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Does housing really lead the business cycle?

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Abstract: The aim of this paper is to characterize the cyclical properties of Spanish real and nominal housing related variables. Our three main results are: First, housing appears to lead the business cycle. Second, fluctuations in home prices are positively related to those of residential investment, suggesting the dominant role of demand factors (e.g. demographics or interest rates) over supply ones. Third, there are interesting asymmetries in cyclical fluctuations: contractions in GDP and housing real variables appear to be briefer than expansions.

Keywords: Housing, Business cycles, Asymmetries, Filtering
JEL Codes: E32, R21, R32, C14

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1. Introduction

The protracted period of sharp house price increases and booming investment in residential construction in most advanced economies has motivated an explosion of papers analysing the housing market. This interest is even stronger at present, as the boom has come to an end: house prices have rapidly decreased in a number of countries and residential investment is dragging down GDP.

Housing markets have multiple interactions with the rest of the economy, so a number of different issues have been addressed in the literature. For instance, a strand of research has analysed to which extent price levels are consistent with economic fundamentals [Ayuso and Restoy (2006), Mikhed and Zemcik (2009)]. Others authors have stressed the role of home wealth as a driver of household consumption on the basis of aggregate [Poterba (2000), L'Hotellerie and Sastre (2006)] and microeconomic data [Case *et al.* (2005), Bover (2005)]. The role of housing in the monetary transmission mechanism has also received a lot of attention, as reviewed in Mishkin (2007). Finally, there is growing work using estimated Dynamic Stochastic General Equilibrium models in which housing serves as a collateral asset [Iacoviello (2005), Iacovello and Neri (2008), Aspachs-Bracons and Rabanal (2009)]

Evidence on volume cycles and the earlier warning signal nature of real housing developments is considerably scanter than for price cycles[1]. Recently, Leamer (2007, 2009) has stressed the substantial effects on United States activity of volume changes in home building. Indeed, 8 out of the last 10 recessions in the US have been preceded by contractions in residential investment. For European countries, evidence for France, Germany, Italy and Spain has been recently made available in a joint project on housing –to which this paper belongs- by the 4 major euro area central banks[2].

The analysis of housing volume cycles in Spain is particularly relevant, given the strong investment in residential construction in the decade prior to 2006, against a background of low interest rates and sizable migration inflows. Real average annual growth of housing investment in this period exceeded 8% and its share in GDP reached record high levels in 2007 (9.3%), almost 5 pp. above 1996 and substantially above that in the euro area or the United States. The marked expansion of housing supply did not prevent a period of soaring house prices, but had a highly beneficial impact on employment in the construction sector: its share in total employment reached 13.8% in 2007, almost 5 pp. above 1996.

After this introduction, the structure of the paper is the following. Section 2 pays particular attention to methodological considerations in the estimation of cycles. Section 3 analyses cyclical features of real and nominal variables in the construction sector. Section 4 is devoted to the analysis of turning points and asymmetries in the response of variables in expansions and contractions. Section 5 concludes.

2. Estimating cycles: methodological considerations

There is a long history in empirical economics in modelling economic cycles. Decompositions of aggregate output into a trend – which accounts for long term growth-, a cyclical component –which measures deviations from this trend corresponding to business cycle frequencies- and an irregular component -which accounts for

1 The leading role of residential construction in the United States with respect to GDP has been stressed in Greene (1997) and Coulson and Kim (2000).

2 Besides this paper, see Álvarez et al. (2009), Bulligan (2009), Ferrara and Koopmann (2009), Ferrara and Vigna (2009) and Knetsch (2009).

very short-term fluctuations- have an intrinsic interest in economic assessments[3]. In this context, a large number of procedures have been developed [Canova (1998) or Mills (2003)].

The concept of cycle or output gap may be seen from different angles, so it is crucial to define beforehand the business cycle concept the researcher is interested in, so as to avoid conceptual confusions. Our aim is to focus attention on procedures that eliminate very slow moving (trend) components and very high frequency (irregular) components, while retaining intermediate (business cycles) components. The desired filter is what is known in the literature as an ideal band-pass filter. This definition is conceptually different from the one used in the DSGE literature –deviations of actual output from that of an economy without nominal rigidities- or in production function approaches –deviations from output consistent with stable inflation. This is also different from other methods that take a purely statistical stand, including those based on Beveridge-Nelson decompositions.

2.1 The ideal band-pass filter

The aim of an ideal band-pass filter is to pass through components of a time series belonging to a pre-specified band of frequencies (pass band), while removing components at higher and lower frequencies. The gain function $G\ (p)$ of a filter determines how the different cyclical fluctuations contribute to the signal.

If $G\ (p_0) = 1$ cyclical fluctuations with period p_0 are fully passed by the filter, whereas if $G\ (p_0) = 0$ they are fully suppressed. In formal terms, the ideal band-pass filter (G_I^{BP}) has a gain function (Figure 1) given by

$$G_I^{BP}\ (p) = \begin{cases} 0 & if\ |p| < p_1 \\ 1 & if\ p_1 \le |p| \le p_2 \\ 0 & if\ |p| > p_2 \end{cases}$$

which means that cyclical fluctuations belonging to the interval [p_1, p_2] pass through the filter untouched, but all other fluctuations are completely removed. Alternatively, the gain function can be expressed in terms of the frequency expressed in radians, taking into account the relationship $p = \frac{2\pi}{\omega}$

2. 2. Butterworth filters

Butterworth filters [Butterworth (1930)] are low-pass or band-pass filters widely used in electrical engineering in their one-sided form. In business cycle analysis, two-sided versions are to be preferred, to avoid phase shifts that would distort the timing of turning points. There are two families of Butterworth filters, which are based on the sine function (BFS) and the tangent function (BFT), respectively. Interestingly, the Hodrick Prescott filter is a particular low pass BFS [Gómez (2001)], so that Butterworth filters are more flexible than the HP filter, suggesting that there may be gains from their use. BFT filters fully suppress high frequency fluctuations, in contrast with BFS, so they are more appropriate for cycle estimation.

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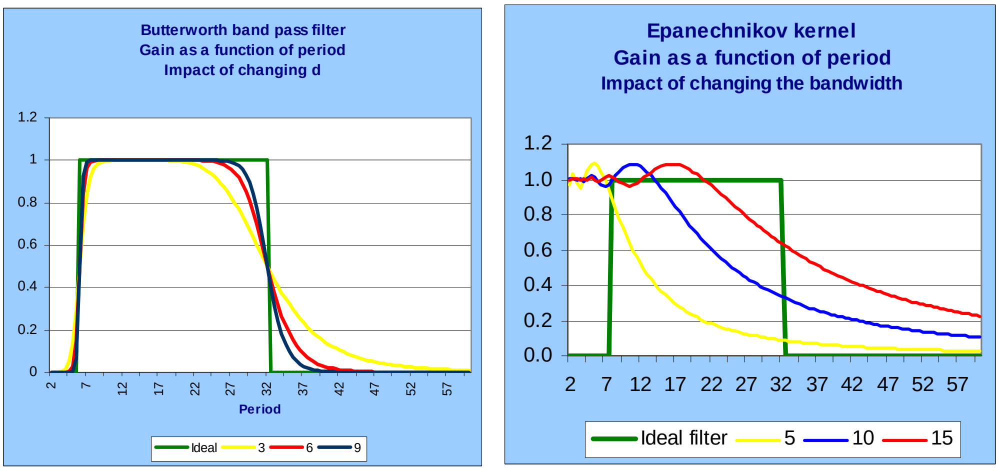
3 For instance, as leading indicators of inflationary pressures or to estimate cyclically adjusted budget balances.

Figure 1



Butterworth band-pass filters in the time domain are symmetric, two sided filters in the lag and forward operator given by

$$BPF(L,F)=\frac{(1-L^2)^d(1-F^2)^d}{(1-L^2)^d(1-F^2)^d+\lambda(1-\alpha L+L^2)^d(1-\alpha F+F^2)^d}$$

where d is an integer parameter, $\alpha=\cos((\omega_{p2}+\omega_{p1})/2)/\cos((\omega_{p2}-\omega_{p1})/2)$, ω_{p1} and ω_{p2} are the lower and upper limits of the band-pass, respectively, and λ is a parameter to ensure that the gain of the filter at a pre-specified period equals one-half. Note that larger values of *d* produce sharper filters, so there is better approximation to the ideal filter[4] (Figure 1). Approximations to the ideal filter are quite good for moderate values of *d*.

These Butterworth band-pass filters admit a model-based interpretation. Specifically, Gómez (2001) shows that the band-pass BFT can be obtained[5] as the best linear estimator, in the mean squared sense, of the signal in the signal-plus-noise model

$$y_t=s_t+\varepsilon_t$$

where s_t follows the model $(1-2\cos\alpha\ L+L^2)^d s_t=(1-L^2)^d\eta_t$ and ε_t and η_t are white noise processes. Note that the autoregressive model for the signal has 2 complex roots of unit modulus.

Gómez (2001) suggests a model-based two-stage procedure to obtain the cyclical component based on Butterworth filters, which can be shown to be identical to joint estimation of all components. In the first stage, the series is extended with ARIMA forecasts and backcasts to minimise the size of revisions and then a model-based trend-cycle component is obtained following the methodology in Gómez and Maravall (2001) [See appendix 0 for further detail]. Second, the band-pass BFT is applied. This method presents several advantages. First, the identification of a model for the first stage decreases the risk of inducing spurious results. For instance, if one tries to obtain a trend from a white noise series, the first stage will lead to the conclusion that no such a trend exists. Second, since optimal forecasts are used, revisions in preliminary estimates are reduced and an earlier detection of turning points is allowed for. Third, use of trends instead of seasonally-adjusted series or raw data leads to less noisy cycles, so the detection of turning points is easier.

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4 Alternatively, the filter can be defined for prespecified deviations in the pass band and stop band of the gain function of the ideal filter. See Gómez (2001).

5 Harvey and Trimbur (2003) give a model-based interpretation for band pass BFS filters.

2.3 Kernel regression

Kernel regression is a well known method in the statistical literature, which has recently been used by Leamer (2007) and IMF (2008) for business cycle analysis. The underlying idea of this nonparametric method is that any function can be well approximated by a Taylor series expansion in the neighbourhood of any point. The approach provides a method for obtaining pointwise estimates. That is, an arbitrary point is chosen and then a local polynomial regression provides an estimate of the trend at that point. The procedure is then repeated for all data points, so to obtain an estimate of the entire trend it is required to fit as many regressions as the number of observations.

Specifically, to estimate the trend for a given date (t_0) a linear regression is fit using only the data in an interval around t_0. The width of the interval used (the bandwidth) is a fixed number (*h*) chosen by the analyst. As *h* gets large, the local polynomial fit approaches the polynomial fit using the whole sample. Specifically,

$$y_t = a(t_0) + b_1(t_0)(t - t_0) + ... + b_k(t_0)(t - t_0)^k + \varepsilon_t \quad t \in [t_0 - h, t_0 + h] \quad t = 1, ..., n$$

Each of these regressions is fit using weighted least squares (WLS), solving the following minimization problem.

$$\min_{a,b} \sum_{t=1}^{n} K\left(\frac{t - t_0}{h}\right)\left((y_t - a(t_0) - b_1(t_0)(t - t_0) + ... + b_k(t_0)(t - t_0)^k\right)^2$$

The trend estimate is then obtained as the fitted value of the above regression.

In our empirical application, we consider kernel regression using an Epanechnikov kernel[6]

$$K(u) = \frac{3}{4}(1 - u^2)I(|u| \leq 1)$$

where u is the argument of the kernel function and $I(|u| \leq 1)$ is an indicator function that takes a value of one if its argument is true, and zero otherwise. The window width (*h*), which determines the number of points used in each regression. Increasing (decreasing) *h* involves using a wider (narrower) interval, which tends to increase (decrease) the smoothness of the trend. We have considered a bandwidth equal to 10.

Álvarez and Cabrero (2009) provide a frequency domain interpretation of kernel regressions. Figure 1 plots the gain function of a linear Epanechnikov kernel with different bandwidths. It is seen that the kernel method provides a reasonable approximation to the ideal filter, except for short-run fluctuations, where it performs quite badly. To avoid this problem and make comparisons with results of the Butterworth filter easier, we do not employ original series in our empirical application, but rather the trend-cycle component using Gómez and Maravall (2001) procedure. This method eliminates very short-run fluctuations, so kernel results that we present do not suffer from their general limitation.

2.4. Comparisons with other filters

In this section, we briefly review some widely used non-parametric procedures to obtain business cycles. This is relevant since other cyclical analyses of the housing sector have employed different procedures. For instance, Ferrara and Vigna (2009) use a band pass Hodrick and Prescott filter and Bulligan (2009) the Baxter and King (1999) filter.

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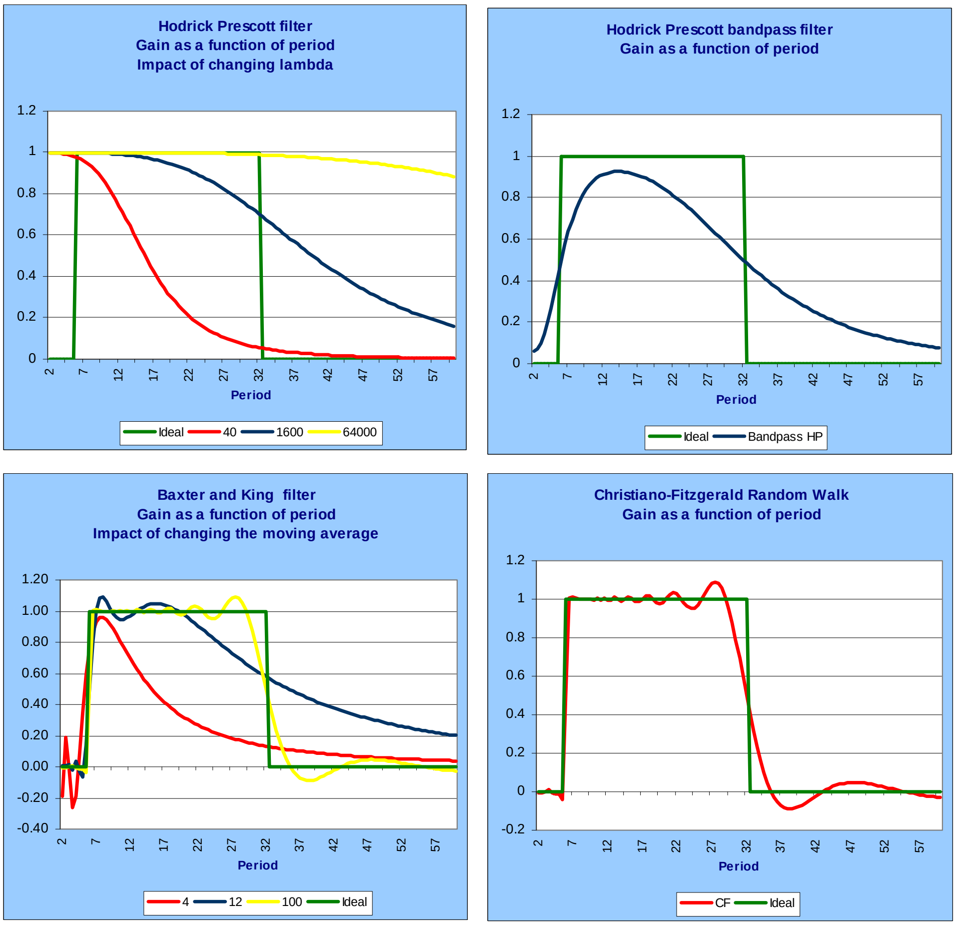
6 Use of alternative kernels, such as biweight,cosine or Gaussian produces very similar results.

Figure 2



2.4.1 Hodrick and Prescott filter

The underlying assumptions of the Hodrick and Prescott (1997) filter are that the trend is stochastic and it varies smoothly over time. The original motivation of the procedure is to obtain a trend balancing its smoothness and the fit to the original series. The parameter λ that characterises the filter determines to which extent fit is traded-off by smoothness. Interestingly, the HP estimator of the cycle may be considered as a high-pass filter [Prescott (1986)]. The cyclical HP filter damps cyclical fluctuations with high periods and leaves short-run cycles barely untouched. The higher value of lambda the more attention is paid to long-term cycles (figure 2).

2.4.2 Hodrick and Prescott bandpass filter

Given the frequency domain interpretation of the Hodrick-Prescott filter, it is natural to design a band pass filter as the difference of two HP filters [Artis *et al.* (2003)], the first working on short run fluctuations (e.g. less than six quarters) and the second one on long run movements (e.g. fluctuations with periods over 8 years). However, as stressed by Iacobucci and Noullez (2005), the bandpass version of the Hodrick Prescott filter cumulates the compression of two standard HP filters and is thus a poor approximation of the ideal bandpass filter (figure 2)

2.4.3 Baxter and King filter bandpass filter

It is well known that the ideal band-pass filter requires an infinite-order moving average. Since series are of finite length in empirical applications, Baxter and King (1999) derive an approximation of the ideal band-pass filter with a symmetric moving average of $2k$+1 terms. The approximation error (figure 2) diminishes by increasing *k*, but this leads to a loss of 2*k* observations (*k* leads and *k* lags). In practice, with quarterly data, k is equal to 12, which entails losing information for the first and last 12 quarters, a great loss for policymakers. Moreover, the gain of the BK filter oscillates around the gain of the ideal filter.

2.4.4 Christiano and Fitzgerald (2003) filter

Christiano and Fitzgerald (2003) provide an alternative band pass filter. Their optimal filter depends on the data generating process, but they find that weights under the assumption that the series is a random walk provide a reasonable approximation. Weights are not symmetric in terms of past and future observations, except in the middle of the data set, so that for each date a different filter is used.

The asymmetry of the filter causes a nonzero phase, which distorts the timing of the different frequency components and the nonstationarity causes the gain and the phase to depend on time. Iacobucci and Noullez (2005) stress the spurious shifts induced in the signal by the Christiano and Fitzgerald filter and show that distortions can be large: some cyclical fluctuations can be shifted up to plus or minus 5 months. Another limitation of this procedure is that the gain can be negative, so peaks (troughs) associated with some cyclical fluctuations could be turned into troughs (peaks).

3. The leading nature of housing

The aim of this section is to determine whether residential investment cycles in Spain tend to precede those in GDP, as in the United States, as well as to characterize the cyclical features of housing related variables in Spain. We also make a limited comparison with results for France, Germany and Italy.

We consider a sample period that starts in 1980:Q1 and ends in 2008:Q4, thus including the last recession. The choice of starting in 1980 tries to strike a balance between having the longest available time series and avoiding substantial changes in the definition of the variables. However, seasonally adjusted quarterly national account estimates prior to 1995 are too noisy, reflecting the fact that the National Institute of Statistics used to pay close attention to trend estimates, rather than to seasonally adjusted series. This has led us to pre-filter (the logs of) all data using the methodology in Gómez and Maravall (2001), which is described in appendix 0. This procedure has the advantage that it provides a clearer signal that helps improve the dating of turning points. Prior to the pre-filtering stage, we have also extended the series with forecasts to obtain an accurate assessment of the cyclical component at the end of the sample (and minimise revisions). Estimates for the 1970 decade have also been considered as initial conditions to improve estimates for the beginning of the sample. Reported statistics refer to the period 1980:Q1-2008:Q4.

Data sources of series used appear in appendix 1, year-on-year growth rates of the variables are plotted in appendix 2 and estimates of the cyclical components are plotted in appendix 3 (Butterworth filter) and 4 (Epanechnikov kernel).

3.1 Housing and other expenditure side GDP components

In this subsection, we focus on the cyclical behaviour of expenditure side GDP components. To that end, we estimate cyclical components mainly using Butterworth and kernel methodologies described above. We also analyse the robustness of our results by considering alternative estimates of cyclical components.

Results using the Butterworth filter and the Epanichnekov kernel are reported in table 1. The first column refers to the volatility of the component, as measured by the ratio of the standard definition of a variable[7] to

7 For clarity of exposition, we refer to the cyclical component as variable X, simple as variable X.

the standard deviation of GDP. The remaining columns report the cross correlation coefficient[8] (ρ_j) between each variable at time t and GDP at t+j. We pay special attention to the (absolute value) maximum cross-correlation coefficient. We say that a variable leads GDP if the maximum correlation corresponds to future output and not to contemporaneous or past output. Formally, a variable X leads, is synchronous or lags GDP if $|\rho_j|$ reaches a maximum for j>0, j=0 or j<0, respectively. We also say that a variable is pro-cyclical (counter-cyclical) if the maximum cross-correlation is positive (negative).

Table 1

Cross correlation of demand components with GDP

Variable	Volatility (*)	Variable leads GDP				Contemp.	Variable lags GDP			
		-4	-3	-2	-1	0	1	2	3	4
Butterworth filter										
Private consumption	1.0	0.48	0.60	0.71	0.77	0.74	0.64	0.51	0.41	0.33
Public consumption	0.6	-0.49	-0.44	-0.36	-0.24	-0.08	0.04	0.12	0.17	0.19
Investment in machinery and equipment	5.0	0.70	0.76	0.82	0.85	0.83	0.76	0.65	0.51	0.35
Residential investment	2.7	0.61	0.69	0.74	0.76	0.75	0.71	0.65	0.57	0.48
Investment in non residential constructi	2.4	0.08	0.16	0.23	0.28	0.31	0.30	0.27	0.24	0.20
Investment in other products	1.6	0.57	0.64	0.67	0.67	0.61	0.53	0.46	0.39	0.33
Exports of goods and services	1.9	0.36	0.52	0.65	0.74	0.74	0.69	0.61	0.52	0.42
Imports of goods and serivces	3.8	0.70	0.78	0.84	0.87	0.85	0.78	0.68	0.55	0.40
Epanechnikov filter										
	Volatility (*)	**Variable leads GDP**				**Contemp.**	**Variable lags GDP**			
		-4	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**
Private consumption	1.1	0.53	0.63	0.72	0.78	0.80	0.79	0.76	0.73	0.72
Public consumption	1.0	0.43	0.51	0.58	0.64	0.70	0.75	0.78	0.78	0.76
Investment in machinery and equipment	5.2	0.79	0.82	0.85	0.86	0.84	0.79	0.71	0.62	0.51
Residential investment	3.8	0.86	0.87	0.87	0.86	0.83	0.79	0.74	0.68	0.61
Investment in non residential constructi	3.4	0.51	0.59	0.66	0.71	0.74	0.75	0.75	0.74	0.72
Investment in other products	2.5	0.87	0.89	0.90	0.89	0.86	0.81	0.76	0.70	0.64
Exports of goods and services	2.0	0.08	0.12	0.15	0.16	0.15	0.11	0.05	-0.01	-0.06
Imports of goods and serivces	3.9	0.78	0.84	0.88	0.90	0.90	0.86	0.81	0.74	0.66

The table shows that residential investment leads GDP, is pro-cyclical and is considerably more variable than total output or consumption (standard errors of estimates are reported in appendices 4 and 5). Residential investment is linked to a higher extent with future output than with contemporaneous output and thus serves as a leading indicator, in line with the results in Leamer (2007, 2009). The maximum correlation coefficient of residential investment with GDP is high, but not perfect (0.76 using the Butterworth filter and 0.87 with the Epanichnekov kernel). The estimated lead varies from 1 to 3 quarters. Further robustness analysis is presented in table 2, in which cross correlations of residential investment and nominal prices with respect to GDP are reported using Hodrick Prescott, band pass Hodrick Prescott, Baxter and King and Christiano and Fitzgerald filters. Using these alternative filters, residential investment leads GDP by 2 or 3 quarters. Maximum correlations are also high (in the 0.59-0.80 range). Larger quantitative differences are observed in terms of volatility, but the robust finding is that residential investment fluctuates considerably more than GDP. Table 3 presents an international comparison: residential investment is also found to lead GDP in Germany, but not in France or Italy (table 3). However, Ferrara and Vigna (2009) using a band pass Hodrick Prescott filter find that French residential investment also leads GDP. For the US, Leamer (2007, 2009) also finds that residential investment leads GDP.

8 Standard errors of correlation coefficients are reported in appendices 4 and 5.

Despite the anticipatory nature of residential investment fluctuations with respect to those in GDP found in the data, attempts in the existing theoretical literature have had limited success [Gangopadhyay and Hatchondo (2009)]. In a standard general equilibrium model with homogeneous agents [Greenwood and Hercowitz (1991)] representative agents react to a positive technology shock by increasing business investment at the expense of residential investment, thus generating a negative comovement between residential and business investment, at odds with the data. David and Heathcote (2005) obtain a positive comovement between both variables in a model with multiple sectors. In their model, positive technology shocks drive down house prices, allowing consumers to buy more houses. This view of supply driven residential cycles is inconsistent with the positive comovement of house prices and residential investment, typically found in the data. Fisher (2007) succeeds in explaining the leadership of residential over business investment, but not with respect to GDP. The idea is that by increasing the size of the house families increase their labour productivity. As a response to a positive productivity shock in the market sector, households first increase their residential investment at the expense of business investment, which allows them to increase their productivity in periods following the shock. Recently, Yuan (2009) has developed a model in which residential investment leads GDP. In his model, agents face collateral constraints and receive a signal about future productivity one period in advance. A good signal about future productivity makes household spend more to intertemporally smooth consumption. Increased expenditures are financed up to a fraction of the value of the house by borrowing at mortgage interest rates, which are lower that for unsecured consumer loans. As a result, agents buy more housing relative to other goods. Though the model is able to account for the leading nature of housing, the way the financial market is modelled is not completely satisfactory. In particular, households typically do not continuously vary the size of mortgages, according to fluctuations in total spending.

Table 2

Cross correlations. Sensitivity to the filter used
Sample: 1980:Q1-2008:Q4

Housing investment vs GDP	Volatility (*)	Residential investment leads GDP				Contemp.	Residential investment lags GDP			
		-4	-3	-2	-1	0	1	2	3	4
HP	3.7	0.74	0.76	0.77	0.76	0.72	0.66	0.58	0.50	0.41
Band pass HP	3.6	0.77	0.80	0.80	0.79	0.76	0.70	0.62	0.53	0.42
Baxter and King	4.4	0.69	0.71	0.71	0.69	0.66	0.55	0.44	0.34	0.25
Cristiano and Fitzgerald	3.8	0.57	0.59	0.58	0.56	0.54	0.42	0.33	0.25	0.19
Butterworth	2.7	0.61	0.69	0.74	0.76	0.75	0.71	0.65	0.57	0.48
Epanechnikov	3.8	0.86	0.87	0.87	0.86	0.83	0.79	0.74	0.68	0.61
House prices vs housing investment	**Volatility (**)**	**House prices leads residential investment**				**Contemp.**	**ouse prices lags residential investme**			
		-4	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**
HP	0.8	0.38	0.46	0.51	0.55	0.58	0.60	0.62	0.62	0.62
Band pass HP	0.9	0.40	0.47	0.53	0.57	0.60	0.63	0.65	0.65	0.64
Baxter and King	0.9	0.32	0.40	0.47	0.52	0.58	0.61	0.65	0.68	0.69
Cristiano and Fitzgerald	0.8	0.24	0.31	0.37	0.43	0.49	0.52	0.55	0.58	0.57
Butterworth	0.6	0.38	0.50	0.59	0.65	0.70	0.72	0.72	0.70	0.64
Epanechnikov	1.0	0.45	0.51	0.57	0.61	0.64	0.68	0.70	0.72	0.74

(*) Standard deviation of variable relative to standard deviation of GDP
(**) Standard deviation of house prices relative to standard deviation of residential investment

Table 3

Leading nature of housing. International comparison								
	Lead of variable with respect to GDP (quarters)				Maximum cross correlation			
	France	Germany	Italy	Spain	France	Germany	Italy	Spain
Residential investment	0	2	0	1	0.53	0.71	0.53	0.76
Building permits	5	5	na	4	0.75	0.59	na	0.75
Housing starts	4	na	na	4	0.58	na	na	0.75

Sample: 1980:Q1-2008:Q4. Butterworth filter

3.2 Additional real and nominal construction variables

The leading nature of housing is considerably clearer when using some indicators, such as housing starts and building permits, instead of residential investment. Indeed, Butterworth and Epanichnekov kernel procedures show that both variables lead GDP by 4 quarters (see appendices 4 to 6). This is explained by the fact that residential investment in national accounts refers to the value of the work of houses in progress. There is, thus, a time lag between the start of a house (or the time a building is authorised to start) and the national account magnitude. As expected, indicators constructed on the basis of housing starts or building permits and a time to build hypothesis lead to a smaller lead with respect to GDP. Building permits and housing starts in France and Germany are also found to lead GDP (Table 3), a result also found for France by Ferrara and Vigna (2009)

The leading nature of residential investment with respect to GDP is not shared by Gross Value Added in construction. This variable also includes non-residential construction, which is either synchronous or lags GDP. The maximum GVA-GDP correlation is considerably lower than the maximum residential investment GDP correlation, probably reflecting the discretionary nature of public construction. Even though at present public construction is being used to stabilize the economy through a fiscal stimulus package, this has not been always the case within the sample period. In Spain, public construction by regional governments and city councils typically is more closely linked to the electoral cycle rather than to the business cycle.

Labour input in the construction sector, measured both in terms of number of workers and full time equivalent workers, is pro-cyclical and lags residential investment using both filters: the Butterworth filter shows a lead of 1 quarter and Epanechnikov kernel of three quarters. The lag of the labour input probably reflects the fact that firms face costs in adjusting the size of their workforce. Material input indicators, such as concrete consumption and production, are pro-cyclical and coincident with GDP.

Nominal house prices and residential investment are pro-cyclical. The examination of the maximum cross correlation coefficient between residential investment and house prices (0.72 using the Butterworth filter and 0.74 using the Epanechnikov kernel) shows positive comovement. This result is also robust to the use of other filters (Table 2). This suggests that demand factors (e.g. demographics or interest rates) appear to have been more important than supply considerations (e.g. technological progress). This is in line with González and Ortega (2009) who find that immigration has played a major role in the recent housing market boom in Spain. Our evidence also points out that price cycles lag volume cycles (1 quarter with the Butterworth filter and 4 quarters using the Epanechnikov kernel), reflecting price stickiness. Results on real house prices are less clear. Real prices are coincident with residential investment using the Butterworth filter, but lag 4 quarters with the Epanechnikov kernel. Results for mortgage credit are also inconclusive.

4. Brevity and violence of expansions and contractions

A recurring theme in discussions about business cycle fluctuations is their asymmetric nature: are contractions of economic activity briefer than expansions? Are contractions more violent than expansions? A number of authors have developed theoretical models than allow for such asymmetries. For instance, in Hansen and Prescott (2005) asymmetries are due to capacity constraints: production takes place at individual plants that may or may not be operated in a given period. In recessions, some plants simply are not used, whereas in booms firms hit capacity constraints. In Kocherlakota (2000) asymmetric business cycles are the results of credit constraints. In contractions, agents would like to borrow, but are unable to obtain the amount they would like, as they have credit constraints. As a result, they have to cut down production. Other authors, such as McKay and Reis (2008), put the emphasis on the labour market: In contractions, firms can quickly dismiss workers, but in booms they need time to find and train workers.

In our empirical analysis, we first determine the turning points of the different variables, so as to segment the sample into periods of expansions and contractions. Specifically, we identify these periods with a binary random variable (S_t) that takes the value unity in expansions and zero in contractions. Then, we consider a number of statistics to characterise the brevity and violence of the cycles.

Turning points are dated non-parametrically, using a variant of the Bry and Boschan (1971) methodology proposed by Harding and Pagan (2002) and called BBQ. Basically, the method first determines peaks (troughs) as the local maxima (minima) in the series. Second, it eliminates some of these preliminary turning points, so as to ensure that expansion (trough to peak) and contraction (peak to trough) phases exceed a pre-specified number of quarters, while completed cycles have a duration of at least a given number of quarters. In our application, we consider durations of 5 quarters for expansions and contractions and 10 quarters for full cycles. Third, it ensures that peaks and troughs alternate.

Appendix 7 presents statistics on the number of peaks, troughs, as well as mean durations and amplitudes of full cycles. In our sample period, we detect around 5 peaks and 4 troughs for the majority of variables. The mean duration of a full cycle (*i.e.* the time from peak to the next peak) is around 6 years, with a quite homogeneous distribution across variables. There are very marked differences, though, in terms of the amplitude of fluctuations. As expected, fluctuations in GDP are less marked than in residential investment, reflecting the smoothness of household consumption. Moreover, fluctuations in short-term indicators, such as housing starts and building permits, are considerably larger than for other variables. Fluctuations in real variables are generally larger than for prices.

To focus on asymmetries, we compute measures of brevity, violence and steepness of variables. Brevity is measured in terms of average duration of expansions (D^E) and contractions (D^C)

$$D^E = \frac{\sum_{t=1}^{T} S_t}{ne} \qquad\qquad D^C = \frac{\sum_{t=1}^{T} (1 - S_t)}{nc}$$

where ne and nc refer, respectively, to the number of expansions and contractions and T is the sample size.

We find that GDP contractions are substantially briefer than GDP expansions (figure 3). Depending on the filter, contractions tend to last slightly above 2 years, whereas expansions last close to 4 years[9]. Asymmetry is less clear for residential investment: using the Epanechnikov kernel contractions are briefer, but the opposite result is found with the Butterworth filter. In contrast, other real indicators, such as housing starts or building permits share the asymmetric pattern. Employment in construction tends to show higher asymmetry than GDP, as in McKay and Reis (2008): contractions last between 2 or 3 years, but expansions typically last close to 5 years. Asymmetry in terms of nominal and real house prices is found to be much less relevant.

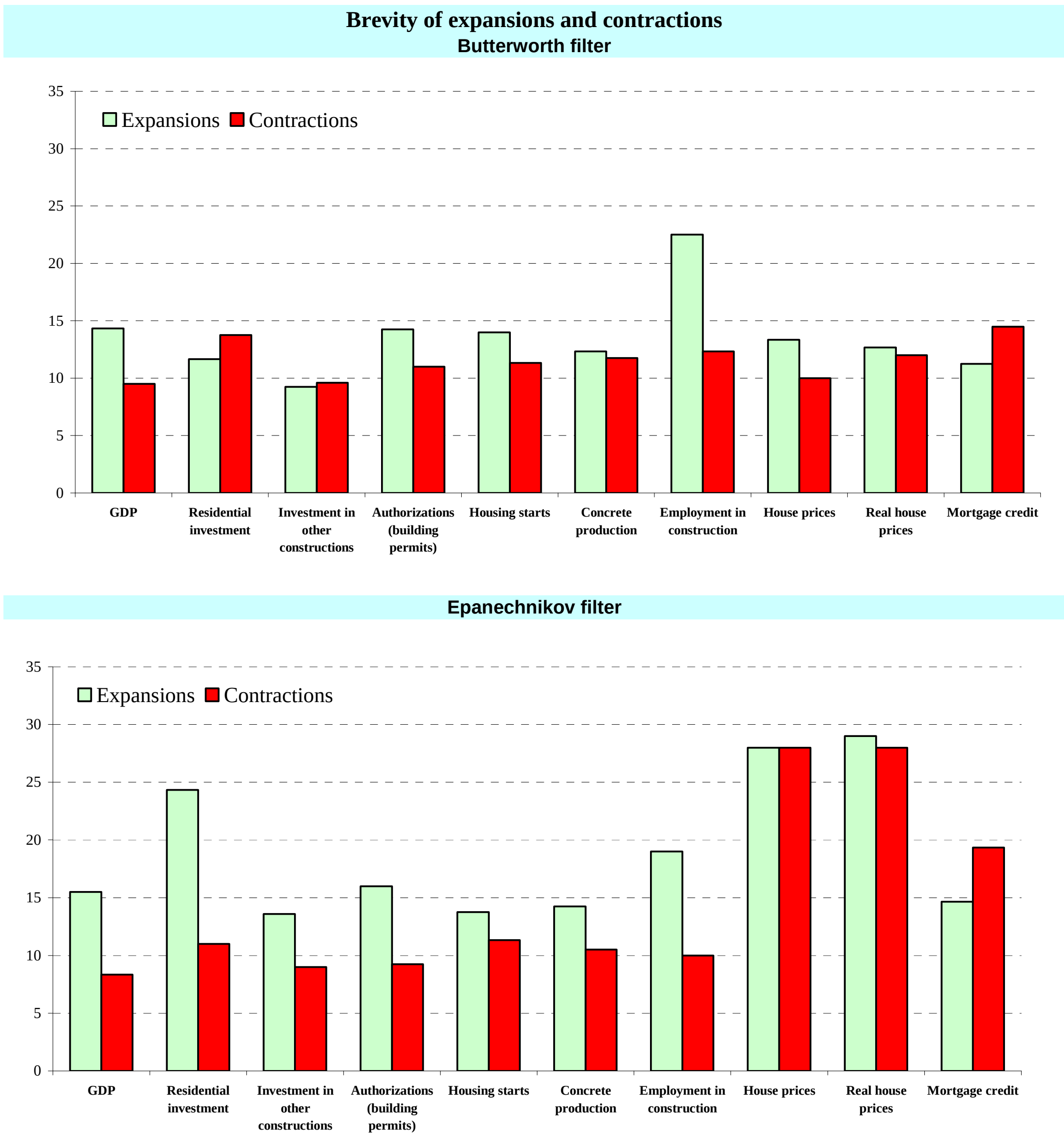


Figure 3

Asymmetry may also refer to the violence of the change. Violence of expansions (A^E) is measured in terms of the change in the series (Δy_t) from a trough to the next peak and violence of contractions as the change of the series from the peak to the following trough. Formally,

9 The difference is economically significant. However, given the simple length, point estimates are fairly imprecise. The null hypothesis that the duration of expansions equals that of contractions is not rejected by the data.

$$A^E = \frac{\sum_{t=1}^{T} S_t \Delta y_t}{ne} \qquad A^C = \frac{-\sum_{t=1}^{T} (1-S_t)\Delta y_t}{nc}$$

Having estimated the cycles for the different variables, a question that arises is whether booms or busts in two series go in tandem. Harding and Pagan (2002) define a coincidence indicator (CI) that measures the fraction of time that two series are in the same (expansionary or contractionary) phase. Formally,

$$CI = \frac{\sum_{t=1}^{T} S_{1t}\ S_{2t} + (1-S_{1t})(1-S_{2t})}{T}$$

where S_{1t} and S_{2t} are binary variables, defined analogously to S_t, that capture if series 1 and 2 are either in expansion or contraction. This measure provides additional information to the standard linear correlation coefficient.

GDP does not show a clear asymmetry in terms of violence: troughs do not appear to be deeper than peaks are tall and the main two filters we use give conflicting signals. Residential investment also does not present a clear pattern: the Epanechnikov kernel shows asymmetry, but this is not shared by the Butterworth filter. There is no consistent evidence of asymmetry for the rest of variables. Statistics of steepness of expansions and contractions – which measure the average gain (loss) per unit of time in an expansion (contraction)- also do not show interesting asymmetric patterns for the different variables.

Table 4

Cyclical clasification of several Spanish construction variables vis a vis GDP

Butterworth filter

Sample period 1980-Q1 - 2008-Q4	Classification	Concordance index Harding and Pagan 2002	Median lead	Median lead (expansions)	Median lead (contractions)
Residential investment	Coincident	**0.8**	**0.0**	3.0	-2.0
Investment in non residential construction	Leading	**0.7**	**2.0**	3.0	-1.0
Building permits	Leading	**0.6**	**1.0**	2.5	1.0
Housing starts	Leading	**0.6**	**4.0**	3.0	7.0
Concrete production	Leading	**0.7**	**1.0**	1.0	0.0
Employment in construction (persons)	Leading	**0.8**	**1.0**	1.0	0.0
Nominal house prices	Coincident	**0.8**	**0.0**	-0.5	0.0
Real house prices	Coincident	**0.8**	**0.0**	0.5	0.0
Mortgage credit	Laging	**0.7**	**-1.0**	0.5	-2.0

Epanechnikov filter

Sample period 1980-Q1 - 2008-Q4	Classification	Concordance index Harding and Pagan 2002	Median lead	Median lead (expansions)	Median lead (contractions)
Residential investment	Leading	**0.6**	**3.5**	6.0	2.5
Investment in non residential construction	Coincident	**0.7**	**0.0**	2.0	0.0
Building permits	Leading	**0.6**	**2.0**	2.0	7.0
Housing starts	Leading	**0.5**	**1.5**	3.0	3.0
Concrete production	Coincident	**0.6**	**0.0**	0.0	5.0
Employment in construction (persons)	Leading	**0.7**	**1.0**	1.0	1.0
Nominal house prices	Leading	**0.6**	**3.0**	3.5	12.5
Real house prices	Leading	**0.6**	**2.0**	3.5	-8.5
Mortgage credit	Coincident	**0.7**	**0.0**	3.0	-3.0

Table 4 and Appendix 8 reports the coincidence indicator for the different construction variables. It is seen that there is substantial comovement of these variables with GDP. Around 70% of the time each variable is in the same expansionary or contractionary phase as GDP. The table also reports the median lead of the turning points in each variable with respect to those in GDP. Results of mean lags confirm those of the previous cross-correlation analysis: housing leads GDP. This is particularly true for housing starts and building permits indicators and somewhat less clear for residential investment. Results for nominal and real prices are not conclusive: the Butterworth filter suggests a coincident role with respect to GDP, but linear kernels show some lead.

In section 4 we have emphasized the leading nature of housing with respect to GDP: housing related variables show a higher correlation with future output than with current or past output. An alternative approach is to analyse whether the turning point in a given variable precedes or not that of GDP. Table 4 reports median lags for all turning points, peaks and troughs. This allows us to check for asymmetries in the lead-lag relationship. We find that the lead of residential investment with respect to GDP in expansions is larger than the lead in contractions.

5. Conclusions

This paper analyses housing volume and price cycles in Spain. We find that residential investment is linked to a higher extent with future output than with contemporaneous or past output and thus serves as a leading indicator of GDP, as found with US data. Earlier signals of future changes in GDP are given by housing starts or building permits. These empirical regularities deserve close attention and more theoretical work is needed to further understand them.

The recent experience of the Spanish economy has shown a marked expansion of housing supply that has not prevented a protracted period of sharp house price rises. It is, therefore, not surprising that we find that fluctuations in home prices have been positively linked to those of residential construction. This supports a view of mainly demand driven housing volume cycles, in line with the observed increase in immigrants and the number of single person households, as well as the drop in interest rates. Among supply factors, technological progress in home building is likely to have played a minor role, but land use constraints probably less so.

Third, there are interesting asymmetries in cyclical fluctuations: contractions in GDP and housing real variables appear to be briefer than expansions. Further, we find that the lead of residential investment with respect to GDP in expansions is larger than the lead in contractions.

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Appendix 0. Model based signal extraction

This appendix provides a brief explanation of unobserved component signal extraction. The reader is referred to Gómez and Maravall (2001) for a more detailed description and to Caporello and Maravall (2004) for the TSW computer program that implements this methodology.

We consider the decomposition of a series x_t into a signal s_t and a noise process n_t

$$x_t = s_t + n_t$$

We further assume that both components follow ARIMA processes.

$$\phi_s(L)\, s_t = \theta_s(L)\, a_{st}$$

$$\phi_n(L)\, n_t = \theta_n(L)\, a_{nt}$$

where $\phi_s(L)$ and $\phi_n(L)$ are prime polynomials, $\theta_s(L)$ and $\theta_n(L)$ do not share a unit root and a_{st} and a_{nt} are orthogonal white noise processes with variances σ_s^2 and σ_n^2, respectively.

Because aggregation of ARIMA models also yields an ARIMA model

$$\phi\ (L)\, x_t = \theta\ (L)\, a_t$$

where a_t is white noise with variance σ^2, $\theta(L)$ is invertible and $\phi\ (L) = \phi_s(L)\,\phi_n(L)$. Further, the following identity holds

$$\theta(L)\, a_t = \phi_n(L)\,\theta_s(L)\, a_{st} + \phi_s(L)\,\theta_n(L)\, a_{nt}$$

Without further restrictions the model is not identified, since there is an infinite number of solutions to the above decomposition. In order to reach identification it is assumed the model for the signal is balanced (the order of the AR polynomial equals that of the MA polynomial) and the canonical property that implies that the smoothest signal is chosen (no additive white noise can be extracted from the signal).

For a particular time series, the Minimum Mean Square Error (MMSE) estimators of the signal is computed using the Wiener-Kolmogorov filter $\nu(L,F)$ applied to the finite series by extending the latter with forecasts and backcasts in order to minimise the size of revisions.

$$\nu(L,F) = \frac{\sigma_s^2}{\sigma^2}\,\frac{\theta_s(L)\phi_n(L)}{\theta(L)}\,\frac{\theta_s(F)\phi_n(F)}{\theta(F)}$$

The filter is symmetric, convergent in the lag and forward operator and centered at t.

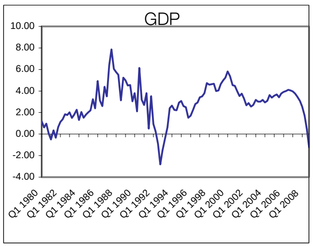
Appendix 1. Database description

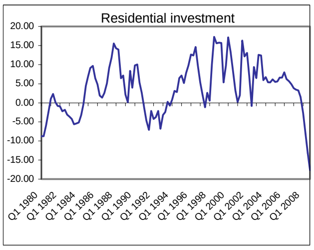
	Database description			
	Variables	**Code**	**Source**	**Comments**
1	**GDP**	**PIB**	QNA. National Institute of Statitistics (INE) and own elaboration	Linkage of national accounts bases 1995 (since 1980 to 1994:Q4) and 2000, using q-o-q growth rates. Index 2000=100
2	**Private consumption**	**CPR**	QNA. National Institute of Statitistics (INE) and own elaboration	
3	**Public consumption**	**CPUB**	QNA. National Institute of Statitistics (INE) and own elaboration	
4	**Investment in machinery and equipment**	**INVEQ**	QNA. National Institute of Statitistics (INE) and own elaboration	
5	**Residential investment**	**VIV**	QNA. National Institute of Statitistics (INE) and own elaboration	
6	**Investment in non residential construction**	**OTCNT**	QNA. National Institute of Statitistics (INE) and own elaboration	
7	**Investment in other products**	**OTROS**	QNA. National Institute of Statitistics (INE) and own elaboration	
8	**Exports of goods and services**	**EX**	QNA. National Institute of Statitistics (INE) and own elaboration	
9	**Imports of goods and serivces**	**IMP**	QNA. National Institute of Statitistics (INE) and own elaboration	
10	**Gross value added in construction**	**VCNT**	QNA. National Institute of Statitistics (INE) and own elaboration	
11	**Building permits**	**VISA**	Architects and Technical Architects´ Associations and own elaboration	Number of buiildings
12	**Housing starts**	**VIVIN**	Ministry of Housing	Number of houses. Includes both subsidized and unsubsidized houses.
13	**Housing in progress index (building permits)**	**VIVI1**	Architects and Technical Architects´ Associations and own elaboration	Index calculated with building permits and an estimated calendar of construction
14	**Housing in progress index (housing starts)**	**VIVI2**	Ministry of Housing and own elaboration	Index elaborated on housing starts and and an estimated calendar of construction
15	**Concrete production**	**PRCEM**		
16	**Concrete consumption**	**CNCEM**		
17	**Employment in construction (persons)**	**OCCSP**	Labour Force Survey (INE)	Thousand of people
18	**Employment in construction sector (FTE)**	**OCCSCN**	QNA and own elaboration	Full time equivalent
19	**Nominal house prices**	**HOPRC**	Ministry of Housing and own elaboration	
20	**Real house prices**	**HOPRR**	INE and own elaboration	
21	**Residential investment deflator**	**DFIVV**	QNA	
22	**Investment in construction deflator**	**DFCST**	QNA	
25	**Mortgage credit**	**CRDHP**	Bank of Spain	

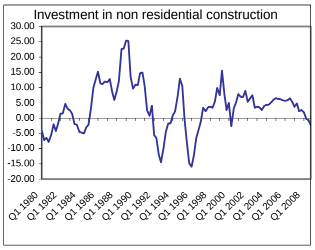
Sample 1980:Q1 2008:Q4

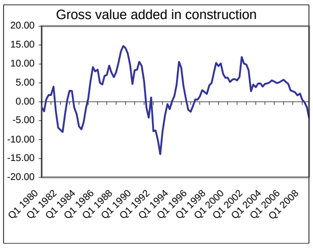
Appendix 2. Seasonally adjusted (or original) series (1980:1 2008:4)

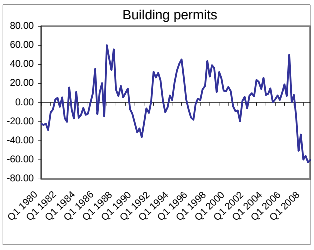
Year on year growth rate

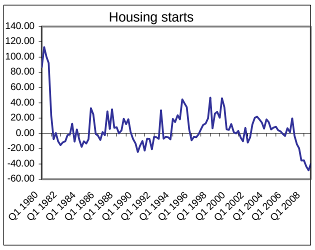


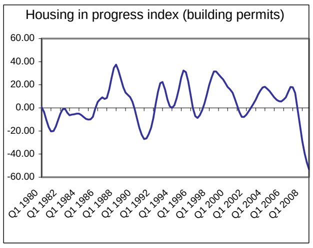


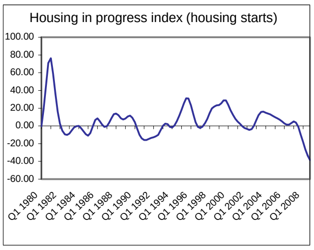


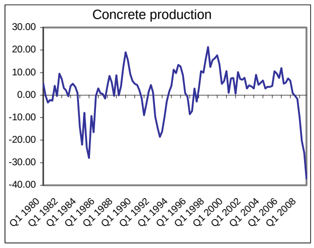


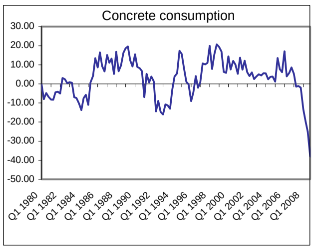


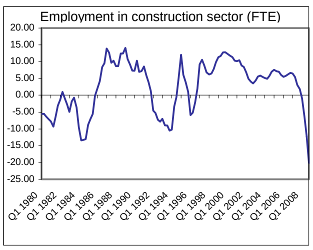


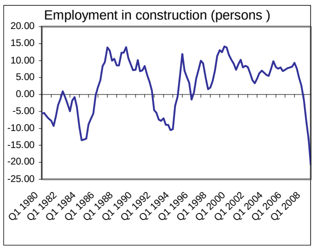


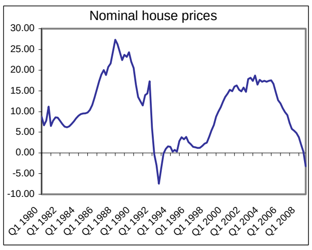


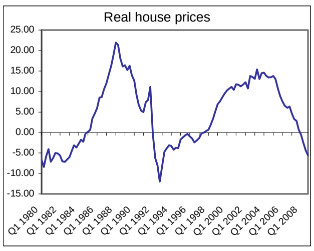


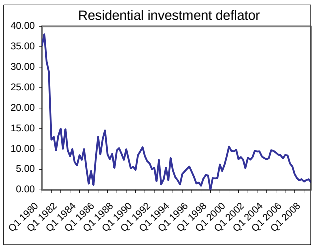


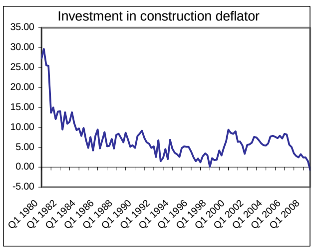


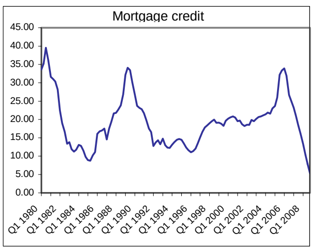






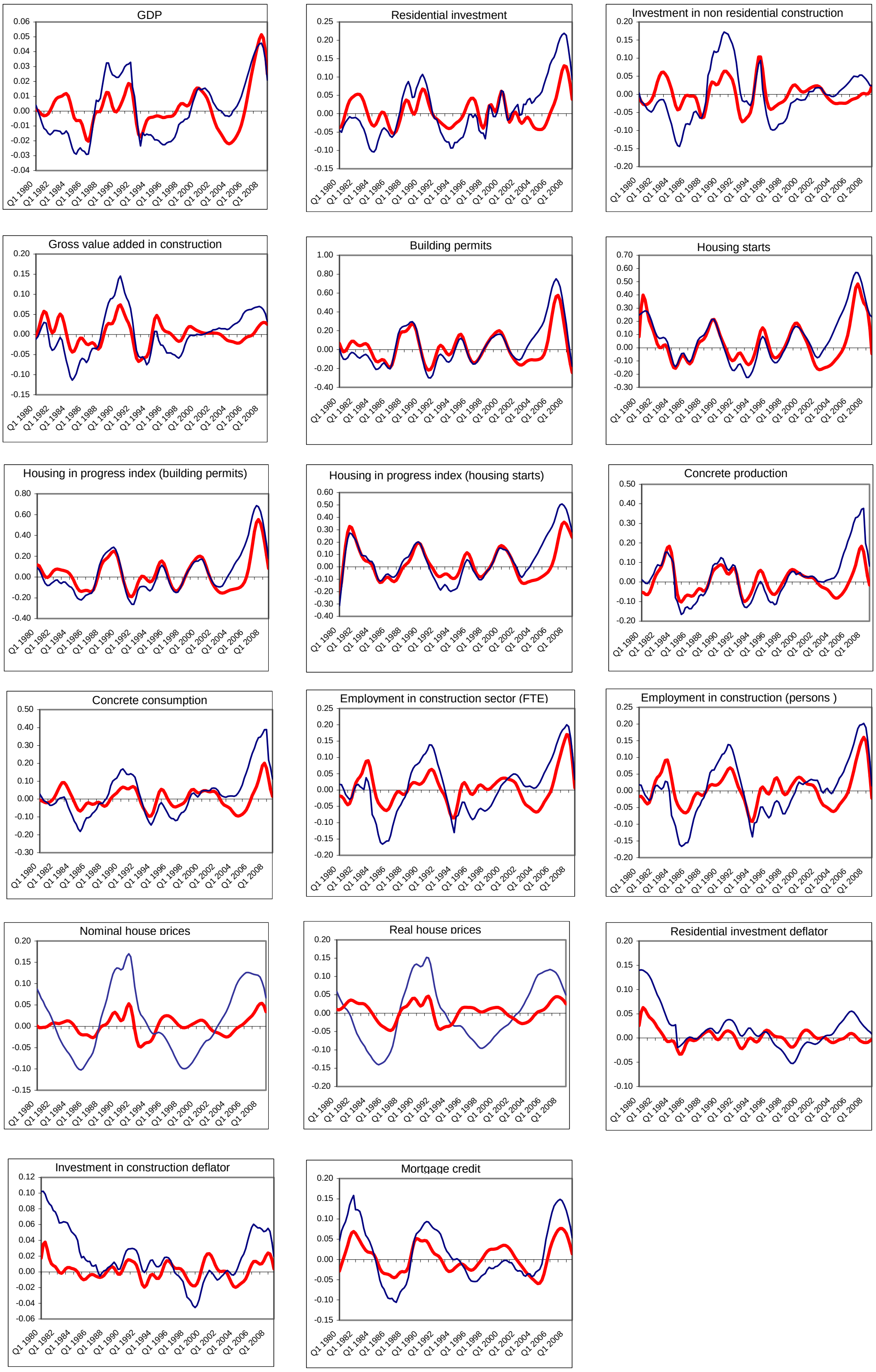






Appendix 3 Seasonally adjusted (or original) series (1980:1 2008:4)

Cyclical components (%)



Red line: Butterworth filter (d=6)
Blue line: Epanechnikov filter (Bw=10)

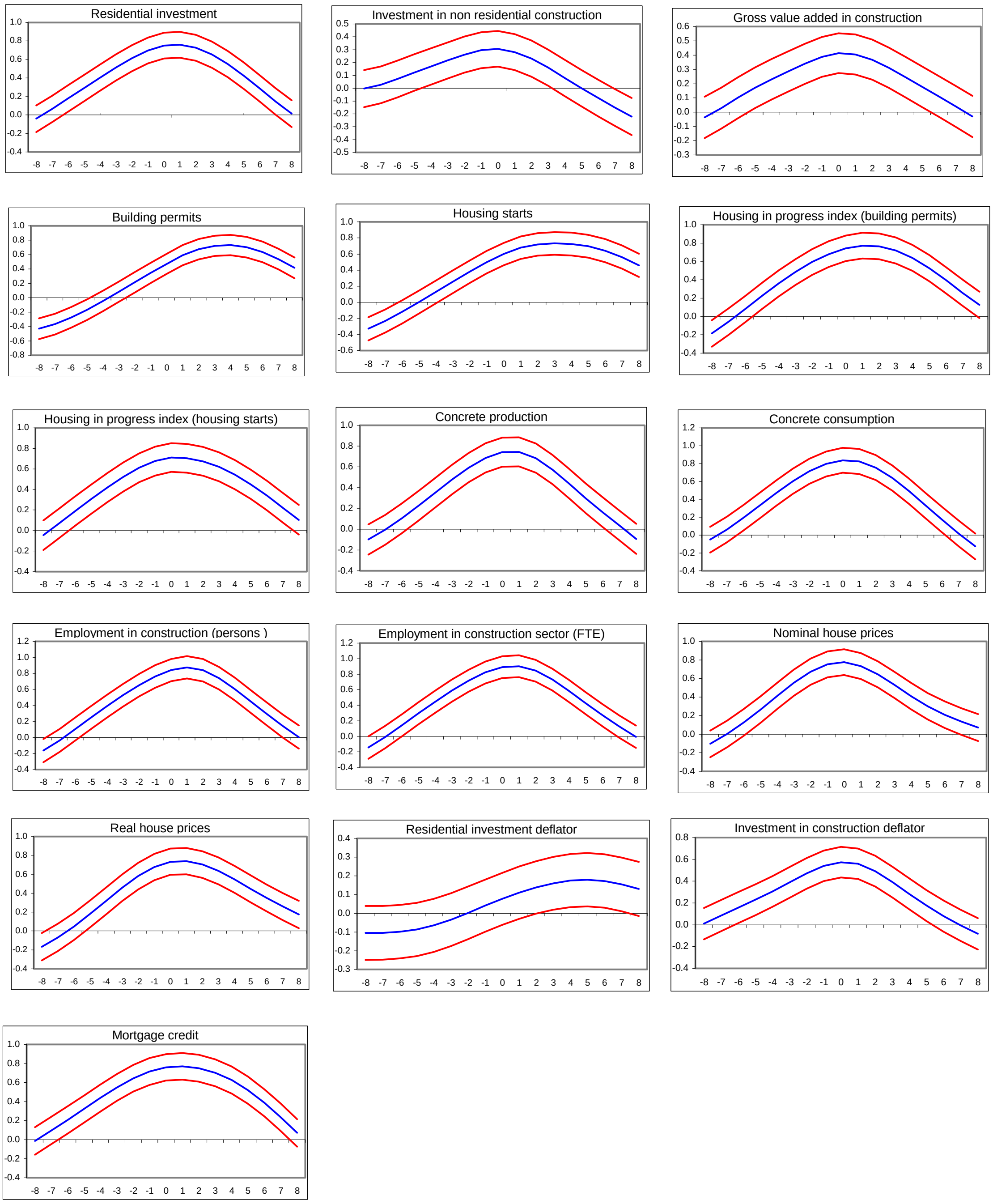
Appendix 4. Cross correlation of several building indicators with GDP

Cross correlation of several building indicators with GDP										
Butterworth filter										
Variable	Volatility	Variable leads GDP				Contemp.	Variable lags GDP			
	(*)	-4	-3	-2	-1	0	1	2	3	4
Residential investment	2.7	0.61	0.69	0.74	0.76	0.75	0.71	0.65	0.57	0.48
Investment in non residential construction	2.4	0.08	0.16	0.23	0.28	0.31	0.30	0.27	0.24	0.20
Gross value added in construction	2.0	0.25	0.31	0.37	0.41	0.41	0.39	0.35	0.31	0.27
Building permits	11.3	0.75	0.73	0.69	0.60	0.47	0.35	0.22	0.09	-0.05
Housing starts	10.4	0.75	0.74	0.72	0.68	0.60	0.50	0.40	0.29	0.15
Housing in progress index (building permits)	10.6	0.68	0.74	0.77	0.77	0.74	0.69	0.62	0.53	0.42
Housing in progress index (housing starts)	9.0	0.59	0.65	0.69	0.71	0.71	0.70	0.65	0.59	0.51
Concrete production	4.7	0.45	0.58	0.68	0.74	0.74	0.70	0.62	0.53	0.42
Concrete consumption	4.0	0.52	0.65	0.76	0.82	0.84	0.81	0.75	0.66	0.56
Employment in construction (persons)	3.4	0.64	0.76	0.84	0.88	0.84	0.77	0.68	0.58	0.47
Employment in construction sector (FTE)	9.2	0.78	0.82	0.81	0.72	0.57	0.44	0.30	0.15	0.00
Nominal house prices(*)	0.6	0.38	0.50	0.59	0.65	0.70	0.72	0.72	0.70	0.64
Real house prices(*)	0.6	0.50	0.61	0.68	0.72	0.73	0.72	0.68	0.62	0.54
Residential investment deflator	1.1	0.17	0.16	0.13	0.10	0.06	0.02	-0.04	-0.10	-0.16
Investment in construction deflator	0.8	0.29	0.40	0.49	0.56	0.57	0.55	0.51	0.46	0.39
Mortgage credit	2.4	0.64	0.71	0.75	0.77	0.76	0.73	0.68	0.61	0.52
Epanechnikov filter										
Variable	Volatility	Variable leads GDP				Contemp.	Variable lags GDP			
	(*)	-4	-3	-2	-1	0	1	2	3	4
Residential investment	3.8	0.86	0.87	0.87	0.86	0.83	0.79	0.74	0.68	0.61
Investment in non residential construction	3.4	0.51	0.59	0.66	0.71	0.74	0.75	0.75	0.74	0.72
Gross value added in construction	2.7	0.70	0.76	0.81	0.83	0.84	0.83	0.80	0.77	0.73
Building permits	11.1	0.73	0.70	0.66	0.60	0.52	0.44	0.35	0.26	0.17
Housing starts	9.1	0.64	0.63	0.62	0.59	0.55	0.50	0.44	0.37	0.29
Housing in progress index (building permits)	10.4	0.76	0.76	0.75	0.73	0.70	0.65	0.59	0.52	0.44
Housing in progress index (housing starts)	8.5	0.64	0.65	0.65	0.64	0.61	0.59	0.55	0.50	0.43
Concrete production	5.8	0.59	0.65	0.70	0.74	0.75	0.72	0.68	0.63	0.56
Concrete consumption	6.1	0.77	0.82	0.87	0.89	0.90	0.88	0.84	0.79	0.73
Employment in construction (persons)	4.1	0.68	0.76	0.83	0.88	0.89	0.88	0.86	0.83	0.78
Employment in construction sector (FTE)	11.6	0.91	0.93	0.92	0.88	0.81	0.73	0.63	0.53	0.43
Nominal house prices(*)	1.0	0.45	0.51	0.57	0.61	0.64	0.68	0.70	0.72	0.74
Real house prices(*)	1.1	0.52	0.58	0.63	0.67	0.69	0.72	0.73	0.74	0.75
Residential investment deflator	2.0	-0.07	-0.04	0.00	0.03	0.06	0.09	0.11	0.13	0.15
Investment in construction deflator	1.6	-0.11	-0.05	0.00	0.06	0.10	0.12	0.14	0.15	0.17
Mortgage credit	3.4	0.19	0.28	0.36	0.43	0.49	0.54	0.57	0.59	0.60

(*) Cross correlation analysed computed with housing investment

Appendix 5. Cross correlation of variables with GDP. Butterworth filter

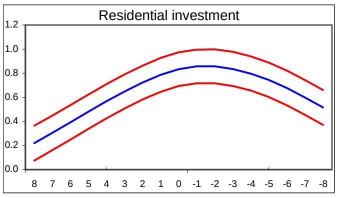
Variable leads (lags) GDP if maximum correlation corresponds to a positive (negative) value in the X-axis

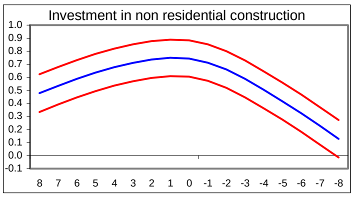


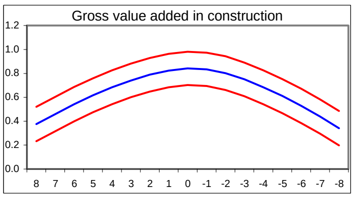
Blue lines: Point estimates
Red lines: Plus/minus 1.5 standard deviation bands

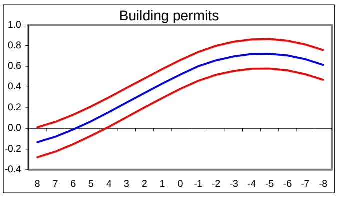
Appendix 6. Cross correlation of variables with GDP. Epanechnikov filter

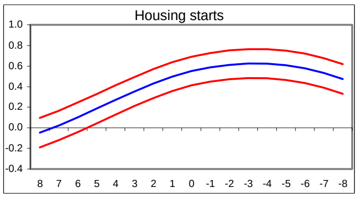
Variable leads (lags) GDP if maximum correlation corresponds to a positive (negative) value in the X-axis

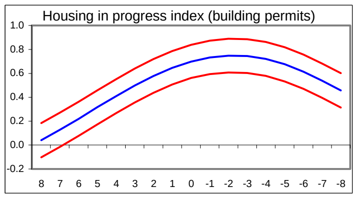


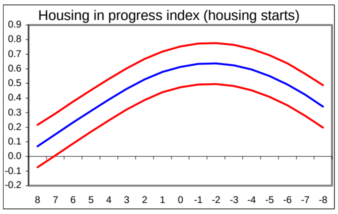


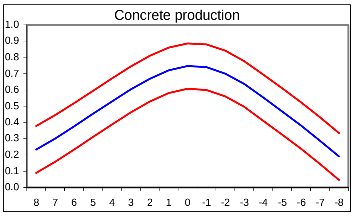


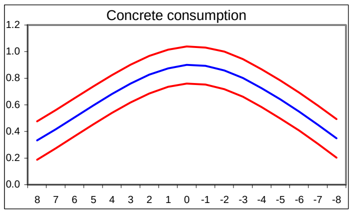


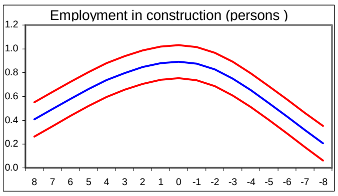


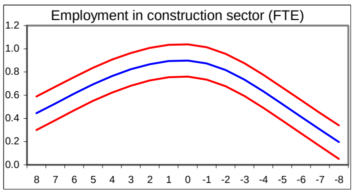


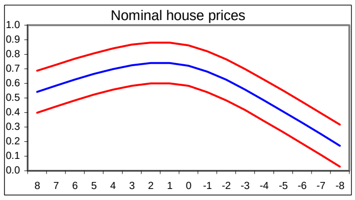


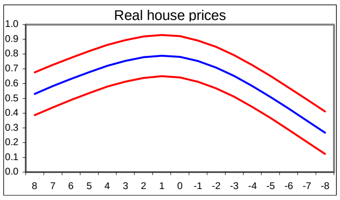


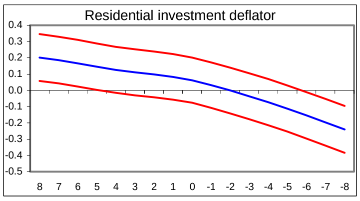


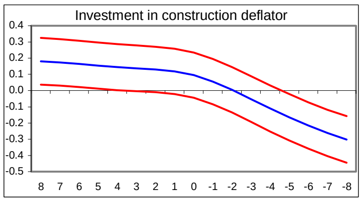


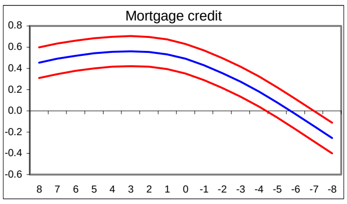












Blue lines: Point estimates
Red lines: Plus/minus 1.5 standard deviation bands

Appendix 7. Cyclical characterisation of GDP and construction variables. Butterworth and Epanechnikov filters.

Cyclical characterisation of GDP and construction variables

Butterworth filter

	Contemporaneous	Standard	Turning points			Mean duration			Mean amplitude			Steepness			Asymmetry	
Sample period: 1980-Q1 - 2008-Q4	correlation	deviation	Peaks	Troughs	Total	Expansions	Contractions	Cycle	Expansions	Contractions	Difference	Expansions	Contractions	Difference	Duration	Amplitude
GDP	1.0	1.5	5	4	9	14.3	9.5	23.8	2.8	3.0	-0.1	0.2	0.3	-0.1	1.5	1.0
Residential investment	0.7	3.9	5	5	10	11.7	13.8	25.4	10.2	10.0	0.1	0.9	0.7	0.1	0.8	1.0
Investment in non residential construction	0.3	3.5	5	6	11	9.3	9.6	18.9	10.4	10.1	0.3	1.1	1.0	0.1	1.0	1.0
Gross value added in construction	0.4	2.9	4	4	8	7.5	13.0	20.5	7.4	6.9	0.6	1.0	0.5	0.5	0.6	1.1
Building permits	0.5	16.5	5	5	10	14.3	11.0	25.3	48.1	35.9	12.2	3.4	3.3	0.1	1.3	1.3
Housing starts	0.6	15.3	5	4	9	14.0	11.3	25.3	39.0	30.8	8.3	2.8	2.7	0.1	1.2	1.3
Housing in progress index (building permits)	0.7	15.6	6	5	11	12.2	11.0	23.2	37.2	32.6	4.7	3.1	3.0	0.1	1.1	1.1
Housing in progress index (housing starts)	0.7	13.2	5	4	9	12.0	12.5	24.5	26.1	31.1	-5.0	2.2	2.5	-0.3	1.0	0.8
Concrete production	0.7	6.9	5	5	10	12.3	11.8	24.1	16.0	18.7	-2.7	1.3	1.6	-0.3	1.0	0.9
Concrete consumption	0.8	5.9	5	5	10	13.7	11.3	24.9	12.9	14.3	-1.5	0.9	1.3	-0.3	1.2	0.9
Employment in construction (persons)	0.8	5.0	4	4	8	22.5	12.3	34.8	13.4	14.1	-0.7	0.6	1.1	-0.5	1.8	1.0
Employment in construction sector (FTE)	0.9	5.1	5	5	10	12.0	11.5	23.5	9.0	10.7	-1.7	0.8	0.9	-0.2	1.0	0.8
Nominal house prices	0.8	2.2	5	5	10	13.3	10.0	23.3	5.7	5.2	0.5	0.4	0.5	-0.1	1.3	1.1
Real house prices	0.7	2.5	5	4	9	12.7	12.0	24.7	5.6	5.8	-0.2	0.4	0.5	0.0	1.1	1.0
Residential investment deflator	0.1	1.6	6	6	12	9.4	9.5	18.9	3.2	2.9	0.3	0.3	0.3	0.0	1.0	1.1
Investment in construction deflator	0.6	1.2	5	4	9	13.7	11.3	25.0	3.3	3.7	-0.3	0.2	0.3	-0.1	1.2	0.9
Mortgage credit	0.8	3.5	5	4	9	11.3	14.5	25.8	7.8	7.7	0.2	0.7	0.5	0.2	0.8	1.0

Cyclical characterisation of GDP and construction variables

Epanechnikov kernel

	Contemporaneous	Standard	Turning points			Mean duration			Mean amplitude			Steepness			Asymmetry	
Sample period: 1980-Q1 - 2008-Q4	correlation	deviation	Peaks	Troughs	Total	Expansions	Contractions	Cycle	Expansions	Contractions	Difference	Expansions	Contractions	Difference	Duration	Amplitude
GDP	1.0	2.0	4	4	8	15.5	8.3	23.8	0.04	0.03	0.01	0.00	0.00	0.00	1.86	1.41
Residential investment	0.8	7.6	3	3	6	24.3	11.0	35.3	0.20	0.12	0.08	0.01	0.01	0.00	2.21	1.63
Investment in non residential construction	0.7	6.9	5	5	10	13.6	9.0	22.6	0.13	0.14	-0.01	0.01	0.02	-0.01	1.51	0.95
Gross value added in construction	0.8	5.5	2	2	4	40.0	13.0	53.0	0.20	0.22	-0.02	0.01	0.02	-0.01	3.08	0.92
Building permits	0.5	22.3	5	5	10	16.0	9.3	25.3	0.53	0.33	0.20	0.03	0.04	0.00	1.73	1.59
Housing starts	0.6	18.2	4	3	7	13.8	11.3	25.1	0.40	0.29	0.11	0.03	0.03	0.00	1.21	1.36
Housing in progress index (building permits)	0.7	20.9	6	5	11	13.2	9.5	22.7	0.41	0.32	0.09	0.03	0.03	0.00	1.39	1.28
Housing in progress index (housing starts)	0.6	17.0	5	4	9	14.0	12.3	26.3	0.36	0.30	0.06	0.03	0.02	0.00	1.14	1.20
Concrete production	0.7	11.6	5	5	10	14.3	10.5	24.8	0.24	0.19	0.06	0.02	0.02	0.00	1.36	1.30
Concrete consumption	0.9	12.2	5	5	10	14.4	8.8	23.2	0.22	0.16	0.05	0.02	0.02	0.00	1.65	1.31
Employment in construction (persons)	0.9	8.3	4	4	8	19.0	10.0	29.0	0.19	0.17	0.01	0.01	0.02	-0.01	1.90	1.09
Employment in construction sector (FTE)	0.9	8.3	4	4	8	19.0	10.0	29.0	0.19	0.17	0.01	0.01	0.02	-0.01	1.90	1.08
Nominal house prices	0.7	7.9	2	2	4	28.0	28.0	56.0	0.25	0.27	-0.02	0.01	0.01	0.00	1.00	0.92
Real house prices	0.8	8.3	2	2	4	29.0	28.0	57.0	0.25	0.25	0.01	0.01	0.01	0.00	1.04	1.02
Residential investment deflator	0.1	4.1	3	2	5	27.5	31.0	58.5	0.08	0.09	-0.01	0.00	0.00	0.00	0.89	0.91
Investment in construction deflator	0.1	3.2	5	4	9	11.0	10.7	21.7	0.04	0.03	0.01	0.00	0.00	0.00	1.03	1.25
Mortgage credit	0.5	6.9	4	3	7	14.7	19.3	34.0	0.15	0.15	0.00	0.01	0.01	0.00	0.76	0.98

Duration: Number of periods in expansion/contraction
Amplitude: Change in the cyclical component between begining and end of the expansion/contraction
Steepness: Ratio between median duration and median amplitude.
Asymmetry: Ratio of median duration (amplitude) of expansions and contractions.
Steepness: Ratio between the duration and amplitude. Shows the intensity of the expansions and contractions

Appendix 8. Cyclical classification of several Spanish construction variables vis a vis GDP. Butterworth and Epanechnikov

Cyclical classification of several Spanish construction variables vis a vis GDP
(Butterworth filter)

Analysed period 1980-Q1 - 2008-Q4	Classification	Concordance index	Ry	Rx	median lag (overall turning	median lag (peaks)	Median lag (throughs)	Coincidence index	Phase lags on GDP Peaks Q4 1983	Q4 1988	Q3 1991	Q1 2000	Q1 2008	Phase lags on GDP Throughs Q3 1986	Q1 1990	Q1 1993	Q1 2004
Residential investment	Coincident	0.8	0.8	0.7	0.0	-3.0	2.0	0.5	-6.0	NC	-5.0	0.0	-1.0	1.0	NC	2.0	3.0
Investment in non residential construction	Leading	0.7	0.7	0.5	-2.0	-3.0	1.0	0.3	-3.0	NC	-4.0	-3.0	NC	5.0	NC	-1.0	1.0
Gross value added in construction	Leading	0.6	0.7	0.8	-3.5	-4.0	-1.0	0.1	-11.0	NC	-4.0	-3.0	NC	-8.0	NC	-1.0	4.0
Building permits	Leading	0.6	0.8	0.7	-1.0	-2.5	-1.0	0.3	-8.0	1.0	NC	-1.0	-4.0	-1.0	4.0	NC	-6.0
Housing starts	Leading	0.6	0.8	0.8	-4.0	-3.0	-7.0	0.1	-13.0	2.0	NC	-2.0	-4.0	-8.0	NC	2.0	-7.0
Housing in progress index (building permits)	Leading	0.7	0.8	0.6	-2.0	-0.5	-4.0	0.3	-5.0	3.0	NC	1.0	-2.0	1.0	NC	-5.0	-4.0
Housing in progress index (housing starts)	Leading	0.6	0.8	0.8	-1.0	-0.5	-5.0	0.3	-10.0	4.0	NC	0.0	-1.0	-6.0	NC	4.0	-5.0
Concrete production	Leading	0.7	0.8	0.7	-1.0	-1.0	0.0	0.4	-1.0	5.0	NC	-4.0	-1.0	-6.0	NC	0.0	2.0
Concrete consumption	Leading	0.7	0.8	0.7	-1.0	-2.0	2.0	0.4	-3.0	NC	0.0	-4.0	-1.0	-6.0	NC	2.0	2.0
Employment in construction (persons)	Leading	0.7	0.8	0.7	-2.0	-3.0	0.0	0.4	-3.0	-4.0	NC	-2.0	-3.0	0.0	NC	2.0	0.0
Employment in construction sector (FTE)	Leading	0.7	0.8	0.7	-1.0	-1.0	0.0	0.5	-1.0	NC	-1.0	0.0	-1.0	-3.0	NC	3.0	0.0
Nominal house prices	Coincident	0.8	0.8	0.7	0.0	0.5	0.0	0.6	0.0	NC	0.0	3.0	1.0	2.0	NC	0.0	-1.0
Real house prices	Coincident	0.8	0.8	0.8	0.0	-0.5	0.0	0.5	-8.0	NC	0.0	0.0	-1.0	1.0	NC	0.0	-3.0
Residential investment deflator	Leading	0.6	1.0	0.8	-1.0	-2.0	-1.0	0.1	-13.0	-1.0	-2.0	3.0	-7.0	-6.0	-1.0	-1.0	0.0
Investment in construction deflator	Leading	0.6	0.8	0.8	-1.0	-1.5	-1.0	0.3	-13.0	NC	-3.0	3.0	0.0	-5.0	NC	-1.0	0.0
Mortgage credit	Laging	0.7	0.8	0.8	1.0	-0.5	2.0	0.5	-8.0	3.0	NC	1.0	-2.0	1.0	NC	2.0	2.0

Cyclical classification of several Spanish construction variables vis a vis GDP
(Epanechnikov filter)

Analysed period 1980-Q1 - 2008-Q4	Classification	Concordance index	Ry	Rx	median lag (overall turning	median lag (peaks)	Median lag (throughs)	Coincidence index	Phase lags on GDP Peaks Q4 1983	Q4 1988	Q3 1991	Q1 2000	Phase lags on GDP Throughs Q3 1986	Q1 1990	Q1 1993	Q1 2004
Residential investment	Leading	0.6	0.6	0.8	-3.5	-6.0	-2.5	0.2	NC	-6.0	-16.0	-1.0	-8.0	NC	3.0	NC
Investment in non residential construction	Coincident	0.7	0.8	0.6	0.0	-2.0	0.0	0.3	NC	-5.0	7.0	-2.0	-5.0	NC	3.0	0.0
Gross value added in construction	Leading	0.7	0.5	1.0	-1.0	-3.0	-2.0	0.4	NC	-5.0	NC	-1.0	-7.0	NC	3.0	NC
Building permits	Leading	0.6	0.8	0.6	-2.0	-2.0	-7.0	0.2	1.0	NC	-2.0	-5.0	-7.0	5.0	NC	-7.0
Housing starts	Leading	0.5	0.6	0.7	-1.5	-3.0	-3.0	0.0	1.0	NC	-3.0	-5.0	NC	NC	2.0	-8.0
Housing in progress index (building permits)	Leading	0.7	0.8	0.5	-3.0	1.0	-4.0	0.3	3.0	NC	1.0	-3.0	-3.0	NC	-4.0	-5.0
Housing in progress index (housing starts)	Leading	0.6	0.8	0.7	-2.0	-2.0	-5.0	0.3	4.0	NC	-2.0	-2.0	-5.0	NC	3.0	-6.0
Concrete production	Coincident	0.6	0.8	0.6	0.0	0.0	-5.0	0.2	5.0	NC	-5.0	0.0	-5.0	NC	1.0	-5.0
Concrete consumption	Coincident	0.6	0.8	0.6	0.0	0.0	-4.0	0.3	NC	-6.0	5.0	0.0	-5.0	NC	3.0	-4.0
Employment in construction (persons)	Leading	0.7	0.8	0.8	-3.0	-3.0	-5.0	0.4	2.0	NC	-3.0	-4.0	-6.0	NC	3.0	-5.0
Employment in construction sector (FTE)	Leading	0.7	0.8	0.8	-1.0	-1.0	-1.0	0.5	NC	-3.0	4.0	-1.0	-4.0	NC	4.0	-1.0
Nominal house prices	Leading	0.6	0.5	1.0	-3.0	-3.5	-12.5	0.1	NC	-1.0	NC	-6.0	-3.0	NC	NC	-22.0
Real house prices	Leading	0.6	0.5	1.0	-2.0	-3.5	8.5	0.1	NC	-2.0	NC	-5.0	-4.0	NC	21.0	NC
Residential investment deflator	Leading	0.5	0.5	0.8	-6.0	-4.5	-13.0	-0.1	NC	-2.0	NC	-7.0	-6.0	NC	NC	-20.0
Investment in construction deflator	Leading	0.7	0.8	0.7	-1.0	-2.0	-1.0	0.3	NC	-2.0	2.0	-7.0	4.0	NC	-1.0	-1.0
Mortgage credit	Coincident	0.7	0.8	0.9	0.0	-3.0	3.0	0.3	NC	-4.0	1.0	-3.0	3.0	NC	15.0	-1.0

Concordance Index: Harding and Pagan (2002)
Ry: Abad and Quilis (2004). Ratio of turning points of the reference series (band pass HP filter) which have correspondence with TP of the the rest of series
Ry: Abad and Qulis (2004). Ratio of turning points of a series which have a correspondence with TP of the reference series (band pass HP filter)
Coincidence index: Abad and Qulis (2004). Index equal 1 implies full coincdence of periods of expansions and contractions. -1, implies full that a period of expansion(contraction) in the series
Phase lag: Lag periods between turning points of reference series and analysed series
NC: No correspondence
Phase lag: Lag periods between turning points of reference series and analysed series