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Abstract

The 2007 sub-prime crisis in the United States, prolonged by a severe economic recession spread over many countries around the world, has led many economic researchers to focus on the recent fluctuations in housing prices and their relationships with macroeconomics and monetary policies. The existence of common housing cycles among the countries of the euro zone could lead the European Central Bank to integrate more specifically the evolution of such asset prices in its assessment. In this paper, we implement a multivariate unobserved component model on housing market variables in order to assess the common euro area housing cycle and to evaluate its relationship with the economic cycle. Among the general class of multivariate unobserved component models, we implement the band-pass filter based on the trend plus cycle decomposition model and we allow the existence of two cycles of different periods. The dataset consists of gross domestic product and real house prices series for four main euro area countries (Germany, France, Italy and Spain). Empirical results show a strong relationship for business cycles in France, Italy and Spain. Moreover, French and Spanish house prices cycles appear to be strongly related, while the German one possesses its own dynamics. Finally, we find that GDP and house prices cycles are related in the medium-term for fluctuations between 4 and 8 years, while the housing market contributes to the long-term economic growth only in Spain and Germany.

Keywords: House prices, Business cycles, Euro area, Unobserved components model.

JEL codes: C13, C32, E32, R21

Résumé

La crise américaine des sub-primes, prolongée par une sévère récession économique mondiale, a incité de nombreux chercheurs à s'intéresser aux fluctuations récentes des prix de l'immobilier résidentiel et à leurs liens avec la macroéconomie et les politiques monétaires. L'existence d'un cycle immobilier commun aux principaux pays de la zone euro pourrait conduire la BCE à intégrer plus précisément l'évolution de ce type d'actif dans son évaluation des conditions économiques pour mener à bien sa politique montaire. Dans ce papier, nous implémentons un modèle multivarié à composantes inobservables sur des variables de prix immobiliers afin d'évaluer l'existence d'un cycle commun à ces variables ainsi que sa dépendance au cycle économique. Parmi la classe des modèles multivariés à composantes inobservables, nous utilisons les modèles dits de *filtre passe-bande*, basés sur une décomposition tendance-cycle des séries, et nous permettons aux modèles d'exhiber deux cycles de fréquences différentes. Le jeu de données utilisé est constitué des séries de PIB et de prix réels de l'immobilier résidentiel pour les quatre principaux pays de la zone euro (Allemagne, France, Italie, Espagne). Les résultats empiriques montrent une relation de forte intensité entre les cycles du PIB français, italiens et espagnols. De plus, les cycles immobiliers français et espagnols apparaissent fortement reliés, alors que le cycle allemand possède sa propre dynamique. Enfin, nous trouvons que les cycles du PIB et de l'immobilier sont reliés sur le moyen terme, pour des fluctuations variant entre 4 et 8 ans, alors que le marché immobilier ne contribue à la croissance économique de long terme uniquement en Espagne et en Allemagne.

Mots clés: Prix immobiliers, Cycles économiques, Zone euro, Modéles à composantes inobservables

Codes JEL: C13, C32, E32, R21

1 Introduction

According to European treaties, the main objective of the Eurosystem is to maintain price stability through a two pillars strategy. In opposition to the Fed, the ECB has clarified that price stability is measured by inflation rates of below, but close to, 2% over the medium term. To get this target, the first pillar consists in an analysis based on a large set of economic and financial indicators and the second pillar gives a role to the money. In this respect, it is well known that asset prices are variables of great interest in the conduct of monetary policy and will certainly be more and more integrated in the future in the monetary policy makers decision process.
Especially, among all asset prices, the monitoring of housing prices is one of the element of regular assessments carried out by central banks. Indeed, housing finance has an impact on the transmission of monetary policy to the economy and a better understanding of the housing sector could lead to more accurate inflation forecasts. Recently, some researchers have put forward that central banks should rather target asset prices instead of inflation in their strategy. For example, Leamer (2007) proposes a monetary policy based on housing starts rather than output gap.

Since the summer 2007 the evolution of housing prices has raised concern as highlighted by the US sub-prime crisis that had strongly affected macroeconomic fluctuations in most of the industrialized countries. Recent economic recessions experienced in those countries have shed light on the role of the housing sector and have led researchers and economists to investigate this specific sector. Regarding the aggregated euro area, assessment of house prices is generally carried out by considering the euro area as whole. However, this evaluation at the aggregate level can hide some country-specific fluctuations. Indeed, to our knowledge, there is no evidence that euro area members housing cycles are synchronized, although several papers have shown that the euro area business and growth cycles cycles are meaningful (see, for example, Anas, Billio, Ferrara & Mazzi (2008) for a review of various euro area cycles dating). The existence of a common housing cycle among the countries of the zone could lead ECB to integrate more easily the evolution of this specific asset price in its assessment. On the other side, if country-specific cycles were too large, this would complicate the task of the ECB.

A wide number of empirical papers have pointed out the existing relationship between housing and business cycles. For example, Leamer (2007) compares the US housing market cycle and the US business cycle as defined by the Dating Committee of the NBER, from 1947 to 2006. By using the contributions to GDP growth during the 8 phases of recession covering the whole period, Leamer points out that the business cycle is in fact a consumer cycle mainly driven by residential investment. Consequently, the author argues that residential investment can be seen as an accurate early warning of oncoming recession. Ahearne, Ammer, Doyle, Kole & Martin (2005) find that real house prices are pro-cyclical, that is co-moving with real GDP, consumption, investment, CPI, budget and current account balances and output gaps. They note also that house price booms are typically preceded by a period of easing monetary policy, but then diminishing slack and rising inflation lead monetary authorities to begin tightening policy before house price peak. We also refer to Iacovello (2005), for a theoretical monetary business cycle model that formalizes the interaction between house prices and the business cycle, or to Goodhart & Hofmann (2008) for empirical evidence of a "significant multidirectional link between house prices, broad money, private credit and the macroeconomy".

Generally, econometric methods involved in empirical comparison of cross-country housing cycles rely on graphical inspection of peaks and troughs as in Ahearne et al. (2005) or standard non-parametric tools, such as contemporaneous or cross-correlations as proposed by Catte, Girouard, Price & André (2004) or Alvarez, Bulligan, Cabrero, Ferrara & Stahl (2009). Parametric modelling has been also requested in order to estimate housing cycles. For example, probit regressions have been considered by Borio & McGuire (2004), van den Noord (2006) or Cunningham & Kolet (2007) in order to estimate the probability of an upcoming peak in the housing cycle. Terrones (2004) explains house prices fluctuations and co-movements by using a dynamic factor model for house price growth and six other key variables applied to 13 industrial countries. Del Negro & Otrok (2007) estimate also a dynamic factor model for the US states to differentiate a common cycle in house prices from local state-specific cycles. Ceron & Suarez (2004) applied various multivariate extensions of the Markov-Switching model in order to discriminate between a common cyclical component and country-specific component on housing prices. They also include in the models four variables with a potential impact on housing cycle, namely GDP growth, unemployment rate, interest rates and inflation rate. VAR models have been also considered to relate housing prices shocks, monetary policy and macroeconomic variables. For example, Del Negro & Otrok (2007) implement a VAR model to assess to what extend expansionary monetary policy in the US is responsible for the increase in houses prices. Also Vargas-Silva (2008) examines the impact of monetary policy shocks on the US housing market using a restricted VAR model. In the multi-country framework, Goodhart & Hofmann (2008) or Assenmacher-Wesche & Gerlach (2009) estimate a panel VAR model with 17 OECD countries including quarterly variables such as GDP, house prices, consumer price index, interest rates.

In this paper, we present an econometric analysis based on unobserved component time series models to capture the house price cycle among the four main euro area countries (Germany, France, Italy and Spain, representing around 80% of the euro area GDP) and to assess its relationship with the economic growth cycle. The class of unobserved component models as introduced by Harvey (1989) can be effective in the signal extraction of business cycles. We refer for example to Azevedo, Koopman & Rua (2006) for a macroeconomic business cycle application in a multivariate setting. We consider the multivariate unobserved component model for modeling housing price fluctuations and business cycles simultaneously. Fadiga & Wang (2009) have also adopted an unobserved component model in their successful approach for identifying common movements and dynamics in the house prices of four main U.S. regions. By specifying different multivariate decomposition models, we empirically identify common trends and cycles in GDP and house price series in the four euro area countries for the period from 1981 to 2008. Specifically, we find a strong relationship for macroeconomic growth cycles in France, Italy and

Spain. Moreover, French and Spanish house price cycles appear to be strongly related, while the German one possess its own dynamics. Finally, we find that the GDP and house prices cycles are related in the medium-term for fluctuations between 4 and 8 years, while the housing market contributes to the long-term economic growth only in Spain and Germany.

2 Unobserved components time series models

Our aim is to show empirical relationships between macroeconomic and housing cycles for Germany, France, Italy and Spain. We focus on the two key variables Gross Domestic Product (GDP) and real house prices (RHP). The unobserved components (UC) time series model provides a valuable methodology for the econometric analysis of time series, see Harvey (1989) for a complete treatment. While an univariate UC model can be regarded as a pure time series model, the multivariate extension allows the establishment of dynamic relations between different time series which may have an economic interpretation. These dynamic interactions can be disentangled into short, medium and long term effects. In this section we introduce our multivariate UC approach for the purpose of analyzing the dynamics of the GDP series and real house prices for the four euro zone countries (France, Germany, Italy and Spain) with the purpose of studying the dynamic relations between the business and housing market cycles. First we briefly introduce the univariate basic form of the model and provide some details of the model which are needed for an understanding of our analysis.

2.1 Univariate unobserved component models

In an UC model, the observed time series is disentangled into components that are formulated as stochastic functions of time and are designed to represent dynamic features such as trend, cycle and irregular noise. A basic decomposition for many macroeconomic time series (in logs) can be based on trend, cycle and noise components where the trend is modelled as a slowly evolving process, the cycle is typically based on a stationary autoregressive moving average (ARMA) process and the noise is often taken as a Gaussian white noise process. The cyclical dynamics for the cycle component can be enforced by having complex characteristic roots in the autoregressive polynomial. It is straightforward in a UC model to introduce additional features such as explanatory variables, interventions and seasonal components. This flexibility is due to the fact that the UC model can be regarded as a special case of the state space model. Therefore, parameter estimation and the signal extraction of the components can be based on the Kalman filter and its related smoothing algorithms. In the state space framework, we can treat multivariate time series, missing observations, mixed frequencies, unevenly recorded data and other data irregularities as part of the standard methodology. A detailed treatment of state space methods is presented in Durbin & Koopman (2001).

We assume that the time series $\{ Y_t \}$ is observed which we routinely transform into logs, that is

$$y_t = \log Y_t, \qquad t = 1, \ldots, n. \tag{1}$$

The UC model decomposes y_t into additive stochastic components as given by

$$y_t = \mu_t + \psi_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{NID}(0, \sigma_\varepsilon^2), \qquad t = 1, \ldots, n, \tag{2}$$

where μ_t represents the trend, ψ_t the cycle component and ε_t the irregular disturbance term. The trend component μ_t in (2) is specified in our applications by the local linear trend model as given by

$$\begin{aligned} \mu_{t+1} &= \mu_t + \beta_t + \eta_t, & \eta_t &\sim \text{NID}(0, \sigma_\eta^2), \\ \beta_{t+1} &= \beta_t + \zeta_t, & \zeta_t &\sim \text{NID}(0, \sigma_\zeta^2), \end{aligned} \tag{3}$$

where β_t represents the drift or slope of the trend μ_t and the disturbances ε_t, η_t and ζ_t are mutually uncorrelated at all lags and leads, for $t = 1, \ldots, n$. Some notable limiting cases of this specification include: if $\sigma_\zeta \to 0$ while σ_η is nonzero the trend is a random walk with drift β_1; if $\sigma_\eta \to 0$ while σ_ζ is nonzero the trend follows a smooth integrated random walk; when both tend to zero, μ_t reverts to a deterministic linear trend. In our empirical section we use a smooth trend specification by restricting σ_η^2 to zero. The initial values of μ_1, β_1 are generally unknown, and will be represented by non-informative or *diffuse* initial distributions.

Fluctuations in economic time series associated with medium-term frequencies related to periods between 1.5 and 8 years are typically interpreted as the business cycle, see Baxter & King (1999)[1]. The dynamic effects related to these medium frequencies appear often less pronounced in the observed economic time series and tend to be of a stationary nature. To incorporare the cyclical dynamics in the time series model, we have the stochastic cyclical component ψ_t with

$$\begin{pmatrix} \psi_{t+1} \\ \psi_{t+1}^* \end{pmatrix} = \rho \begin{bmatrix} \cos\lambda^c & \sin\lambda^c \\ -\sin\lambda^c & \cos\lambda^c \end{bmatrix} \begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix}, \qquad \begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix} \sim \text{NID}(0, \sigma_\kappa^2 I_2), \tag{4}$$

where the three unknown coefficients λ^c, ρ and σ_κ^2 in the cycle equation (4) represent, respectively, the cyclical frequency, the damping factor and the cycle disturbance variance, respectively. The period of the cycle is given by $2\pi/\lambda^c$. For $|\rho| < 1$, $0 < \lambda < \pi$, the cycle ψ_t and the auxilary process ψ_t^* are stationary ARMA(2,1) processes, with variance $\sigma_\kappa^2/(1-\rho^2)$. The cycle collapses into an AR(1) process when λ^c approaches zero. The cycle process (4) is stationary when $|\rho| < 1$ and its unconditional distribution provides the properly defined initial conditions for ψ_t and ψ_t^*. The disturbances κ_t and κ_t^* are specified to be uncorrelated with the disturbances of the other components at all lags and leads, and uncorrelated with the initial distributions.

In case the variance for a particular component is equal to zero, the component is deterministic (rather than a dynamic stochastic process). In case the cycle variance is zero (and usually with the estimate of ρ close or equal to unity), the cycle component is a fixed sine-cosine wave. In case the period of a cycle is zero or as a very large value, the cycle process reduces to an autoregressive process of order one with its autoregressive coefficient equal to ρ.

The UC model can be formulated as a linear state space model specified by the equations

$$\begin{aligned} y_t &= Z\alpha_t + \varepsilon_t, & \varepsilon_t &\sim \text{NID}(0, \sigma_\varepsilon^2), \\ \alpha_{t+1} &= T\alpha_t + \eta_t, & \eta_t &\sim \text{NID}(0, H), \qquad t = 1, \ldots, n, \end{aligned} \tag{5}$$

[1]Sometimes this cycle is also referred to as the growth or deviation cycle Mintz (1969) by opposition to the business cycle as defined by the NBER which refers to expansion/recession cycle. However, in this paper we keep the business cycle terminology to describe those medium-term fluctuations.

where the first equation relates the observation y_t to an unobserved state vector α_t, which contains the trend, cyclical and other components required for describing the model. The state vector is modelled by the vector autoregressive process specified in the second equation, together with an initial distribution for α_1. The system variables Z, T, σ_ε^2, H are chosen to represent a particular model, and will usually depend on unknown parameters, which can be estimated by maximising the Gaussian likelihood function of the model. After replacing the parameters by their estimated values, the unobserved components can be estimated using the Kalman filtering and smoothing equations. For a more complete discussion of state space methods and their applications, we refer to Harvey (1989) and Durbin & Koopman (2001). An introductory text for UC models is Commandeur & Koopman (2007).

2.2 Multivariate unobserved component models

The UC model for univariate time series can be easily extended to multivariate time series. For example, letting y_t denote a $N \times 1$ vector of observations, a multivariate UC model can be applied to the N time series simultaneously. The decomposition model (2) becomes multivariate when its scalar components is replaced by vector components. We then have

$$y_t = \mu_t + \psi_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{NID}(0, \Sigma_\varepsilon), \qquad t = 1, \dots, n, \tag{6}$$

where trend μ_t and cycle ψ_t are stochastic $N \times 1$ vectors. The $N \times 1$ irregular vector ε_t is generated by the multivariate normal distribution with zero mean and variance matrix Σ_ε. The dynamic model specifications (3) for trend μ_t and (4) for cycle ψ_t remain as in the univariate case but the scalar process becomes a vector process. The disturbances in these stochastic specifications also become vectors and are assumed to come from multivariate normal distributions. Specifically, we have

$$\eta_t \sim \text{NID}(0, \Sigma_\eta), \quad \zeta_t \sim \text{NID}(0, \Sigma_\zeta), \quad \kappa_t \sim \text{NID}(0, \Sigma_\kappa), \quad \dot{\kappa}_t \sim \text{NID}(0, \Sigma_\kappa), \quad t = 1, \dots, n.$$

The cycle specification (4) has become a vector equation but the discounting factor ρ and cycle frequency λ are common to all elements of ψ_t. These coefficients are therefore kept as scalars. Harvey & Koopman (1997) define this specification as the similar cycle model. To incorporate cycles with different frequencies in the model, different similar cycle components can be included.

The multivariate extension of the trend-cycle decomposition model (2) is referred to as the seemingly unrelated time series equation (SUTSE) model. The individual slopes in vector β_t are only related through the correlations between the individual disturbances in vector ζ_t as implied by the variance matrix Σ_ζ. The same principle applies to the slope and cycle vector components in the model. The disturbance variance matrices therefore play an important role. In particular, the rank of the variance matrix is of interest. For example, in case Σ_ζ has full rank, all trend disturbances in ζ_t have their own unique source of variation but may be correlated between each other. In case Σ_ζ has lower rank, the individual trend disturbances in ζ_t are generated by a smaller set of independent disturbances. This follows straightforwardly since any variance matrix can be expressed via the Choleski decomposition, that is

$$\Sigma_\zeta = A_\zeta D_\zeta A_\zeta', \tag{7}$$

where A_ζ is a lower unity triangular $N \times r_\zeta$ matrix and D_ζ is a diagonal $r_\zeta \times r_\zeta$ matrix with the rank of Σ_ζ given by r_ζ. In a strict sense, we require a full column rank matrix for A_ζ and positive values on the diagonal of D_ζ for matrix Σ_ζ to have rank r_ζ. Consequently, we have

$$\zeta_t = A_\zeta \zeta_t^*, \qquad \zeta_t^* \sim \mathrm{NID}(0, D_\zeta),$$

and

$$\beta_t = \beta^* + A_\zeta \beta_t^*, \qquad \beta_{t+1}^* = \beta_t^* + \zeta_t^*, \tag{8}$$

where β^* is a fixed vector with $N - r_\zeta$ non-zero values and r_ζ zero values. In this way, all slope variables in β_t have different initial values. In case $r_\zeta < N$ and as a consequence Σ_ζ has a lower rank, ζ_t and β_t are linear combinations of a smaller set of stochastic processes. The same arguments apply to other disturbances and components in the model. A lower rank of the variance matrix can be imposed but it can also be the result of estimation. Testing procedures for common trends and cycles have been developed recently by Nyblom & Harvey (2001).

3 Data

As our aim is to show empirical relationships between macroeconomics and housing cycles for France, Germany, Italy and Spain, we focus on two types of variables, namely Gross Domestic Product (GDP) and real house prices (RHP).

For the GDP series we use official series as released by statistical institutes of each country. GDP series are expressed in volume and are chain-linked. The RHP series are not officially harmonised at the European level, as it is for example the case for inflation measurement through the Harmonized Index of Consumer Prices (HICP). We therefore use the database constructed by the four main National Central Banks of the Eurosystem in the framework of a joint research project on macroeconomics of housing markets and we refer to Alvarez et al. (2009) for a detailed presentation of this data set. Note however that German house prices have been interpolated from an annual frequency by the Deutsche Bundesbank. Last, we use real house prices deflated by using national HICP.

Both types of variables are sampled on a quarterly basis, from 1981 Q1 to 2008 Q4. Thus we integrate the latest fluctuations related to the sub-prime and financial crisis that led to the 2008 economic recession in euro area countries. For each country, GDP and RHP are presented in figures 1 and 2, respectively.

4 Empirical findings

4.1 Preliminary analysis

To obtain a first indication of the dynamic properties of the gross domestic product (GDP) and real house prices (RHP) for the four countries, we present in Figure 3 the correlogram and the sample spectrum for each of the eight time series in first differences. It shows that the series do not share strong common dynamic features, especially for GDP series. The four correlograms for the GDP series do not reveal strong serial correlation in the differences. For Germany there

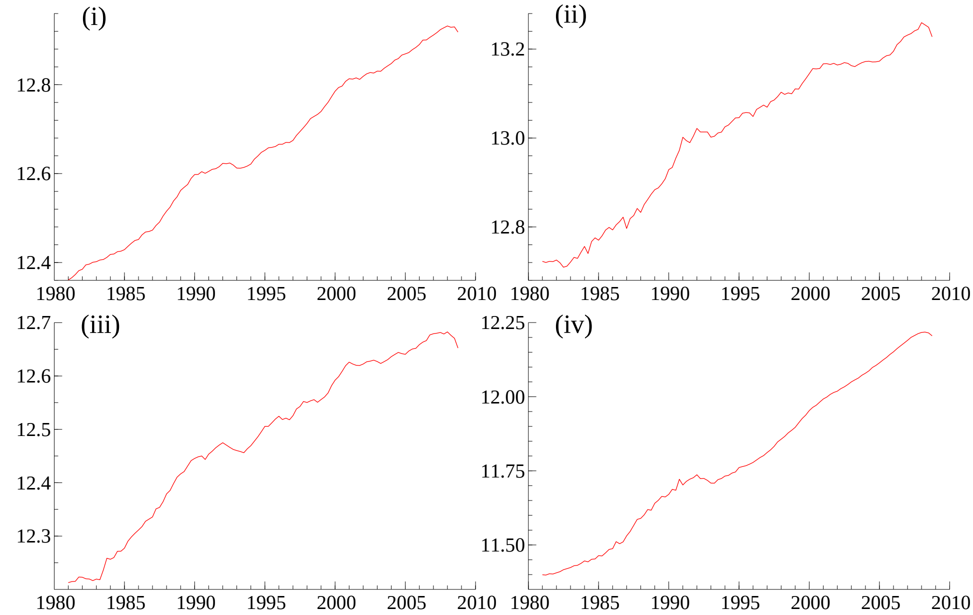

Figure 1: Quarterly time series for period 1981–2008 (28 years) of gross domestic product (GDP) in volumes for countries (i) France, (ii) Germany, (iii) Italy and (iv) Spain.

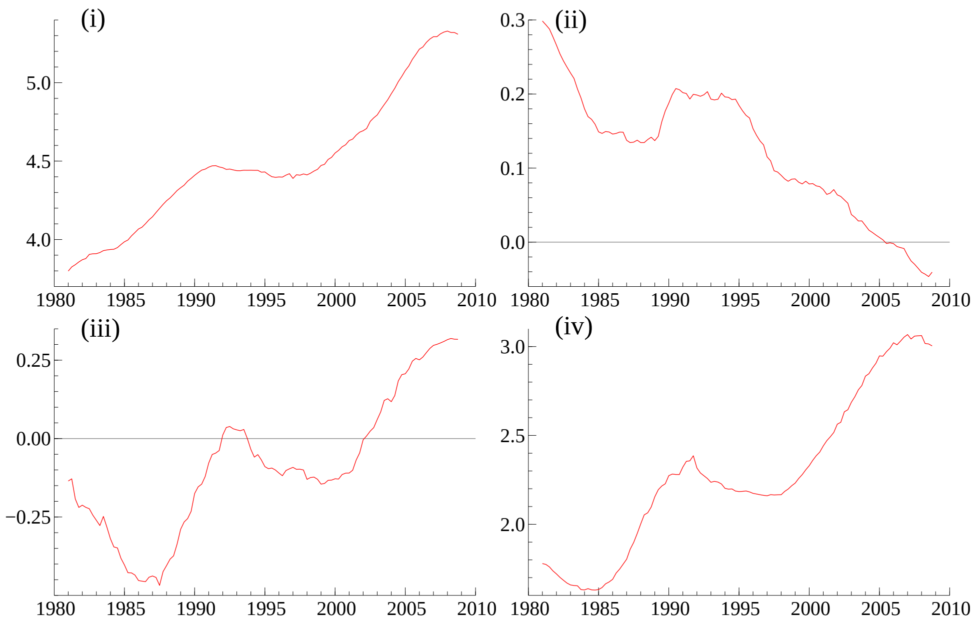

Figure 2: Quarterly time series for period 1981–2008 (28 years) of real house prices (RHP) for countries (i) France, (ii) Germany, (iii) Italy and (iv) Spain.

is almost no lagged dependence with the exception of lag 4 (that is, one year). This may be due to the interpolation carried from annual series. The dynamic properties for the RHP series present more persistence and are somewhat more similar although France also appears to have almost no serial dependence in its first difference. The sample spectra for the time series confirm these findings. Furthermore, they also show that cyclical dynamics in the differenced series are not apparent and do not have many common features. We conclude that the formulation of an unobserved components time series model for the decomposition of the time series into trend, cycle and irregular components requires a parsimonious and somewhat restricted framework. In particular, we refer to parameters that determine the dynamic properties of a time series in an UC time series model. The dynamic and common features in the observed time series may not be sufficiently strong that all parameters of the model can be estimated on the basis of this data-set. We therefore will impose restrictions in the selection of the models. All restrictions will be justified and we will present diagnostic results to provide some evidence that restrictions are sufficiently supported by the data-set.

The spectra of the time series in first differences do not provide much evidence of cyclical dynamics in the data-set. If any, some cyclical activity can be recognised for frequencies associated with longer cycles (the lower frequencies) and with shorter cycles (the high frequencies, say smaller than $0.5 \times 2\pi = \pi$). It is hard to separate these features from the low frequencies of the trend. We therefore propose to formulate a flexible cycle component in our model to capture all possible cyclical features in the data. By considering a component for the cyclical dynamics with a length of, say, 5 years and another component for cyclical dynamics of, say, 12 years, we allow all possible cyclical characteristics in the data to be captured. Further details of the model specification are given below. Here we emphasize that we opt for this specification to accomodate a wide range of cyclical features in the model. To separate the trend dynamics from the (weak) cyclical dynamics, we can impose a smoothness restriction for the trend component.

4.2 Empirical model specification

These preliminary empirical findings has motivated us to base our analysis on univariate and multivariate unobserved components time series models which are discussed in section 2. We include components for trend, cycle and noise. The cycle component is modelled by two separate cyclical processes with different periods, each of them having the parametric form described in equation (4). The first cycle may capture the shorter term dynamics while the second cycle may account for the longer term dynamics in the cycle component. The model for the time series is then given by

$$y_t = \mu_t + \psi_{1t} + \psi_{2t} + \varepsilon_t, \tag{9}$$

where y_t is the observed variable (GDP or RHP for France, Germany, Italy or Spain) at time t. The unobserved variables trend μ_t, irregular ε_t and cycles ψ_{1t} and ψ_{2t} are discussed in section 2. Each unobserved component is driven by stochastic disturbance processes which are not correlated with each other. In case the analysis is for a single time series, the observation y_t and the components μ_t, ψ_{1t}, ψ_{2t} and ε_t are scalar variables.

In case of a multivariate time series analysis and by adopting the notation as used by (7)

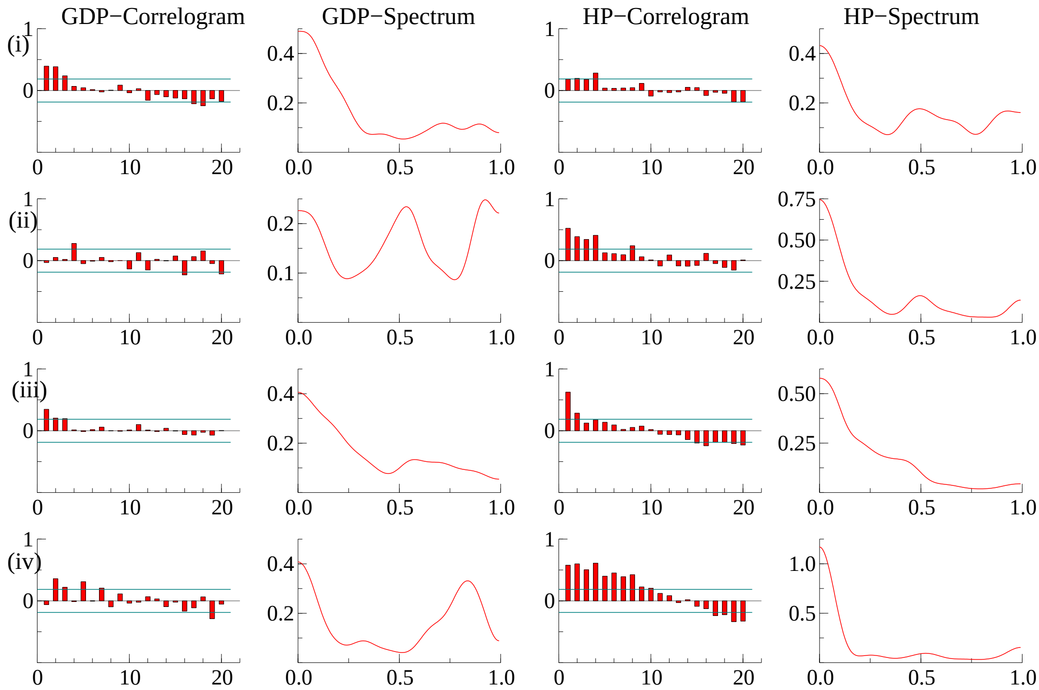

Figure 3: Correlogram and sample spectrum for quarterly growth rate of gross domestic product (GDP) and real house prices (RHP) for (i) France, (ii) Germany, (iii) Italy and (iv) Spain. The sample for each time series covers the years 1981–2008 (28 years). Each time series consist of 112 observations. The x-axes for the spectra is the frequency scaled by 2π so 0.5 is associated with π and 1.0 with 2π.

and (8), we can reformulate model (6) in terms of common factors. Such a decomposition model with trend, two cycles and irregular components together with possible regression effects (X_t) is given by

$$y_t = \mu^* + A_\eta \mu_t^* + A_\kappa^{(1)} \psi_t^{*(1)} + A_\kappa^{(2)} \psi_t^{*(2)} + X_t \delta + A_\varepsilon \varepsilon_t^*, \qquad (10)$$

where factor loading matrices A_η, A_ζ, $A_\kappa^{(1)}$, $A_\kappa^{(2)}$ and A_ε are lower unity triangular $N \times r$ matrices (with $r \leq N$ varying for each loading matrix) and the common components μ_t^*, β_t^*, $\psi_t^{*(1)}$, $\psi_t^{*(2)}$ and ε_t^* are associated with disturbances that have diagonal variance matrices. Common components are of interest for studying the dynamic structures and interactions within a set of time series. For example, common trends imply that economic time series are cointegrated, see the discussion by Stock & Watson (1988). The estimation of the unobserved components trend and cycle together with the maximum likelihood estimation of unknown coefficients is based on state space methods which are applicable to both univariate and multivariate models. Some further details are discussed in the next section.

4.3 Parameter estimation and signal extraction

Parameter estimation is based on the method of maximum likelihood. The likelihood function is routinely evaluated by the Kalman filter for a given value of the parameter vector. A quasi-Newton optimization method is then employed to maximize the likelihood function with respect to the parameter vector. For this purpose, the score function is evaluated numerically using a smoothing algorithm. This approach is implemented in the user-friendly software STAMP 8.0 by Koopman, Harvey, Doornik & Shephard (2007). The Kalman filter and related smoothing algorithms also carry out the estimation of the unobserved components that is often referred to as signal extraction. Finally, the Kalman filter also forms the basis for forecasting. This approach applies to univariate and multivariate models. However, the computational effort becomes more involved when the dimension of y_t increases. It may also be numerically more difficult to find the maximum of the likelihood function with respect to a large dimensional parameter space.

4.4 Univariate analysis for each series

We begin the empirical analysis by analysing the eight time series (the GDP and RHP series for the four countries France, Germany, Italy and Spain) using the univariate UC model as described in section 2.1. The main purpose of the univariate analysis is to verify whether the trend-cycle decomposition based on equation (2) is adequate for each of the eight time serie and whether possible restrictions are appropriate. The estimation results are reported in Table 1. In this Table 1 we indicate this by "–" and it only occurs for the house prices of Spain. All reported variances are relative to the variance of the irregular component of the model. In case, the irregular variance is estimated as zero, the largest variance of a component is chosen as the numeraire.

For all eight time series we report in Table 1 the estimated variances of the disturbances associated with the trend, the two cycle processes and the irregular component. For each cycle component, we further report the estimated values for the discounting factor ρ and the period p (in years). The model decompositions appear to apply for the GDP series with France and

Italy having short business cycle frequencies. Some of the estimated cycle components have zero variances (Germany for Cycle 1; France, Italy and Spain for Cycle 2). We emphasize that the sum of Cycle 1 and Cycle 2 is a stochastic stationary time series process. For the GDP time series, the estimated cycles represent rather short term dynamics (most cycle lengths are less than 5 years) except for Germany which has an estimated cycle length of 13.5 years. These findings confirm the features of the series reported in Figure 3.

In case of the house price series, the trend-cycle decomposition is clearly applicable for house prices in Germany where the cycle lengths are estimated as 4.48 and 2.82 respectively for Cycles 1 and 2 but with Cycle 2 having a low persistence (ρ is estimated as 0.61) such that the cycle process disappears after two or three periods in future. Most dynamical features in the price series are captured by the flexible trend specifications. This is apparent from the relatively high values for the estimated trend variances. It is difficult to capture the stationary dynamics represented by the cycle components in the relatively short time series of 112 quarterly observations which constitute 28 years in the period from 1981 to 2008.

Since all series are decomposed according to a similar model structure, it is of interest to compute the correlations between the extracted cycles. These correlations are reported in Table 2. We first concentrate on the aggregate cycle, that is the sum of Cycle 1 and Cycle 2. The cycle components for GDP can be interpreted as business cycles. First, for each country, correlations between GDP and house prices range from 0.06 for Italy and 0.76 for Spain. The high correlation for Spain reflects the strong contribution of the housing sector to the economic growth in Spain. The GDP-RHP correlations for France and Germany are close to 0.5. Second, we find that the GDP cycles for the four countries are strongly correlated, the correlations range from 0.52 to 0.89. The GDP correlations are highest between France, Italy and Spain while all correlations with Germany are the lowest but still larger than 0.5. The German business cycle is known to be lagging the business cycles of other euro area countries, see for example Alvarez et al. (2009). It may explain the low GDP correlations with Germany. The housing price cycle correlations between countries range from 0.42 to 0.94. The highest correlations are obtained with the house prices of Spain and France and with those of Germany and Italy. Last, the cross-correlation between GDP of one country and the house prices of another country are all relatively low. Particular low values are between France GDP and Germany price (0.23), France GDP and Italy price (0.15) and Italy GDP and German price (0.08). High cross-correlations are obtained between Spanish prices and, on the one hand, French GDP and Italian GDP, on the other hand. Both are larger than 0.6.

When we consider the correlations of the cycles separately for Cycle 1 and Cycle 2, we find that generally the correlations for Cycle 2 are similar to those of the combined cycles. The correlations for Cycle 1 are also similar with the exception of all correlations with Italian housing prices being negative. This is most likely due to the short period of Cycle 1 that is estimated as low as 1.1 years. The other periods for Cycle 1 are estimated at 3 years or higher with the exception of the Germany-RHP Cycle 2.

To enable a stable and consistent model-based analysis for the eight time series, we design a trend-cycle decomposition by enforcing the following restrictions: (i) the relative trend variance is set equal to the low value of 0.03; (ii) the length of Cycle 1 and Cycle 2 are set to 5 and

Table 1: *Estimation results for univariate models for each series*

	France		Germany		Italy		Spain	
GDP		R		R		R		R
Trend *var*	0.65	0.03	0.01	0.03	0.48	0.03	0.10	0.03
Cycle 1 *var*	0.81	0.17	0.00	0.15	3.85	5.75	0.07	0.00
Cycle 1 ρ	0.94	0.90	1.0	0.90	0.87	0.90	0.95	0.90
Cycle 1 p	3.04	5	5.42	5	2.97	5	3.62	5
Cycle 2 *var*	0.00	1	1.81	2.86	0.00	7.79	0.00	2.31
Cycle 2 ρ	1.0	0.95	0.95	0.95	1.00	0.95	1.00	0.95
Cycle 2 p	5.8	12	13.5	12	5.50	12	9.11	12
Irreg *var*	1	0.0	1	1	1	1	1	1
N	7.2	11.4	3.23	5.23	6.58	11.1	27.1	34.9
Q	14.5	24.9	15.1	14.6	9.26	13.3	22.1	24.8
R^2	0.31	0.24	0.11	0.02	0.23	0.12	0.22	0.12
	France		Germany		Italy		Spain	
RHP		R		R		R		R
Trend *var*	0.59	0.03	0.34	0.03	0.00	0.03	0.39	0.03
Cycle 1 *var*	0.00	0.01	0.31	1.51	0.04	0.02	1	0.01
Cycle 1 ρ	1.0	0.90	0.97	0.90	0.96	0.90	0.34	0.90
Cycle 1 p	6.34	5	4.48	5	1.11	5	–	5
Cycle 2 *var*	0.00	2.19	1	19.9	1	49.4	0.00	39.5
Cycle 2 ρ	1.0	0.95	0.61	0.95	0.99	0.95	0.99	0.95
Cycle 2 p	8.37	12	2.82	12	13.3	12	–	12
Irreg *var*	1	1	0	1	0	1	0	1
N	23.8	0.59	5.89	9.95	7.03	8.32	36.1	11.9
Q	10.6	187	55.5	111	13.7	68.4	29.3	127
R^2	0.61	0.25	0.35	0.15	0.56	0.22	0.47	0.28

Note: Parameter estimates for each component are reported. *var* denotes variance of the component relative to the irregular variance (when applicable), ρ is the discount parameter and p is the period of the cycle (in years). Diagnostic test statistics for the standardized one-step ahead prediction residuals are also reported: N is the Jarque-Bera normality test (distributed as a χ^2 variable with two degrees of freedom (df) and 95% critical value 5.99, Q is the Ljung-Box portmanteau test statistic based on the sum of squared sample autocorrelations (from 1st order upto 12th order of the standardized residuals and R^2 is the goodness-of-fit statistic that compares the fit of the model with a simple random walk model. Estimation results are presented for all series and for two model specifications: the UC model (10) with unrestricted parameters and with the restrictions trend var $\sigma^2_\zeta = 0.03$, Cycle 1 $\rho = 0.9$, Cycle 1 $p = 5$, Cycle 2 $\rho = 0.95$ and Cycle 2 $p = 12$ (in columns labelled with R).

12 years respectively; (iii) the persistence parameters ρ are set to 0.9 and 0.95 respectively. These values are chosen after some experimentation but it has been established that the chosen values produce reliable decompositions. Initial justification of these parameter choices is given at the end of section 4.1. With respect to our choice of the cycle lengths 5 and 12 years, we confirm that the standard business cycle length lies between 1.5 and 8 years. However, in Table 1 we have reported estimates of cycle lengths higher than 8 years, in particular, Germany-GDP, Italy-GDP, France-RHP and Italy-RHP. This finding has motivated us to set the long cycle length to 12 years. The short cycle length of 5 years is close to the average of the estimates of Cycle 1 reported in Table 1. It is found that the reported results are not very sensitive to other choices of cycle lengths when they are fixed at values which are sufficiently close to 5 and 12 years. With respect to the choice of the discount factor ρ, the values 0.9 and 0.95 are close to the estimates from univariate models for Cycles 1 and 2, respectively. The relative trend variance is chosen such that trend component is sufficiently smooth. The remaining parameters are estimated. The estimation results are reported in Table 1 where the restricted models are indicated by the letter R in the column headers.

For the restricted models, signal extraction is also carried out by Kalman filter and smoother methods. The implied weight and gain functions of the estimated trend and cycle components from a restricted model are presented in Figure 4. The weight functions are sufficiently wide to produce smooth estimates for trend and cycles. The gain functions show that the decomposition is effective since the trend captures the lowest frequencies, the short cycle appears to weight most heavily on the typical business cycle frequencies while the long cycle captures fluctuations of longer period when they exist. Also a sufficient amount of band-pass properties can be recognised in this set of gain functions. The estimated irregular component captures the remaining high frequencies in its gain function that is not reported in Figure 4.

Although the normality (N) and serial correlation (Q) diagnostics are somewhat better for the unrestricted models and although the goodness-of-fit (R^2) measures are worse for all restricted models, the models still produce an effective decomposition. The restrictions enforce the same decomposition model to all eight series. The importance of each cycle component to each series is still determined via the estimation of the two cycle variances. The model is rather poor in terms of goodness-of-fit for the Germany GDP series but we regard this as the exception. The other series provide satisfactory decompositions based on our trend-cycle model (10).

From the univariate analysis we can conclude that the decomposition model is adequate for our analysis and that the resulting cycles have sufficient features in common to analyze the series further and to search for common dynamic properties.

4.5 Bivariate analysis for each country

The model for a bivariate analysis in which we treat GDP and real house prices simultaneously is considered for each country individually. It is given by

$$y_t = \mu_t + \psi_{1t} + \psi_{2t} + \varepsilon_t,$$

where y_t is a 2×1 vector containing the observations for GDP and real house prices in a given country at time t. The unobservables trend μ_t, business cycle ψ_{1t}, longer cycle ψ_{2t} and irregular

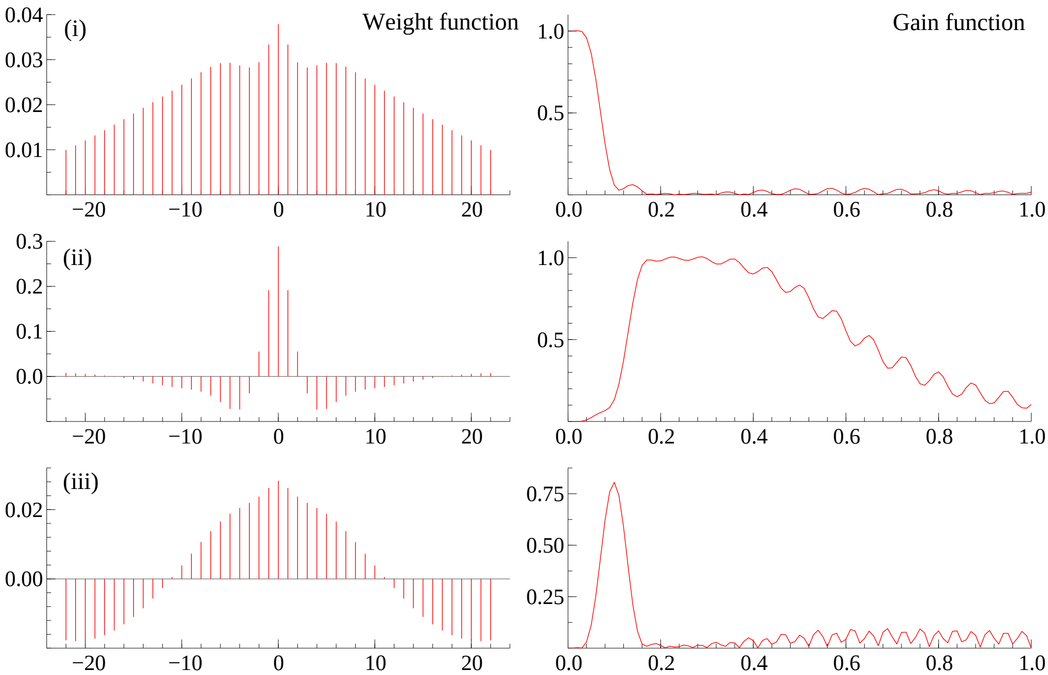

Figure 4: The weight and gain functions for a restricted univariate decomposition model with the components (i) trend, (ii) 5-years short cycle, (iii) 12-years long cycle and (not reported) irregular. The x-axes for the gain functions is the frequency scaled by 2π so 0.5 is associated with π and 1.0 with 2π.

Table 2: *Correlations between cycles extracted from univariate models for each series*

Cycle 1	Fr GDP	Fr RHP	Ge GDP	Ge RHP	It GDP	It RHP	Sp GDP	Sp RHP
Fra GDP	1.00	0.46	0.40	0.24	0.64	-0.46	0.57	0.42
Fra RHP	0.46	1.00	0.29	0.62	0.33	-0.51	0.35	0.39
Ger GDP	0.40	0.29	1.00	0.32	0.75	-0.16	0.67	0.58
Ger RHP	0.24	0.62	0.32	1.00	0.18	-0.52	0.06	0.13
Ita GDP	0.64	0.33	0.75	0.18	1.00	-0.13	0.61	0.65
Ita RHP	-0.46	-0.51	-0.16	-0.52	-0.13	1.00	-0.25	-0.19
Spa GDP	0.57	0.35	0.67	0.06	0.61	-0.25	1.00	0.75
Spa RHP	0.42	0.39	0.58	0.13	0.65	-0.19	0.75	1.00
Cycle 2								
	Fr GDP	Fr RHP	Ge GDP	Ge RHP	It GDP	It RHP	Sp GDP	Sp RHP
Fra GDP	1.00	0.51	0.53	0.23	0.89	0.16	0.90	0.63
Fra RHP	0.51	1.00	0.46	0.44	0.58	0.68	0.68	0.94
Ger GDP	0.53	0.46	1.00	0.52	0.44	0.49	0.62	0.46
Ger RHP	0.23	0.44	0.52	1.00	0.07	0.82	0.22	0.43
Ita GDP	0.89	0.58	0.44	0.07	1.00	0.08	0.90	0.72
Ita RHP	0.16	0.68	0.49	0.82	0.08	1.00	0.29	0.64
Spa GDP	0.90	0.68	0.62	0.22	0.90	0.29	1.00	0.76
Spa RHP	0.63	0.94	0.46	0.43	0.72	0.64	0.76	1.00
Cycle 1 + 2								
	Fr GDP	Fr RHP	Ge GDP	Ge RHP	It GDP	It RHP	Sp GDP	Sp RHP
Fra GDP	1.00	0.51	0.52	0.23	0.83	0.15	0.89	0.61
Fra RHP	0.51	1.00	0.44	0.44	0.52	0.68	0.68	0.94
Ger GDP	0.52	0.44	1.00	0.50	0.54	0.47	0.61	0.44
Ger RHP	0.23	0.44	0.50	1.00	0.08	0.80	0.22	0.42
Ita GDP	0.83	0.52	0.54	0.08	1.00	0.06	0.84	0.64
Ita RHP	0.15	0.68	0.47	0.80	0.06	1.00	0.29	0.64
Spa GDP	0.89	0.68	0.61	0.22	0.84	0.29	1.00	0.76
Spa RHP	0.61	0.94	0.44	0.42	0.64	0.64	0.76	1.00

Note: The reported correlations are for the estimated cycles from the unrestricted univariate analysis for each time series. Since our UC model contains two cycles, we report correlations for each cycle (Cycle 1 and Cycle 2) and for the combined cycle (Cycle 1 +2).

ε_t are also 2×1 vectors. Each unobservable is driven by bivariate stochastic disturbance processes which are correlated. The estimation results for each country are reported in Table 3. In all cases, we obtain for at least one component a high correlation coefficient between GDP and RHP for a specific dynamic process, providing some evidence that the series have common dynamic features. In all countries, except for Italy, the highest correlation between GDP and RHP is found for the estimated business cycle components.

For Italy, the highest correlation is recorded for the irregular component. This may be due to the presence of a shift between the two cycles; it may have vanished the contemporaneous correlation. For the other countries, when looking separately at both medium-term and long-term cycles the situation is interestingly quite different. Indeed, for France, the highest correlation is between medium-term cycles (with a period estimated at 8 years), while there is no dependence between long-term cycles of period 15.6 years. This means that the housing market may have an impact on conjunctural economic activity, but the determinants of long-term economic and housing market cycles may be different. The finding for Spain is also different. We find that both medium-term (8.2 years) and long-term (14.4 years) cycles are strongly correlated (0.95 and 0.82, respectively). These results point out the strong dependence between the housing market and the Spanish economic activity, at both short and long frequencies. This may reveal that the housing market has a major role in macroeconomic developments for Spain. It turns out that for many years the Spanish economy has taken benefit from the boom in the housing sector, both in terms of growth and employment, at least until the recent downturn. It appears that, for the same reasons, the housing market cycle in Germany is strongly correlated to economic activity. The periods of the two German cycles are estimated as 4.3 and 7 years which are typical business cycle frequencies. The negative correlation of cycles with the lowest period may indicate a phase shift between GDP and RHP.

We note that the estimation results indicate that two cycles can be recognised, a short cycle with a period smaller than 8 years and a long cycle with a period larger than 8 years. Germany and Italy appear to possess only shorter cycles while longer cycles are found for France and Spain where the periods are even as high as 15.6 and 14.4 years, respectively. The relationships in housing prices between France and Spain, on one hand, and between Germany and Italy, on the other hand, could stem from the similar dynamics in terms of short and long cycles. These results seem to justify our choices for the restricted univariate model with short and long cycle lengths of 5 and 12 years, respectively, in section 4.4. The restricted model setting can be regarded as the common denominator of the bivariate models that are estimated in this section.

We therefore have also considered the estimation of the bivariate model with the restrictions: (i) the relative trend variance is set equal to the low value of 0.03; (ii) the lengths of the cycles 1 and 2 are set to 5 and 12 years respectively; (iii) the persistence parameters ρ are set to 0.9 and 0.95 respectively. The correlation between the trend disturbances for GDP and RHP is set to zero.

Table 3: *Estimation results for the bivariate model for each country*

	Parameter estimates (Restricted)					Diagnostics		
	GDP var	RHP var	corr.coeff	period	discount ρ		GDP	RHP
FRANCE								
sqr-trend	0.0 (0.03)	0.0 (0.03)	0.00 (0.00)	–	–	N	3.25	13.4
Cycle 1	3.0 (0.68)	3.3 (0.21)	0.88 (0.78)	8.0 (5)	0.98 (0.90)	Q	17.0	17.4
Cycle 2	1.0 (1.75)	126 (229)	0.07 (0.53)	15.6 (12)	0.99 (0.95)	R^2	0.38	0.63
irregular	0.6 (1.00)	1.6 (0.00)	-0.2 (0.00)	–	–			
GERMANY								
sqr-trend	0.0 (0.03)	0.0 (0.03)	0.00 (0.00)	–	–	N	8.52	1.08
Cycle 1	2.5 (0.66)	5.4 (1.33)	-0.6 (-0.3)	4.3 (5)	0.90 (0.90)	Q	6.86	42.1
Cycle 2	3.1 (0.35)	0.5 (0.46)	1.00 (0.95)	7.0 (12)	0.98 (0.95)	R^2	0.39	0.29
irregular	4.3 (1.00)	1.1 (0.00)	0.58 (0.90)	–	–			
ITALY								
sqr-trend	0.1 (0.03)	0.9 (0.03)	-0.2 (0.00)	–	–	N	4.19	4.57
Cycle 1	4.3 (6.92)	16. (1.08)	-0.1 (-0.8)	6.0 (5)	0.92 (0.90)	Q	10.1	8.60
Cycle 2	0.0 (5.23)	8.4 (1654)	0.00 (0.00)	1.1 (12)	0.94 (0.95)	R^2	0.14	0.47
irregular	0.8 (1.00)	1.2 (1.00)	0.96 (1.00)	–	–			
SPAIN								
sqr-trend	0.0 (0.03)	0.0 (0.03)	0.00 (0.00)	–	–	N	9.05	21.7
Cycle 1	3.3 (0.00)	12. (0.00)	0.95 (1.00)	8.2 (5)	0.98 (0.90)	Q	17.5	43.0
Cycle 2	0.0 (1.15)	83. (133)	0.82 (0.61)	14.4 (12)	0.99 (0.95)	R^2	0.45	0.73
irregular	3.9 (1.00)	7.7 (0.00)	-0.4 (0.00)	–	–			

Notes: Periods are expressed in years. The values in parentheses refer to the restricted model specification. Diagnostic test statistics for the standardized one-step ahead prediction residuals are also reported: N is the Jarque-Bera normality test (distributed as a χ^2 variable with two degrees of freedom (df) and 95% critical value 5.99, Q is the Ljung-Box portmanteau test statistic based on the sum of squared sample autocorrelations (from 1st order upto 12th order of the standardized residuals and R^2 is the goodness-of-fit statistic that compares the fit of the model with a simple random walk model.

4.6 Four-variate analysis for GDP and house prices

Next we consider GDP and RHP series for the four countries and model them simultaneously by the similar decomposition model

$$y_t = \mu_t + \psi_{1t} + \psi_{2t} + \varepsilon_t,$$

where y_t is a 4×1 vector of observed GDP or RHP variables for France, Germany, Italy and Spain. After a prior analysis we found that an appropriate decomposition can be based on independent trend μ_t and independent irregular ε_t components. In other words, we impose diagonal variance matrices for the disturbances driving these components. We could also have assumed to include common trends for the four countries. Our preliminary results indicated that imposing independent trends helps in finding country associations for the cycle components. Given our focus on the cycle components, we have opted for independent trend specifications.

An important constraint imposed on the four-variate model is that the cycle disturbances have variance matrices with ranks equal to two. It implies that the euro area cycle is represented by two 5-year cycles and two 12-year cycles. We load the pairs of two cycles on France and Germany. The cyclical dynamics in the GDPs of Spain and Italy are obtained as linear functions of these four cyclical factors. The estimated components (μ_t, ψ_{1t}, ψ_{2t} and ε_t) are graphically presented in Figure 5 for each country.

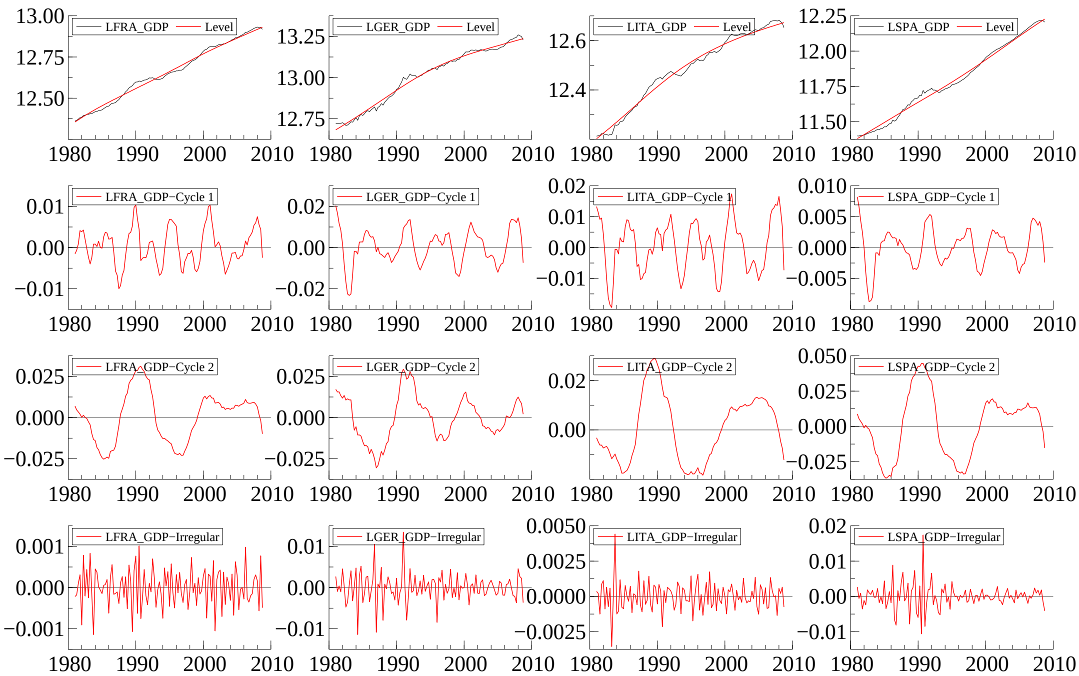

Figure 5: A multivariate trend-cycle(s) decomposition for the GDP of countries (i) France, (ii) Germany, (iii) Italy and (iv) Spain.

The dynamic specification underlying this decomposition is appropriate since the diagnostic statistics are satisfactory. The estimated common dynamics in the cycle components for GDP are reported in Table 4. The business cycles for Germany and France are highly correlated with each other for the long term cycle. The cycles for Italy and Spain are closely connected with the cycle of France although the short-term cycle of Spain is negatively correlated with the one of France. The cycles of Germany strongly affect the business cycles of the other countries although its marginal longer term influence on Italy and Spain is negative. From the estimated long cycles in Figure 5 (Cycle 2) we learn that the negative correlations with Germany are due to the close-to-recession years $2003-2006$ in Germany not experienced by Italy and Spain. In Table 4 we notice the negative loading coefficient for Spain on Germany's GDP Cycle 2 (-0.41) while its corresponding correlation coefficient is positive (0.64). Given the strong correlation of Germany's GDP Cycle 2 with the one of France (0.79) and the strong positive loading coefficient for Spain on France's GDP Cycle 2 (1.79), this apparent contradiction can be clarified.

The same decomposition model is applied to the RHP series for the four countries (see bottom panel of Table 4) and the resulting decomposition is presented in Figure 6. The decomposition model specification is the same but we have restricted the variance of the trend component to enforce it as a smooth function of time. The evidence for common dynamics in the housing cycle within the euro area is less evident. The housing price cycles in France and Germany have correlations that do not exceed the value of 0.4. The 5-year RHP cycle of Italy is strongly and negatively correlated with the one of France while the 5-year RHP cycle of Spain is strongly and negatively correlated with the one of Germany. The 12-year housing price cycle dynamics appear to have common features with those in Spain while a negative correlation exists between Germany and Italy. From Figure 6 we learn that the longer cycles have the same swings from peaks to throughs over time, the timings of the peaks and throughs are different. Therefore the correlations between the long-term RHP cycles are mixed between the countries. However, the correlation matrix for the 12-year RHP cycle is quite similar to the one for the 12-year GDP cycle with the exception that the two underlying factors for France and Germany are less correlated for housing price (0.79 for GDP and 0.38 for RHP).

Note that those results are in line with the comparative analysis carried out by Alvarez et al. (2009) for both GDP and RHP variables, although the periods of cycles involved in both analysis are not exactly identical.

4.7 Multivariate analysis for all eight variables

In this section we carry out a multivariate analysis of all eight variables simultaneously. We collect the GDP and RHP time series for France, Germany, Italy and Spain into the 8×1 observation vector y_t. We consider the multivariate UC model (10) and discussed in section 2.2. Regression effects are not included in the multivariate model. The same restrictions are imposed on the model as those for the bivariate and four-variate models considered earlier (two cycles of periods 5 and 12 years, independent trends, cyclical dynamics of Spain and Italy expressed as linear functions of France and Germany). We limit reporting the estimation results by only presenting the correlation coefficients for the two cycle components. The correlations are presented in Table 5 for the short and long cycles (Cycle 1 and Cycle 2, respectively).

Table 4: *Covariances, correlations and factor loadings for the two cycle components in the four-variate models for GDP and RHP*

	France	Germany	Italy	Spain	France	Germany
GDP Cycle 1 (covariances $\times 10^{-6}$*)*					*factor loadings*	
France	4.11	*0.25**	*0.77**	*-0.40**	1	0
Germany	1.77	11.8	*0.81**	*0.78**	0	1
Italy	5.65	10.1	13.1	*0.27**	1.08	0.69
Spain	-1.04	3.50	1.27	1.65	-0.41	0.35
GDP Cycle 2 (covariances $\times 10^{-6}$*)*						
France	8.08	*0.79**	*0.48**	*0.98**	1	0
Germany	7.94	12.5	*-0.16**	*0.64**	0	1
Italy	3.43	-1.39	6.28	*0.66**	1.42	-1.02
Spain	11.2	9.11	6.73	16.4	1.79	-0.41
RHP Cycle 1 (covariances $\times 10^{-6}$*)*					*factor loadings*	
France	15.5	*0.37**	*-0.89**	*0.05**	1	0
Germany	4.73	10.8	*0.10**	*-0.91**	0	1
Italy	-21.0	1.97	36.2	*-0.50**	-1.64	0.90
Spain	0.89	-14.6	-14.6	23.8	0.55	-1.60
RHP Cycle 2 (covariances $\times 10^{-6}$*)*						
France	44.5	*0.38**	*0.70**	*0.93**	1	0
Germany	4.43	3.13	*-0.40**	*0.69**	0	1
Italy	66.9	-10.3	207.1	*0.38**	2.13	-6.30
Spain	100.4	19.9	88.3	262.8	1.89	3.69

Note: CCorrelations are reported in the upper right part and marked with *. The last two columns report the factor loading matrices $A_\kappa^{(i)}$ in (10) for $i = 1, 2$. For the RHP model we have restricted the variance of the trend ($\sigma_\eta^2 \,/\, \sigma_\varepsilon^2 = 0.03$) to enforce a smooth trend function.

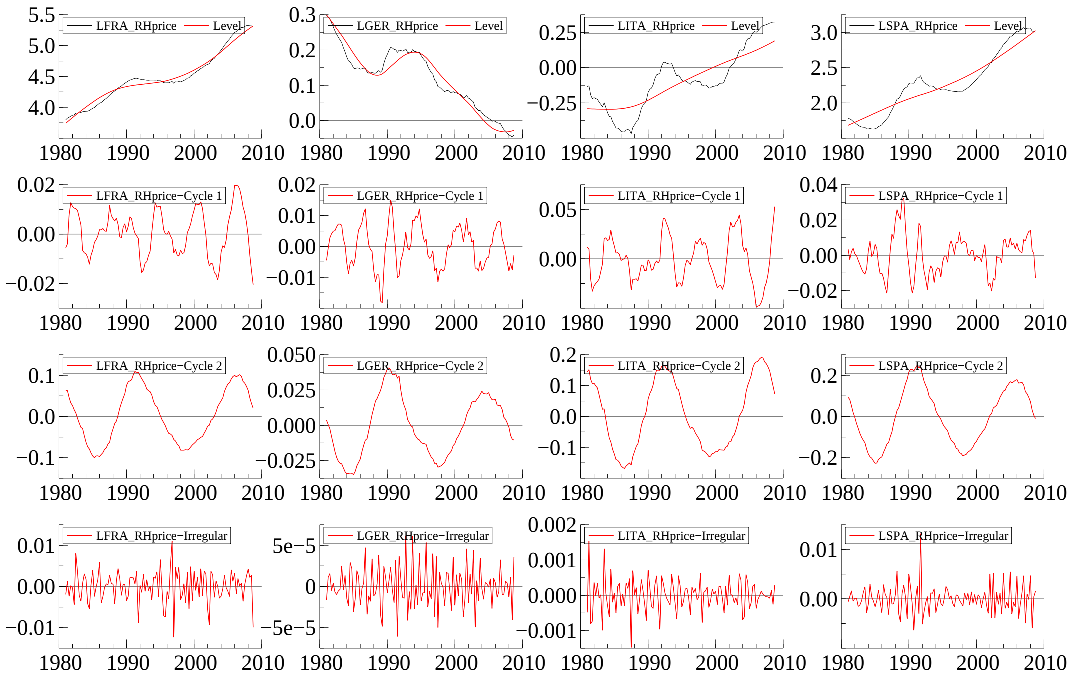

Figure 6: A multivariate trend-cycle(s) decomposition for the RHP of countries (i) France, (ii) Germany, (iii) Italy and (iv) Spain.

From Table 5 we note first that we obtain strong correlations for the 5-year cycles of GDP, they range from 0.66 to 0.88 but there is less evidence for strong correlation for the 12-year cycles of GDP. We find low correlations of the GDP Cycle 2 components with the GDP Cycle 2 component of Germany. However, France and Italy share a common long-term economic cycle. Overall, this finding indicates a strong concordance at the business cycles frequencies among the four countries. In other words, common shocks are driving the euro area business cycle fluctuations, while long-term cycles may have a more idiosyncratic behaviour.

We observe relatively low correlations for real RHP variables among the four countries. For the 5-year RHP cycle, only France and Germany have a positive correlation value while Germany and Spain are strongly but negatively correlated. The negative correlation indicates a phase shift in cycles. For example, it is found in the study of Alvarez et al. (2009) that the Spanish RHP cycle leads other RHP cycles of other euro area countries. With respect to the 12-year RHP cycle, we find two relatively high correlations, those between France and Spain and between Germany and Italy (0.58 and 0.57, respectively).

There is some evidence of relationships between GDP and RHP cycles of specific countries. Some correlations of substance have appeared mainly for the 12-year cycles. An exception is the 5-year cycle for Spain that possesses a positive correlation (0.34) for its GDP and RHP Cycle 1. With respect to Italy, we obtain close to zero correlations between GDP and RHP at the business cycle frequencies. A similar finding is obtained for the estimated Cycle 1 from the bivariate analysis but also, to a lesser extent, for the estimated Cycle 2 (lower frequencies). We further notice the interesting result that a correlation of 0.41 is found for the 12-year cycle in Germany between its GDP and RHP series. This correlation is also obtained for both restricted and unrestricted bivariate models, implying thus a significant contribution of the housing sector to the long-term dynamics of the economy.

Table 5: *Correlations for the two cycle components in the eight-variate model*

		France		Germany		Italy		Spain	
Cycle 1									
		GDP	RHP	GDP	RHP	GDP	RHP	GDP	RHP
France	GDP	1	-0.33	0.67	0.10	0.81	-0.59	0.77	0.13
	RHP		1	0.075	0.65	-0.35	-0.13	-0.12	-0.64
Germany	GDP			1	0.17	0.80	-0.27	0.88	-0.011
	RHP				1	0.055	-0.26	-0.10	-0.95
Italy	GDP					1	-0.037	0.66	0.034
	RHP						1	-0.55	-0.040
Spain	GDP							1	0.34
	RHP								1
Cycle 2									
		GDP	RHP	GDP	RHP	GDP	RHP	GDP	RHP
France	GDP	1	0.95	0.19	0.043	0.72	0.41	0.54	0.50
	RHP		1	0.44	0.24	0.63	0.43	0.57	0.58
Germany	GDP			1	0.41	-0.31	0.26	0.44	0.21
	RHP				1	-0.005	0.57	0.036	0.29
Italy	GDP					1	0.045	0.12	0.37
	RHP						1	0.13	0.099
Spain	GDP							1	0.61
	RHP								1

Note: For this model we have restricted the variance of the trend ($\sigma^2_\eta \, / \, \sigma^2_\varepsilon \, = 0.03$) to enforce a smooth trend function.

5 Conclusions

In this paper, we have implemented several multivariate unobserved component models in order to assess commonalities in the housing and business cycles of the four main euro area countries (France, Germany, Italy and Spain) and to detect cyclical relationships between macroeconomy and the housing sector. Specifically, we have allowed two cycles of different periods in the model specification.

It turns out that we have shown synchronisation among the business cycles of the four countries, leading thus to the existence of common cycles in the euro area. In contrast, there is overall less evidence concerning real house prices, although results may slightly vary according the various multivariate model specification. Indeed, in spite of the proven relationship between France and Spain and of commonalities in the long-term cycles, there is no strong common housing cycles in the euro area. It turns out that specificities and regulations in each country strongly contribute to the evolution of domestic house prices. Finally, we find that the GDP and real house prices cycles are related in the medium-term for fluctuations between 4 and 8 years, while the housing market contributes to the long-term economic growth only in Spain and Germany.

As further research, it would be useful to integrate phase shifts in unobserved components modelling in order to take leads and lags among cycles into account (see for example Ruenstler (2004)). Another useful specification in this framework would be to assess the convergence of housing cycles over recent years by using the approach proposed by Koopman & Azevedo (2008), especially by integrating the last cycle in the analysis. Last we have used real housing prices to evaluate the housing cycle, but other variables could have been considered as for example residential investment, nominal house prices or measures of volume activity (housing starts, buiding permits ...).

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