Department of Economics and Finance

1. Introduction

Understanding economic fluctuations is crucial for the design of effective macroeconomic policies. Policy makers use a variety of demand and supply indicators to monitor economic activity and to identify trends and seasonal patterns (The Economist, 2007). On the demand side, these include private consumption, retail sales, car registrations, electricity consumption, etc.; on the supply side, the most informative series are gross capital formation, which is available at a quarterly frequency, as well as industrial production, electricity production, and capacity utilisation in the industrial sector, which are released at a monthly frequency (Poza, 2020).

The present study focuses on the Industrial Production Index (IPI), which is normally thought to be a good proxy for aggregate production and also to be informative about seasonality in the economy. According to Bulligan et al. (2010): "*The index of industrial production (IPI) is probably the most important and widely analyzed high-frequency indicator, given the relevance of manufacturing activity as a driver of the whole business cycle*".

3. Empirical Analysis

We use quarterly, seasonally unadjusted data on the US Industrial Production Index, for the sample period from 1919Q1 to 2022Q4, which have been obtained from the St. Louis Federal Reserve Bank database.

FIGURES 1 AND 2 ABOUT HERE

Figure 1 displays both the original data and their logged values together with their respective correlograms and periodograms, the latter exhibiting a large value at the zero, long-run frequency. Figure 2 shows instead the first differenced series, a seasonal pattern being clearly visible.

Given the large value of the periodogram at the long-run, zero frequency we focus first on the degree of integration of the series at this frequency. Standard unit root tests (Dickey and 1 0 4;l spectral density function) is used first, and then, given the quarterly frequency of the data, a seasonal AR(1) process is also considered of the following form:

$$= \quad _{-12} + \quad , \qquad = 1, 2, \ldots. \qquad (2)$$

$_t$ is a white noise process. The estimated values of d together with their 95% confidence bands are reported in Table 1 for three different specifications, namely: i) without deterministic terms, ii) with a constant, and iii) with both a constant and a linear time trend.

TABLE 1 ABOUT HERE

In the majority of cases the unit root null hypothesis cannot be rejected. The only exception is the logged series with white noise and seasonal AR disturbances when deterministic terms are included in the model. Given the overwhelming evidence in favour of the presence of unit roots, first differences are then taken of both the raw data and their logged values, the latter being a measure of the growth rate.

After removing the long-run frequency, seasonality is still present in the data as shown by the correlograms and periodograms of the first differenced series displayed in Figure 2. To capture it, we adopt the following specification:

$$= \quad + \sum_{=1}^{4} \quad + \quad , \qquad (1 - \quad ^{4}) \quad = \quad , \qquad (3)$$

where u_t is again a seasonal AR(1) process.

Table 2 reports the estimated coefficients. It can be seen that, for both the original and logged values, the deterministic terms are statistically insignificant in all cases, which represents evidence against deterministic seasonality. The seasonal AR coefficient is insignificant for the original data (0.0006) while significant for the logged seasonal long-memory in both series, the effects of shocks being mean reverting with a hyperbolic rate of decay to zero

References

Adekoya, O.B. (2020). Long Memory in the Energy Consumption by Source of the United States: Fractional Integration, Seasonality Effect and Structural Breaks. Estudios de Economía, Vol. 47, Nº 1, Págs. 31-48.

Arteche, J. (2007). The Analysis of Seasonal Long Memory. The Case of Spanish Inflation. Oxford Bulletin of Economics and Statistics, Vol. 69, Nº 6, Pages 749-772.

Arteche, J. (2012). Standard and seasonal long memory in volatility: an application to Spanish inflation. Empirical Economics 42, 693 712. https://doi.org/10.1007/s00181-010-0446-8.

Bloomfield, P. (1973). An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Bruno, G. and Lupi, Cl. (2003). Forecasting Euro-Area Industrial Production using Business Surveys Data. ISAE Istituto di Studi e Analisi Economica.

Bulligan, G., Golinelli, R., and Parigi, G. (2010). Forecasting industrial production: the role of information and methods. IFC Bulletin No 33. Bank for International Settlements.

Candelon, B. and Gil-Alana, L.A. (2004). Seasonal and long-run fractional integration in the Industrial Production Indexes of some Latin American countries. Journal of Policy Modeling, 26, Pages 301 313.

Dickey, D. A., and W. A. Fuller, (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366), 427-431. doi:10.1080/01621459.1979.10482531

Diebold, F. X. and G.D. Rudebusch, 1991: On the power of Dickey-Fuller tests against fractional alternatives. *Economics Letters,* 35, 155-160. https://doi.org/10.1016/0165 1765(91)90163-F

Dua, P. and Mishra, T. (1999). Presence of Persistence in Industrial Production: The Case of India. Indian Economic Review. Vol. 34, No 1, pp. 23-38.

Elliot, G., Rothenberg, T.J., and Stock, J.H. (1996). Efficient

Hassler, U., and Wolters, J., (1994). On the power of unit root tests against fractional alternatives. Economic Letters 45, 1 5.

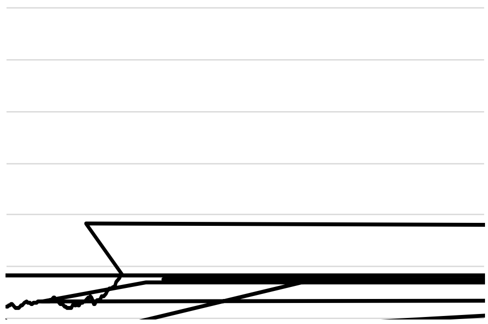
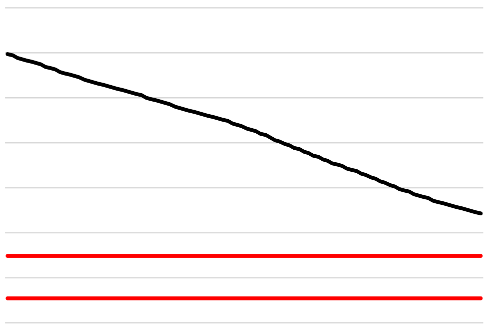
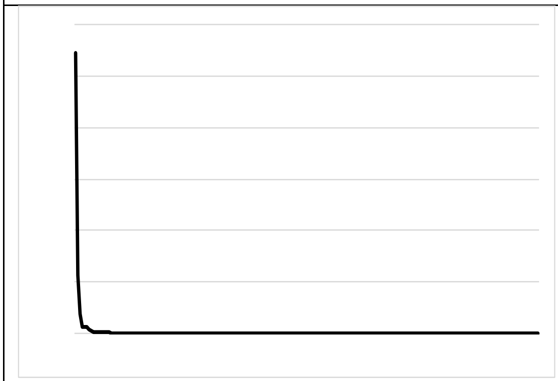
Kwiatkowski, D., Phillips, P.C.D., Schmidt, P., and Y. Shin (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, Journal of Econometrics 54, 159 178.

Lee, D., and Schmidt, P. (1996). On the power of the KPSS test of stationary against fractionally integrated alternatives, Journal of Econometrics 73, 285-302.

Lildholdt, P.M. (2002). Sources of seasonal fractional integration in macroeconomic time series. Centre for Analytical Finance, University of Aarhus, Working Paper, No. 125.

Öksüz Narinç, N. (2018). Modeling and Model Comparison for Industrial Production Index of Turkey, Brazil and G7 Countries. International Journal of Scientific Research and Management. Vol. 6, No 4.

Figure 1: Plots of IPI and log IPI with their correlograms and periodograms

Industrial Production Index	Industrial Production Index (log)
	
First 100 values of the correlogram of IPI	First 100 values of the correlogram of Log IPI
	
Periodogram of IPI	Periodogram of Log IPI
	

The red lines in the correlograms refer to the 95% confidence bands for no autocorrelation.

Figure 2: First differences of IPI and log IPI with their correlograms and periodograms

Industrial Production Index	Industrial Production Index (log)

Table 1: Estimates at the long-run or zero frequency

i) Original data			
Type of errors	No deterministic terms	An intercept	An intercept and a time trend