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Are Business Cycles All Alike? A Bandpass Filter Analysis of Italian and US Cycles

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Are Business Cycles All Alike? A Bandpass Filter Analysis of the Italian and US Cycles*

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Abstract

In this paper, we perform an empirical comparison of Italian and U.S. business cycles. After filtering the time series of the main macroeconomic variables of the two countries, through an approximate bandpass filter, we analyze the cross-correlations between each filtered variable and the filtered GDP, indicator of the business cycle.

We find heterogeneity in business cycle dynamics as regards variables related to the industrial structure (see exports, investment in construction), and to the organization of markets (e.g. stock prices, private consumption), interpreted as effects of local path-dependencies. Cyclical components of prices, labor market variables, and monetary policy indicators are almost invariant across economies, reflecting common international drivers, such as the Federal Reserve Bank monetary policy, and international oil prices.

Keywords: Business Cycles, Bandpass Filter, Cross Correlations, Italian Economy, Macroeconomics.

JEL Classification: C22, E32.

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1 Introduction

In this paper, an international comparison between the statistical properties of Italian and U.S. business cycles is proposed. After filtering the time series of the most relevant macroeconomic variables of the two countries, through an approximate bandpass filter, we study the cross-correlations between each filtered variable and the filtered real GDP, used as benchmark indicator of the business cycle.

The aim of the analysis is to answer to a simple question: "Are business cycles all alike across countries?". We are interested in detecting invariances and diversities in the behavior of the main macroeconomic variables at business cycle frequencies, and in deducing the economic mechanisms - in terms of common and idiosyncratic drivers - behind the observed patterns.

Business cycles are among the most salient features of the aggregate dynamics of industrialized economies. As such, they have been the topic of a large number of theoretical and empirical studies, which typically see macroeconomic dynamics as driven by stochastic trends, resulting from the accumulation of random shocks, with varying degrees of persistence and different periodicities. Business cycle dynamics is mapped into a specific set of short-to-medium run frequencies, and the analysis is usually focused on variables resulting from the application of filters meant to isolate the business cycle component. Many procedures have been deviced, such as linear trend removal, first differencing, the Hodrick-Prescott (1981) filter, wavelets, and the bandpass filter (Baxter and King, 1999).

The latter, characterized by particularly appealing properties, has been first applied by Stock and Watson (1999) on U.S. data. More recently, international comparisons have been performed, e.g. Agresti and Mojon (2001), who focus on E.U. countries. Interestingly, Agresti and Mojon tend to underline the similarities between business cycles in European countries, as well as with the U.S., much more than their differences, so much as to conclude that models conceived originally for the U.S. economy can provide good approximations for E.U. countries, too. On the other hand, even a quick comparison between the Stock-Watson results and works focused on the Italian economy, such as Gallegati and Stanca (1998), shows that cross-country differences are far from negligible.

The present study takes part into the debate, and adds evidence that country-specific features are key in determining which variables prompt and which respond to business cycles. Heterogeneity in business cycle dynamics is detected as regards private consumption, government expenditure, investments, exports, credit, and share prices. On the contrary, business cycle components of prices, wages, employment, unemployment, labor productivity, interest rates, and money aggregates display almost invariant properties across the analyzed economies.

We interpret differences in business cycle properties as effects of local path-dependencies, and invariances as reflecting the impact of common international drivers. Moreover, we put forward some conjectures as to the sources of common and idiosyncratic components. Specifically, international coordination mechanisms such U.S. monetary policy and oil prices may have driven the similar dynamics in money, prices and labor markets in Italy and in the U.S., whereas differences in business cycles may be related to path-dependencies in the industrial structure (see exports, investment in construction), and in the organization and development of markets (cf. stock prices, private consumption).[1]

The paper is organized as follows. In Section 2, we describe the bandpass filter and the cross-correlation analysis, and we explain the criteria utilized for our classification of comovements. Section 3 describes the available dataset and gives an account of the results. Conclusions and perspectives are in Section 4.

2 Methodology

The first quantitative enquiry on business cycle dynamics can be found in the work of Burns and Mitchell (1946), which was based on a careful analysis of a wide set of macroeconomic variables, during the various business cycle stages. It aimed at classifying variables into leading, coincident and lagging, depending on the number of months it takes to reach peaks and troughs of the business cycle. Such a qualitative method is nowadays known as the NBER approach.

As defined by Burns and Mitchell,

> a (business) cycle consists of expansions occurring at about the same time in many economic activities, followed by similar general recessions, contractions and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.

[1]See Arthur (1994), David (1985), and Castaldi and Dosi (2005), for the concept of path-dependence.

Consistent with the above, the empirical analysis of business cycles requires (i) retrieving the business cycle component of each macroeconomic time series, and (ii) estimating comovements between business cycle components of various macroeconomic variables. The former step is the most controversial of the two, as it requires an operational definition of business cycle.

The very idea that macroeconomic variables include a business cycle component is rooted in a widely used methodological tool, the so-called traditional decomposition, or model with unobserved components, according to which a macroeconomic variable (in logs) can be expressed as the sum of trend (T), cycle (C), seasonal (S), and irregular (I) components, as follows:

$$Y = T + S + C + I$$

The trend includes long-term fluctuations of any nature, deterministic (such as linear and quadratic trends), as well as stochastic (e.g. I(1) and I(2) components). The seasonal refers to systematic fluctuations with periodicity shorter than one year. The irregular conveys high-frequency random shocks. Macroeconomics typically focuses on the business cycle component, which is about non-periodic cycles at short-to-medium run frequencies. Harvey (1985), Watson (1986), Clark (1987), and Harvey and Jaeger (1993) are among the main contributors to this methodological stream.

It is worth noting that such a decomposition is crucially based on two assumptions: (a) there exists a log-linear relationship between the observed variable and its unobserved components; (b) components are mutually independent. These are perhaps too restrictive conditions.[2]One would rather like to avoid imposing any specific model on the data.

Therefore, the approach followed here is somewhat different. Following Murray (2003), our working definition of business cycle is what remains of a series, after frequencies outside a given frequency band are filtered out. Notice that the choice of the relevant frequency band was already suggested by Burns and Mitchell's definition. In terms of assumptions, the definition used here is less demanding than the unobserved component model. Spectral methods based on the Fourier Transform seem proper vis-á-vis the implementation of this definition.[3]

[2]See, for instance, Zarnowitz (1997) for critical remarks on the independence between cycles and long-run growth.

[3]A criticism to the Fourier-based approach to spectral analysis as regards empirical macroeconomics is grounded on wavelet analysis. See Ramsey (1999) for a review of wavelets for economists. A recent application to macroeconomic time series is provided by Gallegati, Gallegati, Ramsey, and Semmler (2004).

In this respect, our methodology is line with the early work by Engle (1974), and with more recent analyses by Stock and Watson (1999), Gallegati and Stanca (1998), Agresti and Mojon (2001), and Christiano and Fitzgerald (2003). Hodrick and Prescott's (1981) work and follow-ups can be seen as members of this family, too.

2.1 Estimating the business cycle component

Estimation of the business cycle, as defined above, is usually accomplished by transforming the observed series, through application of a filter. The choice of the proper filter is crucial, in that, as pointed out by Canova (1998; 1999), different methods may affect both the qualitative and quantitative stylized facts of the business cycle.

According to Baxter and King (1999), the ideal filter for business cycle analysis should meet the following properties. First, trend-reduction, i.e., the property of removing long-run trends.[4] Second, high frequency components (i.e. seasonal and irregular) ought to be smoothed out, too. Third, no phase shifts should be induced, meaning that timing relationships between variables should not be altered. This is a key requirement, in that isolating business cycle components is only an intermediate step towards studying comovements. Fourth, one would like the filtering outcome to be independent of the length of the original series. In other words, if the sample is updated as new observations are made available, further application of the filter must yield a series with the first n values equal to the business cycle component previously estimated over a sample size of n. Fifth, it is desirable that the filtered series are able to track the NBER dating of business cycles, which is taken as a benchmark.

Baxter and King (1999) showed that a symmetric and stationary band-pass filter satisfies all the above requirements, while outperforming previous approaches, such as linear trend removal, first differencing, and the Hodrick-Prescott filter. [5]

The starting point is the Cramer representation of a time series, according to which a sequence $\{y_t\}$ can be approximated by an integral sum of mutually

[4]As first shown by Granger (1964), the "typical spectral shape" of a macroeconomic variable is monotonically decreasing, meaning that the bulk of the variance is attributable to very low frequency components (such as long-run trends) and, albeit to a lesser extent, to business cycle (or medium frequency) fluctuations. The strong contribution of frequencies around zero is the reason why business cycle analysis requires a prior detrending of the original series.

[5]See also Zarnowitz and Ozyildirim (2002) for an extensive discussion on this point.

orthogonal random periodic components, with frequencies $\omega \in [-\pi, \pi]$:

$$y_t = \int_{-\pi}^{\pi} e^{i\omega t} \xi(\omega) d\omega \tag{1}$$

Based on the above equation, the variance of y_t can be decomposed as follows:

$$var(y_t) = \int_{-\pi}^{\pi} f_y(\omega) d\omega \tag{2}$$

where $f_y(\omega) = var(\xi(\omega))$ is defined as the power spectrum of y_t. The latter provides information about the contribution of any periodic component to the total variance of y_t.

Suppose now we filter y_t as follows, to yield the new series y_t^*:

$$y_t^* = a(L) y_t \tag{3}$$

where

$a(L) = \sum_{h=-\infty}^{+\infty} a_h L^h$

is a two-sided moving average filter, with infinite leads and lags, expressed as a polynomial in the lag operator L (such that $L^h y_t = y_{t-h}$). The associated spectral representation reads:

$$y_t^* = \int_{-\pi}^{\pi} e^{i\omega t} \alpha(\omega) \xi(\omega) d\omega \tag{4}$$

where $\alpha(\omega) = \sum_{h=-\infty}^{+\infty} a_h e^{i\omega h}$ is the so-called frequency response function, mapping each frequency ω into the extent to which the filter alters the weight of the periodic component $\xi(\omega)$ in the spectral decomposition. Accordingly, the variance of y_t^* is decomposed as follows:

$$var(y_t^*) = \int_{-\pi}^{\pi} |\alpha(\omega)|^2 f_y(\omega) d\omega \tag{5}$$

where $|\alpha(\omega)|^2$ denotes the spectral transfer function, a measure of the effect of the filter on the variance contribution at frequency ω.

The above equations allow to define the outcome of any filtering procedure and, in turn, the filter required for that outcome to be achieved. One may want to isolate frequencies belonging to some interval $[\omega', \omega'']$, $|\omega'| \leq |\omega''|$. In such a case, the ideal filter must satisfy $\alpha(\omega) = 1$ if $\omega' \leq |\omega| \leq \omega''$, $\alpha(\omega) = 0$ otherwise.

In order to meet the trend reduction property, the condition $\alpha(0) = 0$ should hold, so that the filtered series does not display any power at zero frequency. This in turn requires $\alpha(0) = \sum_{h=-\infty}^{+\infty} a_h e^{i0h} = \sum_{h=-\infty}^{+\infty} a_h = 0$, i.e. the application of a symmetric moving average filter in the time domain, with weights summing up to zero.[6]

In practice, the ideal bandpass filter cannot be used: it has to be replaced by an approximate bandpass filter, entailing finite leads and lags, say K. For a given K, the associated frequency response function, denoted as $\alpha_K(\omega)$, is chosen by minimizing a loss function such as

$$Q = \int_{-\pi}^{\pi} |\alpha(\omega) - \alpha_K(\omega)|^2 d\omega \tag{6}$$

In the above criterion, the goodness of the approximation is measured by the integral sum of squared deviations between the approximate and ideal filters.[7] Because the outcome of the above minimization problem is sensitive to K, this ought to be carefully chosen. Of course, as K grows large, one can achieve better approximations, but because $2K$ observations are lost, there is a cost in terms of sample size. Moreover, cutting off the moving average filter gives rise to two distortionary effects: leakage (i.e. overstating frequencies outside of the band of interest) and compression (i.e. underrepresenting the frequencies one wants to focus on). The choice of K must account also for this. The solution to these trade-offs is mainly an empirical matter.[8]

Summing up, the application of a bandpass filter requires setting three parameters: two defining the breadth of the frequency band of interest (lower bound ω' and upper bound ω''); and a cut-off parameter (K). Conditional on these choices, the bandpass filter yields a stationary series, with variance (almost) completely attributable to frequencies between ω' and ω''.

2.2 Estimating Comovements

Once estimates of business cycle components of many macroeconomic variables have been obtained, one can measure their mutual correlations. A common way to do this is to define a benchmark variable, which is thought to represent the business cycle, and to estimate cross-correlations of all other variables with respect to this one, at various leads and lags. This is for example the approach applied by Stock and Watson (1999) to U.S. quarterly data, and by Agresti and Mojon (2001) to quarterly data for E.U. countries.

[6] Another possibility is to apply the filter directly in the frequency domain, but estimates of the spectrum are not unaffected by the length of the series. As an implication, one of the requirements mentioned above cannot be met. See Canova (1998) for an example, and Baxter and King (1999) for a caveat.

[7] A generalization of this loss function, entaling weighted integral sums of squared deviations, is provided by Christiano and Fitzgerald (2003).

[8] Baxter and King recommend to set $K = 12$, because higher values do not lead to significant improvements in the performance of the filter.

The aim is to build a taxonomy of macroeconomic variables according to five dimensions: (i) sign, (ii) magnitude, and (iii) timing (in leads and lags) of the cross-correlations with respect to "the cycle" (i.e. to the benchmark variable representing it); as well as (iv) amplitudes of the fluctuations, and (v) predictive ability.

As commonly done, here we use the filtered GDP as benchmark variable.[9] It may be pointed out that a composite index may provide a better approximation of the business cycle. However, previous work by Gallegati and Stanca (1998), who performed a sensitivity analysis on the benchmark variable, shows that results are robust to the benchmark chosen. We compute cross-correlations between each variable at time t, and the GDP at all leads and lags from $t-6$ to $t+6$. Then, we look at the sign and the magnitude of cross-correlations, and we investigate on the existence of patterns.

A variable is said to be "procyclical" if its cross-correlogram displays positive values around lag zero and resembles the shape of the GDP autocorrelogram; "countercyclical" if the cross-correlogram pattern - in terms of sign and shape - is inverse to the one displayed by the GDP autocorrelogram; and "acyclical" if its cross-correlogram does not exhibit any definite pattern with respect to the GDP autocorrelogram.

As it will be noted, some variables display cross-correlograms which are similar to the GDP autocorrelogram, but slightly "out-of-phase": i.e., reaching their maximum (or minimum if countercyclical) at some different leads or lags. If the absolute maximum (or minimum) is achieved at some GDP lead, then the variable is denoted as "leading", whereas it is called "lagging" in the opposite case. This definition in turn implies that the cross-correlations of leading (lagging) variables tend to decay more slowly than GDP autocorrelations when considering future (past) GDP. Finally, "coincident" variables are those displaying the bulk of their cross-correlation with GDP at lag zero.

Amplitudes of fluctuations can be measured in terms of relative variances, computed with respect to the variance of the filtered GDP. These are useful to distinguish between variables according to whether they are more or less volatile than the cycle.

Finally, further information as to the predictive ability of macroeconomic variables may complement the above set of dimensions. This is obtained through simple, bivariate Granger-causality tests, performed using the GDP and any given variable.[10]

[9]Henceforth, the term "GDP" shall denote the filtered GDP.

[10]Granger causality does not correspond to the causality concept usually referred to in the economic discourse. A variable might well predict GDP growth not because it is a fundamental determinant of GDP growth but just because it embeds information on some third variable which is itself a determinant of GDP growth. In addition, the predictive

3 Empirical Analysis and Results

Our analysis is performed on seasonally-adjusted quarterly data from the OECD Main Economic Indicator and Quarterly Labour Force Statistics data bases. We apply the bandpass filter to the natural logarithm of all the variables that are not expressed in percentage points. Lists of variables are provided in Tables 1 and 2. For most series, the sample period goes from the 1st quarter of 1970 to the 3rd quarter of 2002.[11] In order to define the duration of the Italian business cycle, we follow Stock and Watson's (1999) approach, i.e. we set the lower and upper bounds as the shortest and longest fluctuations experienced by the Italian economy in the period under analysis. Consistent with the chronologies of the Italian business cycles reported by Gallegati and Stanca (1998), frequencies ranging from 9 to 43 quarters are considered. Hence, our upper and lower bounds for Italian series are different from the ones set by Stock and Watson for the U.S. series (6 and 32 quarters). This is justified by the evidence that, in the last 30 years, Italian business cycles have been longer than the American one (see Agresti and Mojon, 2001, more generally on European economies). In line with Baxter and King (1999) and Stock and Watson (1999), we set the cut-off parameter K to 12. However, given that some of our series start as late as 1980, we decided to barter a lower precision with a higher number of usable observations. Hence, following Agresti and Mojon (2001), the filtering is performed using $K = 8$ as well.

3.1 Basic Statistical Properties

Basic properties of the filtered series are shown in Table 3. These table provides information about mean, variance, skewness and kurtosis of each bandpass filtered variables, for $K = 12$. Using a different cut-off parameter ($K = 8$) does not yield significant deviations from the statistics reported in the table[12].

First, let us have a look at variances. In this respect, Italy and U.S. show similar patterns: the most volatile variables are share prices, unemployment,

content of each relation tested in Tables 6 and 7 can be altered by the inclusion of additional variables. Nevertheless, those tests give a quantitative measure of forecasting ability in bivariate relations which theoretical models must be consistent with.

[11]The most important exceptions are the money and credit series, whose sample period goes from the 1st quarter of 1975 to the 4th quarter of 1998, when the EMU became operative.

[12]Fixing $K = 8$ does not significantly alter the cross-correlation structure either. Hence, in the next section, we only report the cross-correlations for $K = 12$.

foreign trade indicators, and investment variables.[13]

Second, by analyzing kurtosis values we notice that there exists a set of variables with negative excess kurtosis (i.e. more platykurtic than a Normal law). This set, which is shared by the two countries, includes total credit to private sector, the official discount rate, and share prices.

Furthermore, the cyclical components of labor market variables and of money aggregates in Italy are more exposed to extreme events than in the U.S. For instance, the excess kurtosis for the growth rate of wages is 1.35 in Italy, as compared to 0.02 in the U.S., and 1.86 for the Italian inflation rate, vis-á-vis 0.66 in the U.S.. We also find the excess kurtosis of Italian employment to be 1.37, much higher than for the U.S. (0.04). Similar results hold for the money aggregates (M1 and M2). The opposite occurs for imports and labor productivity: the distribution of these filtered variables displays larger departures from normality in the U.S. than in Italy.

Finally, U.S. variables within the monetary and foreign trade sectors tend to be less similar to each other, than in Italy. More specifically, the bandpass filtered M1 in the U.S. is almost three times more volatile than M2, while in Italy M1 and M2 display basically the same variance. Furtherly, imports and exports in the U.S. are different in terms of skewness (negative for imports, very close to zero for exports) and as regards excess kurtosis (positive only for imports).

3.2 Cross-correlation Analysis

The results of the cross-correlation analysis for our Italian and U.S. data are summarized in Tables 4 and 5. Each entry is the correlation of each bandpass-filtered variable at time t, with the bandpass-filtered GDP, taken as the benchmark indicator of the business cycle, at all leads and lags within a range of 6 quarters.

A detailed description of results is provided as follows. We proceed for homogeneous groups of variables. The identification of the cyclical nature of the variables analyzed is based on the criteria explained in Section 2.2. Comparisons between our results for the two countries, as well as with the results of previous analyses - specifically, Stock and Watson's (1999) study on U.S. data - are meant to shed light on invariances and specificities of the Italian and U.S. business cycles, and on the robustness of the patterns detected.

GDP Components. Bandpass-filtered variables considered here are:

[13] We can only compare the standard deviations of series that have the same units (e.g. natural logarithm).

private final consumption, government final consumption, gross fixed capital formation (GFCF), exports, and imports. See Figures 1 and 7.

Private final consumption is positively correlated with the GDP over the cycle; in Italy, it is a coincident indicator, whereas it leads the GDP in the U.S. Furthermore, it Granger-causes GDP in Italy (see Table 6), whereas in the U.S., the causality runs in both directions (see Table 7).

The bandpass filtered GCFC is procyclical in both countries. It is a slightly lagging variable in Italy, whereas in the U.S. it is synchronized with the cycle. Differences among the two countries emerge also with respect to Granger-causality relationships between aggregate investment and GDP. Indeed, GCFC does not have any causal relationship with GDP in Italy, whereas it appears to be predicted by the latter variable in the U.S. Interestingly, the analysis of more disaggregated investment series reveals some heterogeneity between the cyclical behaviors of investment in construction (lagging in Italy, coincident in the U.S.). Fig. 2 and lower charts of Fig. 8 illustrate these patterns.

Government final consumption exhibits a coincident and countercyclical behavior in Italy, and a lagging and procyclical pattern in the U.S. However, in both countries, most of the cross-correlations are not significantly different from zero. A possible explanation for this result is that government final consumption includes expenses that tend to vary little with business cycles (e.g. labor retirement payments, health care outlays), as well as the so-called automatic stabilizers.

Both imports and exports display a procyclical pattern. However, while imports tend to be coincident in both countries, exports display opposite behaviors (leading in Italy vs. lagging in the U.S.). Consequently, the trade balance is leading in Italy, lagging in the U.S. These patterns are not rejected by the Granger causality analysis (cf. Tables 6 and 7). In Italy, exports display both causal relations with respect to GDP in a simple bivariate model, whereas they appear to be predicted by GDP in the U.S. Finally, imports do not have any causal relation with GDP in both countries considered.

Production Process. Industrial production, change in stocks, and the rate of capacity utilization are under focus here (see Fig. 3 and the upper charts of Fig. 8). All three are procyclical and coincident indicators. For this group of variables, cross-correlations do not reveal any remarkable differences between Italy and the U.S. More interesting is the bivariate causal relationship between the rate of capacity utilization and the GDP. In the U.S., the former variable helps forecasting the latter, whereas the relationship is inverted in Italy.

Labor Market. Italian total employment and total unemployment are significantly correlated with lagged GDP (cf. Figures 4 and 9).[14] Total employment is procyclical, whereas total unemployment is countercyclical. These correlation patterns are in accordance with those found for the U.S. However, magnitudes are generally higher for U.S. variables. Moreover, the transmission of a GDP shock to the unemployment level requires much more time in Italy than in the U.S.

As implied by the Okun's law, labor productivity, measured as the ratio between GDP and total employment, is expected to be procyclical. This indeed occurs: Figures 4 and 9 display a clearly procyclical and slightly leading pattern for both Italy and the U.S. This is consistent with the evidence of a procyclical total employment.

Prices and Wages. Indicators of prices and wages (Figures 5 and 10) are supposedly characterized by very similar statistical properties. The comparison across countries, however, might reveal interesting information. Cross-correlations with the GDP show that CPI and hourly wage rates are leading and countercyclical variables in both Italy and the U.S. Cross-correlations with lagged GDP are stronger for the CPI than for the wage rate (roughly -0.70 vs. -0.55). Remarkably, magnitudes are very similar across countries.

Relevant differences emerge as the bandpass filtered rates of change come under focus. Indeed, in Italy the CPI inflation and the growth rate of wages are coincident and procyclical, while in the U.S. they tend to lead the cycle, and to be negatively correlated with it.

Notice, however, that the picture is less clear than with respect to level variables. For instance, the U.S. wage growth displays strong cross-correlations (around 0.30) with past GDP. Something similar occurs for other growth rate variables, also in Italy: the relationship of growth rates with the GDP across the cycle is somewhat blurred.

In both countries analyzed bivariate tests do not help discerning clear causality relationships among labor-market variables and GDP or among price variables and GDP. In most cases (cf. Tables 6 and 7) the hypothesis of Granger causality is accepted or rejected in both directions.

Money and Finance. Turning the attention to monetary and financial variables (Figures 6 and 11), we observe that both monetary aggregates analyzed (M1 and M2) exhibit a procyclical and leading pattern in both countries. Furthermore, money appears to Granger-cause output in both countries, as long as larger money aggregates are considered (see Tables 6 and 7).

[14] We have also analyzed the rate of unemployment. However, its pattern is not very different with respect to the one displayed by the unemployment level.

Total domestic credit displays heterogeneity across countries. Credit leads the cycle in Italy, and it is negatively correlated with it. On the contrary, U.S. commercial bank loans tend to lag the cycle, and to have positive cross-correlations. This divergence may stem from the imperfect comparability of the two variables as well as from the different institutional setups characterizing the financial system of the two countries. Nonetheless, it does not seem to affect the ability of credit to predict cyclical movements of GDP. Indeed, all credit variables considered Granger-cause GDP both in Italy and in the U.S.

On the grounds of our results, a countercyclical and leading relationship can be detected between bond yields and the GDP over the business cycle. Indeed, the cross-correlation with lagged GDP is negative in both countries, between -0.50 and -0.60. Similar results seem to hold for official discount rates, although positive cross-correlations with past GDP are pretty strong. The Granger causality tests in Table 7 provide additional evidence on the links between interest rates and output movements in the U.S.: both short and long term interest rates display predictive ability with respect to GDP in the U.S.[15] As far as Italy is concerned, official discount rates appear to be predicted by GDP, whereas no causal relation emerges between bond yields and GDP.

Overall, the foregoing findings support the idea that, in the analyzed period, monetary policy has been effective, although with some lag.[16]

The results on share prices indicate a lagging procyclical pattern in Italy. The cross-correlations with GDP from time t onwards are not significantly different from zero, suggesting the absence of any forecasting property of the Italian stock prices during the period analyzed. The bivariate Granger tests in Table 6 confirm the foregoing conjecture. A different result holds for the U.S., where stock prices are moderately procyclical and tend to lead the cycle. Nonetheless, also in the U.S. they lack any bivariate causal relationship with GDP.

3.3 Summary and Discussion of Results

In discussing results, we shall go through the main similarities and differences between business cycle comovements in Italy and in the U.S.

First, both countries share very similar comovement patterns as regards employment, price and wage levels, labor productivity, as well as money aggregates and interest rates. In other words, comovements of price levels and

[15]In the U.S. long term interest rates are also Granger-caused by GDP.

[16]We preferred not to analyze measures of the real interest rate. We were dissuaded by the big uncertainty surrounding the construction of any measure of that variable.

quantities in the labor and monetary markets are similar across countries. In both, CPI, wages and interest rates are leading and countercyclical indicators of the business cycle. Money, and labor productivity are leading too, but procyclical. Labor market series are lagging; unemployment is countercyclical, whereas employment is procyclical.

Relevant differences are instead detected as to consumption, government expenditure, investments, exports, credit, and share prices. More in detail, U.S. expansions seem to be anticipated by increases in consumption, government expenditure, and stock prices, and followed by wider availability of commercial bank loans, by greater investment in machinery and equipment, and by surges in import.

This does not occur in Italy, where decreases in credit and increases in imports and in the rate of capacity utilization typically signal that the economy is going to expand, while positive changes in stock prices and in construction investments tend to show up with some lag.

Finally, in both countries CPI and wage inflation rates are characterized by peculiar cross-correlation patterns. Indeed, according to Zarnowitz (1997), growth rates naturally tend to decrease in absolute value at the end of each stage of a business cycle (expansions as well as contractions), i.e., just before reaching a peak or a trough. On the contrary, their absolute value increases quite rapidly at the inset of a new stage. As an implication, they display positive contemporaneous correlation with the last part of a contraction, and with the inset of an expansion, but a negative one with the last part of an expansion and with the inset of a contraction. By definition, a procyclical (countercyclical) variable is characterized by positive (negative) contemporaneous correlation with the cycle, regardless of the stage. Hence, our procyclicality and countercyclicality concepts might not fit the analysis of growth rates.

4 Conclusions

In this paper, we have compared the statistical properties of Italian and U.S. business cycles. After filtering the time series of the most relevant macroeconomic variables of the two countries, through an approximate bandpass filter, we have analyzed the cross-correlations between each filtered variable and the filtered real GDP, used as benchmark indicator of the business cycle.

Interestingly, it appears that which variables prompt and which respond to business cycles depends on country-specific features, despite the similar level of development of the two countries. Heterogeneity in business cycle dynamics is detected as regards variables related to the industrial structure (see imports, investment in construction), and to the level of organization and development of markets (cf. stock prices, private consumption). On the contrary, business cycle dynamics of labor market and monetary policy variables is basically invariant across the analyzed economies, despite some well-known differences (e.g. in unemployment rates).

The distinction between country-specific and invariant properties is based on some fundamental questions: Can one identify common drivers of international business cycles? And which mechanisms lay behind common trends and idiosyncratic factors?

Macroeconomic variables in two countries can behave in a similar way just as a result of random forces, or because their dynamics are driven by common trends. Cross-country heterogeneities in business cycle behaviors, instead, signal that local driving mechanisms are most important.

If we can identify international coordination mechanisms which tie economic fluctuations of different countries together, then we expect invariances to show up only as regards the economic sectors which are directly involved. Among the possible examples: (i) the existence of a leader-follower relationship as to monetary policies (the Italian central bank as a follower of the U.S. Federal Reserve policy moves); (ii) the exposure to common price shocks, such as those affecting oil prices (oil being a pervasive input in both economies, and its price being set by a cartel such as the OPEC).

The variables most likely affected are interest rates, money aggregates, prices, wages, employment, and unemployment. Notice that cross-country similarity in cyclical properties of labor market variables in not a trivial result: these markets are organized in quite different ways in Italy and in the U.S. One may thus expect their dynamics to differ quite substantially. Finding common cross-country properties means that the effect of idiosyncratic factors is more than offset by the effect of common drivers. In other words, institutional differences in labor market organizations do not show up in data so much as the impact of international trends.

Whenever we find significant differences in cyclical dynamics, we can interpret them as the effect of relevant idiosyncratic factors, outcomes of path-dependent growth processes. Different initial conditions can lead to dramatic diversities in dynamics. First, substantially different sectoral structures can emerge, implying, for instance, different patterns of imports and exports. A second possible outcome is diversity in the way financial and credit markets are organized, and relatedly in their actual impact in the economy. For instance, the credit market design can strongly affect the ability of consumers to borrow money, and thus determine more or less strict constraints on, say, their intertemporal allocation of income between consumption and saving.

As a conclusion, our results imply that business cycle dynamics can be described in terms of (i) path-dependent processes and (ii) coordination mechanisms. Partially quoting Burns and Mitchell, we can see a national business cycle as a sequence of expansions, recessions, contractions and revivals occurring at about the same time in many economic activities; such a sequence preserves its properties across countries, to the extent that international coordination mechanisms more than offset the effect of idiosyncratic factors engendered by local path-dependent processes. Broader comparative studies are needed in order to assess the robustness of our conclusions.

References

[1] Agresti A., and B. Mojon, 2001, "Some Stylised Facts on the Euro Area Business Cycle", European Central Bank, working paper 95.

[2] Arthur B., 1994, *Increasing Returns and Path-Dependence in the Economy.* Ann Arbor, Mich, University of Michigan Press.

[3] Baxter M., and R.G. King, 1999, "Measuring Business Cycles: Approximate Bandpass Filters for Economic Time Series", *The Review of Economics and Statistics* 61, 197-222.

[4] Bergman U.M., M.D. Bordo, and L. Jonung, 1998, "Historical Evidence on Business Cycles: The International Experience" in *Beyond Shocks: What Causes Business Cycles?*, Conference Series n.42 Federal Reserve Bank of Boston.

[5] Burns A.F., and W.C. Mitchell, 1946, *Measuring Business Cycles.* New York, NBER.

[6] Canova F., 1998, "Detrending and Business Cycle Facts", *Journal of Monetary Economics* 41, 475-512.

[7] Canova F., 1999, "Does Detrending Matter for the Determination of the Reference Cycle and the Selection of Turning Points?", *The Economic Journal* 109, 126-50.

[8] Castaldi C., and G. Dosi, 2005, "The Grip of History and the Scope for Novelty. Some Results and Open Questions on Path Dependence", forthcoming in A. Wimmer and R. Koessler, (eds.), *Understanding Change.* London, Palgrave.

[9] Christiano L.J., and T.J. Fitzgerald, 2003, "The Band Pass Filter", *International Economic Review* 44, 435-465.

[10] Clark P.K., 1987, "The Cyclical Component of Economic Activity", *Quarterly Journal of Economics* 102, 797-814.

[11] David P.A., 1985, "Clio and the Economics of QWERTY", *The American Economic Review* 75, 332-337.

[12] Engle R.F., 1974, "Band Spectrum Regression", *International Economic Review* 15, 1-11.

[13] Gallegati M., M. Gallegati, J. Ramsey, and W. Semmler, 2004, "The U.S. Phillips Curve by Time Scale Using Wavelets", *Computing in Economics and Finance* 308.

[14] Gallegati M., and L.M. Stanca, 1998, *Le Fluttuazioni Economiche in Italia 1861-1995: ovvero il Camaleonte e il Virus dell'Influenza.* Torino, Giappichelli.

[15] Granger C.W.J., 1964, *Spectral Analysis of Economic Time Series.* Princeton, NJ, Princeton University Press.

[16] Harvey A.C., 1985, "Trends and Cycles in Macroeconomic Time Series", *Journal of Business and Economic Statistics* 3, 216-227.

[17] Harvey A.C., and A. Jaeger, 1993, "Detrending, Stylized Facts, and the Business Cycle", *Journal of Applied Econometrics* 8, 231-247.

[18] Hodrick R., and E. Prescott, 1981, "Post-war U.S. Business Cycles: An Empirical Investigation", Working Paper, Carnegie-Mellon University; printed in *Journal of Money, Credit and Banking* 29 (1997), 1-16.

[19] Kydland F. and E. Prescott, 1990, "Business Cycles: Real Facts and a Monetary Myth", *Federal Reserve of Minneapolis Quarterly Review*, Spring 1990, 3-18.

[20] Murray C.J., 2003, "Cyclical Properties of Baxter-King Filtered Time Series", *Review of Economics and Statistics* 85, 472-476.

[21] Ramsey J., 1999, "The Contribution of Wavelets to the Analysis of Economic and Financial Data", *Philosophical Transactions of the Royal Society of London* A 357, 2593-2606.

[22] Stock J.H., and M.W. Watson, 1999, "Business Cycle Fluctuations in US Macroeconomic Time Series", in Taylor J. and M. Woodford (eds.), *Handbook of Macroeconomics.* Amsterdam, Elsevier Science.

[23] Watson M.W., 1986, "Univariate Detrending Methods with Stochastic Trends", *Journal of Monetary Economics* 18, 49-75.

[24] Zarnowitz V., 1992, "Business Cycles: Theory, History, Indicators and Forecasting", *NBER Studies in Business Cycles*, vol. 27. Chicago, University of Chicago Press.

[25] Zarnowitz V., 1997, "Business Cycles Observed and Assessed: Why and How They Matter", NBER Working Paper 6230.

[26] Zarnowitz V., and A. Ozyildirim, 2002, "Time Series Decomposition and Measurement of Business Cycles, Trends, and Growth Cycles", NBER Working Paper 8736.

Code	Definition	Units	Period
1	Gross Domestic Product, s.a.	1995 EUR bln	1970Q1 - 2002Q3
2	Private Final Consumption, s.a.	1995 EUR bln	1970Q1 - 2002Q3
3	Government Final Consumption, s.a.	1995 EUR bln	1970Q1 - 2002Q3
4	Gross Fixed Capital Formation, s.a.	1995 EUR bln	1970Q1 - 2002Q3
5	GFCF, Machinery and Equipment, s.a.	1995 EUR bln	1970Q1 - 2002Q3
6	GFCF, Construction, s.a.	1995 EUR bln	1970Q1 - 2002Q3
7	Exports, Goods and Services, s.a.	1995 EUR bln	1970Q1 - 2002Q3
8	Imports, Goods and Services, s.a.	1995 EUR bln	1970Q1 - 2002Q3
9	GDP Implicit Price Level, s.a.	1995=100	1970Q1 - 2002Q3
10	Industrial Production ISIC C-E, s.a.	1995=100	1970Q1 - 2002Q3
11	BSS Rate of Capacity Utilization	percentage	1970Q1 - 2002Q1
12	Change in Stocks, s.a.	1995 EUR bln	1970Q1 - 2002Q3
13	Total Employees, All Activities, s.a.	-	1970Q1 - 2002Q3
14	Total Unemployment, s.a.	-	1970Q1 - 2002Q3
15	Unemployment Rate, s.a.	percentage	1970Q1 - 2002Q3
16	Labor Productivity (1/13)	-	1970Q1 - 2002Q3
17	Hourly Wage Rate, Industry	1995=100	1970Q1 - 2002Q3
18	Wage Inflation (rate of change of 17)	percentage	1970Q2 - 2002Q3
19	CPI, All Items	1995=100	1970Q1 - 2002Q3
20	Price Inflation (rate of change of 19)	percentage	1970Q2 - 2002Q3
21	Real Wage (17/19)	-	1970Q1 - 2002Q3
22	Monetary Aggregate M1, s.a.	EUR bln	1975Q1 - 1998Q4
23	Monetary Aggregate M2, s.a.	EUR bln	1975Q1 - 1998Q4
24	Total Domestic Credit	EUR bln	1975Q1 - 1998Q4
25	Total Credit to Private Sector	EUR bln	1975Q1 - 1998Q4
26	Official Discount Rate	percentage p.a.	1970Q1 - 1998Q2
27	Share Prices, ISE MIB Storico	1995=100	1975Q1 - 2002Q3
28	Bond Yields	percentage p.a.	1970Q1 - 1998Q2
29	USD/EUR Exchange Rate, end period	USD/EUR	1970Q1 - 2002Q3
30	Real Effective Exchange Rate	1995 = 100	1970Q1 - 2002Q3

Table 1: List of variables, Italy

Code	Definition	Units	Period
1	Gross Domestic Product, s.a.	1996 USD bln	1970Q1 - 2002Q3
2	Private Final Consumption Expenditures, s.a.	1996 USD bln	1970Q1 - 2002Q3
3	Government Final Consumption Expenditures, s.a.	1996 USD bln	1970Q1 - 2002Q3
4	Gross Fixed Capital Formation, s.a.	1996 USD bln	1970Q1 - 2002Q3
5	GFCF, Machinery and Equipment, s.a.	1996 USD bln	1970Q1 - 2002Q3
6	GFCF, Construction, s.a.	1996 USD bln	1970Q1 - 2002Q3
7	Change in Stocks, s.a.	1996 USD bln	1970Q1 - 2002Q3
8	Exports, Goods and Services, s.a.	1996 USD bln	1970Q1 - 2002Q3
9	Imports, Goods and Services, s.a.	1996 USD bln	1970Q1 - 2002Q3
10	Industrial Production ISIC C-E, s.a.	1995=100	1970Q1 - 2002Q3
11	Capacity Utilization Rate, s.a.	percentage	1970Q1 - 2002Q3
12	Civilian Employment, s.a.	-	1970Q1 - 2002Q3
13	Unemployment Total, s.a.	-	1970Q1 - 2002Q3
14	Unemp % Civ. Labor Force, s.a.	percentage	1970Q1 - 2002Q3
15	Hourly Earnings, Total Private, s.a.	1995=100	1970Q1 - 2002Q3
16	Wage Inflation (rate of change of 15)	percentage	1970Q1 - 2002Q3
17	CPI All Items, s.a.	1995=100	1970Q1 - 2002Q3
18	CPI Inflation (rate of change of 17)	percentage	1970Q1 - 2002Q3
19	Money Supply M1, s.a.	USD bln	1975Q1 - 1998Q4
20	Money Supply M2, s.a.	USD bln	1975Q1 - 1998Q4
21	Commercial Banks Loans, s.a.	USD bln	1975Q1 - 1998Q4
22	Federal Funds Rate	percentage p.a.	1970Q1 - 1998Q2
23	Government Composite Bonds (>10 years)	percentage p.a.	1970Q1 - 1998Q2
24	Share Prices: NYSE Common Stocks	1995=100	1975Q1 - 2002Q3
25	Real Effective Exchange Rate	1995 = 100	1970Q1 - 2002Q3
26	Real Wage (15/16)	-	1970Q1 - 2002Q3
27	Labor Productivity (1/12)	-	1970Q1 - 2002Q3

Table 2: List of variables, USA

	Italy				USA			
Variable	Mean	Std.Dev.	Skewness	Exc. Kurt.	Mean	Std.Dev.	Skewness	Exc. Kurt.
GDP	0.0012	0.0124	0.5495	0.9444	-0.0001	0.0157	-0.4931	0.6989
Private Final Consumption	0.0008	0.0129	0.4573	-0.2624	-0.0006	0.0125	-0.2596	0.1676
Government Final Consumption	0.0009	0.0077	0.4052	-0.2741	-0.0012	0.0077	0.1270	0.0254
GCFC	-0.0005	0.0296	-0.1438	0.1482	-0.0011	0.0435	-0.4256	0.0330
GCFC Machinery & Equipment	0.0007	0.0468	-0.3449	0.0767	0.0007	0.0438	-0.2676	-0.0508
GCFC Construction	-0.0010	0.0232	0.0265	-0.3359	-0.0020	0.0474	-0.6846	0.4033
Exports	0.0004	0.0311	0.6593	0.1408	0.0039	0.0373	0.1770	-0.3176
Imports	0.0006	0.0416	0.0874	-0.2575	-0.0036	0.0477	-1.0746	1.2880
Industrial Production	0.0023	0.0314	0.1129	0.4450	0.0004	0.0301	-0.4400	0.8751
Change in Stocks	0.5367	4.6652	0.3115	0.1689	0.7679	20.8229	-0.0840	0.3241
Rate of Capacity Utilization	-0.0015	1.5882	-0.1567	0.5163	0.1014	2.7837	-0.4944	0.8573
Total Employment	-0.0002	0.0101	0.9780	1.3735	0.0005	0.0102	-0.3699	0.0397
Total Unemployment	0.0023	0.0489	-1.0664	-0.2888	0.0015	0.1040	0.3762	0.0303
Unemployment % Total Labor Force	0.0287	0.3714	-0.7042	0.1685	0.0064	0.7476	0.8075	0.6601
Labor Productivity	0.0017	0.0119	0.4476	0.4434	-0.0005	0.0080	-0.3963	1.4132
Hourly Wage Rate	0.0073	0.0181	0.0787	0.2787	0.0013	0.0075	1.0929	0.7150
CPI All Items	0.0037	0.0185	-1.3198	-0.6231	0.0020	0.0147	0.1335	0.4439
Real Wage	0.0019	0.0042	1.2568	1.1240	-0.0007	0.0107	0.2965	0.5532
Hourly Wage Rate, (rate of change)	0.0005	0.0056	0.1557	1.3573	-0.0000	0.0023	0.3478	0.0136
CPI All Items (rate of change)	0.0005	0.0048	0.4354	1.8604	0.0003	0.0040	0.6775	0.6629
M1	0.0116	0.0173	0.3526	0.6679	0.0066	0.0299	0.3531	-0.7945
M2	0.0114	0.0183	-0.8025	1.3530	0.0030	0.0112	-0.4501	-0.4161
Total Credit to Private Sector	0.0051	0.0263	0.3356	-0.8368	0.0038	0.0221	-0.3261	-0.4424
Official Discount Rate	0.0582	1.5344	-0.0402	-0.5742	0.0957	1.7195	0.6495	-0.3905
Bond Yields	0.0493	1.3112	0.5509	0.1321	0.0427	0.7740	0.4017	0.6631
Real Effective Exchange Rate	-0.0015	0.0327	0.0999	-0.1802	-0.0044	0.0369	1.1238	-0.9113
Share Prices	-0.0047	0.2125	0.5488	-0.5630	-0.0014	0.0685	-0.0729	-0.5775

Table 3: Summary statistics of bandpass filtered Italian macroeconomic variables, with $K = 12$.

	GDP												
Series	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
GDP	-0.35	-0.21	0.04	0.36	0.67	0.91	1.00	0.91	0.67	0.36	0.04	-0.21	-0.35
Private Final Consumption	0.03	0.15	0.32	0.51	0.67	0.78	0.78	**0.64**	**0.41**	**0.14**	**-0.12**	**-0.34**	**-0.48**
Government Final Consumption	**0.18**	**0.12**	0.04	-0.04	-0.11	-0.15	-0.14	-0.09	-0.01	0.08	0.16	0.23	0.26
Gross Fixed Capital Formation	0.02	0.22	0.43	0.62	0.76	0.82	**0.77**	**0.61**	**0.39**	**0.17**	-0.01	-0.16	-0.24
Exports	**-0.47**	**-0.47**	**-0.41**	**-0.30**	**-0.15**	**0.02**	0.20	0.33	**0.41**	**0.45**	**0.47**	**0.47**	**0.47**
Imports	-0.27	-0.18	-0.01	0.22	0.47	0.70	0.83	0.82	0.67	0.44	0.19	**-0.05**	**-0.23**
GFCF Machinery & Equipment	-0.26	-0.08	0.16	0.42	0.66	0.84	0.90	0.81	0.60	0.35	0.11	-0.09	-0.23
GFCF Construction	**0.45**	**0.63**	**0.73**	**0.73**	0.65	**0.49**	**0.28**	**0.05**	**-0.12**	**-0.22**	**-0.25**	**-0.24**	-0.21
Industrial Production	-0.49	-0.35	-0.10	0.22	0.53	0.79	0.92	0.86	0.64	0.36	0.08	-0.15	-0.28
Change in Stocks	-0.61	-0.54	-0.33	-0.03	0.30	0.60	0.77	0.76	0.58	0.32	0.03	-0.21	**-0.37**
Rate of Capacity Utilization	-0.67	**-0.57**	**-0.35**	**-0.04**	**0.30**	0.61	0.82	0.86	0.75	0.56	0.36	0.19	0.08
Total Employees All Activities	0.26	0.36	0.44	0.51	**0.54**	**0.52**	**0.43**	**0.26**	**0.07**	**-0.11**	**-0.26**	**-0.38**	-0.44
Unemployment Total	**-0.51**	**-0.63**	-0.64	-0.54	**-0.34**	**-0.08**	**0.21**	**0.44**	**0.55**	**0.53**	**0.42**	**0.27**	0.11
Unemployed % Total Labor Force	-0.51	-0.61	-0.61	-0.52	-0.35	-0.11	0.16	0.38	0.50	0.52	0.47	0.36	0.25
Labor Productivity	-0.72	-0.64	-0.41	-0.06	0.32	0.63	0.80	0.81	0.67	0.41	0.09	**-0.18**	**-0.31**
CPI All Items	0.03	0.11	0.16	0.15	0.09	-0.03	-0.21	-0.39	-0.54	-0.64	-0.69	-0.69	-0.63
Hourly Wage Rate	-0.18	-0.12	-0.06	-0.02	-0.02	-0.09	-0.21	-0.35	-0.47	-0.56	-0.59	-0.56	-0.45
CPI All Items (rate of change)	**-0.26**	**-0.15**	0.05	0.28	**0.51**	**0.65**	**0.66**	**0.53**	**0.32**	**0.09**	-0.14	-0.32	-0.43
Hourly Wage Rate (rate of change)	-0.20	-0.21	-0.12	0.03	0.22	0.38	**0.45**	**0.40**	**0.26**	0.05	-0.19	-0.41	-0.56
Real Wage	-0.30	-0.30	-0.27	-0.21	-0.15	**-0.09**	**-0.05**	**-0.03**	**-0.02**	**-0.02**	**0.00**	**0.05**	**0.12**
M1	-0.51	-0.42	-0.27	-0.10	0.07	0.21	0.32	0.40	0.45	0.45	0.40	0.30	0.17
M2	**-0.69**	**-0.64**	-0.53	-0.37	-0.19	-0.01	0.15	0.29	0.41	0.48	0.49	0.44	0.32
Total Domestic Credit	-0.19	-0.24	-0.29	-0.34	-0.37	-0.41	-0.44	-0.47	-0.49	-0.49	-0.45	-0.37	-0.24
Total Credit to Private Sector	0.32	0.26	**0.17**	**0.05**	**-0.08**	**-0.21**	**-0.32**	**-0.43**	**-0.52**	**-0.59**	**-0.64**	**-0.65**	**-0.63**
Share Prices	0.35	0.35	0.30	0.23	0.16	0.10	0.05	0.02	0.00	-0.01	0.00	0.01	0.04
USD/EUR	0.25	0.33	0.37	0.38	0.37	0.35	0.32	0.29	0.27	0.26	0.26	0.25	0.20
Real Effective Exchange Rate	0.36	0.39	0.39	0.34	0.28	0.21	0.14	0.07	0.02	-0.02	-0.06	-0.12	-0.19
Official Discount Rate	**-0.10**	**-0.01**	0.12	0.27	0.38	0.41	0.32	0.12	-0.14	-0.40	-0.62	-0.76	-0.77
Bond Yields	0.31	0.29	0.27	0.23	0.16	0.06	-0.09	-0.26	-0.40	-0.52	-0.59	-0.61	-0.56

Table 4: Cross-correlation coefficients of bandpass-filtered variables vs. the filtered GDP: Italy. $K = 12$. *Bold*: cross-correlations significantly different from U.S. ones.

							GDP						
Series	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
GDP	-0.16	-0.02	0.20	0.46	0.71	0.91	1,00	0.91	0.71	0.46	0.20	-0.02	-0.16
Private Final Consumption	-0.27	-0.12	0.08	0.32	0.57	0.76	0.88	0.90	0.85	0.73	0.58	0.43	0.30
Government Final Consumption	0.54	0.50	0.40	0.28	0.14	0.02	-0.06	-0.11	-0.13	-0.13	-0.12	-0.11	-0.10
Gross Fixed Capital Formation	-0.17	0.04	0.29	0.55	0.79	0.93	0.96	0.88	0.73	0.53	0.33	0.16	0.03
Exports	0.34	0.39	0.45	0.50	0.49	0.43	0.31	0.16	0.01	-0.14	-0.29	-0.42	-0.52
Imports	-0.45	-0.24	0.04	0.35	0.62	0.79	0.84	0.80	0.70	0.59	0.48	0.40	0.33
GFCF Machinery & Equipment	-0.04	0.18	0.43	0.68	0.86	0.93	0.89	0.76	0.59	0.39	0.19	0.03	-0.09
GFCF Construction	-0.26	-0.08	0.15	0.42	0.68	0.87	0.95	0.92	0.80	0.62	0.42	0.25	0.12
Change in Stocks	-0.58	-0.49	-0.29	0.00	0.31	0.55	0.66	0.63	0.50	0.32	0.16	0.07	0.04
Rate of Capacity Utilization	-0.36	-0.18	0.07	0.37	0.64	0.83	0.90	0.87	0.76	0.61	0.44	0.30	0.18
Civilian Employment	0.06	0.25	0.48	0.70	0.88	0.95	0.92	0.79	0.61	0.40	0.19	0.02	-0.12
Unemployment Total	0.08	-0.11	-0.35	-0.60	-0.81	-0.92	-0.92	-0.83	-0.66	-0.47	-0.28	-0.12	0.01
Labor productivity	-0.46	-0.38	-0.21	0.05	0.36	0.65	0.83	0.88	0.80	0.63	0.42	0.24	0.12
CPI All Items	0.37	0.27	0.14	-0.02	-0.19	-0.35	-0.50	-0.62	-0.71	-0.76	-0.77	-0.75	-0.69
Hourly Earnings Total Private	0.06	0.06	0.05	0.01	-0.05	-0.14	-0.24	-0.33	-0.41	-0.48	-0.53	-0.55	-0.52
CPI All Items (rate of change)	0.25	0.25	0.21	0.13	0.01	-0.15	-0.30	-0.42	-0.46	-0.44	-0.38	-0.33	-0.29
Hourly Earnings Total Private (rate of change)	-0.05	0.12	0.25	0.28	0.22	0.11	-0.02	-0.11	-0.18	-0.24	-0.31	-0.40	-0.43
Real Wage	-0.46	-0.32	-0.15	0.03	0.21	0.38	0.51	0.60	0.66	0.68	0.66	0.61	0.55
M1	-0.20	-0.25	-0.28	-0.27	-0.21	-0.11	0.03	0.16	0.26	0.33	0.36	0.37	0.36
M2	-0.05	-0.12	-0.18	-0.20	-0.19	-0.13	-0.04	0.06	0.15	0.22	0.27	0.31	0.35
Commercial Bank Loans	0.52	0.66	0.74	0.77	0.71	0.59	0.40	0.20	0.02	-0.08	-0.12	-0.10	-0.09
Share prices	0.24	0.08	-0.08	-0.18	-0.18	-0.08	0.09	0.26	0.36	0.34	0.23	0.07	-0.06
Federal Funds Rate	0.35	0.41	0.48	0.55	0.58	0.54	0.43	0.25	0.02	-0.22	-0.43	-0.59	-0.68
USA Government composite bonds (> 10 years)	-0.02	0.00	0.05	0.12	0.16	0.15	0.07	-0.07	-0.23	-0.39	-0.50	-0.54	-0.53

Table 5: Cross-correlation coefficients of bandpass-filtered variables vs. the filtered GDP: USA. $K = 12$.

	Cause GDP	GDP Caused
Series	F-stat	F-stat
Private Final Consumption	5.230	2.308
	(0.000)	(0.051)
Government Final Consumption	1.006	1.386
	(0.419)	(0.237)
Gross Fixed Capital Formation	0.938	2.001
	(0.460)	(0.086)
Exports	2.599	2.478
	(0.030)	**(0.038)**
Imports	1.053	2.195
	(0.392)	(0.062)
GFCF Machinery and Equipment	2.805	3.048
	(0.021)	**(0.014)**
GFCF Construction	0.919	5.066
	(0.472)	**(0.000)**
Industrial Production	1.470	2.607
	(0.207)	**(0.030)**
Change in Stocks	3.731	1.880
	(0.004)	(0.105)
Rate of Capacity Utilization	1.722	4.577
	(0.138)	**(0.001)**
Total Employees All Activities	1.946	1.922
	(0.094)	(0.098)
Unemployment Total	1.987	1.356
	(0.088)	(0.248)
Unemployed % Total Labour Force	1.433	1.283
	(0.220)	(0.278)
Labor Productivity	2.072	1.641
	(0.076)	(0.157)
CPI All Items	3.104	4.998
	(0.012)	**(0.000)**
Hourly Wage Rate	3.220	3.324
	(0.010)	**(0.008)**
CPI All Items (rate of change)	3.185	4.869
	(0.011)	**(0.001)**
Hourly Wage Rate (rate of change)	2.502	4.840
	(0.036)	**(0.001)**
Real Wage	1.527	0.956
	(0.189)	(0.449)
M1	1.986	3.168
	(0.095)	**(0.014)**
M2	2.563	2.257
	(0.037)	(0.061)
Total Domestic Credit	2.768	0.404
	(0.026)	(0.844)
Total Credit to Private Sector	2.461	0.780
	(0.044)	(0.568)
Share Prices	0.659	0.238
	(0.656)	(0.944)
USD/EUR	2.615	1.874
	(0.030)	(0.107)
Real Effective Exchange Rate	0.685	0.468
	(0.636)	(0.799)
Official Discount Rate	2.137	3.415
	(0.070)	**(0.008)**
Bond Yields	0.855	0.382
	(0.515)	(0.860)

Table 6: Granger causality tests, bivariate models with each variable and the GDP, and five lags: Italy. $K = 12$. p-values are in brackets. *Bold*: values for which the null (no causality) is rejected at 5%-significance level.

	Cause GDP	GDP Caused
Series	F-stat	F-stat
Private Final Consumption	2.595	2.530
	(0.031)	**(0.034)**
Government Final Consumption	3.172	2.556
	(0.011)	**(0.033)**
GFCF	1.434	3.644
	(0.220)	**(0.005)**
Exports	0.984	5.536
	(0.432)	**(0.000)**
Imports	1.128	2.115
	(0.351)	(0.071)
GFCF Machinery and Equipment	1.008	1.291
	(0.418)	(0.275)
GFCF Construction	4.991	4.947
	(0.000)	**(0.000)**
Change in Stocks	2.530	5.347
	(0.034)	**(0.000)**
Rate of Capacity Utilization	4.103	0.988
	(0.002)	(0.429)
Civilian Employment	3.622	3.192
	(0.005)	**(0.011)**
Unemployment Total	5.082	2.020
	(0.000)	(0.083)
Labor productivity	3.621	3.069
	(0.005)	**(0.013)**
CPI All Items	3.971	3.771
	(0.003)	**(0.004)**
Hourly Earnings Total Private	3.842	1.887
	(0.003)	(0.104)
CPI All Items (rate of change)	2.234	6.827
	(0.058)	**(0.000)**
Hourly Earnings Total Private (rate of change)	3.758	3.165
	(0.004)	**(0.011)**
Real Wage	3.375	0.648
	(0.008)	(0.664)
M1	3.798	2.792
	(0.005)	**(0.025)**
M2	2.388	1.136
	(0.049)	(0.352)
Commercial Bank Loans	4.822	2.093
	(0.001)	(0.080)
Share prices	0.615	1.025
	(0.688)	(0.409)
Federal Funds Rate	4.287	2.691
	(0.002)	**(0.027)**
USA Government composite bonds (>10 years)	5.348	0.822
	(0.000)	(0.538)

Table 7: Granger causality tests, bivariate models with each variable and the GDP, and five lags: U.S. $K = 12$. p-values are in brackets. *Bold*: values for which the null (no causality) is rejected at 5%-significance level.

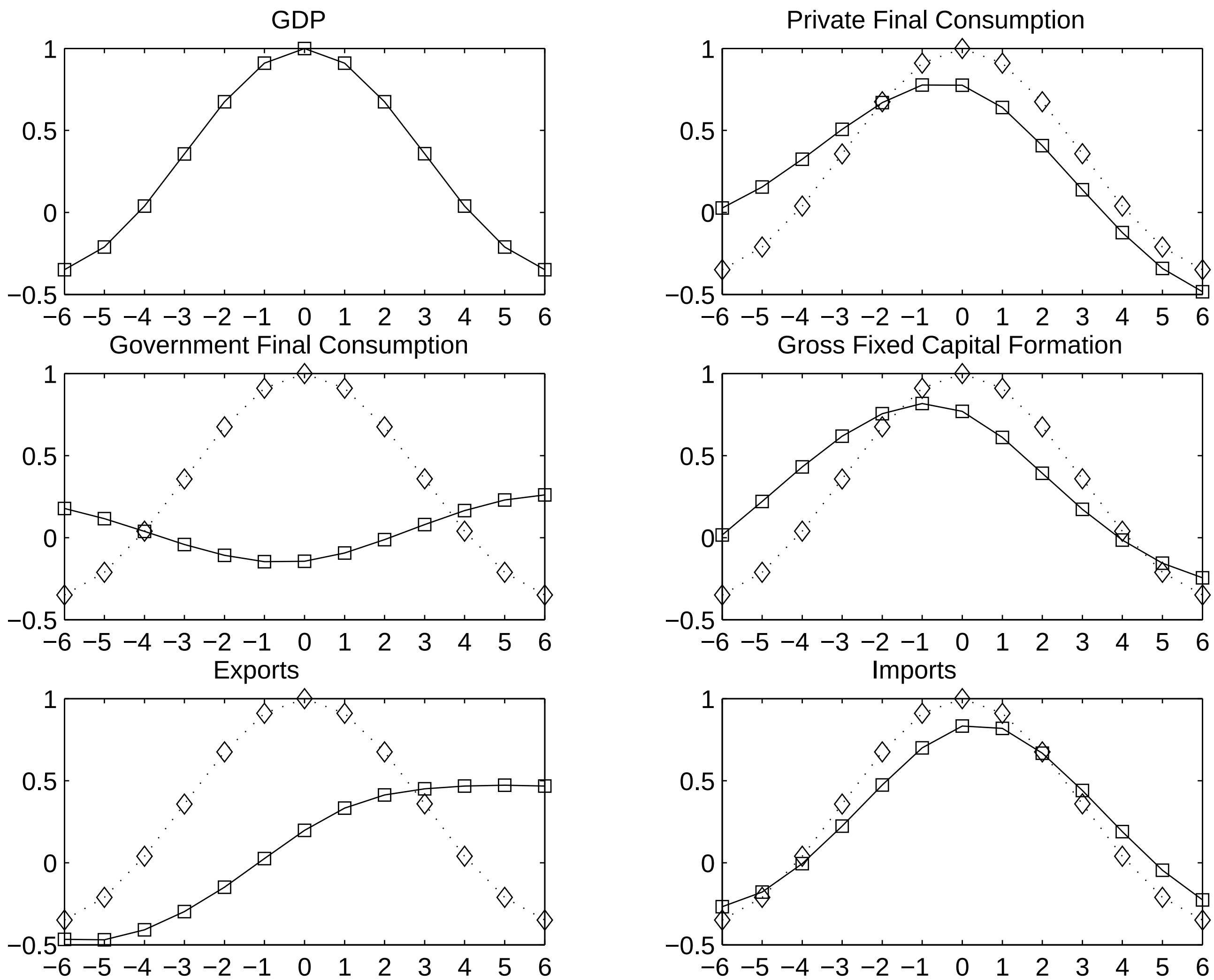

Figure 1: Cross-correlograms, Italian data: GDP components.
Diamonds: GDP autocorrelation. *Squares*: GDP component.

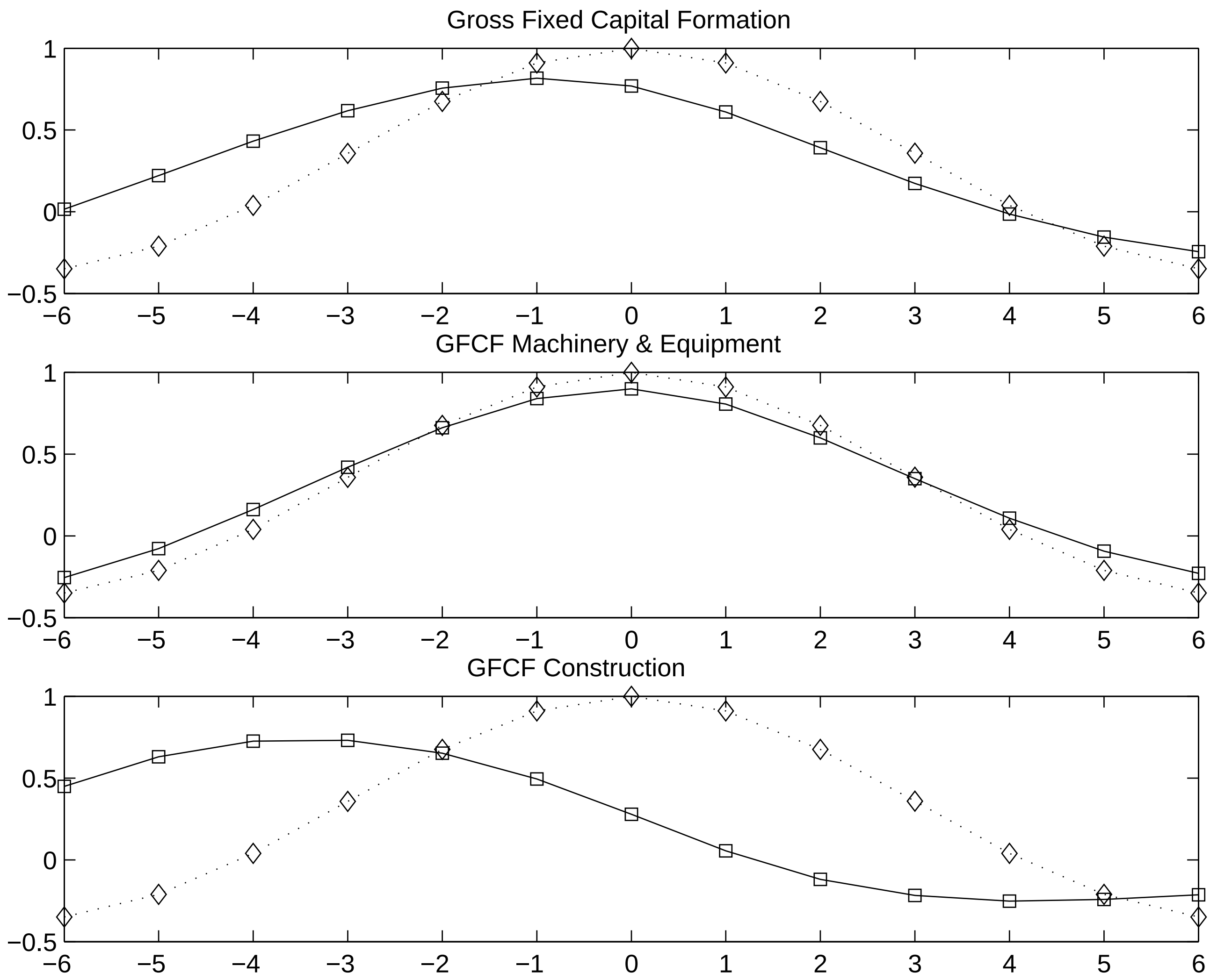

Figure 2: Cross-correlograms, Italian data: investment components.
Diamonds: GDP autocorrelation. *Squares*: investment component.

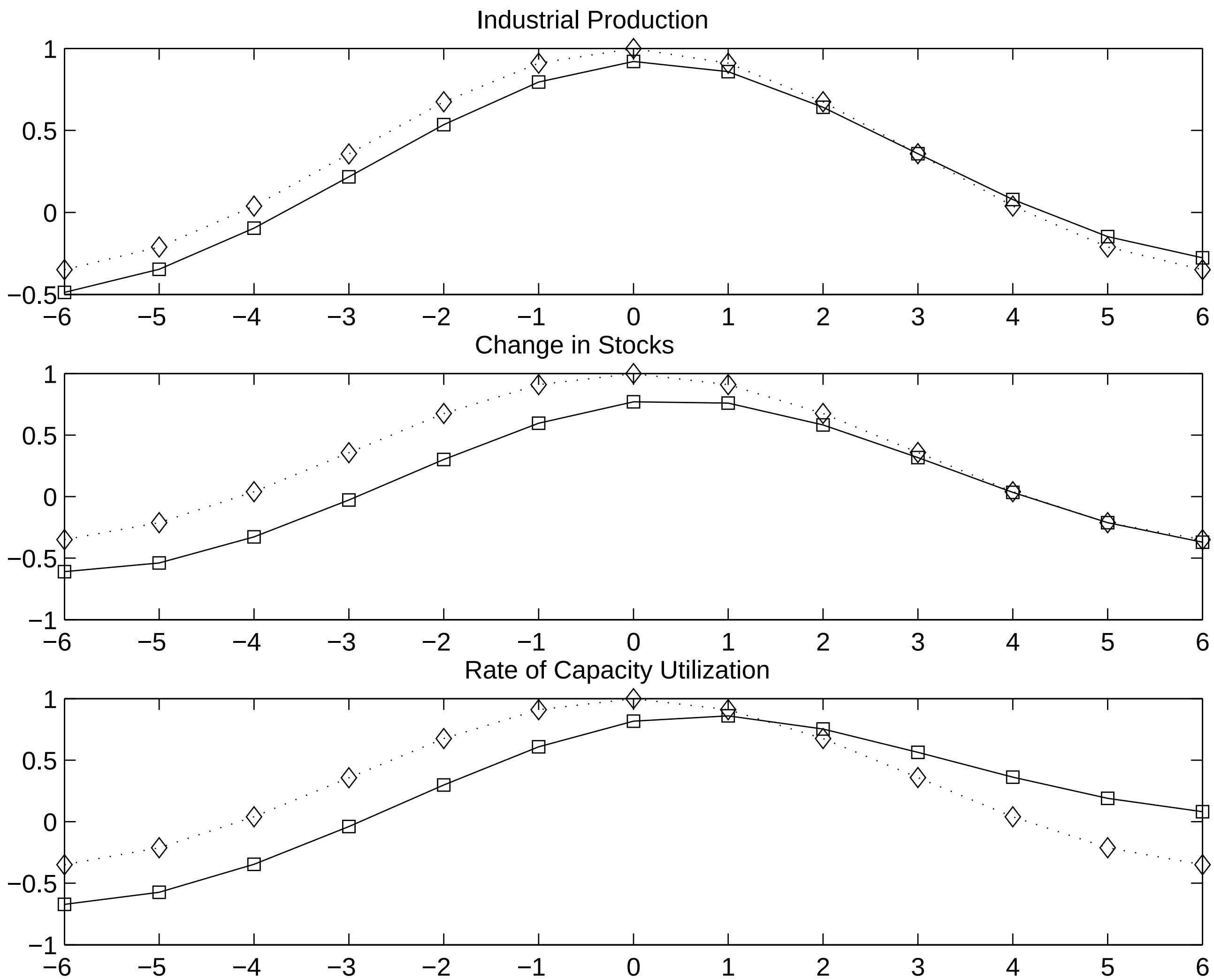

Figure 3: Cross-correlograms, Italian data: production variables.
Diamonds: GDP autocorrelation. *Squares*: production variable.

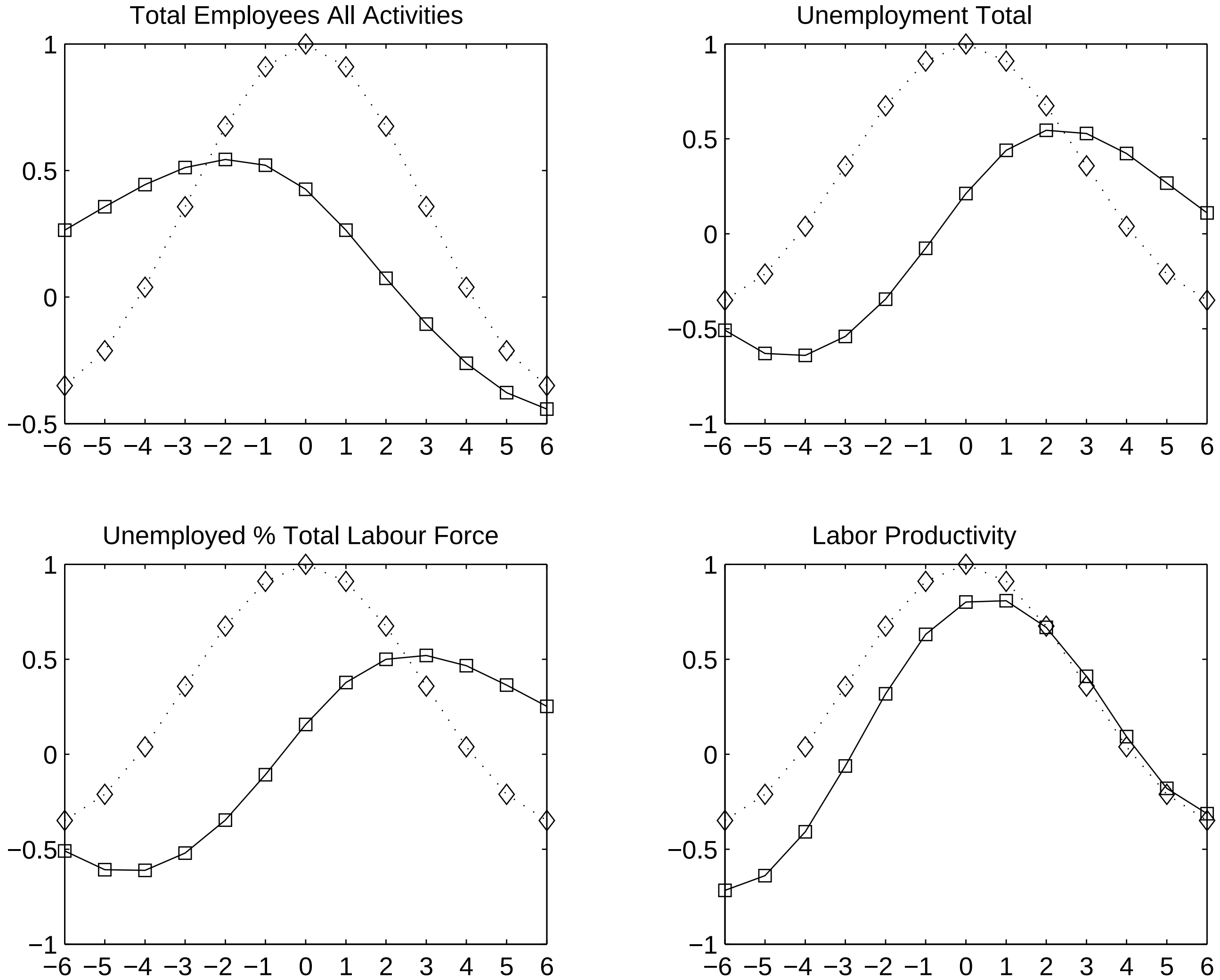

Figure 4: Cross-correlograms, Italian data: labor market variables.
Diamonds: GDP autocorrelation. *Squares*: labor market variable.

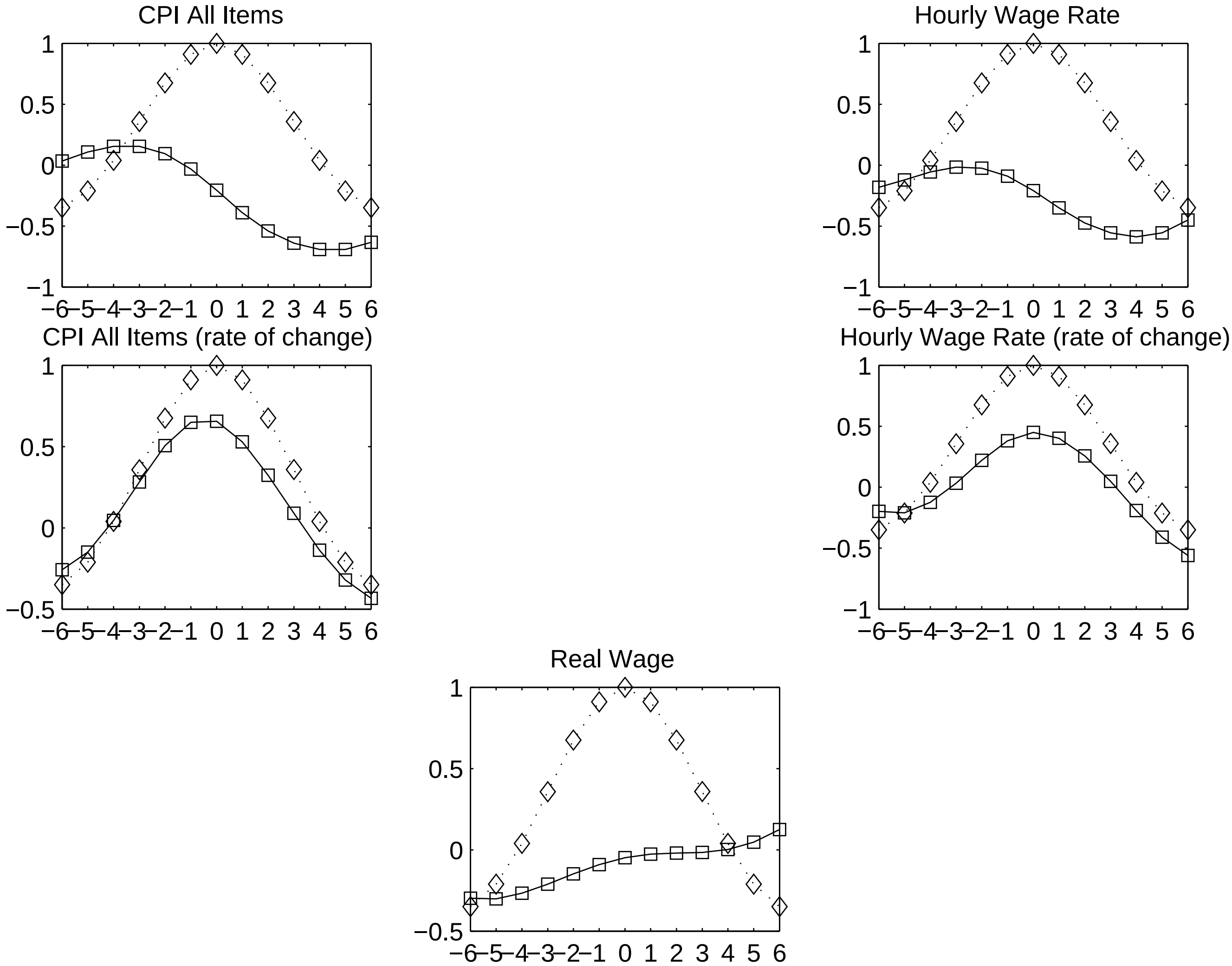

Figure 5: Cross-correlograms, Italian data: prices and wages.
Diamonds: GDP autocorrelation. *Squares*: prices and wages variable.

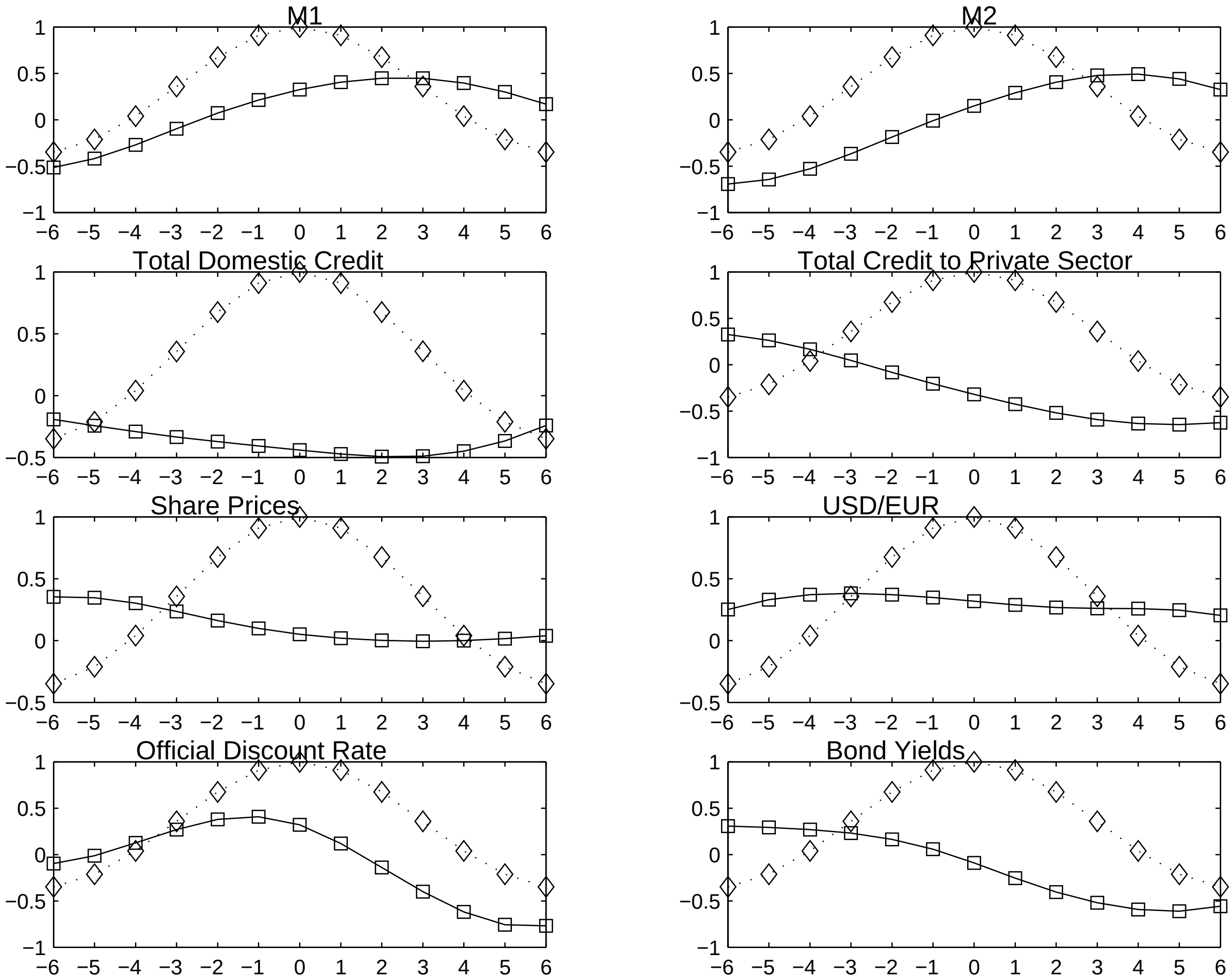

Figure 6: Cross-correlograms, Italian data: monetary and financial variables. *Diamonds*: GDP autocorrelation. *Squares*: monetary and financial variable.

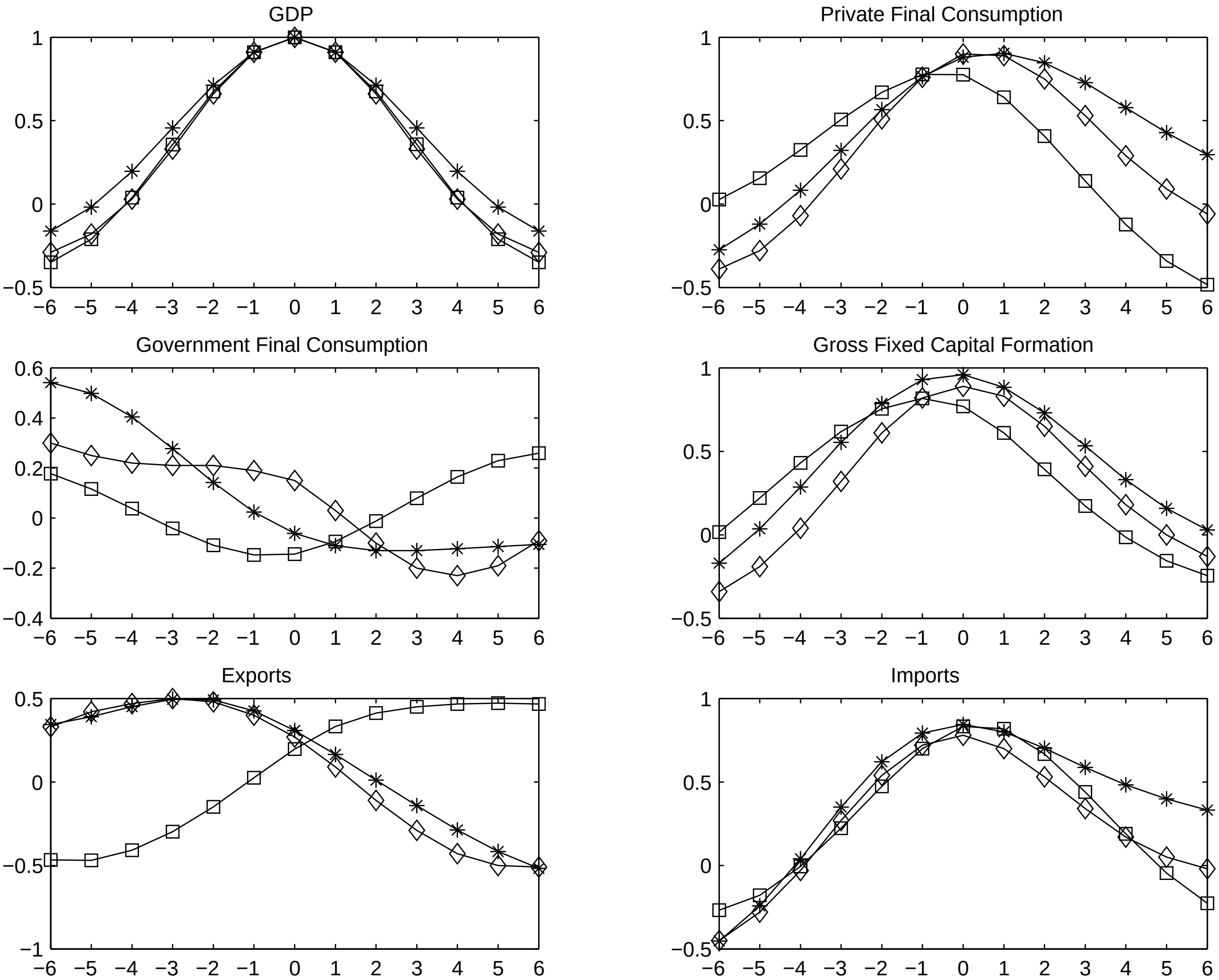

Figure 7: Cross-correlograms, Italian ad U.S. data: GDP components. *Squares*: Italian data. *Asterisks*: U.S. data. *Diamonds*: Stock and Watson data.

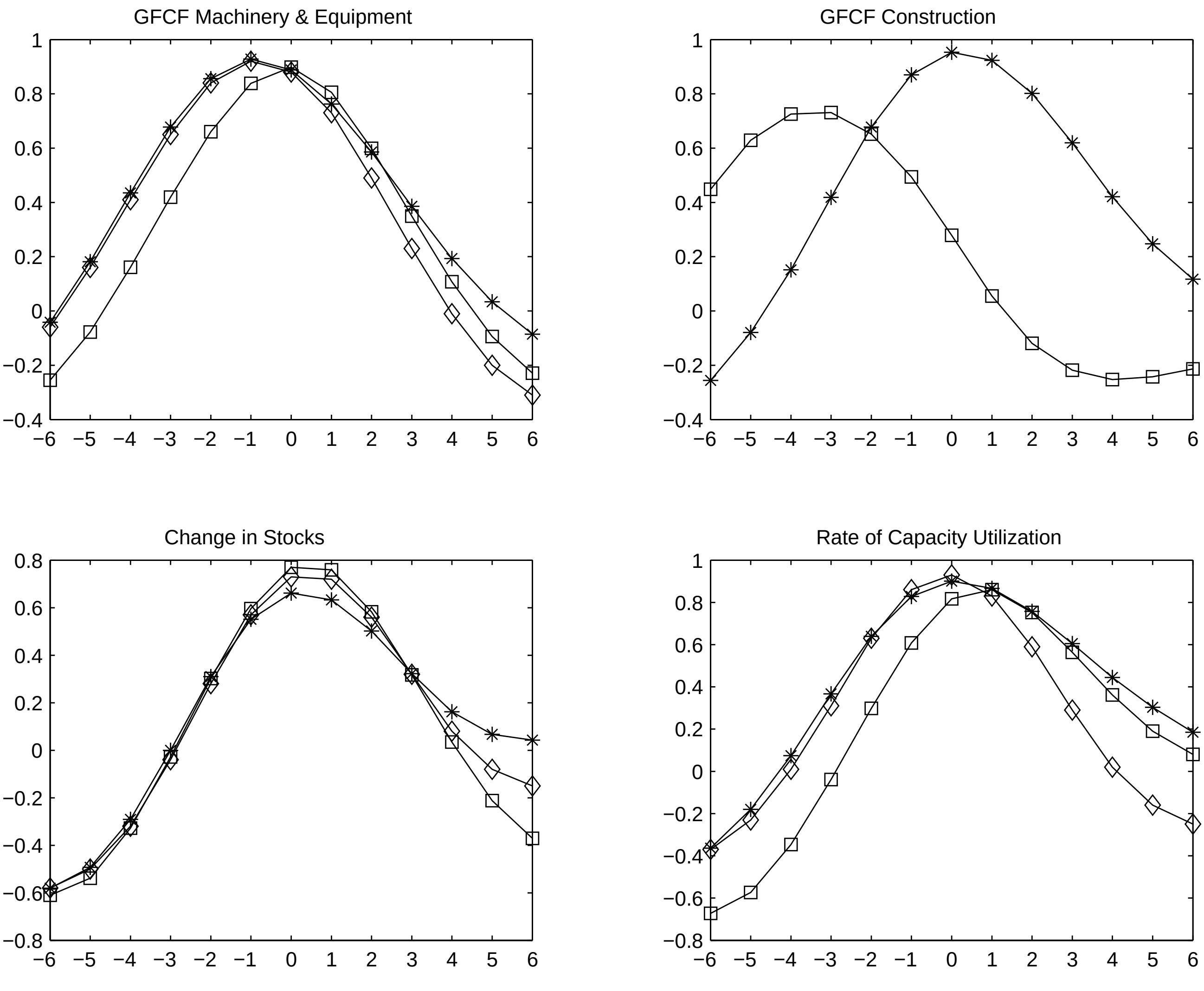

Figure 8: Cross-correlograms, Italian ad U.S. data: production variables and investment components. *Squares*: Italian data. *Asterisks*: U.S. data. *Diamonds*: Stock and Watson data.

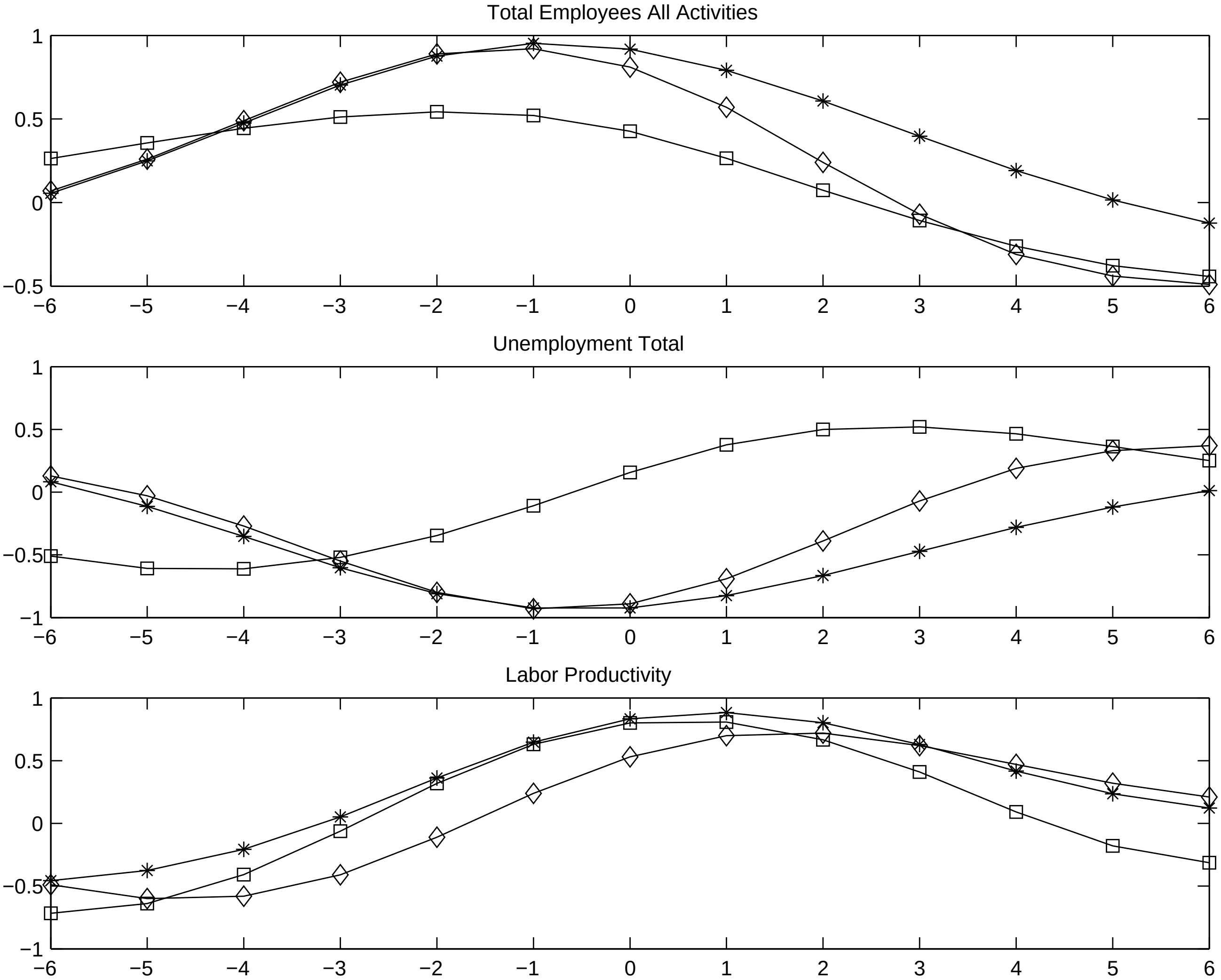

Figure 9: Cross-correlograms, Italian ad U.S. data: labor market variables. *Squares*: Italian data. *Asterisks*: U.S. data. *Diamonds*: Stock and Watson data.

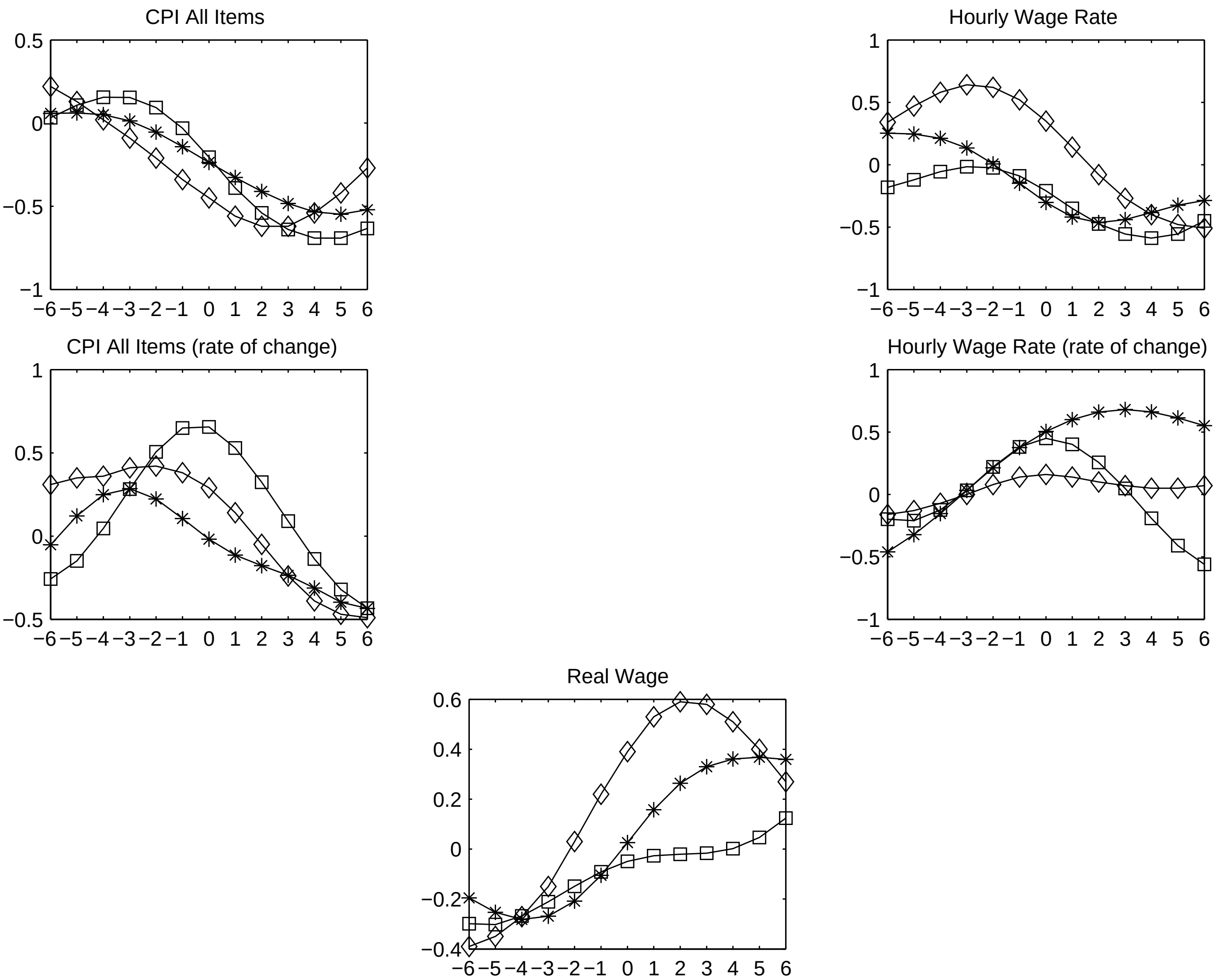

Figure 10: Cross-correlograms, Italian ad U.S. data: prices and wages. *Squares*: Italian data. *Asterisks*: U.S. data. *Diamonds*: Stock and Watson data.

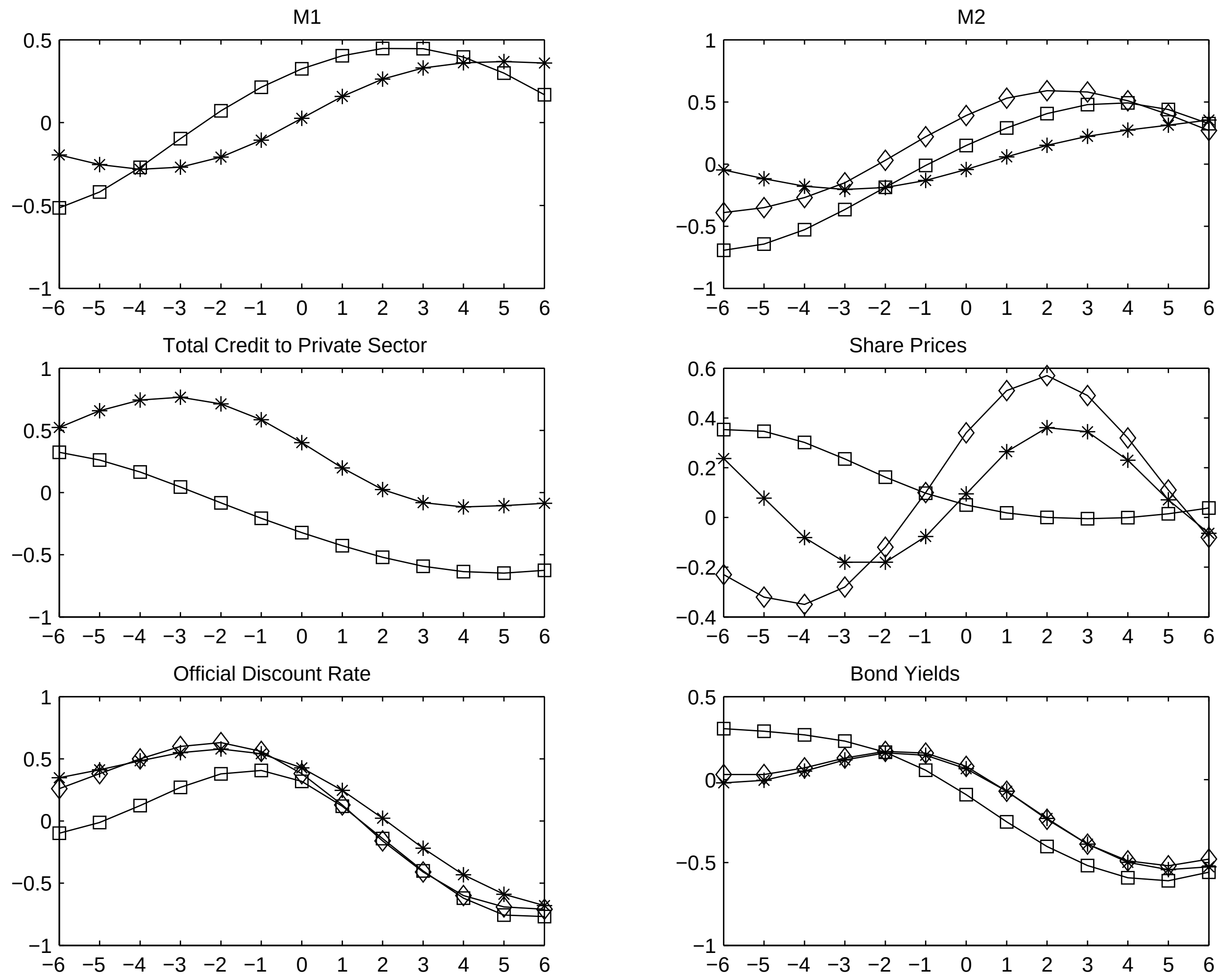

Figure 11: Cross-correlograms, Italian ad U.S. data: monetary and financial variables. *Squares*: Italian data. *Asterisks*: U.S. data. *Diamonds*: Stock and Watson data.