The relationship between the PMI and the Italian index of industrial production and the impact of the latest economic crisis

by Valentina Aprigliano
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(Working papers)

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Abstract

Survey data attract considerable interest as timely and reliable series for assessing the state of the economy. We investigate the relationship between the manufacturing PMI and the Index of Industrial Production (IPI) for Italy, with a special focus on the effects of the latest crisis. The manufacturing PMI tracks a medium-to-long run component of the IPI quarterly growth rate, which is estimated by a one-sided multivariate Wavelet filter. This filter provides more efficient estimates at the end of the sample than the Baxter and King method. Furthermore, the Wavelet basis allows us to take into account the time-varying oscillations of a series caused by the large negative shocks characterizing the latest global crisis, while the non-parametric framework does not force us to conclude definitely for the occurrence of structural breaks not yet testable rigorously.

JEL Classification: C5, E3.
Keywords: Wavelet analysis, principal component analysis, business cycle.

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1 Introduction

Survey data attract considerable interest among analysts as a means of assessing the current state of the economy. One of the most highly appreciated feature is their timely release, unlike the main real economic aggregates, which are issued with a significant delay with respect to the reference period. The timeliness of survey data helps to improve both the real-time inference and the forecasting ability.\footnote{See also Altissimo et al. [1] and [2].} This paper deals with the information provided by the Purchasing Manager Index (PMI) for the manufacturing sector to track Italian economic activity. More precisely, we are interested in the relationship between the Italian manufacturing PMI series and the Industrial Production Index (IPI) growth rate, with special focus on the effects of the latest global economic crisis.

The PMI provides information about the spread of the improvement (deterioration) in business conditions without measuring its magnitude. For this reason, the PMI is also called a diffusion index. Moreover, the PMI displays a smoother dynamics than the IPI growth rate. According to the results of some recent studies,\footnote{See Sánchez [17].} it may be tested the hypothesis for which the PMI respondents give answers conveying information about the underlying tendency of the economic activity rather than the latest monthly variations. Despite this evidence, there have been many attempts to use the PMI to forecast the short-run behavior of the IPI growth rate by relying on a linear relationship.\footnote{See Harris [11] and Koenig [13].} The poor forecasting ability of the PMI during particularly sharp falls in the IPI series suggests the presence of a structural break in this linear relationship. For instance, Goldman Sachs [9] defines the PMI as a nonlinear survey indicator when it reaches extremely low values. In these cases, the linear relationship turns out not to be very useful for assessing the industrial production growth. This argument would seem particularly appropriate with respect to the latest global recession.

However, we will show that the use of the manufacturing PMI to track the short-run dynamics of the IPI growth rate in a linear regression setting provides not very significant results for the Italian economy. We therefore found it more interesting to study the relationship between the manufacturing PMI and a medium-to-long-run component of the IPI growth rate. We also argue that what could be interpreted as a structural change in the relationship between the variables of interest might reflect the temporary...
impact of the large shocks affecting the economy in the last period. The poor performance of the PMI in grasping the intensity of the last trough of the IPI growth rate may not be due to the occurrence of a structural break as it seems more likely to be a consequence of the nature of the PMI series.

We propose a frequency-domain analysis, which allows us to study the effects of the crisis by frequency components and their time-varying contribution to the overall variance of the series. Given a real-time perspective, we will construct a one-sided filter based on the soft-threshold estimator applied to the wavelet decomposition of the quarterly growth rate of the IPI (q-o-q IPI). This filter has been constructed in a multivariate framework. Indeed, we have exploited the relationship between the manufacturing PMI and the q-o-q IPI as a further de-noising criterion to extract the target. Our non-parametric approach is expected to provide a more flexible way of dealing with the effects of the latest economic crisis on the economic aggregates and on their relationships.

The paper is organized as follows. Section 2 provides an intuitive overview of the Wavelet Analysis by citing the main references. Section 3 contains the description of the data used. The analysis of the relationship between the manufacturing PMI and the IPI growth rate is illustrated in Section 4. Section 5 concludes.

2 A Short Introduction to Wavelets

The frequency-domain analysis of the time series is traditionally accomplished using the Fourier Analysis. However, the latter cannot provide any information about the changes of the spectrum in time. This fact becomes relevant when the time interval considered is characterized by some events that considerably affect the spectrum of the series.

The Wavelet Analysis solves this problem efficiently. The wavelets were introduced by Grossmann et al. [10] and Meyer [15]. They are non-periodic functions, \( \psi(x) \), providing an orthonormal basis of \( L^2(\mathbb{R}) \) with good localization properties both in the time-domain and in the frequency-domain. A complete treatment of the wavelets applied to the time series analysis is provided by Percival et al. [16].

In order to provide an intuitive overview of the Wavelet Analysis, we refer mainly to Mallat [14].

A signal is decomposed into orthogonal components called \textit{resolution}

\footnote{See also Brillinger [5] [6] and Brockwell et al. [7].}
levels, which are the analogues of the frequency components in the Fourier Analysis. Each resolution level is characterized by a certain amount of detail, which represent the information conveyed. The lower resolution levels correspond to the lower frequency components, while the higher resolution levels convey more detailed information so as the higher frequency components contain more noise. This is known as the multiresolution decomposition of a signal. More formally, given the signal \( f(x) \) we get a coarse approximation-component at the resolution level \( 2^J \), \( A_{2^J} f \), and the detail signals, \( D_{2^J} f \), at the resolutions \( 2^j \), for \( 1 \leq j \leq J \) and \( j \in \mathbb{Z} \). \( A_{2^J} f \) is obtained by projecting \( f(x) \) on the orthonormal basis formed by the dilation and the translation of the scaling function, \( \phi(x) \), which is equivalent to a low-pass filter, whose frequency band is \([0, \pi/2^J]\). \( D_{2^J} f \) results from the projection of \( f(x) \) on the dilation and the translation of the wavelet function, \( \psi(x) \), which corresponds to a band-pass filter with frequency band \([\pi/2^J - j, \pi/2^J - j - 1]\). Finally, we obtain the orthogonal wavelet representation

\[
(A_{2^J} f, (D_{2^J} f)_{1 \leq j \leq J})
\]

which can basically be interpreted as a decomposition of the original signal, \( f(x) \), in a set of independent time-frequency components.

3 Data and Descriptive Statistics

The time period we consider goes from August 1997 to February 2010. In particular, we investigate the relationship between the IPI growth rate and the PMI before September 2008, and then we examine how it has been affected by the latest global crisis.

All the series we use throughout the analysis are seasonally adjusted by means of dummy variables.

3.1 PMI

The Italian manufacturing PMI is constructed on the basis of monthly surveys conducted across more than 450 companies. The sample is grouped according to the Standard Industrial Classification (see Table (1) for a more detailed description). Each company contributes to the PMI depending on its share in the total manufacturing output.

In the report on manufacturing, eleven indices are produced corresponding to some of the most important variables in a company’s production

6The first applications of the Wavelet Analysis were in the Image Processing field, from
<table>
<thead>
<tr>
<th>Industries</th>
<th>Super-sectors</th>
<th>Sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic materials</td>
<td>Chemicals</td>
<td>Forestry &amp; paper</td>
</tr>
<tr>
<td></td>
<td>Basic resources</td>
<td>Industrials metals</td>
</tr>
<tr>
<td>Industrials</td>
<td>Construction &amp; materials</td>
<td>General industrials</td>
</tr>
<tr>
<td></td>
<td>Industrial goods &amp; services</td>
<td>Electronics &amp; elect. equip.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Industrial engineering</td>
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<td></td>
<td>Industrial transportation</td>
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<tr>
<td></td>
<td></td>
<td>Support services</td>
</tr>
<tr>
<td>Consumer goods</td>
<td>Automobiles &amp; parts</td>
<td>Beverages</td>
</tr>
<tr>
<td></td>
<td>Food &amp; beverages</td>
<td>Food producers</td>
</tr>
<tr>
<td></td>
<td>Personal &amp; household</td>
<td>Household goods</td>
</tr>
<tr>
<td></td>
<td>Goods</td>
<td>Personal goods</td>
</tr>
<tr>
<td>Healthcare</td>
<td>Healthcare</td>
<td>H.C. equip. &amp; services</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pharmaceuticals &amp; biotech.</td>
</tr>
<tr>
<td>Consumer services</td>
<td>Media</td>
<td></td>
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<tr>
<td>(ex. retail)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Travel &amp; leisure</td>
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<tr>
<td>Financials</td>
<td>Banks</td>
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<td>Financial services</td>
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<td></td>
<td>Real estate</td>
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<td>Technology</td>
<td>Technology</td>
<td>Software &amp; computer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Services</td>
</tr>
</tbody>
</table>

Table 1: Industries covered by the manufacturing PMI survey.
process. The managers are asked whether output, new orders, new export orders, backlogs of work, stocks of finished goods, employment, output prices, input prices, suppliers' delivery times, quantity of purchases, stock of purchases have increased/decreased/not changed with respect to the previous month. The answers are used to construct the corresponding eleven diffusion indices and finally the manufacturing PMI as a weighted aggregation of some of them.\textsuperscript{8}

By construction, the PMI cannot actually be defined as a quantitative variable. Indeed, the PMI does not measure the magnitude of a phenomenon, rather its spread across firms. Furthermore, it displays smoother dynamics than some real aggregates such as the IPI. This fact should be taken into account when choosing the most appropriate transformation of the IPI growth rate for the analysis.

3.2 Industrial Production

In order to select the most appropriate transformation of the IPI growth to be tracked by the PMI, we rely on some descriptive statistics in both the time and the frequency domain.

A preliminary consideration can be made about the three main transformations we will consider. These are essentially the year-on-year, quarter-on-quarter and month-on-month growth rates.\textsuperscript{9} It is worth emphasizing that the PMI actually conveys monthly information. As a consequence, the y-o-y IP is likely not to be a suitable choice. On the other hand, the m-o-m transformation displays a huge short-term volatility, quite different from the smoother PMI.

It is reasonable to expect that the q-o-q transformation of the IPI behaves well for the purposes of our analysis, as shown in Figure (1). Here, we plot

\textsuperscript{7}The effects of the global crisis worsened considerably since September 2008. We therefore consider it an interesting threshold date.

\textsuperscript{8}The percentage of increase, decrease and no change answers are given weights equal to 1.0, 0 and 0.5 respectively. Finally, the PMI is obtained as a weighted aggregation of the New Order Books Index (0.3), Output Index (0.25), Employment Index (0.2), Suppliers’ Delivery Times Index (0.15) and Stocks of Purchases Index (0.1). For instance, a level 100 of the PMI indicates that all the companies recorded an improvement in the above variables. A 50 level of the PMI could indicate both that 50 per cent of the companies recorded an improvement, while the remaining 50 per cent recorded a deterioration and the extreme case in which all the companies observed no change in their activity.

Each diffusion index is seasonally adjusted using dummy variables.

\textsuperscript{9}For the sake of brevity, we will indicate these transformations with y-o-y, q-o-q and m-o-m respectively.
Figure 1: The q-o-q IPI and the manufacturing PMI with their the turning points.

the two series of interest with their turning points, detected by the Bry-Boschan algorithm adapted to the quarterly data. The two series display four coincident turning points. On the other hand, it is worth pointing out the period of stagnation experienced by the q-o-q IPI, i.e. from May 2000 to August 2004, unlike the PMI. Table (2) reports the turning points.

The spectral analysis further supports the previous considerations. In Figure (2) we plot the cohesion between the variables. It measures the association between the two signals by frequency components.\footnote{The cohesion is the Fourier transform of the correlation between two variables. For more details see also Brockwell et al. \cite{7}.} The q-o-q IPI displays a higher cohesion with the manufacturing PMI at lower frequency bands than the m-o-m and y-o-y IPI. This preliminary analysis anticipates some results obtained from the multiresolution analysis introduced in the next section. If we look at the cohesion measured in the sample including the latest crisis, we observe that it increases in the frequency band $[\pi/2, \pi/4]$ (corresponding to [4,8]quarters). Finally, let us observe the not negligible cohesion between the variables in the highest frequency bands, which should be taken into account in the rest of the analysis.

Finally, Figure (3) plots the estimated power spectral densities (PSD)
Table 2: Turning Points

<table>
<thead>
<tr>
<th>Series</th>
<th>T\textsuperscript{b}</th>
<th>P\textsuperscript{c}</th>
<th>T</th>
<th>P</th>
<th>T</th>
<th>P</th>
<th>T</th>
<th>P</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPI</td>
<td>Nov-98</td>
<td>May-00</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>Aug-04</td>
<td>May-06</td>
<td>Feb-09</td>
</tr>
<tr>
<td>PMI</td>
<td>0</td>
<td>0</td>
<td>Nov-01</td>
<td>May-02</td>
<td>May-03</td>
<td>May-04</td>
<td>---</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

\textsuperscript{a} The empty cells indicate no turning point detected by the Bry-Boschan algorithm; the zero value represents perfectly coincident turning points of the series.

\textsuperscript{b} Trough.

\textsuperscript{c} Peak.

Figure 2: Cohesion between the q-o-q IPI and the PMI in the sample not including the latest crisis (red line) and in the sample including the crisis (blue line).
The PSD of the q-o-q IPI seems to span a wider frequency band than that of the manufacturing PMI. Nevertheless, the noisiest frequencies have less relative importance in the dynamics of the q-o-q IPI. On the other hand, as we can see in Figure 4, the PSD of the y-o-y IPI is mostly concentrated in the lowest frequency bands, while the PSD of the m-o-m IPI has a predominant role in the highest frequency components.

3.3 Testing the Threshold-50 Rule

The provider of the PMI indicates the value 50 of the index as a threshold which would discriminate between expansion phases (index above 50) of manufacturing activity and contraction phases (index below 50). This fact seems consistent with the main feature of the PMI, which tracks a smooth component of the IPI series. Indeed, the overall dynamics of the PMI standing above (or below) a certain threshold would provide information about an entire cyclical phase of the IPI. Therefore, it seems interesting to investigate the problem more thoroughly. To this end, we rely on the Discriminant Analysis (DA).

Both the spectra are consistently estimated by the Yule-Walker method.

In Section 4 we will provide a more detailed analysis of the dynamics of the two series by studying how the informative weight of each frequency band may change in time.
The DA\textsuperscript{13} is a statistical device for classifying a set of observations into two or more groups according to some statistically significant decision rule. The latter is estimated on the basis of a selected \textit{training sample}. The remaining part of the sample (let us call it the \textit{testing sample}) is used to test the suitability of the decision rule by computing the \textit{classification error}, i.e. the percentage of misclassified observations. The DA is very sensitive to the sample dimension. We found it more convenient, therefore, to implement the DA on a particular transformation of the original IPI series, i.e. the third-difference of the center three-term moving average ($\Delta_3\text{mave}_3\text{IPI}$). This transformation actually represents the monthly version of the q-o-q IPI.

We estimate two different decision rules.\textsuperscript{14} The first one representing the \textit{threshold-50} rule of thumb, while the second one would identify a higher value than 50 as threshold.\textsuperscript{15} The classification errors we incur by classifying the sample observations according to these decision rules are respectively

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4.png}
\caption{Power Spectral density of the y-o-y and m-o-m IPI.}
\end{figure}

\textsuperscript{13}For a more detailed treatment of the Discriminant Analysis see also Jolliffe [12].
\textsuperscript{14}The classification rule is based on the Mahalanobis distance.
\textsuperscript{15}The training sets are constructed by selecting two different subsequent time intervals according to the rules of thumb we want to test. The first time period (April 2001 - December 2003) serves as training set for the 50-threshold rule, while the second one (September 1999 - March 2001) is the training set relative to the > 50-threshold rule. Indeed, the latter set involves significant deviations from the 50-threshold rule.
4.55 per cent and 6.7 per cent. Figure (5) plots the results. All the blue circles, which represent the negative growth rate group in the testing sample, are expected to be below the line along the $\Delta_3\text{mave}_3$ IPI zero level, according to each classification algorithm. Thus, all the blue circles above the blue line represent missclassified units (and vice versa for the red circles).

We can conclude that a PMI above 50 is consistent with industrial activity in an expansionary phase. Furthermore, this rule of thumb seems not to be affected dramatically by the latest global crisis.

4 The Model and the Results

In this section we propose the construction of a multivariate one-sided filter using the wavelet decomposition and the soft-threshold estimator to estimate in real time the non-observable low-frequency component of the q-o-q IPI.\textsuperscript{16} Given this real time perspective, one of the most appreciable characteristics of the filter we propose is its one-sided nature, which allows us to overcome the main shortcoming of two-sided symmetric filters such as the Baxter and King one, i.e. the end-of-sample inefficiency of the estimates.

In order to analyze the effects of the latest global crisis, we will look at the variables and their relationship by frequency components. We claim

\textsuperscript{16}The soft-threshold estimator applied on the wavelet decomposition of a series was introduced by Donoho et al. [8]. It basically consists in "killing" the wavelet components which contribute less (under a certain threshold value) to explaining the variance of a signal.
that the latest turmoil period has not provoked any structural break in the relationship between the manufacturing PMI and the q-o-q IPI. Instead, the crisis is reflected in the change of the spectral densities of the series, which display an acceleration, i.e. a shift of their spectrum towards higher frequencies.

To this end, we can exploit the main advantage yielded by the wavelet analysis, i.e. the time-localization of the spectrum. By applying a wavelet filter we can see how the contribution of each frequency component to the total variance of a series changes depending on the time-interval we consider.

In order to strengthen our point, we first briefly introduce the results of the regression analysis, which is an approach widely adopted in the existing literature.\footnote{See for instance E. F. Koenig (2002) \cite{Koenig}.} Let us specify a simple regression model

\[ IPI_t = \beta_0 + \beta_1 PMI_t + \epsilon_t \]  

where \( IPI_t \) is the q-o-q IPI value at time \( t \) and \( PMI_t \) is the level of the manufacturing PMI at time \( t \).\footnote{For the sake of simplicity, we will drop the q-o-q specification as regards the IPI variable and the manufacturing as regards the PMI in all the cases in which it does not create confusion.} We found that it performs poorly in an \( R^2 \) sense. Indeed, the adjusted \( R^2 \) is equal to 0.3308. Furthermore, the fitted IPI looks far smoother than the original series (see Figure (6)).

If we augment the simple model (2) with a quadratic PMI as a second

\[ IPI_t = \beta_0 + \beta_1 PMI_t + \epsilon_t \]
regressor and include the crisis in the sample, we get an improvement of the $R^2$ reaching the value of 0.69.\footnote{We refer to the adjusted $R^2$.} This is essentially due to the large trough involving all the economic aggregates during the latest recession. The quadratic term seems to work well simply because it grasps the intensity of the recent deep downturn of the entire economy. In the light of this consideration, we must be careful to conclude for the existence of a structural break in the relationship between the IPI and the PMI, which is not yet testable rigorously because the small number of observations.

The following analysis is set up in a non-parametric framework, which provides a more flexible device to take into account the effects of the latest crisis without definitely inferring the occurrence of a structural break. In the next subsection we apply the multivariate wavelet de-noising procedure to the sample ending before the crisis, i.e. from August 1997 to August 2008. Finally, we will extend the analysis to the sample including the crisis, i.e. from August 1997 to February 2010.

4.1 Multivariate Wavelet De-noising before the Crisis

In the following we focus on the frequency bands (expressed in terms of length of period) $[32,64]q$, $[16,32]q$, $[8,16]q$, $[4,8]q$, $[2,4]q$, so that we can isolate the pure short-term component (with period shorter than 4 quarters) and the long-term one (with period between 32 and 64 quarters) from those bands which are usually referred to as ”business cycle”.

Figure (7) shows how each scale-component contributes to the overall variance of both series in time. The role of each component remains fairly stable throughout all the period considered; indeed, we observe a quite homogenous oscillation. The quantitative counterpart of the graphical results is reported in Table (3).

As regards the PMI, we note the predominant role of the $[16;32]q$ component, which explains almost 60 per cent of the PMI’s total volatility and the marginal role of the short-term components ($[2,4]q$ and $[4,8]q$ bands). As for the IPI, we find a relatively smaller contribution of the $[16;32]q$ component and a relatively larger contribution of the short-term ones ($[2,4]q$ and $[4,8]q$ bands account for 35 per cent of the total variance of the q-o-q IPI). Finally, the role of the $[>32]q$ component is negligible for the variance of the IPI, as expected. The correlation between the two series can help to discern at which frequency bands the two series mostly co-move. Table (4) suggests a relatively high degree of co-movement between the IPI and the
Figure 7: Plot of the reconstructed detail components (before crisis).

<table>
<thead>
<tr>
<th>Resolution level</th>
<th>PMI (levels)</th>
<th>IPI (q-o-q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (&gt; 32)q</td>
<td>0.0781</td>
<td>0.0531</td>
</tr>
<tr>
<td>Level 2 [16,32]q</td>
<td>0.5940</td>
<td>0.3570</td>
</tr>
<tr>
<td>Level 3 [8,16]q</td>
<td>0.2723</td>
<td>0.2323</td>
</tr>
<tr>
<td>Level 4 [4,8]q</td>
<td>0.0458</td>
<td>0.1557</td>
</tr>
<tr>
<td>Level 5 [2,4]q</td>
<td>0.0097</td>
<td>0.2018</td>
</tr>
</tbody>
</table>

Table 3: Sample not including the crisis.

<table>
<thead>
<tr>
<th>Resolution level</th>
<th>Before-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (&gt; 32)q</td>
<td>0.9601</td>
</tr>
<tr>
<td>Level 2 [16,32]q</td>
<td>0.9762</td>
</tr>
<tr>
<td>Level 3 [8,16]q</td>
<td>0.8451</td>
</tr>
<tr>
<td>Level 4 [4,8]q</td>
<td>0.3722</td>
</tr>
<tr>
<td>Level 5 [2,4]q</td>
<td>0.4143</td>
</tr>
</tbody>
</table>

Table 4: Sample not including the crisis.
PMI at the lowest frequency bands ([32,64]q and [16,32]q components). It is worth pointing out that the short term components, identified by the [2,4]q interval, are not negligibly correlated.

We proceed to estimate the medium-to-long-term component of the IPI by exploiting the information provided by the PMI, while preserving the specific contribution of each frequency-component and its varying oscillation during some particular economic phases. We take advantage of the stochastic relationship between the signals (the high correlation among the noisy components of the series), leading to an additional de-noising effect. More formally, the two series form the following system:

\[ IPI_t = f_{IPI}^t + \xi_{IPI}^t \]  \hspace{1cm} (3)
\[ PMI_t = f_{PMI}^t + \xi_{PMI}^t \]  \hspace{1cm} (4)

where the component \( \xi^i \) is the mean-zero noisy part of the \( i^{th} \) variable \( i = IPI, PMI \), while \( f^i \) is the signal, i.e. \( E(i_t) = f_t^i \). As we have found, the very short-term components do not satisfy the condition \( E(\xi^i \cdot \xi^j) = 0, \forall i \neq j \). In other words, a positive shock to the PMI index is likely to be associated with a positive shock to the IPI. In order to exploit to the maximum extent all the existing correlation, we rotate the system along the principal component directions of the data.\(^{20}\) This transformation is implemented in the wavelet-domain. We compute the matrix of eigenvectors, \( V \), of the variance/covariance matrix of the two variables in the wavelet-domain, \( S \). These eigenvectors represent the orthogonal directions we use to rotate the system. Given the lowest resolution level \( J \) fixed equal to 5,\(^{21}\) the wavelet-decomposition of the IPI and of the PMI is given by \( (A_{2J}, (D_{2j})_{1 \leq j \leq J}) \), where \( A_{2J} \) is a \( n_{aJ} \times 2 \) matrix containing the \( n_{aJ} \) wavelet coefficients of the approximate-component of each series, while \( D_{2j} \), for \( j = 1, \ldots, J \) are \( n_{dJ} \times 2 \) matrices containing the \( n_{dJ} \) wavelet coefficients of the detailed-components. Now, all these coefficients are rotated in the following way:

\[ A_{2J}^* = A_{2J} V \]  \hspace{1cm} (5)
\[ D_{2j}^* = D_{2j} V, \text{ for } j = \ldots, J \]  \hspace{1cm} (6)

\(^{20}\)An equivalent approach was used in Aminghafari et al. [3].
\(^{21}\)This level of resolution allows us to obtain the long-term component of each series at the frequency band [32,64]q.
The rotated system is expressed as follows

\[ IPI_t^* = f_t^{IPI} + \xi_t^{IPI} \]  \hspace{1cm} (8)

\[ PMI_t^* = f_t^{PMI} + \xi_t^{PMI} \]  \hspace{1cm} (9)

where the star index indicates the rotated variables. The condition \( E(\xi^{*i} \cdot \xi^{*j}) = 0 \) is now satisfied.

Finally, we apply the filter based on the soft-threshold estimator on the \( IPI^* \). In other words, we keep only the wavelet coefficients which contribute most to the variance of the IPI series, according to a threshold value, \( \tau \). The latter is chosen consistently with the threshold parameter suggested by Donoho et al. [8], i.e. it strictly depends on the information provided by the IPI and on the dimension of the sample, \( \tau = \frac{\lambda_1}{\lambda_1 + \lambda_2} \sqrt{2 \log T} \), where the \( \lambda_s \) are the two eigenvalues of \( S \) and \( T \) is the number of observations.

In order to assess the ability of our filtered series to track the target, we use as a benchmark the Baxter & King estimation of the \([4,32]q \) component of the IPI (let us call it the BK series), which is known to perform well in the center of the sample. \(^22\) Figure (8) plots the results.\(^ {23}\) The wavelet-filtered series seems to be consistent with the cyclical phases of the q-o-q IPI. In particular, it accounts for the period of stagnation going from May 2000 to August 2004. Finally, it is interesting to observe the performance of the two filtered series at the end of the sample. The wavelet-filtered series signals a downward sloping tendency of the target, while the BK series seems to indicate a recovery.

### 4.2 Multiresolution Analysis after the Crisis

From an inspection of the multiresolution decomposition of the q-o-q IPI in the complete sample, in Figure (9), we find that some of the frequency components display greater oscillation when the latest crisis occurred. In particular, the \([4,8]q \) and \([8,16]q \) components acquired greater importance in explaining the variance of the two series, as shown in Table (5). On the other hand, the contribution of the lower frequency components in explaining the total variance of the q-o-q IPI falls drastically from 5.3 per cent to 1.8 per cent, while it remains stable for the manufacturing PMI. As a consequence, the q-o-q IPI displays more unstable dynamics. The relationship between the

\(^{22}\)See Baxter and King [4].

\(^{23}\)The end-of-sample observations are cut in both figures plotting the results, owing to the two-sided nature of the BK filter.
two variables has also accelerated, i.e. their higher frequency components comove more than before the crisis. For the sake of clarity, in Table (6) we collect the results for both the periods considered. The correlation of the low frequency components \([16,32]q\) has decreased by one half with respect to the period before the crisis, while the correlation between the components \([4,8]q\) has increased considerably.

The wavelet de-noising procedure turns out to be particularly useful in this case. The wavelet filter allows us to include in the analysis the changing amount of oscillations that some of the IPI’s and the PMI’s components display in their dynamics. Figure (10) shows the results. The multivariate-wavelet filtered series suitably resembles the shape of the medium-to-long-run component of the q-o-q IPI estimated by the Baxter & King method. However, the former filter yields more efficient real-time estimates than the latter. This is due firstly to its one-sided non-symmetric nature. Furthermore, it may be a suitable consequence of taking into account the time-varying contribution of each frequency component to the overall variance of the series. It is worth noting how the wavelet filter grasps well the deep trough occurring in the last period.
Figure 9: Plot of the reconstructed detail components (Crisis).

<table>
<thead>
<tr>
<th>Resolution level</th>
<th>PMI (levels)</th>
<th>IPI (q-o-q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (&gt; 32)q</td>
<td>0.0699</td>
<td>0.0180</td>
</tr>
<tr>
<td>Level 2 [16,32]q</td>
<td>0.2633</td>
<td>0.2660</td>
</tr>
<tr>
<td>Level 3 [8,16]q</td>
<td>0.5557</td>
<td>0.4694</td>
</tr>
<tr>
<td>Level 4 [4,8]q</td>
<td>0.1015</td>
<td>0.1944</td>
</tr>
<tr>
<td>Level 5 [2,4]q</td>
<td>0.0096</td>
<td>0.0522</td>
</tr>
</tbody>
</table>

Table 5: Sample including the crisis.

<table>
<thead>
<tr>
<th>Resolution level</th>
<th>Crisis</th>
<th>Before-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (&gt; 32)q</td>
<td>0.6231</td>
<td>0.9601</td>
</tr>
<tr>
<td>Level 2 [16,32]q</td>
<td>0.4979</td>
<td>0.9762</td>
</tr>
<tr>
<td>Level 3 [8,16]q</td>
<td>0.8442</td>
<td>0.8451</td>
</tr>
<tr>
<td>Level 4 [4,8]q</td>
<td>0.7220</td>
<td>0.3722</td>
</tr>
<tr>
<td>Level 5 [2,4]q</td>
<td>0.3749</td>
<td>0.4143</td>
</tr>
</tbody>
</table>

Table 6: Comparison between the sample including/not including the crisis.
Figure 10: Wavelet filter (solid line) and BK filter (dotted line) compared with the sample q-o-q IPI (red dots).

5 Conclusions

In this work we have dealt with the relationship between the manufacturing PMI and the q-o-q IPI for the Italian economy, with a specific interest in the effects of the latest global crisis.

The manufacturing PMI tracks well the dynamics of the medium-to-long-run component of the q-o-q IPI, which is the target of the analysis. This is confirmed by the analysis of the 50-threshold rule, which has shown the overall behavior of the Markit index above (below) the level 50 to be suitably consistent with the expansionary (contraction) phase of the q-o-q IPI.

An important consequence is that we can exploit the timely release of the manufacturing PMI to make an up to date inference on the unobservable smooth component of the q-o-q IPI.

Given this real-time perspective, we constructed a one-sided filter based on the soft-threshold estimator applied to the wavelet decomposition of the q-o-q IPI. This filter was constructed in a multivariate framework. Indeed, we exploited the relationship between the manufacturing PMI and the q-o-q IPI as a further de-noising criterion to extract the target.

The multivariate-wavelet filtered series tracks the medium-to-long-run
component of the q-o-q IPI estimated by the Baxter & King method. Furthermore, we are able to include in the analysis the effects of the large shocks caused by the latest period of turmoil without arguing about their permanent or temporary nature, which is not rigorously testable yet. We circumvent the rigidity imposed by a pure parametric approach, such as the regression analysis, which further performs poorly in modeling the point-value relationship between the two variables of interest for the Italian economy.

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