Uhlig (2002) for the quarterly data corresponding to a cyclical period of 15-17 years. 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 the multivariate UC model.

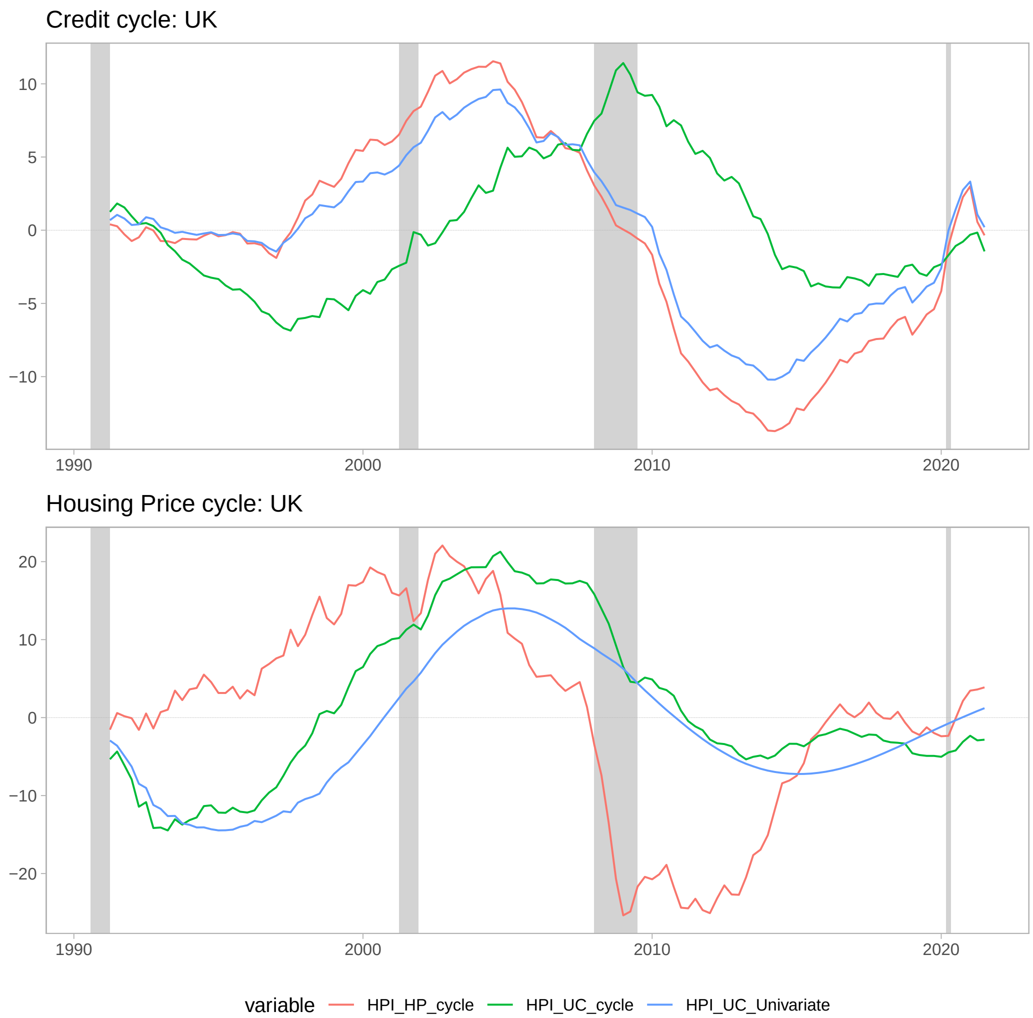

Figure 7: Comparing Multivariate UC cycles with alternate decompositions: UK

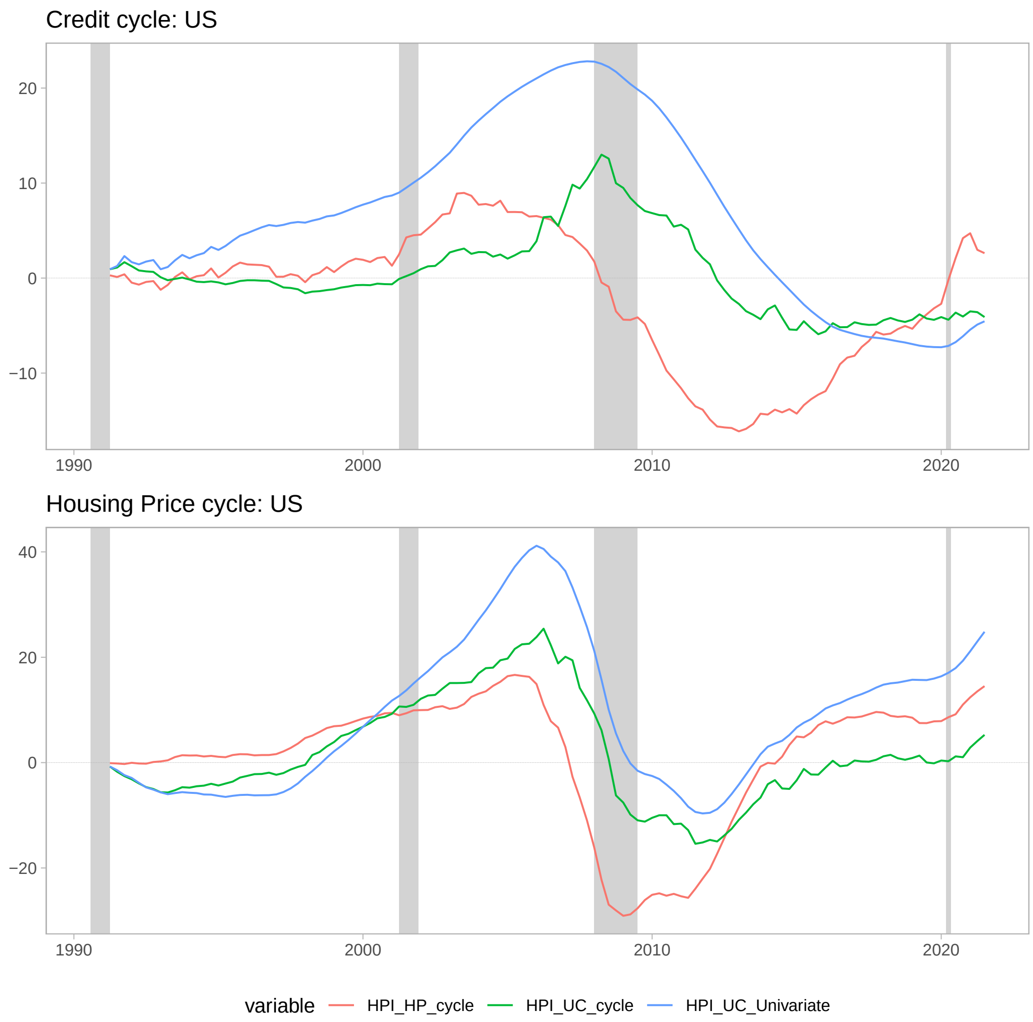

Figure 8: Comparing Multivariate UC cycles with alternate decompositions: US

The results from Figure 7 and Figure 8 suggest that the estimate of trends and cycles obtained from the multivariate UC model can capture the dynamics of the two variables during the sample period. The two univariate models fail to generate realistic trends 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 on 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 counterpart 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 a valuable pay-off in utilizing information from extracting permanent and transitory components of credit to household and house prices index to study the dynamics of the two variables.

7 Conclusion

My study is based on the idea that house prices and credit are jointly determined, affecting each other in the short and long run. I 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 house prices is associated with an increase in household credit above its long-run trend. My multivariate model captures the dynamic 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 find evidence to support that a house prices gap can positively predict a household credit gap. These findings suggest 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. More robust optimal constraints on parameters to ensure stability and model robustness rather than an ad-hoc approach to selecting weights. Lastly, it would be meaningful to link the information from this paper's causal effect coefficients estimates to the bigger picture regarding macroprudential policy models that includes housing price and household credit, such as systemic financial stability model[8] or house price growth-at-risk models[9].

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Appendix

8 Model Estimation - Initial Values Selection

The starting values/priors for vector autoregressive parameters in matrix F from equation 2.10 are taken from VAR regression of the one-sided HP filter cycle decomposition of the series with $\lambda = 125,000$.

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 $var(\tau_{0|0}) = 100 + 50 * random$, with the random value drawn from a uniform distribution (0,1). While other measures of the starting covariance are set to be at their unconditional mean values.

Means and standard deviations for the prior distributions shown in subsection A.2 are also derived from the information extracted using the method above. All autoregressive parameters are jointly correlated in a multivariate normal distribution, while the variance parameters have inverse gamma distributions. The shape and scale parameters of a gamma distribution can be deducted using the methods of moments from the estimated means and variances. Lastly, the prior distribution for correlation coefficients are set to be normal distribution with arbitrary unassuming means of near zero and standard deviations of 0.25.

9 Random-Walk Metropolis Hasting Sampler

The Bayesian method is a full information-based approach that uses all moments of the observations. Together with reasonable constraints on parameters to ensure the stability of the model, we can estimate complex time series state-space models. I use the last 1 million draws from the 1.5 million (Markov chain Monte Carlo) MCMC chains for the analysis of the posterior distribution. The posterior and prior distribution graphs and the posterior chains can show us evidence of convergence or estimation stability. The posterior chain in Figure A.7 shows that there is a lack of convergence of the estimates compared to other models. This could be a signal that the model estimation is misspecified.

The steps to implement a Random-Walk Metropolis Hasting sampler in a state-space setting with a Kalman filter can be referred to in chapter 5 from (Blake & Mumtaz, 2017).

9.1 Posterior and Prior Distribution

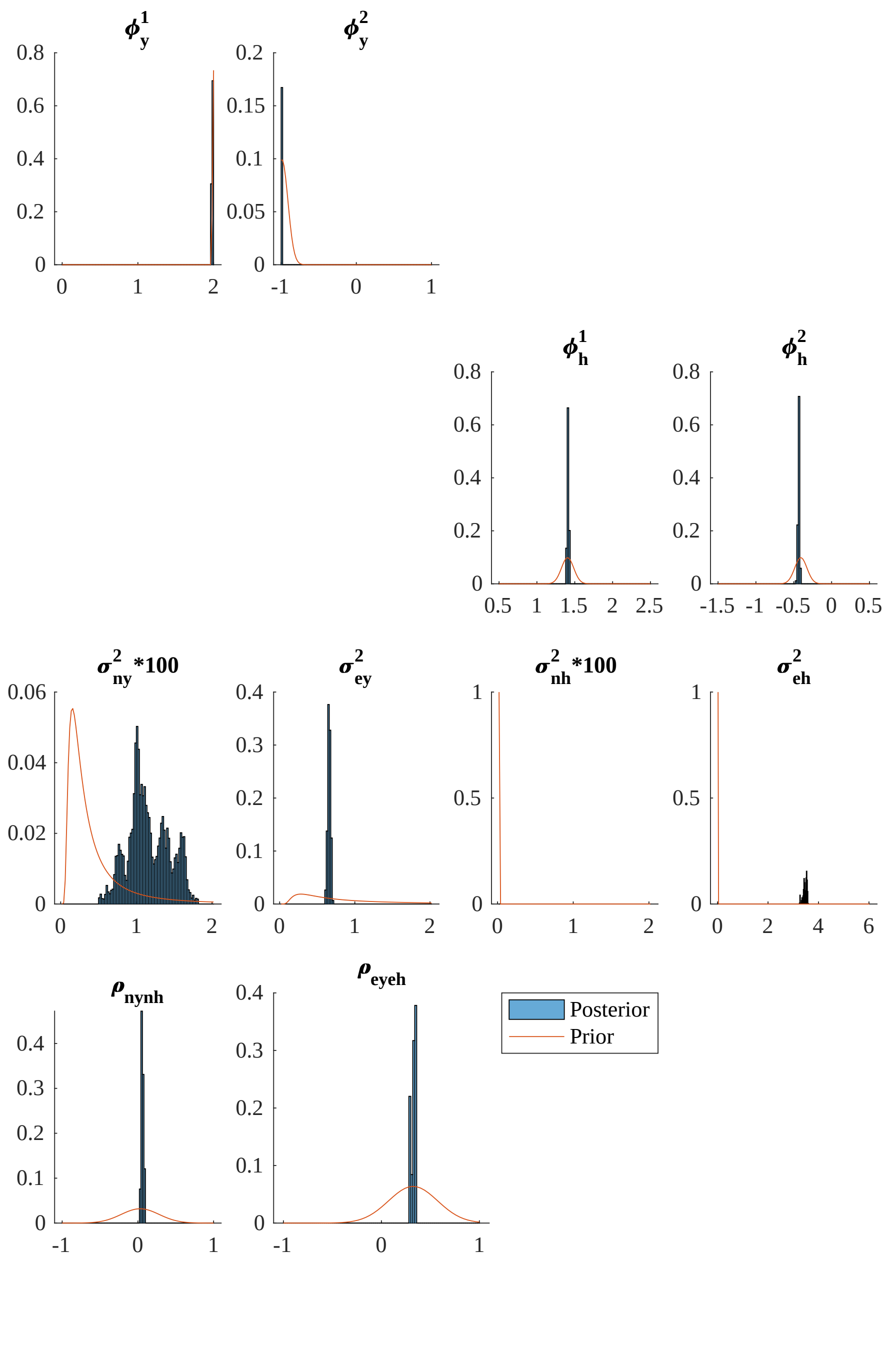

Figure 9: UK VAR(2) - Posterior and Prior Distribution

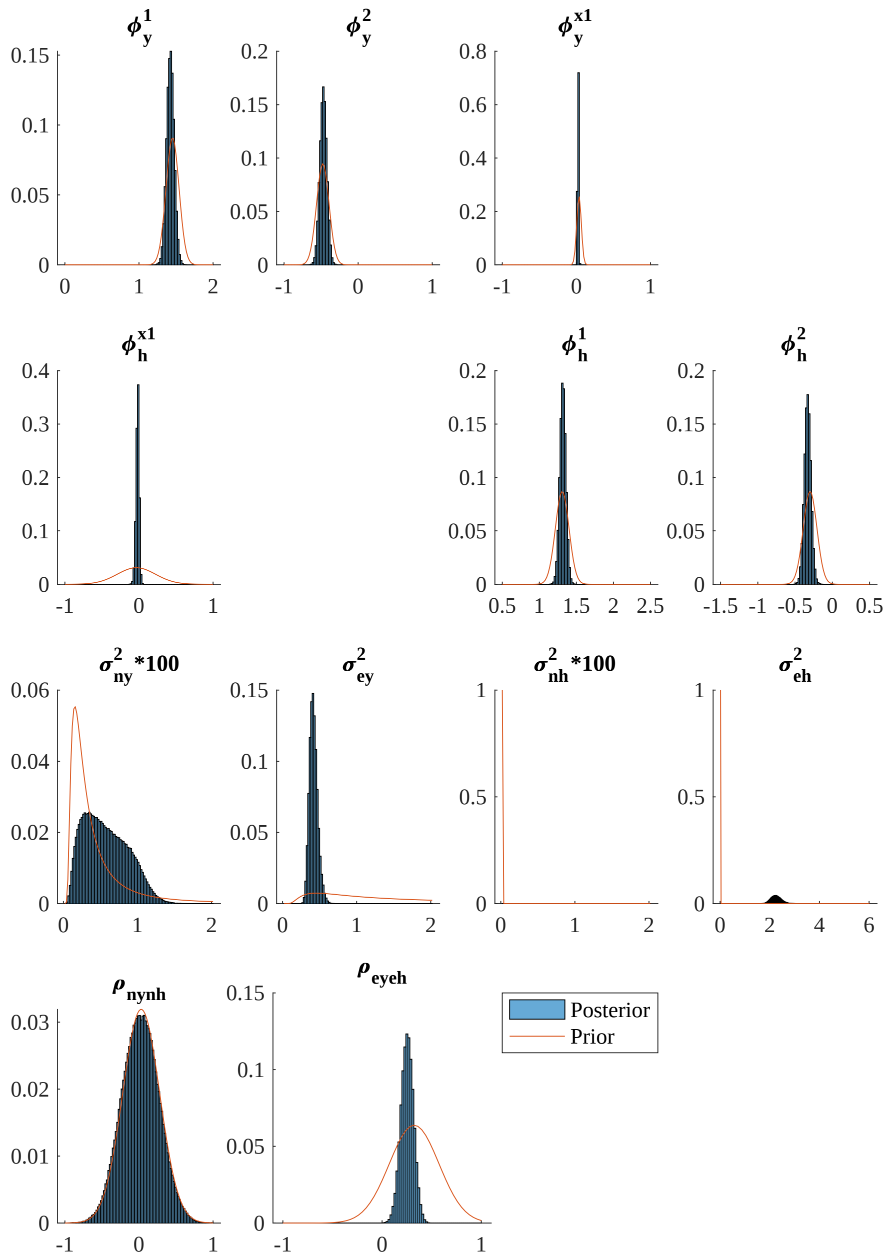

Figure 10: UK VAR(2) 1 cross-lag - Posterior and Prior Distribution

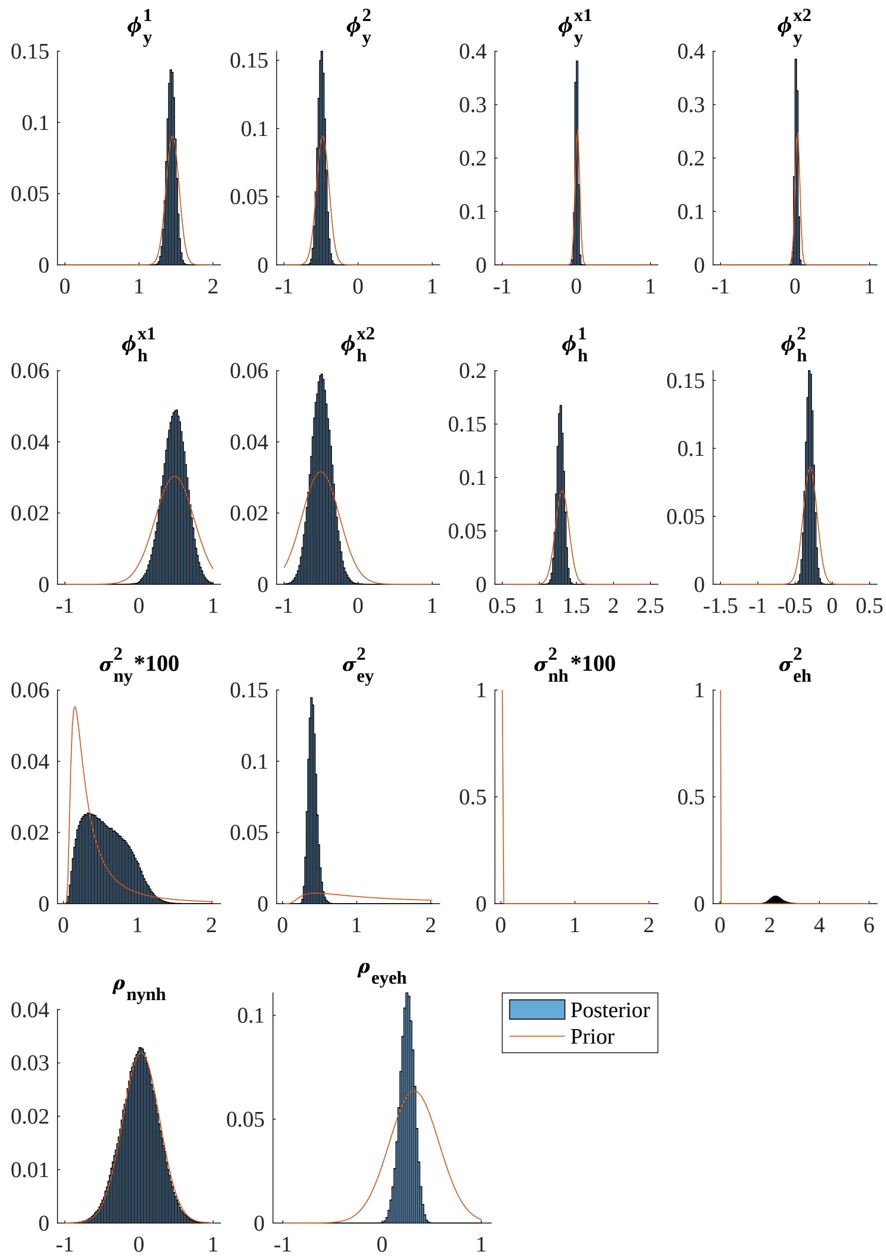

Figure 11: UK VAR(2) 2 cross-lags - Posterior and Prior Distribution

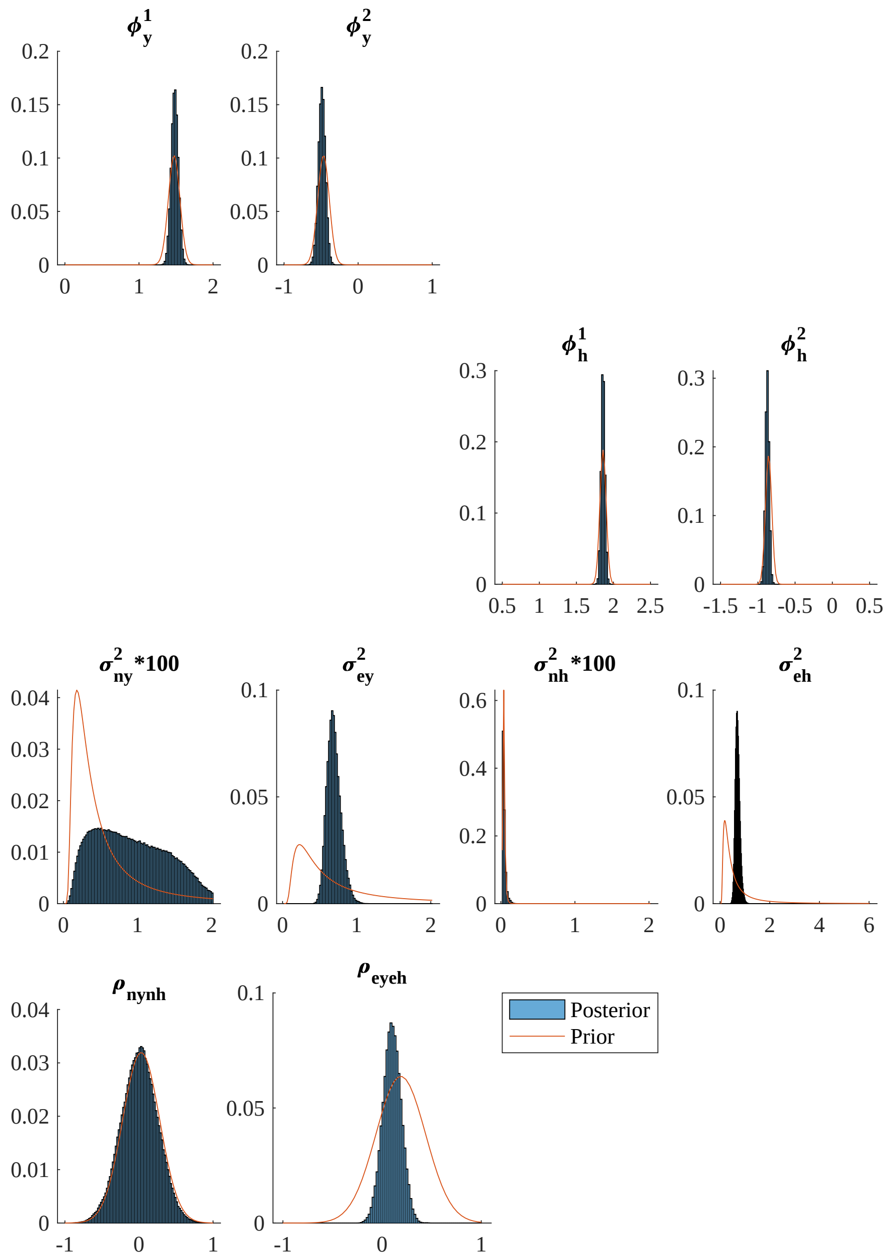

Figure 12: US VAR(2) - Posterior and Prior Distribution

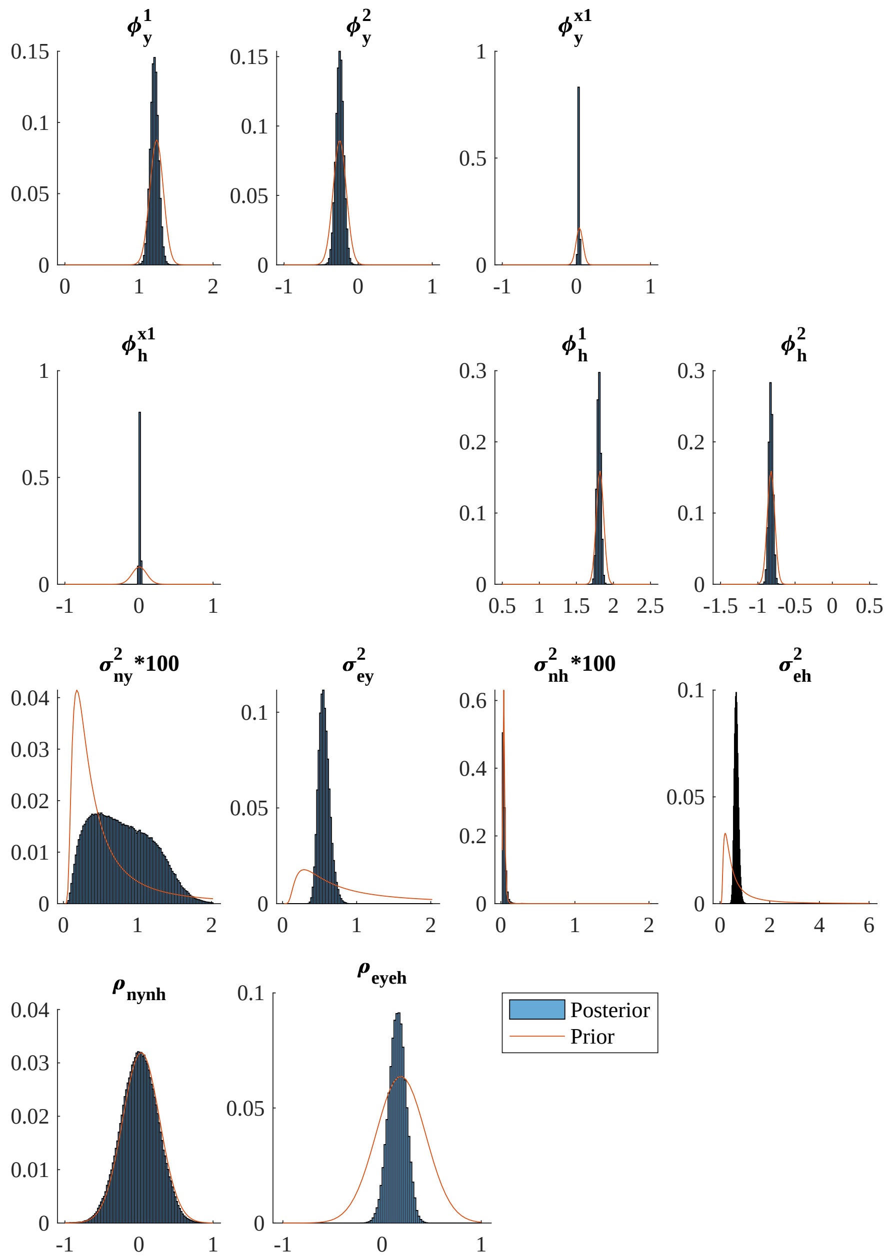

Figure 13: US VAR(2) 1 cross-lag - Posterior and Prior Distribution

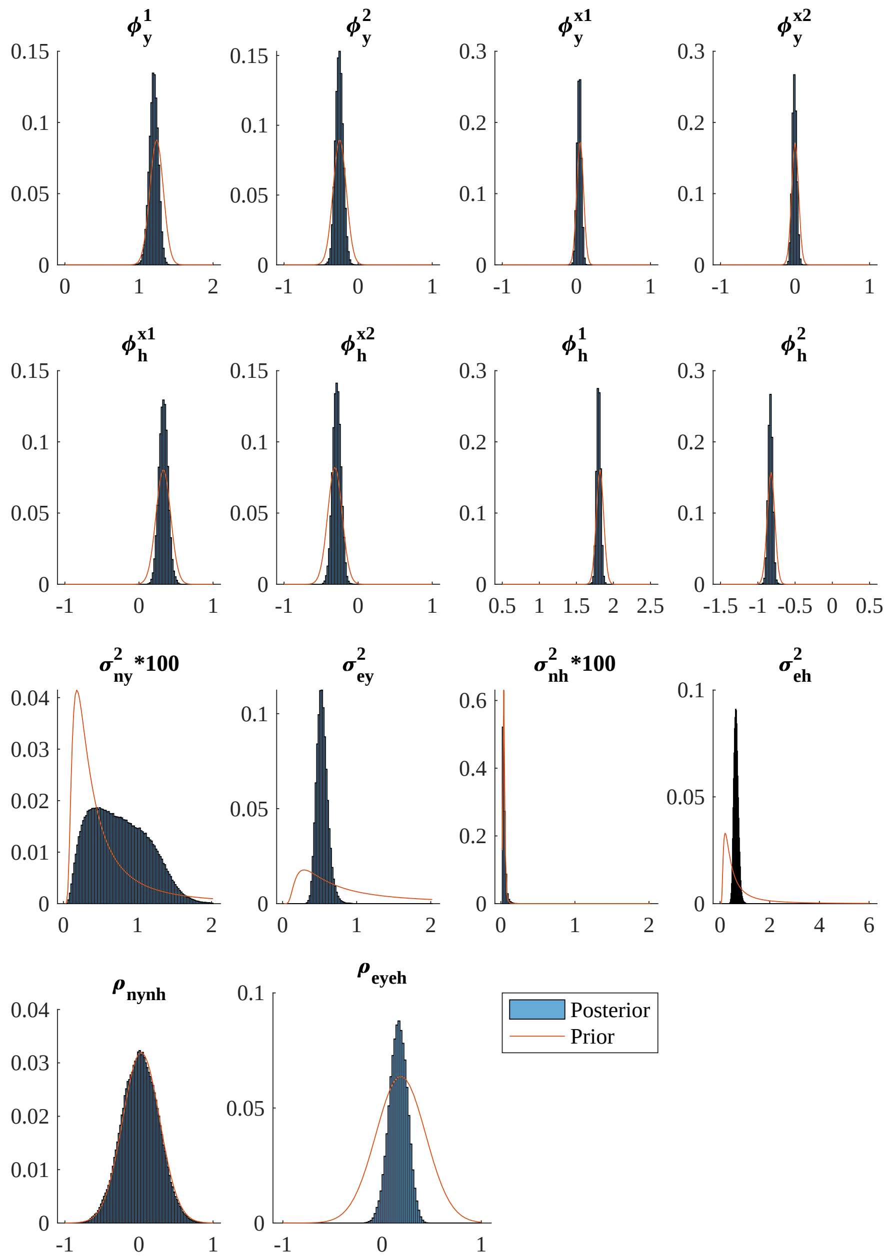

Figure 14: US VAR(2) 2 cross-lags - Posterior and Prior Distribution

9.2 Posterior Chain

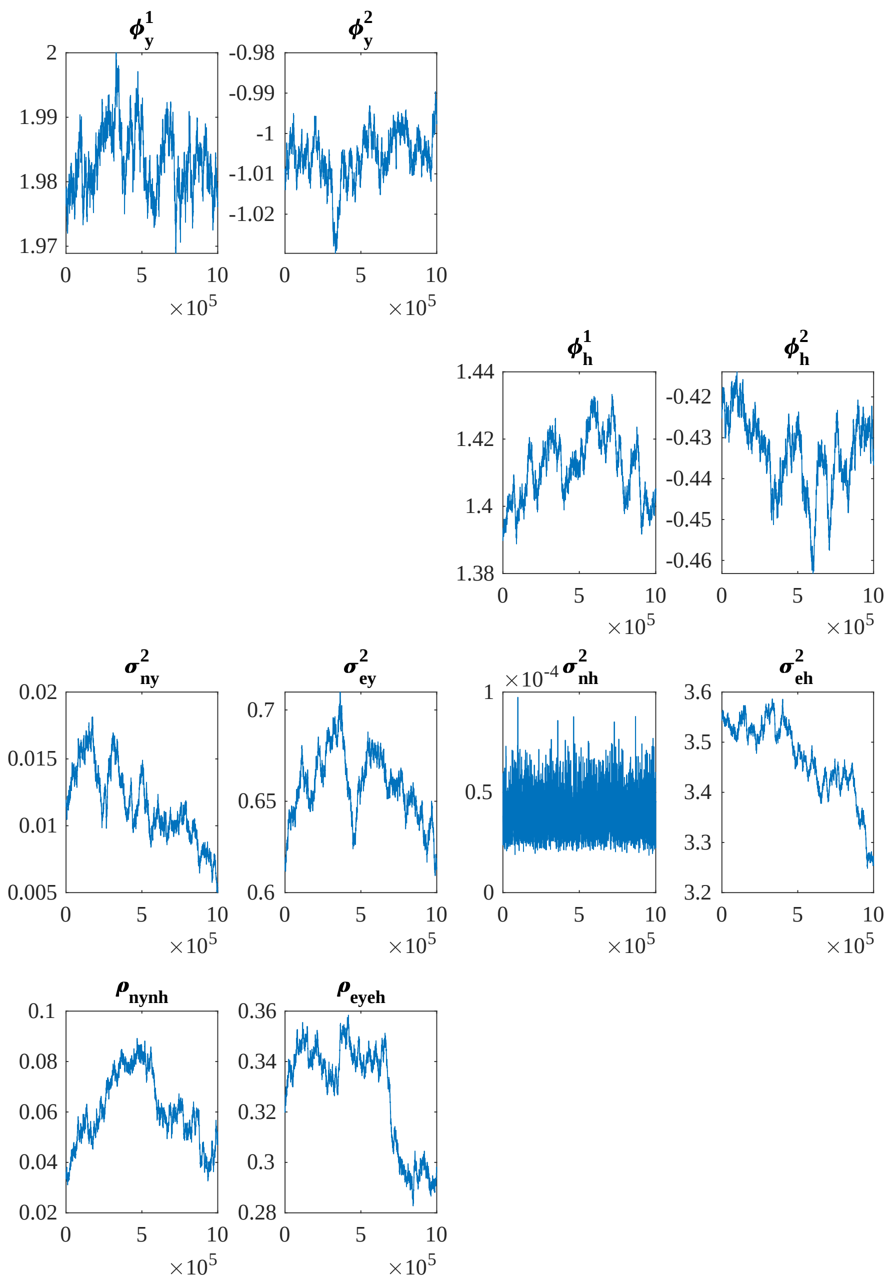

Figure 15: UK VAR(2) - Posterior chain

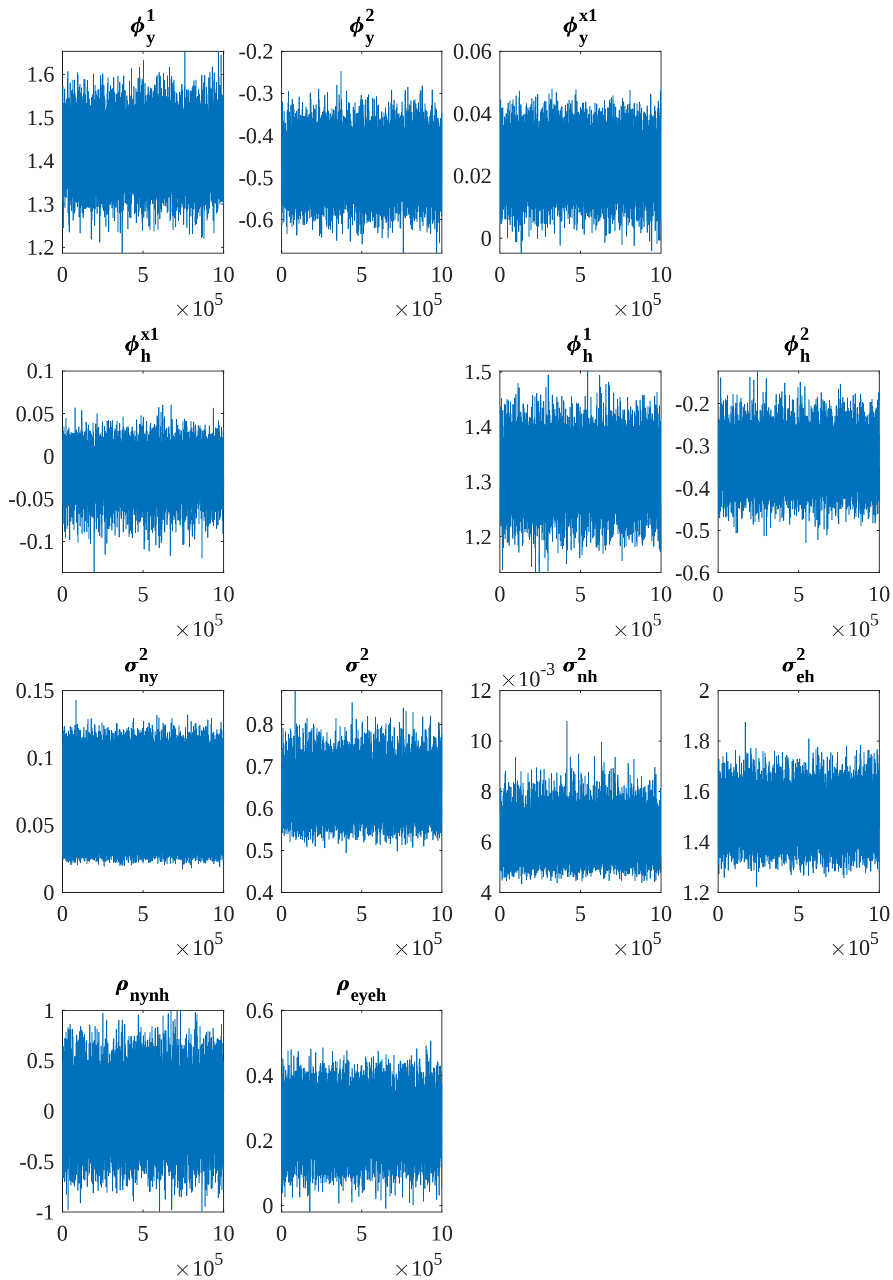

Figure 16: UK VAR(2) 1 cross-lag - Posterior chain

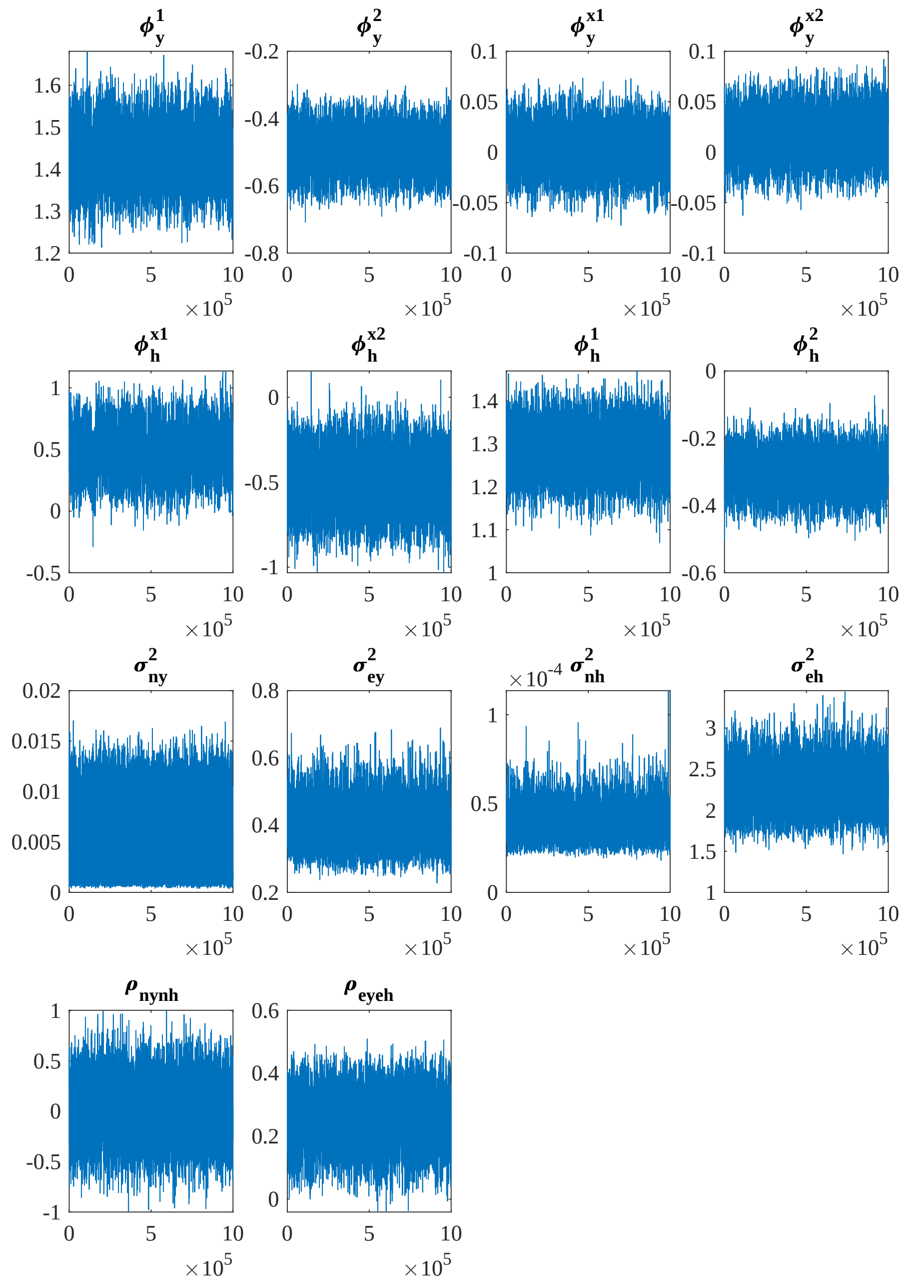

Figure 17: UK VAR(2) 2 cross-lags - Posterior chain

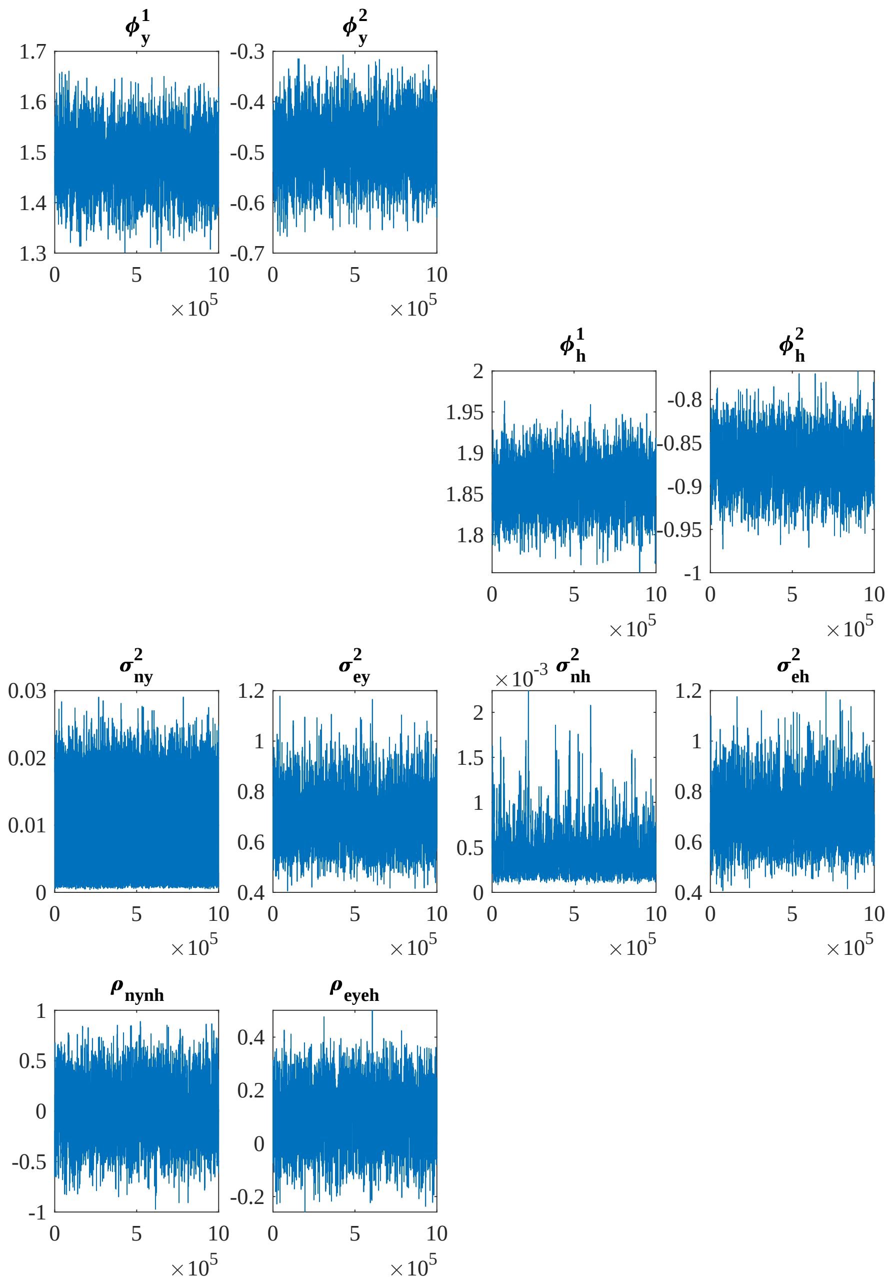

Figure 18: US VAR(2) - Posterior chain

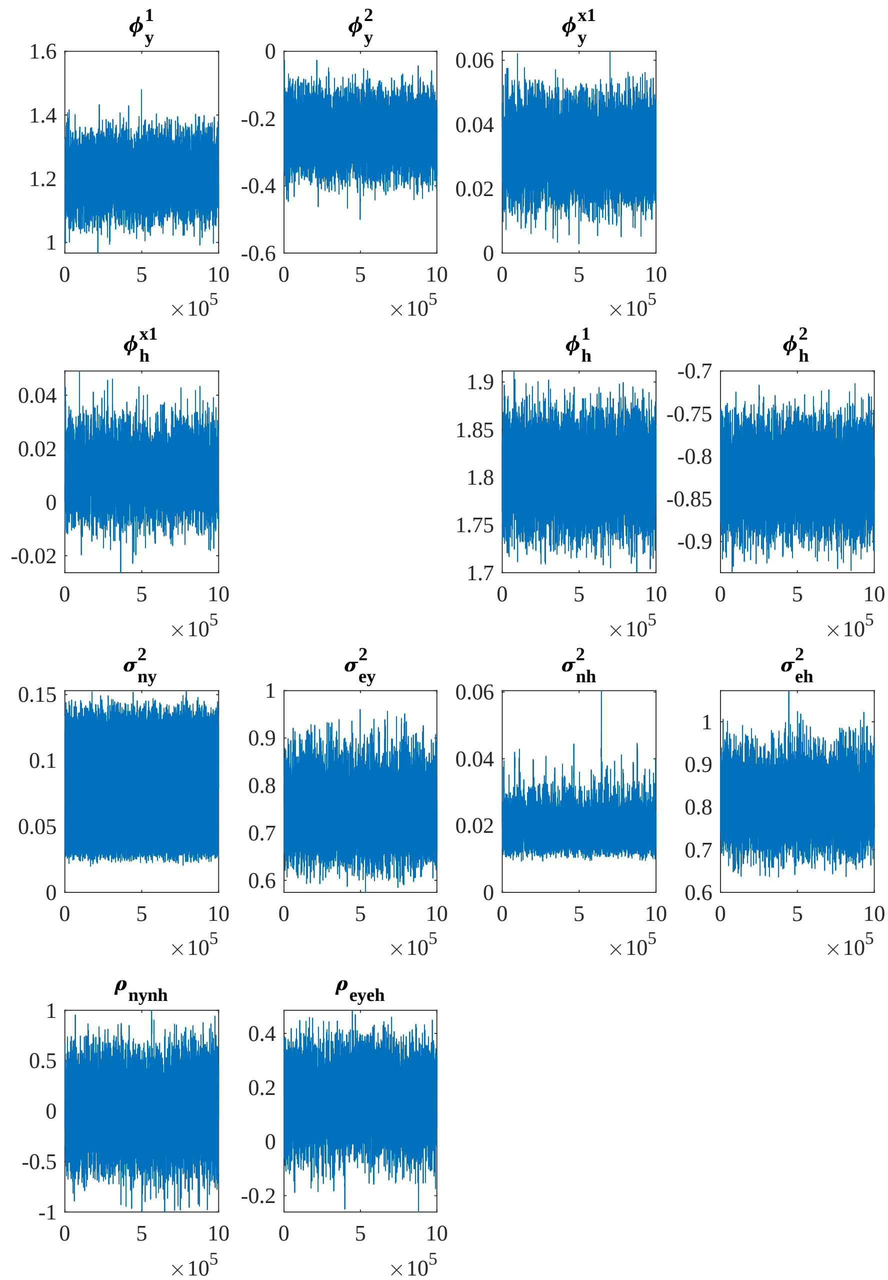

Figure 19: US VAR(2) 1 cross-lag - Posterior chain

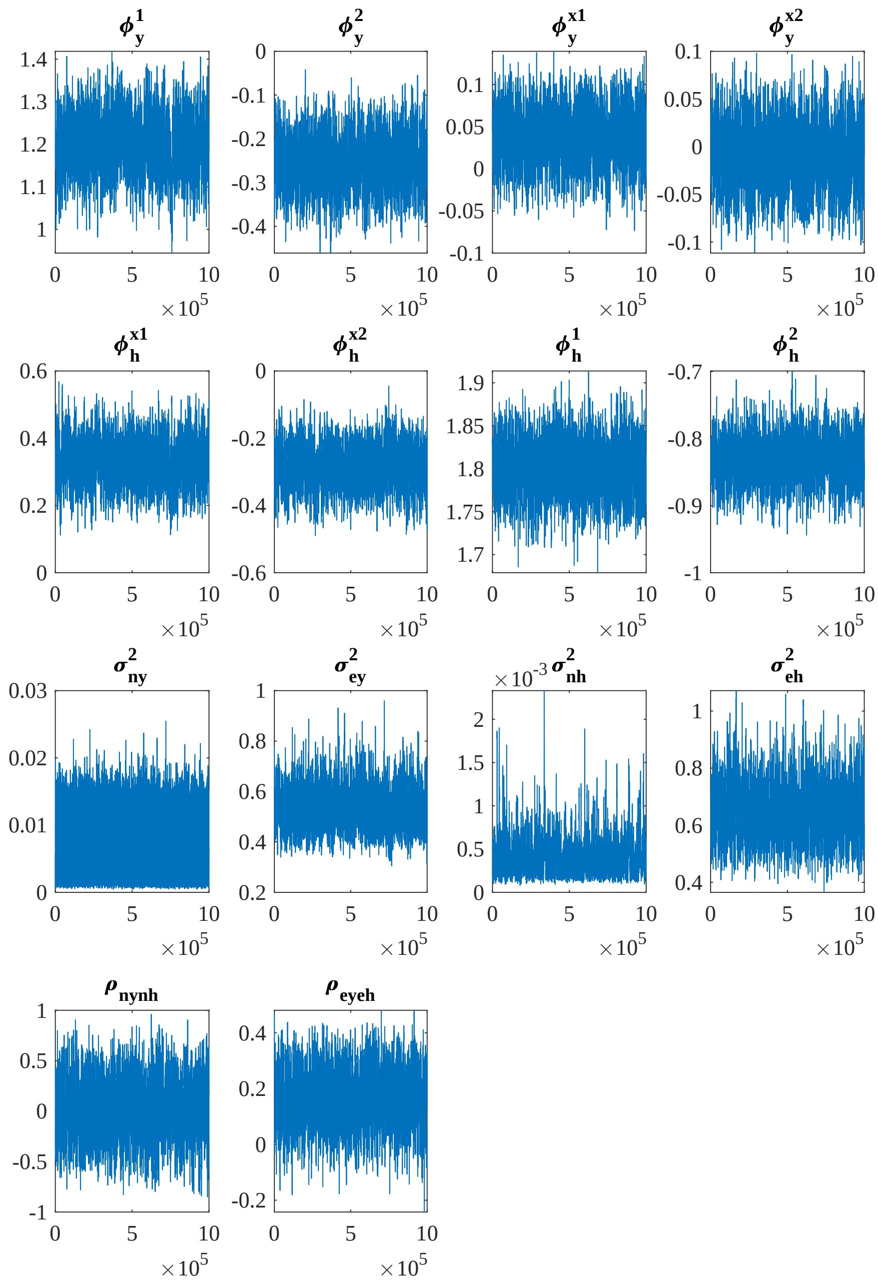

Figure 20: US VAR(2) 2 cross-lags - Posterior chain

9.3 Graphs of other Countries

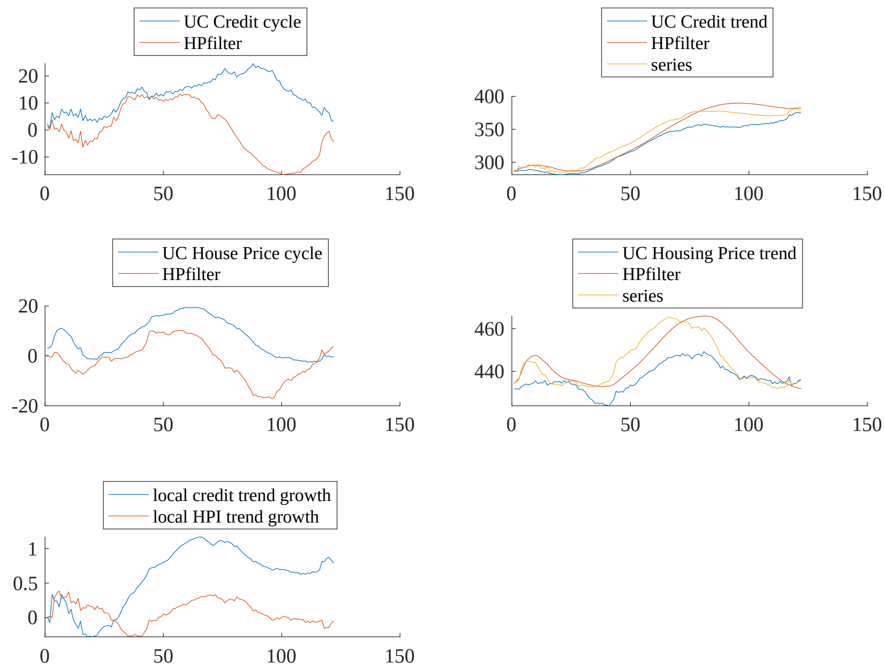

Figure 21: Italy VAR(2) 1 cross-lag - Unobserved Components

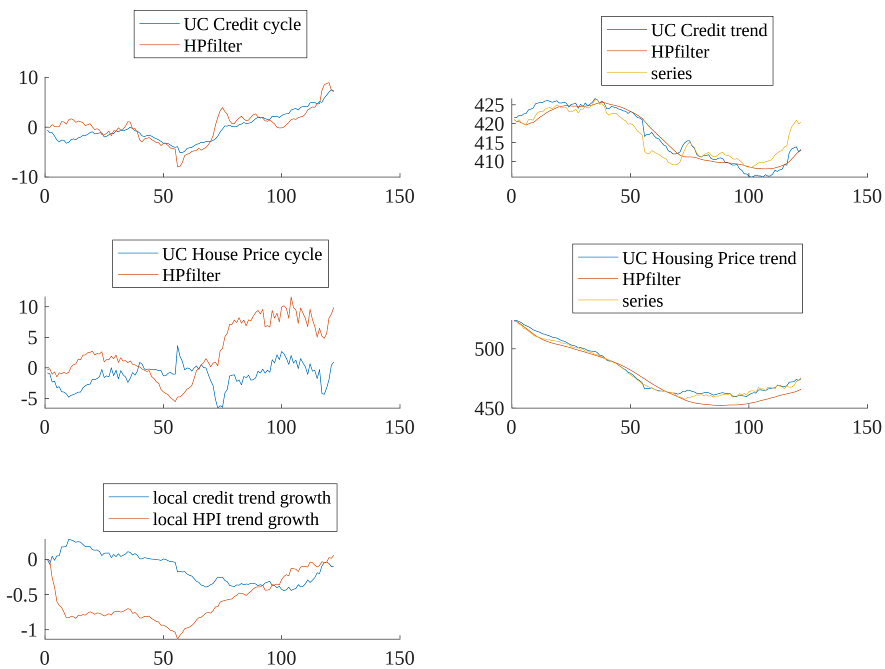

Figure 22: Japan VAR(2) 1 cross-lag - Unobserved Components