Economic Modelling 38 (2014) 504–511

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Persistence and cycles in US hours worked

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ARTICLE INFO

Article history:
Accepted 28 January 2014
Available online 26 February 2014

JEL classification:
C32
E24

Keywords:
Hours worked
Fractional integration
Cycles
Technology shocks

ABSTRACT

This paper analyses monthly hours worked in the US over the sample period 1939m1–2011m10 using a cyclical long memory model. This model, which is based on Gegenbauer processes, is characterised by autocorrelations decaying to zero cyclically and hyperbolically, with a spectral density that is unbounded at a non-zero frequency. One reason for choosing this specification is that the periodogram of the hours worked series has a peak at a frequency away from zero. The empirical results confirm that this model works extremely well for hours worked, and it is then employed to analyse their relationship with productivity. It is found that hours worked increase on impact in response to a technology shock (though the effect dies away rapidly), consistently with Real Business Cycle (RBC) models.

1. Introduction

This paper proposes a modelling approach for hours worked by production workers in the US. This is an important variable since it can be seen as an indicator of the state of the economy. Authors such as Glosser and Golden (1997) argue that firms tend to respond to business cycle conditions by decreasing or increasing hours worked before hiring or laying off workers.

Although the relationship between business cycles and hours worked and their response to technology shocks has been extensively investigated, this is still a controversial issue. Gali (1999), Francis and Ramey (2005) and Gali and Rabanal (2004) found that, contrary to the implications of Real Business Cycle (RBC) models, they decline in response to a technology shock. These results were challenged, among others, by Christiano et al. (2003) who presented evidence that instead hours worked increase following a technology shock.[2] Both types of studies use similar empirical (VAR) frameworks, the crucial difference between them being in the treatment of the hours worked variable. In particular, the former authors model it as a nonstationary I(1) variable whilst the latter assume that it is a stationary I(0) process. More recently, Gil-Alana and Moreno (2009) allow the order of integration of hours worked to be fractional, i.e. I(d), and find that the value of d depends on the specific series examined, although in general it lies in the interval between 0 and 1. They also find that per capita hours fall on impact in response to a technology shock.

All three approaches taken in the studies mentioned above implicitly assume a high degree of persistence in hours worked that should result in a large peak in the periodogram (or in any other estimate of the spectral density function) at the zero frequency. The model used in the present study is instead based on Gegenbauer processes and is characterised by autocorrelations decaying to zero cyclically and hyperbolically along with a spectral density that is unbounded at a non-zero frequency. The reason for choosing this specification is that the periodogram of the hours worked series is found to exhibit a peak not at the zero frequency, as implied by the previous models, but instead at a frequency away from zero, which can be captured by Gegenbauer processes as explained in the following section.[3] Our results confirm that this model works extremely well for hours worked, and it is then employed to analyse their relationship with productivity, finding a positive (though rapidly dying away) effect of shocks, as suggested by Real Business Cycle (RBC) models.

The outline of the paper is as follows. Section 2 briefly describes the different types of long range dependence or long memory models used in the paper. Section 3 presents the data. Section 4 discusses the empirical results and their implications for the debate on the relationship between hours worked and technology shocks, whilst Section 5 contains some concluding remarks.

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[1] We are grateful to Tommaso Proietti for kindly supplying the dataset. The second-named author gratefully acknowledges financial support from the Ministry of Education of Spain (ECO2011-2014 ECON Y FINANZAS, Spain) and from a Jeronimo de Ayanz project of the Government of Navarra.
[2] For further evidence, see Gambetti (2005) and Pesavento and Rossi (2005).

[3] The peak at a non-zero frequency is found for the whole sample (1939 m1–2011 m10) as well as for shorter subsamples.

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http://dx.doi.org/10.1016/j.econmod.2014.01.026

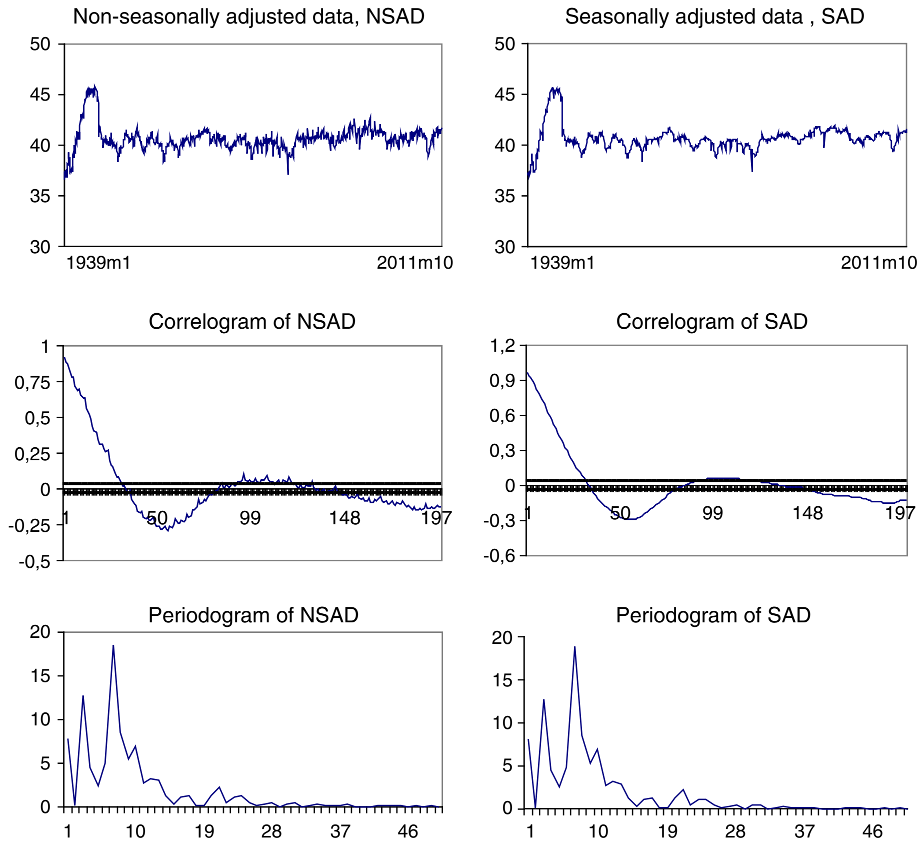

Fig. 1. Time series plots (hours worked), correlograms and periodograms. The thick lines in the correlograms represent the 95% confidence band for the null hypothesis of no autocorrelation. In the periodograms, the horizontal axis refers to the discrete Fourier frequencies $\lambda_j = 2\pi j/T$, j = 1, …, T/2.

2. A long-memory model

For the purposes of the present study, we define anI(0) process $\{x_t, t = 0, \pm 1, \ldots\}$ as a covariance stationary process with spectral density function, $f(\lambda)$, that is positive and finite at any frequency. Alternatively, it can be defined in the time domain as a process such that the infinite sum of the autocovariances is finite. This includes a wide range of model specifications such as the white noise case, the stationary autoregression (AR), moving average (MA), and stationary ARMA models.

In general, the I(0) condition is a pre-requisite for statistical inference in time series analysis. However, a series might be nonstationary, i.e. the mean, the variance or the autocovariances may change over time. For this case specifications with stochastic trends have usually been adopted under the assumption that the first differenced process is stationary I(0), and thus valid statistical inference can be drawn after differencing once. More specifically, x_t is said to be I(1) if:

$$(1-L)x_t = u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

where L is the lag operator ($Lx_t = x_{t-1}$) and u_t is I(0) as defined above. If u_t is ARMA(p, q), then x_t is said to be an ARIMA(p, 1, q) process.

The above model has been extended in recent years to the fractional case, since the differencing parameter required to render a series stationary I(0) might not necessarily be an integer (usually 1) but might be a fractional value. In this context, x_t is said to be I(d) if:

$$(1-L)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{2}$$

with $x_t = 0$, $t \le 0$,[4] and u_t is again I(0). Note that the polynomial on the left-hand-side of Eq. (2) can be expanded, for all real d, as

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots.$$

Thus, if d in Eq. (2) is an integer value, x_t will be a function of a finite number of past observations, whilst, if d is not an integer, x_t depends upon values of the time series in the distant past, and the higher the value of d is, the higher the level of dependence is between the observations. In a similar way, x_t in Eq. (2) also admits an infinite moving average (MA) representation, and the impulse responses are then also affected by the magnitude of d: the higher the value of d is, the higher the responses will be. If d is smaller than 1, the series is mean reverting, with shocks having temporary effects, and disappearing in the long run. On the other hand, if $d \ge 1$, shocks have permanent effects unless appropriate policy actions are adopted.

If $d > 0$ in Eq. (2) x_t displays long range dependence (LRD) or long memory. There are two definitions of LRD, one in the time domain and the other in the frequency domain. The former states that given a

[4] This condition is required for the Type II definition of fractional integration, widely employed in empirical studies. For an alternative definition (Type I) see Marinucci and Robinson (1999).