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Abstract

This paper uses the multivariate unobserved components model with phase shifts to analyse the interaction of interest rates, output, asset prices and credit in the US. We find close linkages amongst cyclical fluctuations in the variables.

Keywords: Asset Prices, Credit, Business Cycles, Multivariate Unobserved Components Models. **JEL classification:** C32, E32, E44, E51, G0.

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1 Introduction

The severity of the recent financial crisis and the following deep recession has revived interest in the links between asset prices, credit market conditions and economic activity. Economic theory and empirical evidence suggest that developments in financial markets affect the aggregate demand through consumption wealth effects, investment balance sheet effects, and their impact on business confidence. During the boom period, higher credit availability boosts asset prices by expanding liquidity, and the private sector accumulates high levels of debt on the expectation of further rises in asset prices, whilst assets serve as collateral (see e.g. Bordo and Jeanne, 2002). When asset prices fall, the decline in the value of the collateral induces consumers to cut back expenditure and firms to reduce investment spending, leading to additional reductions in asset prices, bank lending and economic output.[1]

A number of recent empirical studies identify strong linkages between financial cycles and business cycles. These studies typically proceed in two steps: firstly, by utilising univariate techniques, such as the Hodrick-Prescott (HP) filter or the Harding and Pagan (2002) algorithm, to identify cyclical fluctuations in asset prices, credit and output; and subsequently by either employing correlation/regression analysis to examine the links between these cyclical components (see e.g. Claessens *et al.* 2011), or by adopting an event study approach (see e.g. Mendoza and Terrones (2008)).[2] This approach, however, does not appropriately account for the endogenous nature of cycles in asset prices, credit and output. Another strand of the literature has utilised VAR analysis in order to deal with endogeneity (see e.g. Assenmacher-Wesche and Gerlach, 2010; Goodhart and Hofmann, 2008).

The novelty of this paper consists in the implementation of a multivariate unobserved components model containing the phase shift mechanism used by Runstler (2004) and Koopman and Azevedo (2008) to investigate feedback effects among monetary policy, credit conditions, asset valuations and real economic activity in the United States (US). Our approach allows us to simultaneously decompose the relevant series into trends and cyclical components at different frequencies (business and longer-term cycles) and accounts for the possibility of common trends and cycles. Therefore, compared with VAR based studies our approach additionally identifies links between cyclical fluctuations in the raw (non-differenced) data at different frequencies and can reveal leading and lagging relationships.[3] Furthermore, in relation to previous studies that

[1]See e.g. Bernanke and Gertler (1989) for a theoretical model with financial frictions which exhibits crucial interactions between asset prices, credit and economic activity.

[2]Having identify credit booms episodes, Mendoza and Terrones (2008) construct seven-year event windows around them to examine the behaviour of macroeconomic and financial indicators.

[3]This addresses the issue discussed by Engle (1974) that the economic variables interact differently across the

examine the links between financial cycles and business cycles, we employ a multivariate structural time-series model that can avoid the potential distortions caused by the use of the HP (see e.g. Harvey and Jaeger, 1993, Cogley and Nason, 1995) and bandpass filters (see e.g. Murray, 2003). Finally, estimated model parameters can provide a more coherent and systematic measure of cyclical correlations.

The paper is structured as follows. Section 2 presents the model. Section 3 describes the dataset and empirical results. Section 4 concludes.

2 Econometric framework

Our basic model allows us to decompose $Y_t = [y_t, r_t, hp_t, sp_t, c_t]'$ to vectors of trends (μ_t), cyclical components, which include short-cycles (ψ_{1t}) and long-cycles (ψ_{2t}), and irregular components (ε_t) such that:

$$Y_t = \mu_t + \psi_{1t} + \psi_{2t} + \varepsilon_t, \quad \varepsilon_t \backsim NID(0, \Sigma_\varepsilon) \tag{1}$$

where $y_t, r_t, hp_t, sp_t, c_t$ denote measures of real output, short-term interest rates, real house prices, real stock prices and credit, respectively.

The trend component intends to filter out low-frequency dynamics from the data and is modelled as multivariate random walk process:

$$\mu_t = \mu_{t-1} + \beta + \eta_t, \quad \eta_t \backsim NID(0, \Sigma_\eta). \tag{2}$$

The consideration of both short-cycles and long-cycles is consistent with Lucas and Koopman (2005), and provides the best fit for our dataset. These cyclical components are modelled using the first-order trigonometric cycle specification introduced by Harvey and Jaeger (1993):

$$\begin{bmatrix} \psi_{it} \\ \psi^*_{it} \end{bmatrix} = \phi_i \begin{bmatrix} \cos(\lambda_i) I_N & \sin(\lambda_i) I_N \\ -\sin(\lambda_i) I_N & \cos(\lambda_i) I_N \end{bmatrix} \begin{bmatrix} \psi_{it-1} \\ \psi^*_{it-1} \end{bmatrix} + \begin{bmatrix} \kappa_{it} \\ \kappa^*_{it} \end{bmatrix}, \tag{3}$$

$$Var \begin{bmatrix} \kappa_{it} \\ \kappa^*_{it} \end{bmatrix} = \begin{bmatrix} \Sigma_{i\kappa} & 0 \\ 0 & \Sigma_{i\kappa} \end{bmatrix},$$

where $i = 1, 2$ and $N = 5$. Both κ_{it} and κ^*_{it} are serially and mutually uncorrelated. The parameters $0 \leq \phi_i < 1$ and λ_i denote the damping factor and cycle frequency, respectively. The

frequency spectrum.

duration of the cycle is equal to $2\pi/\lambda_i$

In order to account for the possibility of leading/lagging relationships between the cyclical components of the different economic and financial variables contained in our system, we include a phase shift mechanism (see also Runstler, 2004; Koopman and Azevedo, 2008) in Eq. (1):

$$\begin{aligned} Y_t &= \mu_t + diag\left\{\cos\left(\lambda_1 \xi\right)\right\} \psi_{1t} + diag\left\{\sin\left(\lambda_1 \xi\right)\right\} \psi_{1t}^* \\ &\quad + diag\left\{\cos\left(\lambda_2 \zeta\right)\right\} \psi_{2t} + diag\left\{\sin\left(\lambda_2 \zeta\right)\right\} \psi_{2t}^* + \varepsilon_t, \end{aligned} \tag{4}$$

where ξ and ζ are (5×1) vectors:

$$\begin{aligned} \xi &= \left[\xi_1, \xi_2, \xi_3, \xi_4, \xi_5\right], \\ \zeta &= \left[\zeta_1, \zeta_2, \zeta_3, \zeta_4, \zeta_5\right], \end{aligned} \tag{5}$$

The elements in ξ and ζ measure the phase shifts between short-cycles and long-cycles, respectively. In order to provide a clear interpretation of the leading and lagging relationships between cyclical components in the five time-series, we restrict the first elements, ξ_1 and ζ_1, to zero. As real GDP is the first variable in the Y_t vector, the short and long output cycles are used as the reference for the phase shifts of the remaining cycles in ψ_{1t} and ψ_{2t}. The phase shift between the two short (long) cycles, j and k, is calculated as $\xi_j - \xi_k$ $(\zeta_j - \zeta_k)$ for $j, k = 1, ..., 5$, with a positive value indicating that cycle k leads cycle j, and vise versa, while a zero value implies that cycles are concurrent.

Cycles are related through their disturbances (κ_{it}) as implied by the variance-covariance matrix $\Sigma_{i\kappa}$ which can be expressed using the Choleski decomposition:

$$\Sigma_{i\kappa} = A_{i\kappa} D_{i\kappa} A_{i\kappa}'.$$

If $\Sigma_{i\kappa}$ has full rank, all cycles have their own unique source of variance but may be still correlated with each other via the off-diagonal elements. However, if the rank of $\Sigma_{i\kappa}$ is less than full, common cyclical components exist. In this case, $A_{i\kappa}$ is a $(5 \times r_{i\kappa})$ lower unity triangular matrix and $D_{i\kappa}$ is a $(r_{ik} \times r_{i\kappa})$ diagonal matrix, where $r_{i\kappa} < 5$. This rank-related principle also applies to the trend and irregular components.

Finally, the autocovariance function subject to phase shifts for ψ_{it} is defined as:

$$\begin{aligned} \Gamma(s) &= \phi_1^{|s|} \left(1-\phi_1^2\right)^{-1} \Sigma_{i\kappa} \odot \cos(\Lambda_s), \Lambda_s = \lambda(s\mathbf{1}\mathbf{1}' + \mathbf{1}\xi_{ij}' - \xi_{ij}\mathbf{1}'), \\ s &= 0, 1, 2..., \end{aligned} \tag{6}$$

where $\mathbf{1}$ is a vector $(1, ...1)'$.

We adopt the Bayesian approach to estimate the model parameters and the unobserved components. By combining the prior distribution with the likelihood function evaluated using the Kalman filter, we obtain the posterior distribution of parameters.[4] A random walk Metropolis-Hastings algorithm is used to generate a million draws from the posterior distribution. To ensure convergence, we discard the first 400,000 draws and take every 50th draw from the last 600,000 draws.[5]

3 Data and empirical results

Quarterly data on the real GDP (y_t), the federal funds rate (r_t), real house prices (hp_t), real stock prices (sp_t) and total credit (c_t; sum of business, consumer and real estate loans) were collected for the US over the period 1965Q1-2010Q3.[6]

Our results support the presence of common cyclical components at both short-run and longer-run frequencies, while the evidence in favor of common trend components is not particularly strong.[7] Table 1 reports estimates of the common cycle model with phase shifts. Specifically, the preferred specification contains three short common cycles and four long common cycles, thereby indicating that the cyclical components are more correlated in the shorter-run. The duration of the cycles is estimated to around 6 and 15 years for the short-run and the longer-run components, respectively. Therefore, the former (short-run cycle) corresponds to the business cycle frequency. The posterior means and standard deviations of the phase shifts provide stronger indication that cycles are not concurrent in the business cycle frequency, as opposed to the longer-run. Specifically, focusing on the business cycle frequency results, we find that output cycles lead those in interest rates and credit, by around four quarters, thereby suggesting that developments in the real economy influence the future path of both the price and

[4]We set the variance of the proposal distribution equal to the scaled inverse Hessian obtained from the numerical maximisation. The scaling parameter is chosen to ensure an acceptance rate of 25%-40%. The prior distribution for the parameters is available upon request.

[5]Geweke convergence diagnostics for the model parameters are available upon request.

[6]Our data source is the FRED database (http://research.stlouisfed.org/fred2/). Nominal asset prices and credit were converted into real terms using the consumer price index.

[7]Marginal log-likelihood values are available upon request.

quantity of credit. Stock price cycles tend to lead output cycles by around two quarters but the evidence is statistically weak. Finally, house price and output cycles appear to be concordant.

Tables 2 and 3 show the cross-correlations of the variables' cyclical components at the business cycle and longer-run frequency, respectively, implied by Eq. (6). The magnitude of the cross-sectional correlations shown in Tables 2 and 3 is consistent with the phase-shift evidence in Table 1. For instance, as shown in Table 3, in the longer run all correlations are maximized (in absolute value) at $t = 0$ in line with the findings that the phase-shifts between longer cycles are statistically insignificant from zero.

We find that the longer-run output cycle is positively correlated with asset prices, while the longer-run cyclical component of interest rates is negatively correlated with that of both output and asset prices at all leads and lags. These findings are in line with the present value approach to asset pricing. At the business cycle frequency, we find that output and asset price cycles lead the interest rate cycle in a pro-cyclical fashion, while their lagged values are negatively correlated with the interest rate cycle. This suggests that a rise in output and asset prices tends to be followed by higher interest rates, while rising interest rates will negatively impact both output and asset prices. In addition, the house price (stock price) cycle appears to be more strongly related to output cycles in the business cycle (longer-run) frequency, potentially indicating that in the longer-run, other fundamentals, such as supply side factors, may also be important for property market developments. Furthermore, the correlation between stock and house price cyclical components is positive and much stronger in the business cycle frequency.

In the longer-run, the relationship between asset prices and credit cycles is positive both at leads and lags. This evidence is consistent with the role of assets as collateral, whereby a rise in asset prices leads to higher credit, and with (positive) liquidity effects on asset prices from higher credit availability. At the business-cycle frequency, asset price cycles lead the credit cycle; however, lagged asset price cycles are negatively related to the credit cycle, suggesting that a rise in credit leads to lower asset prices via higher interest rates. Specifically, while in the longer-run credit and interest rate cycles are negatively related, in line with credit demand arguments, the business cycle frequency correlation is positive which may suggest that monetary policy tightens when credit booms.

Figures 1 and 2 plot the cyclical components of the variables at the business cycle and long-run frequency, respectively. In Figure 1 we can see that cyclical downturns in output at the business cycle frequency closely match the NBER recession periods. We can also observe that output cycles lead interest rates and credit cycles. Moreover, at the business cycle frequency, stock market upturns and downturns are much more severe than those in output, while house price and credit fluctuations are more aligned with the output cycle. On the other hand, as we can see in Figure 2, since the mid-1980s longer-run house price and credit booms and busts are more pronounced in comparison with output fluctuations. This suggests that credit and house prices have become more volatile during the period of financial liberalisation.

4 Conclusions

This paper uses the multivariate unobserved components model with phase shifts to analyse the interaction among interest rates, output, asset prices and credit in the US. We find that in the longer run the cyclical components of these variables are concurrent and asset prices are consistent with the underlying fundamentals in line with the present value approach to asset valuation. At the business cycle frequency, output and asset prices tend to lead interest rate and credit in a pro-cyclical fashion.

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Table 1: Phase-shifts and cycles

	Business Cycle				Longer Cycle			
	Prior ξ_j		Posterior ξ_j		Prior ζ_j		Posterior ζ_j	
	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.
r_t	0.00	2.50	-4.050	0.912	0.00	2.50	0.653	2.446
sp_t	0.00	2.50	1.888	1.248	0.00	2.50	0.917	2.321
hp_t	0.00	2.50	0.121	0.936	0.00	2.50	-0.360	2.374
c_t	0.00	2.50	-4.052	0.918	0.00	2.50	-0.568	2.382
	Prior ϕ_1		Posterior ϕ_1		Prior ϕ_2		Posterior ϕ_2	
	0.50	0.20	0.962	0.012	0.50	0.20	0.983	0.006
	Prior λ_1		Posterior λ_1		Prior λ_2		Posterior λ_2	
	0.314	0.10	0.256	0.022	0.157	0.10	0.100	0.012

Notes: Phase shifts are measured in quarters.

Table 2: Cross-correlation for business cycles

s	-6	-4	-3	-2	-1	0	1	2	3	4	6
$\psi^y_{1t+s}, \psi^r_{1t}$	0.636	0.783	**0.784**	0.732	0.624	0.465	0.241	0.019	-0.189	-0.368	-0.610
$\psi^y_{1t+s}, \psi^{sp}_{1t}$	-0.283	0.045	0.230	0.415	0.586	0.730	**0.773**	0.763	0.704	0.605	0.324
$\psi^y_{1t+s}, \psi^{hp}_{1t}$	0.003	0.400	0.589	0.751	0.875	**0.947**	0.889	0.778	0.625	0.443	0.049
$\psi^y_{1t+s}, \psi^c_{1t}$	0.621	0.764	**0.766**	0.714	0.609	0.454	0.235	0.018	-0.185	-0.360	-0.596
$\psi^r_{1t+s}, \psi^{sp}_{1t}$	-0.625	-0.560	-0.463	-0.326	-0.155	0.040	0.230	0.390	0.514	0.596	**0.627**
$\psi^r_{1t+s}, \psi^{hp}_{1t}$	-0.673	-0.422	-0.231	-0.008	0.233	0.477	0.655	0.777	0.841	**0.846**	0.699
$\psi^r_{1t+s}, \psi^c_{1t}$	0.018	0.292	0.419	0.528	0.609	**0.655**	0.609	0.528	0.419	0.291	0.018
$\psi^{sp}_{1t+s}, \psi^{hp}_{1t}$	0.321	0.624	0.733	0.800	**0.817**	0.779	0.632	0.457	0.265	0.070	-0.278
$\psi^{sp}_{1t+s}, \psi^c_{1t}$	**0.458**	0.436	0.376	0.285	0.168	0.029	-0.114	-0.239	-0.339	-0.410	-0.457
$\psi^{hp}_{1t+s}, \psi^c_{1t}$	0.498	**0.603**	0.599	0.553	0.466	0.339	0.165	-0.006	-0.165	-0.300	-0.480

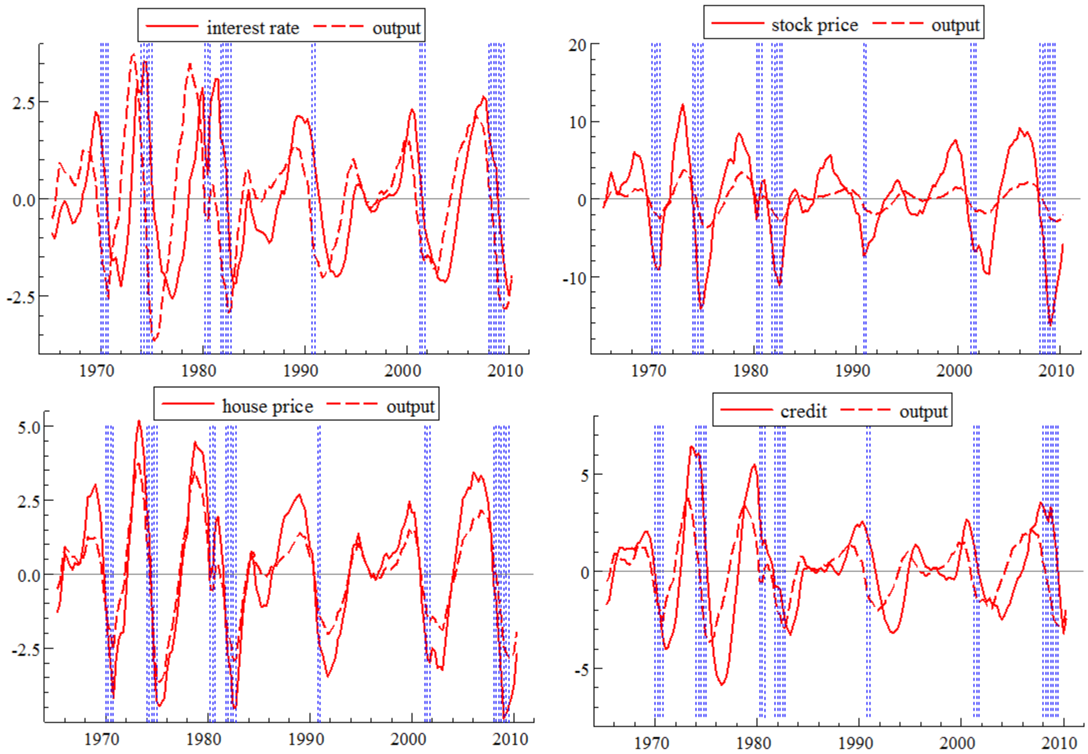
Notes: s denotes the number of leads ($s < 0$) and lags ($s > 0$) in quarters of the first variable with respect to the second variable in the first column. Bold indicates the highest correlation (in absolute value).

Table 3: Cross-correlation for long cycles

s	-12	-8	-6	-4	-1	0	1	4	6	8	12
$\psi^y_{2t+s}, \psi^r_{2t}$	-0.181	-0.418	-0.525	-0.617	-0.717	**-0.738**	-0.727	-0.652	-0.574	-0.479	-0.254
$\psi^y_{2t+s}, \psi^{sp}_{2t}$	0.186	0.454	0.576	0.683	0.800	**0.826**	0.815	0.738	0.654	0.549	0.301
$\psi^y_{2t+s}, \psi^{hp}_{2t}$	0.109	0.212	0.257	0.294	0.331	**0.337**	0.328	0.285	0.245	0.197	0.090
$\psi^y_{2t+s}, \psi^c_{2t}$	0.241	0.459	0.552	0.628	0.702	**0.713**	0.694	0.599	0.511	0.408	0.180
$\psi^r_{2t+s}, \psi^{sp}_{2t}$	-0.155	-0.334	-0.413	-0.481	-0.551	**-0.565**	-0.554	-0.492	-0.429	-0.353	-0.178
$\psi^r_{2t+s}, \psi^{hp}_{2t}$	-0.076	-0.138	-0.164	-0.184	-0.203	**-0.205**	-0.199	-0.169	-0.142	-0.112	-0.045
$\psi^r_{2t+s}, \psi^c_{2t}$	-0.196	-0.345	-0.407	-0.456	-0.499	**-0.504**	-0.487	-0.411	-0.344	-0.267	-0.102
$\psi^{sp}_{2t+s}, \psi^{hp}_{2t}$	0.129	0.226	0.266	0.298	0.325	**0.328**	0.317	0.267	0.223	0.173	0.065
$\psi^{sp}_{2t+s}, \psi^c_{2t}$	0.355	0.609	0.713	0.794	0.862	**0.868**	0.837	0.700	0.580	0.446	0.158
$\psi^{hp}_{2t+s}, \psi^c_{2t}$	0.227	0.454	0.553	0.635	0.717	**0.732**	0.714	0.624	0.537	0.435	0.204

Notes: See Table 2 Notes.

Figure 1: Business cycle components



Notes: Shaded areas correspond to NBER recession periods.

Figure 2: Long-term cycle components