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Robust Stylized Facts on Comovement for the Spanish Economy[1]

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RESUMEN
En este artículo desarrollamos la propuesta de André, Pérez y Martín (2002) de describir los hechos estilizados relativos a movimientos comunes de variables macroeconómicas usando series temporales preblanqueadas. En primer lugar, mostramos la robustez del método empleado mediante algunos ejemplos. En segundo lugar, contrastamos su relevancia empírica revisando los hechos presentados para la economía española en el trabajo de Dolado, Sebastián y Vallés (1993).

Palabras clave: Hechos estilizados, comovimiento, función de correlación cruzada, Filtro HP, preblanqueo.

ABSTRACT
In this article we further develop the suggestion of obtaining stylized facts on comovement on the basis of prewhitened time series proposed in André, Pérez and Martín (2002). Firstly, we show some examples on the robustness of the method. Secondly, we test the relevance of such a proposal by revisiting some of the existing stylized facts on comovement for the Spanish economy in Dolado, Sebastián and Vallés (1993).

Keywords: Stylized Facts, Comovement, Cross Correlation Function, HP-Filter, Prewhitening.

JEL classification: E32, C22.

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[1] Agradecemos a Alfonso Novales y Ricardo Martín sus comentarios. A Javier Vallés le agradecemos sus sugerencias y el que nos proporcionará los datos que nos han permitido realizar el ejercicio empírico que hay en el artículo.

1 Introduction

Since the 1980s and the early 1990s the study of business cycle facts as originally envisaged by Burns and Mitchell (1946) has become a core branch of study in economics. Lucas (1977), and Kydland and Prescott (1990) are two leading examples. The business cycle is usually defined as the recurrent fluctuations of some aggregate time series – such as GNP – from trend. Based on this view, business cycle regularities are usually defined as the observed statistical properties of the deviations from trend in different aggregative time series – see Lucas (1977).

This clear and widely accepted view, when implemented in practice, implies at least two decisions for the researcher. The first decision is on the summary statistics that should be presented, normally being cross correlation functions, autocorrelation functions, standard deviations, or more sophisticated statistics like cointegration relationships, etc. The second decision is on the detrending procedure. Provided that most economic time series exhibit a nonstationary behaviour, it is necessary to filter the series, i.e. to extract a stationary component. Selecting a specific filter involves assigning a different amount of weight on each business cycle frequency to obtain the trend and the cycle components. Unfortunately the filtering procedure crucially affects the shape of the autocorrelation functions and, as a consequence, it could affect the observed statistical properties of such filtered variables. Canova (1998) tests the practical relevance of the filter selection by examining the cyclical properties of a set of US macroeconomic time series using a variety of detrending methods and finds that both quantitatively and qualitatively stylized facts vary widely across detrending methods.

Regarding these two decisions, in this paper we take the pragmatic approach in André, Pérez and Martín (2002) (APM hereafter). On the one hand, among the variety of available detrending methods, we focus on the filter by Hodrick and Prescott (1980) (HP-filter hereafter) for it is widely used in an important branch of the academic literature, as well as several economic institutions[1]. As many other methods do, the HP-filter transforms a series into two components: the trend component, nonstationary, and the cycle, which is a stationary component. On the other hand, we are interested in analysing comovements by means of the cross correlation function (CCF henceforth) between each selected economic variable and the Gross National Product or the Gross Domestic Product (GNP and GDP hereafter), as it is done in Kydland and Prescott (1990), Backus and Kehoe (1992), Dolado, Sebastián and Vallés (1993) or Fiorito and Kollintzas (1994).

APM propose a method of obtaining stylized facts regarding the comovements among economic variables, by using the cross-correlation function between prewhitened filtered variables. The main feature of this procedure is that the stylized facts so obtained reflect only the non-systematic behavior of the series, and not the correlation between the cyclical components, that depends on the specific trend/cycle decomposition performed on the variables. APM test the relevance of such an approach by comparing the stylized facts reported by Kydland and Prescott (1990) for the American economy with and without prewhitening.

The aim of our article is twofold. First, we offer some further arguments and evidence to support the statement that the methodological proposal in APM is robust to the filtering procedure employed by relying on the non-systematic component in the original

[1]See for example European Commission (1995) or the papers in Banca d'Italia (1999).

data, if properly applied. Second, we compute a set of stylized facts on comovement for the Spanish economy and compare them to those offered in the classical work by Dolado, Sebastián and Vallés (1993). We obtain some qualitatively differences after prewhitening, but these differences are quite small as compared with those found by APM for the American economy. This means that the comovement behavior of the macroeconomic time series in Spain is mainly driven by the non–systematic components of them, i.e. the irregular shocks affecting macroeconomic aggregates.

The rest of the paper is organised as follows. In Section 2 we describe the methodology, and in Section 3 we provide two examples to assess its robustness. In Section 4 we apply the methodology to compute some stylized facts for the Spanish economy, and compare them with those obtained by Dolado, Sebastián and Vallés (1993). Section 5 concludes.

2 Methodology

Let us pose the problem of decomposing a given time series into different components by means of a structural time-series model as in Harvey (1989) or Harvey and Jaeger (1993)[2],

$$y_t = \mu_t + \psi_t + \epsilon_t, \qquad t = 1, 2, ...T \tag{1}$$

where y_t is the observed series, μ_t is the trend, ψ_t is the cycle, and ϵ_t is the irregular component such that $\epsilon_t \sim$ iid $N(0, \sigma_\epsilon^2)$. The trend is a local linear trend defined as

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \qquad \eta_t \sim iid \;\; N(0, \sigma_\eta^2) \tag{2}$$

$$\beta_t = \beta_{t-1} + \xi_t, \qquad \xi_t \sim iid \;\; N(0, \sigma_\xi^2) \tag{3}$$

[2]In order to simplify the discussion, we will assume that the series do not have any seasonal behavior. In the empirical applications, we use seasonally adjusted data.

where β_t is the slope and the normal white-noise disturbances, η_t and ξ_t, are independent to each other. The stochastic cycle, ψ_t, can be generated as a combination of flexible functions of sines and cosines, subject to random disturbances. The disturbances in all three components are taken to be independent to each other.

This is a quite general modelling strategy in that it encompasses most of the usual detrending procedures as particular cases. For example, if $\sigma_\xi^2 = 0$ the model for the trend becomes a random walk. If, in addition, $\sigma_\eta^2 = 0$, it becomes a deterministic trend line. A somewhat relevant particular case is the HP filter, that may be rationalized as the optimal estimator of the trend component in (1) with the restrictions $\psi_t = 0 \; \forall t$, $\sigma_\eta^2 = 0$, and $\sigma_\xi^2/\sigma_\epsilon^2 = 1/\lambda$, where λ is a given number. For large samples and t not near the beginning or the end of the series it can be shown that the optimal filter that gives the detrended observations, say y_t^{HP}, is shown to be (see, for example, King and Rebelo (1993)):

$$y_t^{HP} = C(B)\, y_t \tag{4}$$

where,

$$C(B) = \left[\frac{[1-B]^2 \left[1-B^{-1}\right]^2}{1/\lambda + [1-B]^2 \left[1-B^{-1}\right]^2} \right] \tag{5}$$

B denotes the lag operator, and the parameter λ penalizes the variability of the trend with respect to the variability of the series. For quarterly time series the value usually chosen is $\lambda = 1600$, implying a value for the ratio $\sigma_\xi^2/\sigma_\epsilon^2$ of 0.000625, so that the fraction of the total noise that goes into the trend is quite small, reflecting the usual belief in macroeconomics that the underlying trend should be smooth.

The application of the HP filter to the real US GNP series, with this particular value of λ, yields a detrended series which is difficult to distinguish from the cycle extracted from the estimation of the structural model given by (1), (2), (3), and a model for ψ_t, as shown by the maximum likelihood estimations of Harvey and Jaeger (1993). Thus, the HP filter effectively decomposes the series into a smooth trend plus a cycle. Furthermore, this result suggests that a superficial comparison with the structural model signals that the cyclical component obtained from HP filtering (the detrended seriesy_t^{HP}) includes the irregular movements in the series[3] hence capturing basically all the non-systematic behavior of the series. This reasoning applies to other popular univariate filters such as the Baxter and King (1995) filter.

Given the low fraction of the total noise affecting y_t that the smooth trend assumption allocates to the trend component, this component can be thought of as being essentially systematic, in the sense of predictable. The cycle, in turn, can be thought of as possessing both a systematic (or predictable) and a nonsystematic (or nonpredictable) behavior.

As a consequence, the HP cyclical component can be seen as a mixture of (i) the largest part of the non-systematic or purely random component of the original series and, (ii) a stationary systematic component, which can be assimilated to the inertia or autocorrelation pattern of the cycle. Any observed statistical property of the filtered series can be thought of as being caused by a two-fold effect coming from these two different ingredients. Different filtering methods, being consistent with the smooth-trend principle, may differ in the way they assign the systematic component into trend and cycle, but all

[3]For other variables such as prices or monetary aggregates, Harvey and Jaeger (1993) show that HP filtering may change substantially the volatility and periodicity properties of an estimated cyclical component. In any case, this will not affect the substance of our subsequent discussion.

of them have in common that most of the nonsystematic behavior is allocated to the cycle. Consequently, if we compare the cycle obtained by applying different detrending methods to the same original series, their estimated systematic behavior would differ, but the estimated nonsystematic component should be essentially the same and basically identical to the purely random behavior which is present in the original series.

Prewhitening is an econometric procedure that consists of filtering a series in order to extract all the systematic autocorrelation behavior from it, so that a white noise stochastic component is obtained[4]. Assume that a given time series y_t is representable by a linear model of the general ARIMA class $\phi(B)\, y_t = \theta(B)\, a_t$, where a_t is a white noise variable, and $\phi(B)$, $\theta(B)$ are polynomials in B. Premultypling y_t by an estimate of $\theta^{-1}(B)\, \phi(B)$ provides a prewhitened version of y_t, which is an estimate for a_t, a white noise variable representing the purely stochastic component of y_t. Prewhitening has been traditionally performed with ARIMA specifications, but the basic concept applies to any other econometric representation. An ad-hoc prewhitening procedure could be designed to address any econometric setting, depending on the available information. APM suggest the construction of CCF's among prewhitened series in order to compute stylized facts concerning comovement among economic time series[5].

If the series y_t, following the above mentioned ARIMA process is HP-filtered, the

[4]See Box et al. (1994).

[5]Box et al. (1994) propose the use of prewhitening for the identification of transfer function models. They show that the CCF between the prewhitened input and the transformed output is directly proportional to the impulse response function. Haugh and Box (1977) employ prewhitening for the identification of dynamic distributed lag bivariate models, and Jenkins and Alavi (1981) for the identification of multivariate time series models

dynamic properties of y_t^{HP} can be studied by means of the expression

$$y_t^{HP} = \Pi(B)\ a_t \tag{6}$$

where

$$\Pi\left(B\right) \equiv C\left(B\right) \frac{\theta\left(B\right)}{\phi\left(B\right)} \tag{7}$$

and $C\left(B\right)$ is given in (5). Thus, the autocorrelation pattern of y_t^{HP} is determined by the polynomial $\Pi(B)$. The comovement between two time series (as measured by the CCF) independently transformed with an univariate filter may be crucially affected by such filtering procedure. To understand this issue, note that, as proven by Bartlett (1946, 1955) the CCF of two autocorrelated processes reflects a mixture of the cross effects between both processes and the autodependence of each of them, as measured by the autocorrelation function (ACF). We can conclude that, in order to obtain a stationary cyclical component, the HP filter (or any other univariate filter) necessarily imposes a specific autocorrelation pattern on the series that crucially affects the shape of the CCF. This is the reason why the CCF between two independently filtered series, and hence the stylized facts concerning the comovements between such series, can be affected by a univariate filter.

Provided that the detrended series y_t^{HP} can be represented by the model described above, it follows that the linear transformation $\Pi^{-1}\left(B\right)$, when applied to y_t^{HP}, produces the original white noise variable component a_t. The CCF obtained from two prewhitened time series is determined just by the non-systematic behavior of the series, and not by the autocorrelation pattern which crucially depends on the filtering procedure. To perform such a procedure in practice, prior to computing the CCF between two stationary time series –obtained by HP-filtering or any other procedure– for each one of the series one would need to: i) obtain an estimate $\hat{\Pi}(B)$ of $\Pi(B)$, and ii) generate the prewhitened series $\hat{a}_t = \hat{\Pi}^{-1}(B)\ y_t^{HP}$.

3 Robustness of the method

In the previous section we have argued that, if we compare different cycles obtained by detrending the same series with different methods, their systematic behavior could be very different, but the nonsystematic behavior should be mostly the same. If we perform an adequate prewhitening transformation (that will be series-dependent) in order to extract the nonsystematic component, we would obtain basically the same result. In this sense, the CCF obtained from prewhitened time series is independent of the filtering procedure employed. Apart from the theoretical reasons given in the previous section, we present two sets of examples that may help the reader in the assessment of the robustness and the usefulness of the so computed CCFs.

Example 1: Robustness regarding the filtering procedure We select two widely-used filters, the HP filter and the first-difference filter. We also select some widely used US time series: quarterly GNP, private consumption, investment, and labor productivity. For labor productivity we select two definitions: GNP over manhours employed per week, and GNP over total employed hours worked in manager establishments. To ease the comparability of the results we use the same series as in Kydland and Prescott (1982).

Following Kydland and Prescott (1982) for a given variable X and GNP, the examined comovements are classified as follows. If $\rho(j)$, $j \in (0, \pm1, \ldots, \pm5)$, denotes the cross correlation between GNP_t and X_{t-j}, we say that X is *procyclical* (*countercyclical*) if the maximum value of ρ is positive (negative) and not very close to zero. In particular, for $0.5 \leq |\rho(j)| < 1$ we use the adverb *strongly* , for $0.2 \leq |\rho(j)| < 0.5$ we use the adverb *weakly* and, when $0 \leq |\rho(j)| < 0.2$ we say that the series are *acyclical.* We also say that the cycle of X is *leading*, *contemporaneous* or *lagging* the cycle of GNP as $\rho(j)$ reaches a maximum for $j > 0$, $j = 0$ or $j < 0$.

[INSERT FIGURES 1 and 2]

Figure 1 presents the CCFs of GNP with private consumption and investment. Regarding the correlation with consumption, the message one would draw from the two filtering procedures would be slightly different: consumption would be procyclical and contemporaneous in the case of the first-difference filter, and procyclical but lagging the cycle with the HP filter; regarding the maximum correlation, the HP would predict a stronger correlation. When one uses prewhitened variables to compute the CCF, the differences disappear as both CCFs are almost identical. As regards investment, both filters lead to the same conclusion in both prewhitening and non-prewhitening based CCFs, even when the dynamics around the dominant correlation are somewhat different in the non-prewhitening based CCFs cases.

More differences are apparent from Figure 2 when looking at labor productivity measures. Attending at the HP-filtered CCFs there is a clear difference between the CCFs of GNP with both measures of productivity. The differences fade when working with the prewhitened HP-filtered variables. Also, there are no discrepancies between the messages of the CCFs between HP-filtering and first-difference-filtering when computing the CCFs on the basis of prewhitened variables, while it is the case when not prewhitening.

Example 2: Avoiding misleading inferences With this example we try to put forward a different point. In this case we propose an example in which from artificially simulated and filtered series, we get a misleading message regarding the stronger correlation, and the inferred cyclical position, that is clarified when prewhitening the variables. We simulate two random walks. $y_{1,t} = y_{1,t-1} + e_{y_1,t}$ and $y_{2,t} = y_{2,t-1} + e_{y_2,t}$, where the innovations $e_{y_1,t}$ and $e_{y_2,t}$ are correlated according to the following scheme,

$$\begin{aligned} e_{y_1,t} &= \epsilon_{y_1,t} \\ e_{y_2,t} &= \rho_1 \, e_{y_1,t-1} + \rho_2 \, e_{y_1,t-2} + \epsilon_{y_2,t} \end{aligned} \tag{8}$$

and $\epsilon_{y_1,t}$, $\epsilon_{y_2,t}$ are white noise processes with zero mean and variance $\sigma_{\epsilon_{y_1,t}}$ and $\sigma_{\epsilon_{y_1,t}}$ respectively. We chose $\rho_1 = -0.3$ and $\rho_2 = 0.3$, arbitrarily. The series y_{1t} and y_{2t} are defined by construction to be stationary in first differences. Irrespective of the method used to render the time series stationary, and provided that the only source of comovement that have been imposed to the data is the dependence structure between $e_{y_1,t}$ and $e_{y_2,t}$, the results obtained should not be very different from the structure coming from (8), i.e., a contemporaneous correlation of around -0.3 and a one-period lagged correlation of around 0.3. A result very different from this could be seen as misleading.

[INSERT FIGURE 3]

Figure 3 plots the average of 1000 random realizations of size 150 of the random processes $\epsilon_{y_1,t}$ and $\epsilon_{y_2,t}$. While the prewhitened CCFs disclose the underlying structure relating the two simulated time series, the non-prewhitened CCFs present quite misleading readings. The non-prewhitened plot would signal the first variable clearly leading the other one by two quarters and being procyclical. The results appear to be robust with respect to the relevant parameters of the experiment: sample size, length of the simulated time series, values for ρ_1 and ρ_2. In case a given macroeconomic variable were to be well represented by the stochastic structure described above as the data generating process, an analyst would be mislead by the non-prewhitened CCFs.

4 White stylized facts for the Spanish economy

In order to test the practical relevance of our discussion for the Spanish economy, we have replicated the results in Dolado, Sebastián and Vallés (1993) (DSV hereafter) for the Spanish economy without and with prewhitening. We use exactly DSV data in order to make the results fully comparable. The data are seasonally adjusted quarterly figures, and cover the period 1970 to 1991.

Concerning the prewhitening procedure, the operators $\hat{\Pi}(B)$ in (6) are assumed to be purely autoregressive models, and they are estimated by Ordinary Least Squares. The white noise null hypothesis of the obtained prewhitened series is tested with the Box-Pierce statistic $Q = n \sum_{k=1}^{10} r_k^2$, where n denotes the number of observations minus the order of $\hat{\Pi}(B)$, and r_k is the k-th autocorrelation of a_t in (6). The results of the test are then confirmed by visual inspection of the ACF as suggested by Box et al. (1994). The autoregressive order is adjusted until the null hypothesis is not rejected. Depending on the specific variable under analysis, the required order varies from 2 to 5. The variables under study and the estimated models are presented in Table 1. Table 2 presents the CCF's resulting from prewhitened series.

[INSERT TABLE 1 and 2]

Comparing the results with and without prewhitening, we obtain two sets of results. On the one hand, for some variables, although the specific numerical values of the CCF's differ, the business cycle comovement results with and without prewhitening are qualitatively the same. In these cases, we can conclude that the comovement behavior of such series is mainly determined by the non-systematic component and is not qualitatively affected by the autocorrelation pattern of the cycle. On the other hand, some results vary after prewhitening, meaning that the cycle of the series (as measured by the HP-filtered series), because of its autocorrelation pattern, shows a comovement behavior qualitatively different from the one which is present in its underlying stochastic component.

Table 3 summarizes the figures in Table 2 and compares its main features with those in DSV.

[INSERT TABLE 3]

In DSV, (the cyclical component of) private consumption is shown to be strongly procyclical and lead output by one quarter. These results, jointly with the fact that consumption is more volatile than output, seemingly contradicts the consumption smoothness predicted by the Permanent Income/Life Cycle hypothesis. After prewhitening, the random component of private consumption turns out to be still a procyclical variable but not a "strongly procyclical" variable as suggested by DSV. Furthermore, we find no clear evidence about consumption leading output by one quarter. Rather, the response of consumption to output seems to spread from two quarters before the cycle to one quarter after the cycle, being the latter the (lightly) stronger effect. To some extent, this evidence is more likely to match the Permanent Income/Life Cycle hypothesis, as far as private consumers seem to respond positively to income shocks, but the response is "weaker" than that reported by DSV and it spreads in a smoother way along several quarters.

As regards investment behavior, DSV show that both total and fixed investment are strongly procyclical and move contemporaneously with the cycle, while inventory investment is shown to be basically acyclical, with slightly positive contemporaneous and one-period-lagged correlation with output, that can be seen as negligible. Once prewhitened, total investment turns out to be still procyclical (the same conclusion as in DSV) but it seems to lead the cycle by one period instead of being contemporaneous. This evidence is more coherent with the common belief of investment as an economic engine or leading indicator of growth. Fixed investment is also procyclical, but it lags the cycle by one period. A rather remarkable result concerns inventory investment which, in Table 3, is shown to be weakly countercyclical and lead the cycle by two quarters. This evidence is coherent with a standard belief in basic macroeconomic theory: when the economic activity begins to speed up, demand increases and firms' inventories fall. At the outset of a recession, a falling demand causes inventories to accumulate, so that inventories should lead negatively the cycle.

The surprising conclusion regarding government consumption is the same as in DSV: it is procyclical and contemporaneous with the cycle. In fact, the positive contemporaneous correlation with output is calculated to be even larger than before prewhitening. DSV explain this fact saying that large components of government spending (transfers, subsidies) which are though to behave countercyclically, are excluded from the definition of government consumption, and the expenditures on goods and services are perhaps adjusted to compensate (in a procyclical fashion) for those movements. Provided the parallelism between both results (with and without prewhitening) the rather plausible explanation of DSV can also fit the prewhitened version.

DSV show net exports as a percentage of GDP to be weakly countercyclical and move with a one period lead. While exports appear to be weakly procyclical and lead output by two or three quarters, imports are strongly procyclical and lead output by just one period. After prewhitening, our results concerning imports and net exports are analogous to those of DSV, meaning that the comovement properties of these variables mainly depend on the shocks affecting foreign trade. Concerning exports, the prewhitened version of this variable appears to be basically uncorrelated with output. To interpret this evidence, we can rely on the fact that exports primarily depend on the consumption decisions of our commercial partners, and not on our national production and income shocks. The correlation of the cycle of this variable with that of GDP can be essentially attributed to the autocorrelation of the series (for example, due to international spillover effects) rather than to the correlation among random shocks.

The results concerning employment are virtually identical to those of DSV if it is measured by total employment or by wage earners employment. Nevertheless, facts regarding labor productivity seems to be different. Instead of being procyclical, labor productivity, according to the prewhitened facts, appears as countercyclical. This is consistent with a demand-determined keynesian view of productivity. It is also in line with an Okun Law rule-of-thumb in which a one percent increase in output leads to a more than one percent increase in labor, as it is the case in some recent estimates for the Spanish economy (see Virén (2001)).

Regarding monetary facts, a broad measure of money, M4, and the velocity of money are presented in the Table. While the conclusions for the velocity of money are the same as those in DSV, we obtain a different result for M4. Specifically, the presumption that money leads output is confirmed with this evidence, as opposed to the evidence obtained by DSV. The countercyclical behavior of M4 can be explained in a framework in which perceived increases in money are the cause of increases in prices, which in turn, via a Fisher-type relation, might lead to increased interest rates and a falling output. The facts for prices shown in the next row of the Table are consistent with this reasoning.

Concerning the correlations of GDP with the terms of trade, when the energy prices are excluded the result is similar to that in DSV and coherent with the behavior of prices. When energy prices are included, this being an exogenous source of shocks to the economy, there is no perceived correlation, while in the case of DSV there seems to be a strange procyclical behavior.

5 Concluding remarks

In this article we work out the proposal to obtain stylized facts regarding the comovements among economic variables presented in André, Pérez and Martín (2002). This method is based on using the cross-correlation function between prewhitened variables. The stylized facts obtained with this procedure reflect only the non-systematic stochastic behavior of the series. Thus, the main advantage of this approach is that it is independent, if properly applied, of the specific trend-cycle decomposition performed on the variables.

We show two examples on the robustness of the method regarding the filtering procedure, and how it is useful to avoid potential misleading inferences that might appear in some circumstance when analyzing the cross correlogram calculated using the non-prewhitened (HP-filtered) time series.

We also present the effects of applying prewhitening to compute the stylized facts for the Spanish economy calculated by Dolado, Sebastián and Vallés (1993). In most cases, non-prewhitened and prewhitened cross-correlation functions conveyed the same qualitative message, as a difference with the facts for the US economy presented in André, Pérez and Martín (2002), indicating that the comovement patterns between the economic variables in the Spanish case would not be crucially affected by the systematic autocorrelation properties of the filtered time series, but it would rather be basically determined by the random (unpredictable) components. A possible explanation for this fact could be related to more frequent government shocks in the Spanish case as compared to the US case.

In the cases of inventories, labor productivity, and the terms of trade both correlograms differ qualitatively signalling that the comovements are crucially affected by the autocorrelation properties of the series, and consequently by the specific trend-cycle decomposition performed. We advance some plausible interpretations for the different facts obtained.

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Table 1: Estimated univariate models used to prewhiten the Spanish macroeconomic time series. For a given variable X_t the estimated models are of the form $(1-\phi_1 B-\phi_2 B^2-\phi_3 B^3-\phi_4 B^4-\phi_5 B^5)X_t = a_t$. Under each column labelled with a ϕ_i coefficient we show the OLS-estimate for the parameter, and the t-statistic in parenthesis. The column labelled *B-P* refers to the Box-Pierce statistic for examining the null hypothesis of a_t being a white noise, and the column *P-value* is the P-value of the test.

Variable	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	$B-P$	P-value (%)
GDP	1.99 (18.67)	-1.35 (-7.03)	0.27 (2.63)	—	—	23.87	20
Private Consumption	1.76 (20.09)	-1.76 (-12.02)	1.40 (9.52)	-0.60 (-6.87)	—	7.18	78
Government Consump.	1.98 (20.58)	-1.56 (-9.63)	0.46 (4.95)	—	—	18.95	9
Investment	1.73 (17.73)	-1.59 (-9.02)	1.10 (6.33)	-0.43 (-4.62)	—	11.75	38
Fixed	1.59 (21.80)	-0.70 (-9.73)	—	—	—	19.13	12
Inventory	1.22 (11.57)	-1.12 (-7.12)	0.58 (3.72)	-0.29 (-2.74)	—	9.48	58
Exports	1.92 (20.35)	-1.80 (-9.81)	1.23 (6.81)	-0.49 (-5.46)	—	12.44	33
Imports	2.16 (20.61)	-2.01 (-8.61)	1.00 (4.31)	-0.26 (-2.57)	—	6.46	84
Net Exports	2.08 (21.15)	-1.98 (-9.45)	1.21 (5.81)	-0.44 (-4.59)	—	10.73	47
Employment	0.94 (9.48)	-0.09 (-0.62)	-0.01 (-0.06)	0.39 (2.82)	-0.54 (-5.39)	8.35	60
Wage earners	0.90 (8.51)	0.22 (1.57)	-0.29 (-2.15)	0.21 (1.51)	-0.29 (-2.76)	19.87	3
Labor Productivity	0.82 (8.01)	-0.20 (-1.51)	-0.04 (-0.33)	0.33 (2.44)	-0.45 (-4.46)	13.48	20
Wage earners	0.89 (8.66)	0.04 (0.27)	-0.23 (-1.73)	0.30 (2.18)	-0.37 (-3.63)	17.33	7
M4	1.16 (2.51)	-0.38 (-4.25)	—	—	—	14.15	36
Velocity	1.39 (15.19)	-0.52 (-5.92)	—	—	—	5.73	96
Prices	1.85 (18.03)	-1.22 (-6.99)	0.29 (3.21)	—	—	3.53	99
Terms of trade	1.64 (25.11)	-0.79 (-12.11)	—	—	—	19.33	11
Non energy	1.01 (9.76)	-0.09 (-0.61)	-0.32 (-2.31)	0.30 (2.12)	-0.30 (-3.03)	19.01	4
Exchange rate	1.19 (11.55)	-0.33 (-3.23)	—	—	—	10.99	61

Table 2: Stylized facts on comovement for the Spanish economy. Prewhitened version of a set of selected facts in Dolado, Sebastián and Vallés (1993).

Variable X	Cross correlation of real GDP$_t$ with X_{t+i}										
	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
GDP	-0.05	-0.33	0.18	-0.14	0.03	1.00	0.03	-0.14	0.18	-0.33	-0.05
Private Consumption	-0.05	-0.08	0.04	0.24	0.14	0.17	0.26	0.00	0.06	-0.13	-0.08
Government Consumption	0.03	-0.28	-0.05	-0.02	0.04	0.47	0.12	-0.05	0.05	-0.10	-0.01
Investment	-0.10	0.08	-0.20	-0.10	0.51	0.10	0.21	0.24	-0.28	0.08	-0.08
Fixed	-0.18	0.00	0.07	0.00	-0.06	0.17	0.42	0.10	0.02	0.10	-0.16
Inventory	-0.08	0.12	-0.09	-0.28	0.12	0.07	0.04	0.16	-0.08	0.15	0.00
Exports	-0.06	0.18	0.05	-0.03	0.08	-0.09	0.06	-0.02	-0.20	0.03	0.05
Imports	-0.14	0.10	0.01	0.18	0.43	-0.02	0.08	0.09	-0.32	0.01	0.07
Net Exports	0.08	0.08	0.04	-0.19	-0.29	-0.08	-0.05	-0.04	0.20	0.08	0.03
Employment	-0.02	0.12	0.11	0.11	0.11	0.04	0.26	-0.09	0.11	0.18	-0.13
Wage earners	0.00	0.06	0.01	0.20	0.18	0.05	0.19	-0.13	0.07	0.17	-0.13
Labor productivity	-0.02	-0.23	-0.18	0.17	0.19	0.19	-0.01	0.04	-0.29	-0.26	0.06
Wage earners	-0.08	-0.16	-0.06	0.04	0.10	0.08	-0.08	0.05	-0.25	-0.23	0.13
M4	-0.26	-0.18	0.09	0.00	0.05	0.09	0.08	0.10	0.01	0.09	0.11
Money velocity	-0.13	-0.10	-0.06	-0.07	0.04	0.05	0.06	0.07	-0.01	-0.02	0.00
Prices	-0.22	0.07	-0.02	-0.34	0.04	0.00	0.09	0.17	-0.14	0.17	-0.16
Terms of trade	0.11	0.08	0.06	0.18	0.08	0.10	0.06	-0.18	-0.13	-0.06	0.08
Non energy	-0.07	-0.15	0.05	-0.04	-0.05	0.10	0.03	0.01	-0.22	-0.18	0.26
Exchange rate	0.10	0.15	-0.01	0.22	-0.02	-0.03	0.02	-0.05	0.10	0.05	0.15

Table 3: Stylized facts on comovement for the Spanish economy. Comparison of a set of selected facts in Dolado, Sebastián and Vallés (1993) with and without prewhitening.

Variable	Facts from non-prewhitened series	Facts from prewhitened series
Private Consumption	Strongly procyclical, 1 quarter lead	Weakly procyclical, 1 quarter lag
Government Consumption	Weakly procyclical, contemporaneous	Weakly procyclical, contemporaneous
Investment	Strongly procyclical, contemporaneous	Strongly procyclical, 1 quarter lead
Fixed	Strongly procyclical, contemporaneous	Weakly procyclical, 1 quarter lag
Inventory	Acyclical	Weakly countercyclical, 1 quarter lead
Exports	Weakly procyclical, 2-3 quarters lead	Acyclical
Imports	Strongly procyclical, 1 quarter lead	Weakly procyclical, 1 quarter lead
Net Exports	Weakly countercyclical, 1 quarter lead	Weakly countercyclical, 1 quarter lead
Employment	Strongly procyclical, 1 quarter lag	Weakly procyclical, 1 quarter lag
Wage earners	Strongly procyclical, 1-2 quarters lead	Weakly procyclical, 2 quarters lead
Labor productivity	Weakly procyclical, 1 quarter lead	Weakly countercyclical, 3 quarter lag
Wage earners	Weakly procyclical, contemporaneous	Weakly countercyclical, 3 quarters lag
M4	Weakly procyclical, contemporaneous	Weakly countercyclical, 5 quarters lead
Money velocity	Weakly countercyclical, 4-5 quarters lead	Weakly countercyclical, 5 quarters lead
Prices	Weakly countercyclical, 4-5 quarters lead	Weakly countercyclical, 2 quarters lead
Terms of trade	Strongly procyclical, 5 quarters lead	Acyclical
Non-energy	Weakly countercyclical, 2 quarters lag	Weakly countercyclical, 3 quarters lag
Exchange rate	Weakly procyclical, unclear	Weakly procyclical, 2 quarters lead

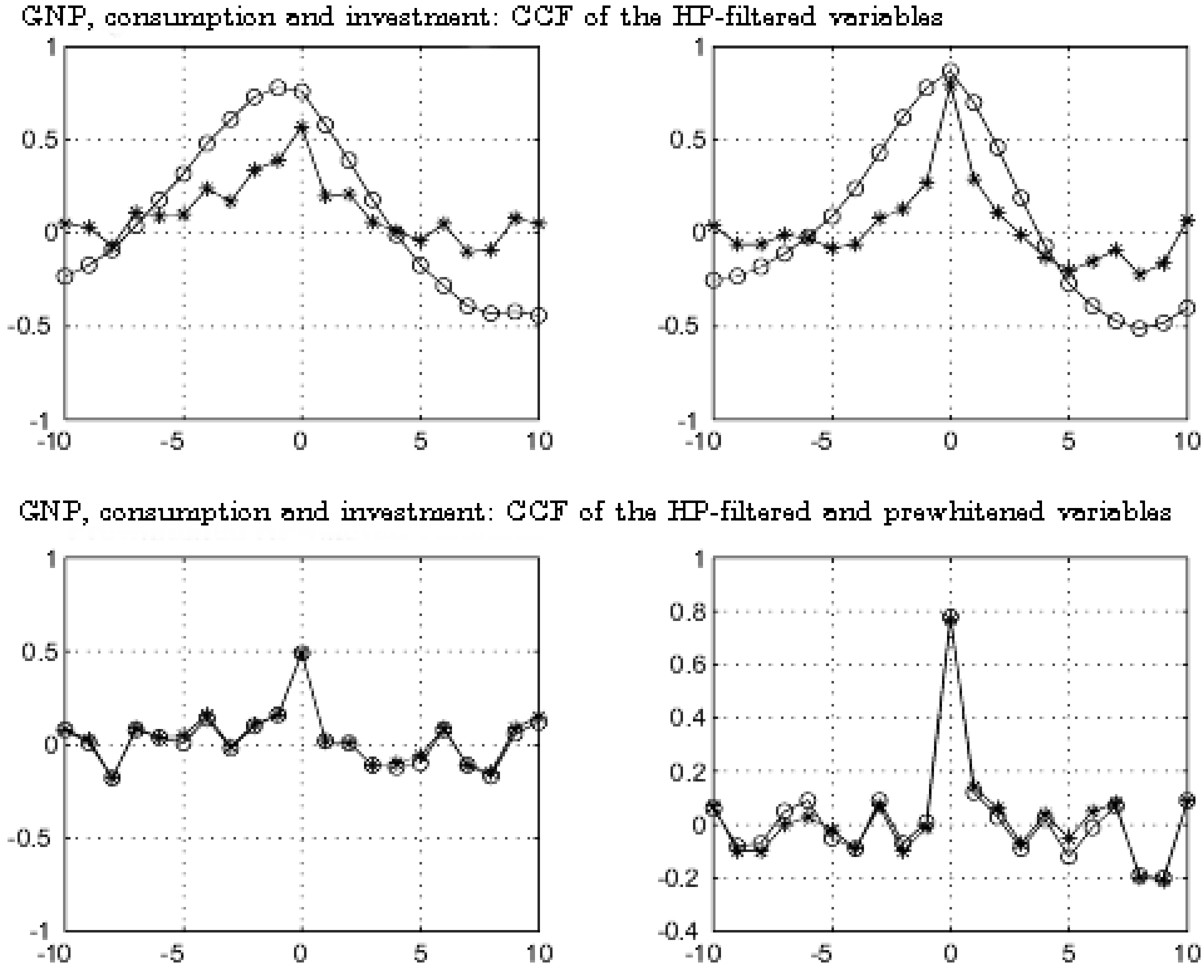

Figure 1: CCF of GNP with private consumption (left column) and CCF of GNP with investment (right column). The circled line represents the CCF obtained from HP-filtered series, while the line with asterisks represents the CCF obtained from series filtered with the first difference filter. Seasonally adjusted quarterly US data, 1954-1989 (Kydland and Prescott (1982) data).

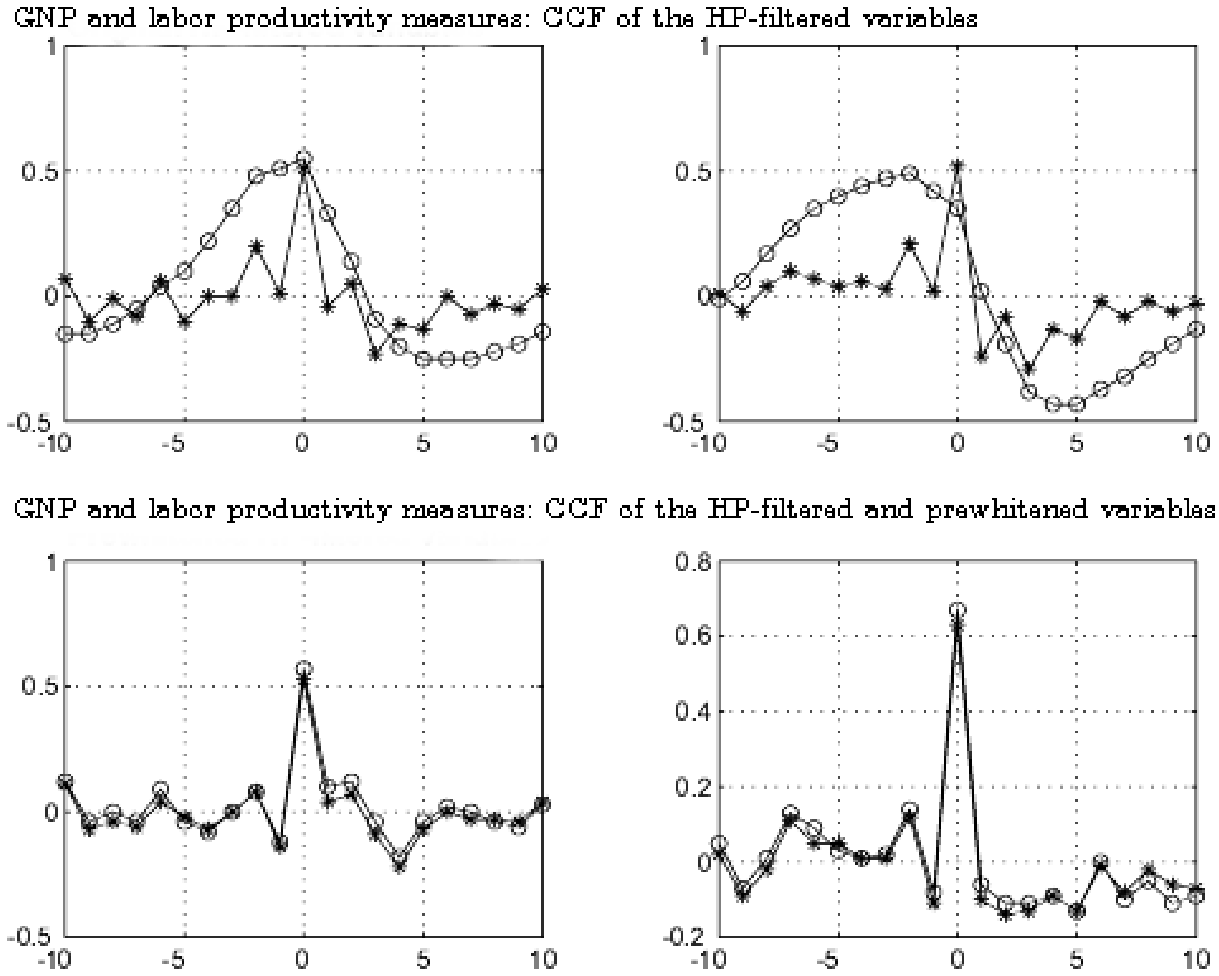

Figure 2: CCF of GNP with labor productivity, measured as: (1) GNP/manhours employed per week (left column), and (2) GNP/total employed hours worked in manager establishments (right column). Both concepts of employment are quarterly averages of monthly data. The circled line represents the CCF obtained from HP-filtered series, while the line with asterisks represents the CCF obtained from series filtered with the first difference filter. Seasonally adjusted quarterly US data, 1954-1989 (Kydland and Prescott (1982) data).

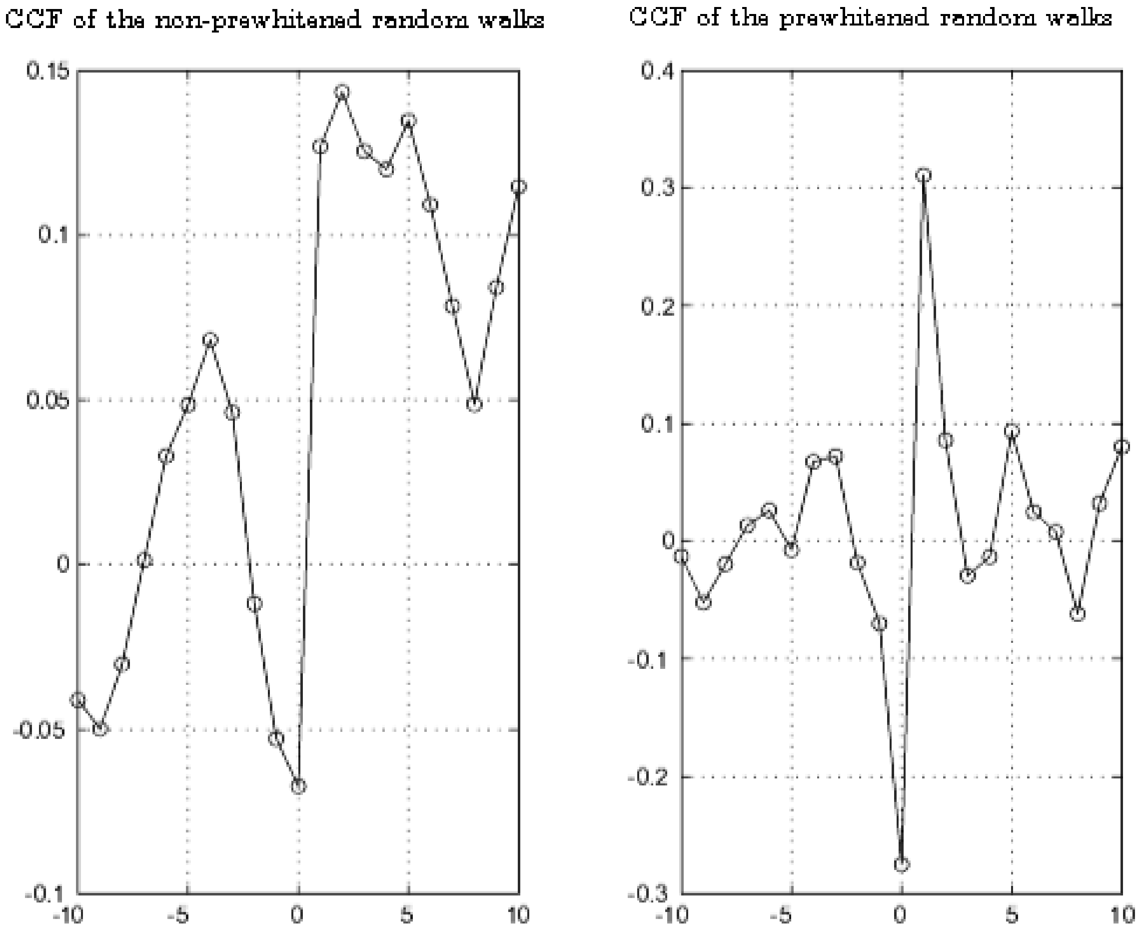

Figure 3: CCF of two HP-filtered random walks (left: non-prewhitened, right:prewhitened) $y_{1,t} = y_{1,t-1} + e_{y_1,t}$, $y_{2,t} = y_{2,t-1} + e_{y_2,t}$, where the innovations $e_{y_1,t}$ and $e_{y_2,t}$ are correlated according to the following scheme, $e_{y_1,t} = \epsilon_{y_1,t}$, $e_{y_2,t} = -0.3\ e_{y_1,t-1} + 0.3\ e_{y_1,t-2} + \epsilon_{y_2,t}$. CCFs: averages of 1000 independent simulations of size 150 of the shocks.