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Javier García Enríquez, Josu Arteche González y Arantza Murillas Maza

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Universidad del País Vasco
Euskal Herriko Unibertsitatea

Facultad de Ciencias Económicas.
Avda. Lehendakari Aguirre, 83
48015 BILBAO.

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Fractional Integration Analysis and its Implications on Profitability: the Case of the Mackerel Market in the Basque Country

J. García[a,b*], J. Arteche[a], and A.Murillas[c]

Abstract

This paper analyses weekly prices for mackerel landed by the inshore fleet at the ports of the Basque Country in 1995-2008, using new econometric techniques never before applied to the fishing market. The idea is to learn to what extent fishermen can pass on the effects of negative shocks (e.g. fuel price increases) to their ex-vessel prices. This will give an idea of the profitability of the fishery in question. To that end, a cyclical ARFIMA model is adjusted to the series analysed, then the impulse-response function is constructed. Among other things, the behaviour of this function shows that possible increases in production costs are not being passed on to prices, which lowers the profitability of fishing. In view of these results, it is suggested that fishermen need to be able to pass the shocks that they suffer on to prices if the profitability of this fleet is to be assured.

Keywords: Seasonality, impulse-response function, long memory, fishing market, mackerel.

[a] Dpt. of Applied Economics III (Econometrics and Statistics), University of the Basque Country, Lehendakari Aguirre 83, 48015 Bilbao, Spain.
[b] Dpt. of Foundations of Economic Analysis II, University of the Basque Country, Lehendakari Aguirre 83, 48015 Bilbao, Spain.
[c] AZTI-Tecnalia, Technological Institute for Fisheries and Food, Marine Research Division. Txatxarramendi Ugartea, 48395 Sukarrieta, Spain.
*Corresponding author. Tel.: +34 946013773; fax: +34 946017123.
E-mail address: javier.garcia@ehu.es

1 Introduction

The analysis of prices in fishing markets has taken on increasing importance in recent years because, among other reasons, of interest in understanding and finding answers to the problems of low (and even negative) profitability which the fishing industry has been suffering for some decades. The problem is not specific to a single subsector or to any specific market, region or country: it has become an ongoing characteristic of practically all the fishing markets of the European Union (EU).

To understand trends in ex-vessel (dockside) fish prices, aspects such as the general context of the regulations under which fisheries operate in the EU, the individual characteristics of the different fleets making catches and the price formation systems used to allocate dockside prices must be taken into account, among others.

The EU fishing market is conditioned by the Common Fisheries Policy (CFP). At the heart of the CFP is a system for limiting catches by establishing controls on total catches from the same stock known as Total Allowable Catch (TAC). In the particular case of the mackerel, limitations on TAC, the number of vessels fishing and the behaviour of fishermen themselves (landing catches in excess of the TAC) are the main factors affecting the eventual price at source. The price of mackerel may also depend, albeit to a lesser extent, on other factors such as fishing areas and the techniques used.

Along with the above, another key factor in determining prices at source in this market is the system for setting prices and the strategy of the traders who dominate the system and do not allow new purchasers to enter. As in most other European ports, the so-called "Dutch auction" system is used. This system does not ensure Pareto efficiency or, as would be desirable, maximise profits on the part of the seller (the fisherman), all of which ultimately limits the value added to the catch.[1]

This paper seeks to extend knowledge of the grass-roots domestic fishing market of the Basque Country by examining its pricing trends and studying the fishing activity of the inshore fleet, which has traditionally caught three main species: anchovy –*Engraulis encrasicholus*–, albacore tuna –*Thunnus alalunga*– and mackerel -*Scomber scombrus*–, though the paper focuses only on this last species. This fishery was chosen as a case study for the following reasons: (i) because it is one of the most important fisheries available to the Basque inshore fleet, and one which is in general of enormous economic and social importance for the countries of the Atlantic Arc of Europe; and (ii) because the low profitability of this fleet is one of the main causes for concern for the sector itself and for the authorities, and it is desirable to find out how far and how fast the various shocks suffered by the fleet are passed on to prices.

The industry itself sees price increases through a policy of effective reductions in catches (above the TAC) as the only viable option among the alternative solutions suggested for the problem of low first-sale profitability of mackerel. As a result, in

[1] The Dutch auction system does not guarantee maximum profits for fishermen because, as pointed out by Compés (1994), profit maximisation in a Dutch auction is incompatible with the likelihood of obtaining the item auctioned.

recent years it has been argued that there is a need for policies such as a system of quotas on catches per fisherman per day, over and above the TAC regulation system. This measure was finally implemented officially in 2009, following a voluntary pilot scheme carried out by the Spanish fishing industry itself during the mackerel campaign of 2008. In this context there is a great need for studies such as the one proposed here, to enable more to be learned about the behaviour of prices for this species, in response to demand from the industry itself and the authorities.

Studies of the behaviour of price series for fishing products have traditionally considered them as integrated of order one or I(1) (see, for instance, Gordon et al., 1993, Gordon & Hannesson, 1996, Jiménez-Toribio and García-del-Hoyo, 2006, Setälä et al., 2008) so that innovative changes have permanent effects on the levels of series, but in fact the prices of some fisheries (the mackerel is a case in point) follow a path that can hardly be placed in that category. Here, therefore, we use a more flexible framework and admit the possibility that the process governing the trends in prices may be I(d) [2], with $0 \le d \le 1$.

In that context, we propose the use of econometric techniques that enable the exact degree of memory of a time series to be detected, such as long memory analysis and seasonal and cyclical long memory. Specifically, it is suggested that a cyclical *ARFIMA* model be adjusted, given the flexibility and adaptability of such models to the exact degree of memory at different frequencies. This model is applied to a series of weekly prices for mackerel landed by the inshore fleet at the ports of the Basque Country between 1995 and 2008. Once the model is adjusted, the impulse-response function (hereinafter called the IRF) is defined. The behaviour of this function could serve as an indicator of the ability of fishermen to pass on to prices the effects of the various shocks that affect their activities, and thus also could serve as an indicator of the profitability of the fishery in question.

Recent papers in the literature on this topic that have used similar techniques include Arteche & Robinson (2000), Gil-Alaña & Robinson (2001), Cheung & Lai (2001), Gadea & Mayoral (2006), Arteche (2007), etc. However, as far as we know, there are no previous papers that apply these techniques to the fishing industry.

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[2] A series x_t is said to be I(d) if $(1-L)^d x_t$, where L is the lag operator such that $L^n x_t = x_{t-n}$, is a process with a finite, non null spectral density at zero frequency.

The rest of the paper is structured as follows. Section 2 describes the case study selected, i.e. the North-east mackerel stock and the operations of the Basque inshore fishing fleet. Section 3 sets out the method used. Section 4 presents the results of the empirical application. The paper ends with an outline of the main conclusions reached.

2 Case Study: Management of the Mackerel Fishery and the Basque Inshore Fleet

This section briefly describes various aspects of the North-east Atlantic mackerel (NEAM) fishery, such as stock distribution, the current management system via the setting of a TAC, exploitation by various national and foreign fleets and, in particular, the activity of the Basque inshore fleet.

All figures on the activities, catches landed and revenues of the Basque fleet are taken from the AZTI-Tecnalia Fisheries Database (hereinafter called the AZTI-Tecnalia DB)[3]. Figures on catches landed by the Spanish and foreign fleets are taken from the International Council for the Exploration of the Sea, ICES (2009), while TACs per annum are taken from the various regulations that have appeared year by year in the Official Journal of the European Union.

2.1 Mackerel stock and fisheries

Mackerel can be found all over the Atlantic, from Norway to Portugal. It is distributed throughout the North Atlantic in both the East (including the Baltic, the Mediterranean and the Black Sea) and the West. It is a highly migratory species which moves towards the northern end of its distribution in summer and towards the south in winter. The ICES assumes that there is a single great stock of mackerel in Europe – the North-east mackerel stock – and thus sets a single TAC.

Following record catches in 1979 (totalling 843,155 t), fishing mortality gradually began to fall. However in 1993 a catch of 825,036 t resulted in a major increase. This increase in the mortality rate was deemed unsustainable by scientists, and as a result the TAC was reduced from 1993 onwards. From that year on, catches decreased steadily to

[3] The AZTI-Tecnalia DB contains biological and economic information provided by the fleet itself. In particular, it contains data on catches landed at the ports of the Basque Country vessel by vessel and by fishing trip for each species. Notice that a fishing trip is counted each occasion on which a vessel lands a catch at a port.

a historical minimum of 472,652 t in 2006. A breakdown by countries shows that most of the catches in the past 5 years have been made by the fleets of the UK, Norway, Spain and Ireland (Table 1).

Table 1. Mackerel catches (in tonnes) broken down by countries in the North-East Atlantic (Sub-areas IIIa & IV, VI, VII, VIII & IX).*

	2004	**2005**	**2006**	**2007**	**2008**	**Total**
UK	172,785	152,801	95,815	133,688	112,145	667,234
Norway	147,069	106,434	113,079	131,198	118,050	615,830
Spain	34,455	52,753	54,136	62,946	64,637	268,927
Ireland	60,631	45,687	40,664	49,260	44,759	241,001
Denmark	25,665	23,212	24,219	25,223	26,726	125,045
Netherlands	27,498	22,734	24,157	24,234	19,900	118,523
Germany	23,244	19,040	16,608	18,214	15,502	92,608
France	20,264	16,337	14,953	20,038	15,602	87,194
Faroe Islands	12,379	9,739	12,067	13,151	11,166	58,502

* Source: own work based on ICES (2009)

2.2 Stock management

The mackerel stock is managed year by year via TACs set by areas. Although the ICES provides advice on permissible exploitation levels for the distribution of the stock as a whole, that advice is then applied in two different TACs: one for the Southern Area (VIIIc and IXa), which, as can be seen in Figure 1, takes in the northern and north-eastern coasts of Spain and the coast of Portugal, and the other for the rest of the stock distribution (the Western Area).

The quota assigned to Spain in the Southern Area fell from 33,120 t in 2001 to 22,256 t in 2008. However, even though this resource is not in the best of situations, the Basque fleet (and indeed the Spanish fleet in general) has the capacity to catch much more than the quota allocated under the TAC, and indeed has done so in some years, as can be seen in Table 2 (note that in 2003 the quota was not exceeded due to the environmental disaster that befell the fishery following the sinking of the oil tanker *Prestige* off Spain's northern coast). Moreover, captures in the Southern Area have increased sharply since 1996 (when they totalled 31,000 t). This increase has taken place at a time when a reduction in catches in all areas was recommended, and has resulted in the TAC for each area being exceeded by ever greater quantities, as can be seen in Table 2.

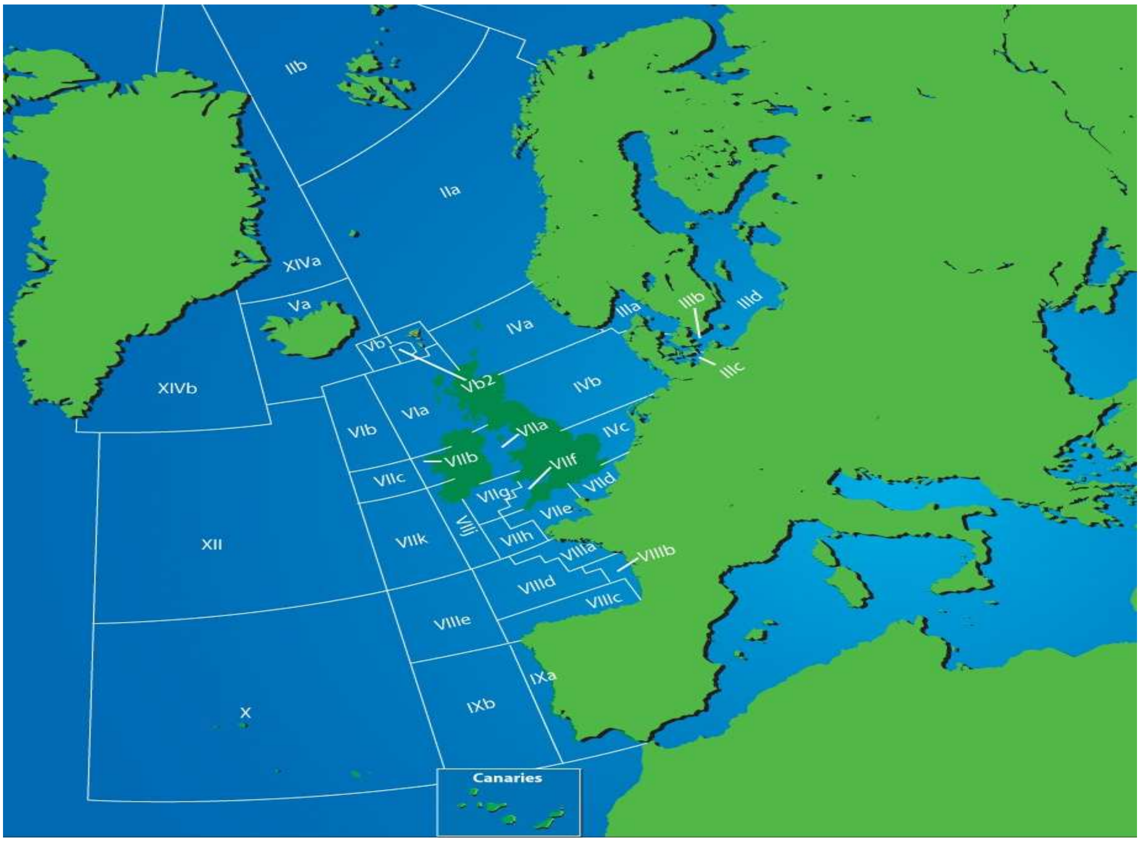

Figure 1. ICES fishing areas in the North-east Atlantic (Source: European Commission).

2.3 The mackerel fishery developed by the Basque inshore fleet

In the Basque Country the most widely used inshore techniques for catching mackerel are hand-lines and purse seine nets, though relatively insignificant amounts of the species are also caught with gillnets and bottom-set long-lines. The line and purse seine vessels based in the Basque Country account for 90-95% of the mackerel landed at Basque ports (with the remainder coming from vessels whose home ports are in Cantabria, Asturias and Galicia).

Fishing operations at Basque ports with these techniques accounted for 22-54% of the total catches landed by the Spanish fleet in ICES Divisions VIIIc and IXa[4] from 2001 to 2008. Table 2 shows the trends over time in the relative importance of mackerel catches by Basque vessels (using all techniques) as a proportion of overall Spanish catches and the TAC in ICES Divisions VIIIc and IXa.

[4] Spanish catches come from Division VIIIc and, to a lesser extent, from IXa (ICES, 2009). From 1990 onwards it was permissible to catch to 3000 tonnes of the TAC set for zones VIIIc and IXa in Division VIIIb. In 2005 the figure was raised to 25,000 t.

Table 2. Comparison of mackerel catches (in tonnes) in Divisions VIIIc & IXa.*

	2001	2002	2003	2004	2005	2006	2007	2008
TAC allocated to Spain (southern area)	33,120	33,874	28,846	26,625	20,500	21,574	24,405	22,256
Catch by Basque fleet (all techniques)	21,834	17,545	6,316	14,395	22,180	16,973	22,007	26,528
Spanish catches	40,079	46,641	23,027	32,374	47,958	50,088	60,174	57,310
Basque catches/TAC for Spain	66%	52%	22%	54%	108%	79%	90%	119%
Basque catches/Spanish catches	54%	38%	27%	44%	46%	34%	41%	46%
% TAC exceeded by Spain	21%	38%	-20%	22%	134%	132%	147%	157%

* Source: own work based on data from ICES (2009) and the AZTI-Tecnalia DB.

Hand-line and purse seine vessels fishing for mackerel are extremely important in the overall context of fishing operations by the Basque inshore fleet. Mackerel is the number one species in terms of catches landed in the Basque Country (using all fishing techniques), accounting for 36-48% of the total volume of fish landed by the inshore fleet from 2001 to 2008 (though in 2003 the figure dropped to 14% due to the temporary ban imposed in the fishery following the sinking of the oil tanker *Prestige*)[5]. In terms of income, it is the number three species, accounting for around 11% of the total revenues of the inshore fleet (just 5% in 2003), behind albacore tuna and anchovy[6]. However the income represented by this fishery varies according to its role in the overall activities of each vessel over the year (vessels do not fish for the same species all year long). Thus, the Basque hand-line fleet obtains between 22% and 40% of its revenues from this fishery, though the percentage of earnings may be higher among those vessels that do not take part in the troll line campaign in summer (a technique that accounts for 40% of the fleet's total revenues). Moreover, with the crisis that has hit the anchovy fishery in recent times there have been years in which the figure has risen to 45%. For the Basque purse seiner and live bait fleet this fishery accounts for between 6% and 18% of annual earnings, depending on the scale of catches of albacore tuna, anchovy and bluefin tuna.

[5] 80% of the total catch landed by the inshore fleet is accounted for by 5 species: albacore tuna, mackerel, anchovy, horse mackerel and sardine. From 2005 onwards, anchovy decreased in volume and more chub mackerel and bluefin tuna were caught.
[6] 70% of the total revenues of the inshore fleet come from 3 species: albacore tuna, anchovy and Mackerel. From 2005 onwards anchovy decreased in volume and more horse mackerel and bluefin tuna were caught.

3 Methodology

Since the paper by Granger (1966) numerous studies have obtained long-memory empirical evidence in economic data series. Long memory is linked to the persistence of certain time series, so that autocorrelation gradually tends towards zero. This indicates that even though they may be transitory, the effects of innovations may last for a long time. This behaviour is not comparable with stationary *ARMA* models, which are characterised by an exponential decrease in autocorrelations and therefore in the effects of innovations, or with the extreme degree of persistence found in unit root models, where innovations have permanent effects.

A stationary stochastic process x_t is said to have long memory if its autocovariances $\gamma_j = E[(x_t - E(x_t))(x_{t-j} - E(x_t))]$ meet the following condition:

$$\sum_{j=0}^{\infty} \left|\gamma_{\mathrm{j}}\right| = \infty \tag{1}$$

so that the time dependence of the series shows high levels of persistence. Alternatively, the long memory of x_t means that its spectral density satisfies the following:

$$f(\omega + \lambda) \rightarrow \infty \text{ when } \lambda \rightarrow 0 \tag{2}$$

at a frequency $\omega \in [0, \pi]$.

The best-known case is that of the trend long memory or the frequency $\omega = 0$, when the autocovariances show the following asymptotic behaviour:

$$\gamma_j \sim Gj^{2d-1} \text{ when } j \rightarrow \infty \tag{3}$$

where $a \sim b$ denotes that a/b $\rightarrow 1$, G is a finite constant and d is the memory parameter measuring the degree of persistence, which satisfies $-1/2 < d < 1/2$, since $d < 1/2$ is required for the process to be stationary and $d > -1/2$ for it to be invertible. Unlike the exponential decrease in autocorrelations found in stationary processes with weak dependence, γ_j in (3) decreases hyperbolically so that (1) is met if $d > 0$. If, moreover, the autocovariances decrease monotonically, condition (3) is equivalent to a spectral density function that behaves as follows:

$$f(\lambda) \sim \mathrm{C}\lambda^{-2d} \text{ when } \lambda \rightarrow 0^{+} \tag{4}$$

where $0 < \mathrm{C} < \infty$, so that (2) is satisfied whenever $d > 0$. In fact, it is the case of $0 < d < 1/2$ that shows long memory or strong persistence, so conditions (1) and (2) are met. When $d = 0$ the process shows weak dependency or short memory, and if

$-1/2 < d < 0$ it is said to show antipersistence, though this last case is seldom found in economics and usually only appears due to over-differentiation.

Although the most widely analysed case is $\omega = 0$, long memory can appear at any other frequency $\omega \in (0, \pi]$, reflecting the existence of a persistent cycle with a period of $2\pi / \omega$. Thus, x_t can be said to show seasonal and/or cyclical long memory if its spectral density function satisfies the following:

$$f(\omega + \lambda) \sim C|\lambda|^{-2d} \text{ when } \lambda \to 0 \tag{5}$$

where $-1/2 < d < 1/2$ guarantees that the series is stationary and invertible.

Processes that satisfy (5) are known as SCLM (Seasonal and Cyclical Long Memory, Arteche & Robinson, 2000). When the spectral density function meets (5) for all seasonal frequencies $\omega_h = 2\pi h / s, h = 1, 2, ..., \lfloor s/2 \rfloor$, where s is the number of observations per year and the memory parameter *d* may vary over *h*, the process is said to have seasonal long memory. However, for non seasonal time series it may behave cyclically, so that equation (5) is satisfied at one or more frequencies $\omega \in (0, \pi]$. The behaviour in the time doamin is determined by a slow, fluctuating decrease in the autocovariance function that shows up in a form such that :

$$\gamma_j \sim G \cos(j\omega) j^{2d-1} \text{ when } j \to \infty \tag{6}$$

where *G* is a finite constant and the scale of the fluctuations depends on ω.

Fractionally integrated *ARMA* models (*ARFIMA* models) that meet (3) and (4) have become generalised in those cases where the frequency of interest is other than zero and (5) and (6) are satisfied. Thus, Andel (1986) and, in greater depth, Gray et al. (1989, 1994) analyse the so-called Gegenbauer processes:

$$(1 - 2L\cos\omega + L^2)^d x_t = u_t \tag{7}$$

where u_t is weakly stationary. The most typical case is when u_t follows a stationary and invertible *ARMA(p,q)* process. In this case (7) is known as a *GARMA* (Gegenbauer *ARMA*) process.

To allow different degrees of persistence over different frequencies, Chan & Terrin (1995), Chan & Wei (1988), Giraitis & Leipus (1995) and Robinson (1994) use the following model:

$$(1-L)^{d_0} \prod_{j=1}^{h-1} (1 - 2L\cos\omega_j + L^2)^{d_j} (1+L)^{d_h} x_t = u_t \tag{8}$$

where ω_j can be any frequency in the interval $(0,\pi)$ and u_t follows a stationary and invertible *ARMA(p,q):* $\Phi_p(L)u_t = \Theta_q(L)\varepsilon_t$ process, where $\Phi_p(L) = 1-\phi_1 L - ... - \phi_p L^p$, $\Theta_q(L) = 1+\theta_1 L + ... + \theta_q L^q$ have not roots in common and ε_t is white noise. Models of this type are hereinafter referred to as cyclical *ARFIMA* models or $ARFIMAC(p,q)\times(\omega_0,d_0)\times...\times(\omega_h,d_h)$, where ω_j and d_j are the *j*-th frequency and its associated memory parameter, respectively, with $j=0,...,h$, where *p* and *q*, respectively, are the orders of the autoregressive and moving average polynomials of u_t.

There is often a need to learn the effect and duration of an innovative change on a series under analysis. To that end its IRF is calculated. This is defined as a unitary random shock at the level of the series *j* periods ahead. It is calculated via the sequence of moving average (*MA)* expansion coefficients:

$$MA(\infty): x_t = \sum_{j=0}^{\infty} \pi_j \varepsilon_{t-j} \tag{9}$$

where the IRF would therefore be $(\pi_0, \pi_1, \pi_2, \pi_3, ...)$. Thus, for a model such as (8) the IRF is calculated on the basis of:

$$x_t = (1-L)^{-d_0} \prod_{j=1}^{h-1} (1-2L\cos\omega_j + L^2)^{-d_j} (1+L)^{-d_h} \frac{\Theta_q(L)}{\Phi_p(L)} \varepsilon_t = \pi(L)\varepsilon_t = \sum_{j=0}^{\infty} \pi_j \varepsilon_{t-j} \tag{10}$$

where the polynomial $\pi(L)$ is formed by the product and division of different finite ($\Phi_p(L)$ y $\Theta_q(L)$) and infinite ($(1-L)^{-d_0}$, $(1-2L\cos\omega_j + L^2)^{-d_j}$, $(1+L)^{-d_h}$) polynomials.[7]

For estimating model (8) this paper uses a two-stage procedure:

Stage 1. Each memory parameter is estimated semiparametrically using Whittle's local method (Robinson, 1995). Following the extension by Arteche and Robinson (2000) for the case of SCLM models, they are obtained as follows:

$$(\hat{d}, \hat{C}) = \arg\min_{d,C} \frac{1}{2m} \sum_{j=\pm 1}^{\pm m} \left\{ \log C \left|\lambda_j\right|^{-2d} + \frac{I(\omega + \lambda_j)}{C\left|\lambda_j\right|^{-2d}} \right\} \tag{11}$$

[7] For a more detailed description of how the IRF is calculated in long memory models, see Arteche (2007, pp. 768-769)

where *m* is the bandwidth such that at least $\frac{1}{m}+\frac{m}{T}\rightarrow 0$ when $T\rightarrow\infty$, T is the sample size, $\lambda_j=\frac{2\pi j}{T}$ are the Fourier frequencies and $I(\lambda_j)$ is the periodogram for the series x_t, defined as $I(\lambda_j)=\frac{1}{2\pi T}\left|\sum_{t=1}^{T}x_t e^{-i\lambda_j t}\right|^2$.

This estimator is semiparametric or local in nature, and thus makes for consistent estimators which are robust to incorrect specifications of the model at frequencies far from ω, since there is no need to parameterise the spectral density at those frequencies. Moreover, Arteche & Robinson (2000) derive the asymptotic distribution for $-1/2<\mathrm{d}<1/2$:

$$\sqrt{2m}(\hat{d}-d)\xrightarrow{d}N(0,1/4) \tag{12}$$

which means that it is possible to make an inference so as, for instance, to check the hypothesis that short memory exists or $d=0$. Note that when $\omega=\{0,\pi\}$, since the periodogram is symmetric around those frequencies, only *m* frequencies are used in estimating *d*, so the asymptotic distribution would be:

$$\sqrt{m}(\hat{d}-d)\xrightarrow{d}N(0,1/4) \tag{13}$$

for $-1/2<\mathrm{d}<1/2$.

Stage 2. The polynomials for the *ARMA* process, $\Phi_p(L)$ and $\Theta_q(L)$, are estimated using conventional parametric techniques (especially maximum likelihood) applied to the filtered series with the polynomials $(1-L)^{\hat{d}_0}$, $(1-2L\cos\omega+L^2)^{\hat{d}_j}$ and $(1+L)^{\hat{d}_h}$ ($j=1,...,h-1$), constructed with the estimators $\hat{d}_0$, $\hat{d}_j$ and $\hat{d}_h$ obtained in Stage 1.

This two-stage method at least ensures the consistency of memory parameter estimators should there be a misspecification of the parametric model that governs u_t. This also ensures the correct estimation of the asymptotic component of the IRF, since it is finally governed by the memory parameters.

4 Empirical Analysis

This section analyses the prices of the mackerel landed at the main ports of the Basque Country as per the AZTI-Tecnalia DB, with a view to proposing a model that reflects their behaviour over time and enables conclusions about that behaviour to be drawn. A weekly series is used, running from the first week of January 1995 to the last week of December 2008, with a total of 728 observations. The prices are for fish landed by the Basque inshore fleet (mainly using purse seine nets and lines) and handled by the fishermen's association known as "cofradía", allocated by a Dutch auction system. The frequency of auctions depends on the fishing trips[8], and in this sense the price series has not presented an uniform time guideline but rather it is constructed synthetically from the aggregate prices per fishing trip. Each observation is obtained as the weighted average (based on the volume of catches in kg.) of the selling prices obtained in the various fishing trips each week, and is therefore expressed in euros per kg. To ensure a total of 52 observations in all years, the first week of the year is considered to mean the first seven days of January and the last week of the year is considered to have 8 days (9 in leap years).

Figure 2 shows the logs of the series of weekly prices for mackerel over time. The market for this species is characterised by a lack of any upward trend in the price series since, at least in the fresh fish market, the supply of mackerel far exceeds demand[9]. The gap is due to issues which are related to both demand (a relatively unattractive product for end consumers) and supply (vessels catch as much mackerel as allowed, or indeed more, with no regard for market demand, so supply can be considered as rigid). These relative characteristics of supply and demand for mackerel push prices down at source and, as a result, reduce the profitability of the activity. Note, for instance, that although catches in 2003 totalled just 36% of the figure for 2002 (as a result of the Prestige tanker disaster) prices remained similar to those for 2002 and there were no changes in their structure. As usual in econometrics, the logs of the price series are used rather than the original series in order to stabilise variance, which has been observed to increase slightly in the last few years considered.

[8] The activity related to the mackerel fishery is usually daily in the sense that each fishing trip usually covers one fishing day, after which vessels return to the ports to sell the fish.

[9] Thus, a freezer complex has been set up at the port of Bermeo (Bizkaia) mainly to acquire the mackerel not sold at the market due to lack of demand (or when the selling price is below a pre-set minimum). However, this complex has limited storage space, though it has recently been enlarged in response to the gap between supply and demand.

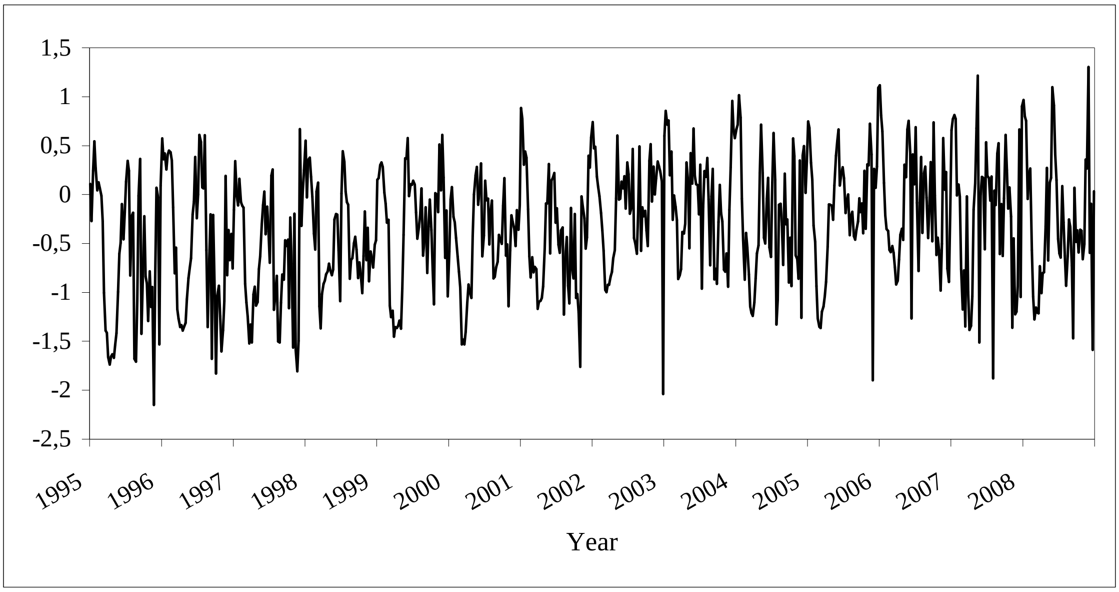

Figure 2. Log of mackerel prices at source.

4.1 Cyclical Integration Analysis

As can be seen in Figure 2, the behaviour of the series of prices for mackerel (with no significant trends) can hardly be classed as belonging to category I(1), as is conventional for price series in general (see, for instance, Arteche 2007) and fish prices in particular. In turn, the behaviour of the sample autocorrelation function (hereinafter called the ACF) shown in Figure 3 for 520 lags (10 years), with autocorrelations far from one and with slow decay towards zero, supports the idea that the price series analysed cannot be considered as I(1). Indeed, the ACF has the typical shape of a long memory process, i.e. a gradual decline towards zero, rather than the exponential decline which is typical of short memory processes or the absence of decline found in infinite memory processes. In this specific case, the long memory of the series seems to be dominated by a 26-week (half-year) cycle. This paper therefore analyses and estimates semiparametrically the orders of integration of the various persistent cycles that make up mackerel price series.

Figure 4 shows the periodogram of the price series where three major spectral peaks can be observed. The highest is at scaled frequency 28, which corresponds to a 26-week (half-year) cycle. The second highest is at scaled frequency 42, associated with a 17.33-week (four-month) cycle. The third and last peak is associated with frequency zero, which shows the long term changes or trend in the series.

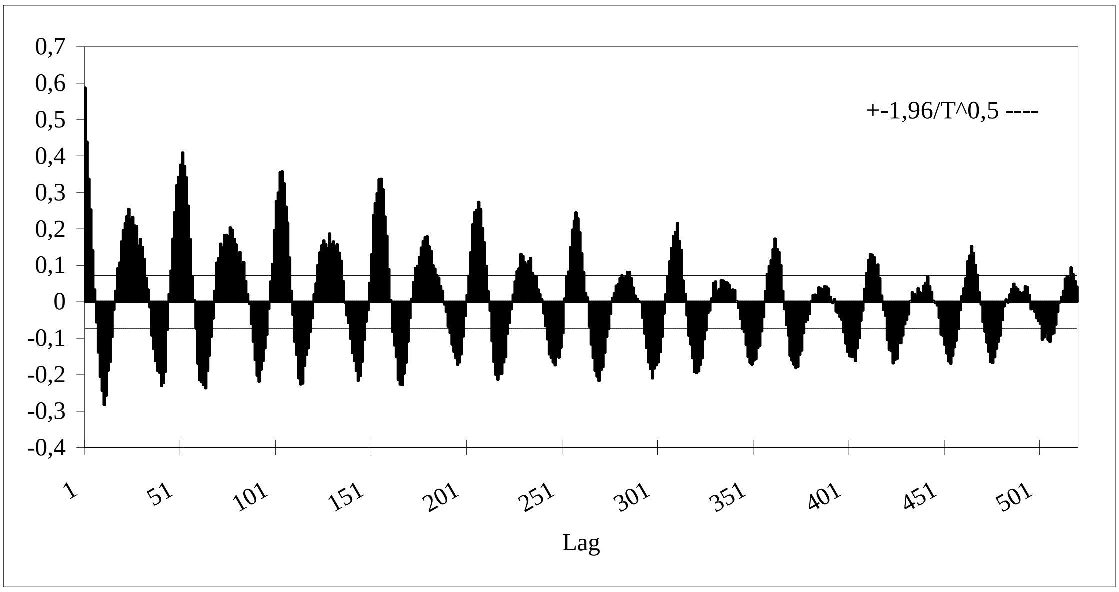

Figure 3. ACF of the log of mackerel prices at source.

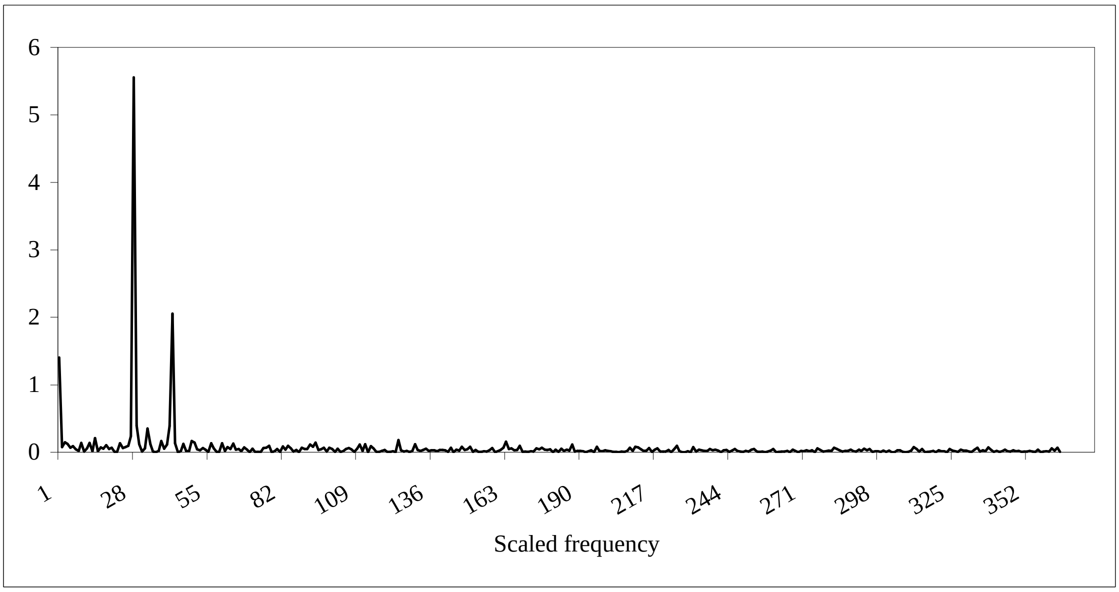

Figure 4. Periodogram of the log of mackerel prices at source.

The appearance of a half-year cycle as apparently the most important is due to the fact that prices hit their maximum level approximately every six months (winter and summer). The behaviour of minimum and maximum prices can be explained by the seasonal nature of fishing as an activity, with maximum catches in spring when the mackerel shoals pass by the Northern Spanish coast, and minimum catches in summer, when the shoals have moved away from Spanish fishing grounds. Outside the inshore campaign, catches also reach a local maximum in autumn and a local minimum in winter, before the inshore campaign begins.

Economic cycles may be deterministic, stochastic or both. Given that no deterministic trends are observed, only the stochastic nature of the zero frequency cycle is analysed[10]. The nature of the half-year and four-month cycles, however, is unknown, so checks are run for both stochastic and deterministic components. For filtering and modelling stochastic components, the Gegenbauer filter is used, as defined in (7), while deterministic components are modelled using dummy variables, which is equivalent to using sine-cosine functions (Hannan, 1963). The sequence is as follows: first, stochastic seasonality is analysed and then, once any such seasonality has been revealed, an analysis is run to see whether any deterministic component remains in the series. The stochastic component is modelled before the deterministic component because if seasonal dummy variables are used with series which are $I_{\omega}(1)$[11] there is a very high probability of finding spurious relationships in some of the seasonal frequencies (Abeyshinge, 1991). Moreover, according to simulations run by Abeysinghe (1994), when a small series with seasonal unit roots is regressed on a set of seasonal dummies, the ACF of the residuals of that regression behaves as if a stationary process were involved even if the unit roots are not eliminated. Memory parameter estimations are not affected by the potential presence of deterministic seasonality since, as shown by Arteche (2002), any such seasonality only affects the periodogram at the seasonal frequency (provided that, as is the case here, the length of the series is a whole multiple of the number of observations per year) and that frequency is not used in the estimation.

To facilitate the analysis desired here, the whole of the above-mentioned procedure is applied to the centred series of logs of prices, denoted by x_t. Using the centred series does not distort the results at all, since having an average other than zero only affects the periodogram at frequency zero, which is not used in any case for estimating the memory parameters.

Starting with the trend cycle, Whittle's local method is used as explained in Section 3 to estimate the memory parameter at frequency zero. Figure 5 shows the estimates of d_0 for different bandwidths ($m = 2,3,...,28$). Following the recommendations of Taqqu and Teverovsky (1996), an intermediate bandwidth value is selected (neither very high nor very low) corresponding to an area of stable estimates of

[10] Indeed, when the first differences of the series is regressed on a constant, it is not significant.

[11] A series x_t is said to be $I_{\omega}(d)$ if $(1-2L\cos\omega+L^2)^d x_t$ is a process with a finite, non null spectral density at frequency ω.

d_0. As shown in Figure 5, this stable intermediate area could be considered to run approximately from $m = 14$ to $m = 22$. Values of m below 14 make for markedly erratic estimates, while with bandwidths $m > 22$ the effect of the strong seasonal peak at scaled frequency 28 may result in a negative bias in the estimates, especially if $m = 28$, when the estimates drop to zero. As a consequence, it was decided to take a bandwidth of $m = 18$, where the estimate of d_0 is 0.40 ($\hat{d}_0 = 0.40$), which is significantly different from zero, in view of the asymptotic distribution in (13).

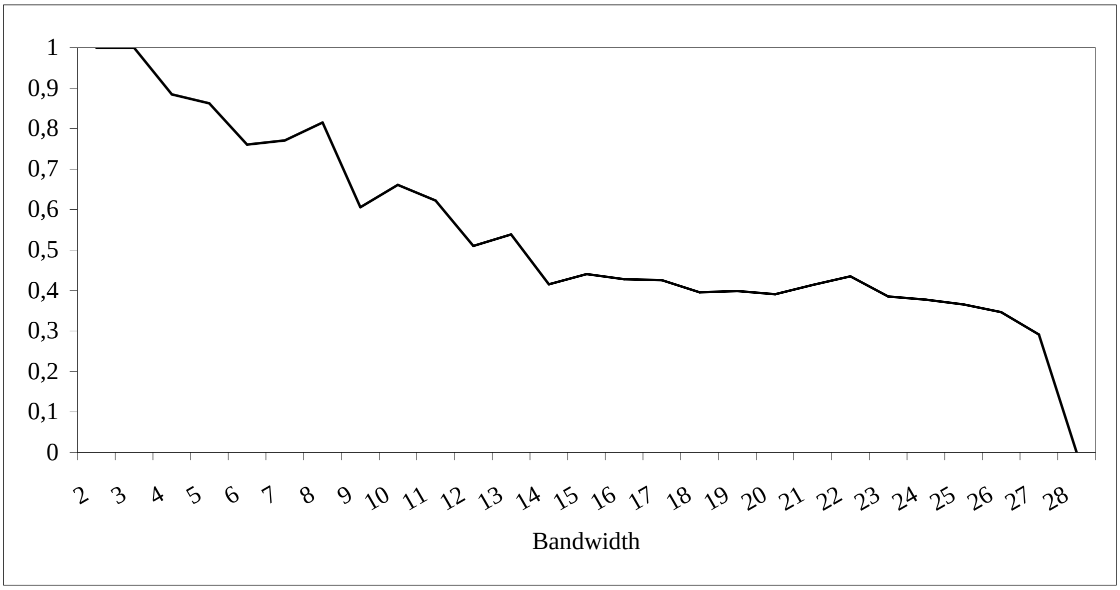

Figure 5. Estimation of the memory parameter at frequency zero ($\hat{d}_0$).

The next step is to run an analysis similar to the one carried out for the trend cycle in the case of the seasonal cycles. Beginning with the half-year cycle, Whittle's local method is used to estimate the memory parameter at scaled frequency 28, i.e. $\omega_{28} = 0.2417$ in radians. Figure 6 shows the estimates of d_{28} for different bandwidths (specifically for $m = 2,3,...,14$). Following the recommendations of Taqqu & Teverovsky (1996) once again, any bandwidth value within an intermediate area where the associated estimates of d_{28} are stable can be selected. As shown on Figure 6, the stable intermediate area can be considered to run approximately from $m = 6$ to $m = 12$. Values of m below 6 make for markedly erratic estimates, while with bandwidths of $m > 12$ the effect of the seasonal peak at scaled frequency 42 seriously biases the estimates. Specifically, it was decided to take a bandwidth of $m = 10$, where the estimate of d_{28} is 0.28 ($\hat{d}_{28} = 0.28$), which once again is significantly different from zero.

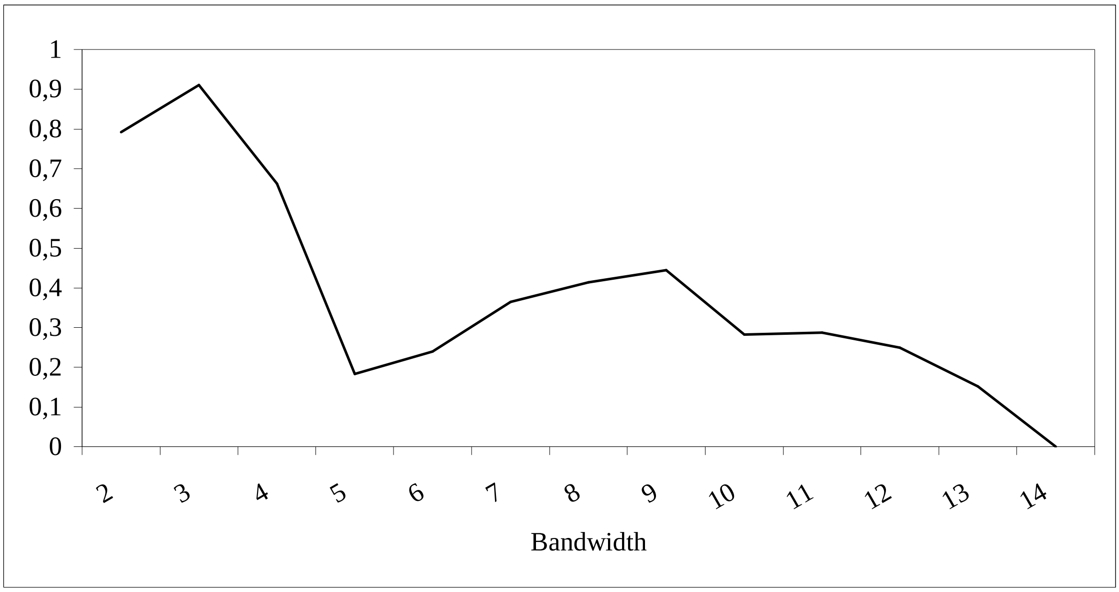

Figure 6. Estimation of the memory parameter at frequency 28 ($\hat{d}_{28}$).

Finally, the case of the four-month cycle was analysed in the same way. Figure 7 shows the memory parameter estimates for that cycle for different bandwidths (specifically $m = 2, 3, ..., 14$). In this case the intermediate stable area can be associated with the range [9,12]. From $m = 12$ upwards the influence of the peak at scaled frequency 28 causes the estimates of d_{42} to drop. The bandwidth selected was $m = 10$, which not only falls within the stable area but also enables comparisons of the two seasonal peaks analysed to be drawn under a homogenous framework. The estimate of d_{42} is 0.12 ($\hat{d}_{42} = 0.12$).

However, for this case the null hypothesis of short memory cannot be rejected at scaled frequency 42 ($d_{42} = 0$), since the t-statistic, $t = 1.07$ does not exceed the critical value for a 95% significance level.

Note that since the estimates are lower than 0.5, the price series analysed can be considered to be weakly stationary. Given the stationary nature of both the seasonal component and the trend in the series, the effect of a shock due, for instance, to an increase in oil prices, disappears in the long term. This goes some way towards explaining the stability in prices observed for this species. The innate characteristics of the market and the fishing strategy of the fleet analysed explain why persistence is much lower than usual in series of this type.

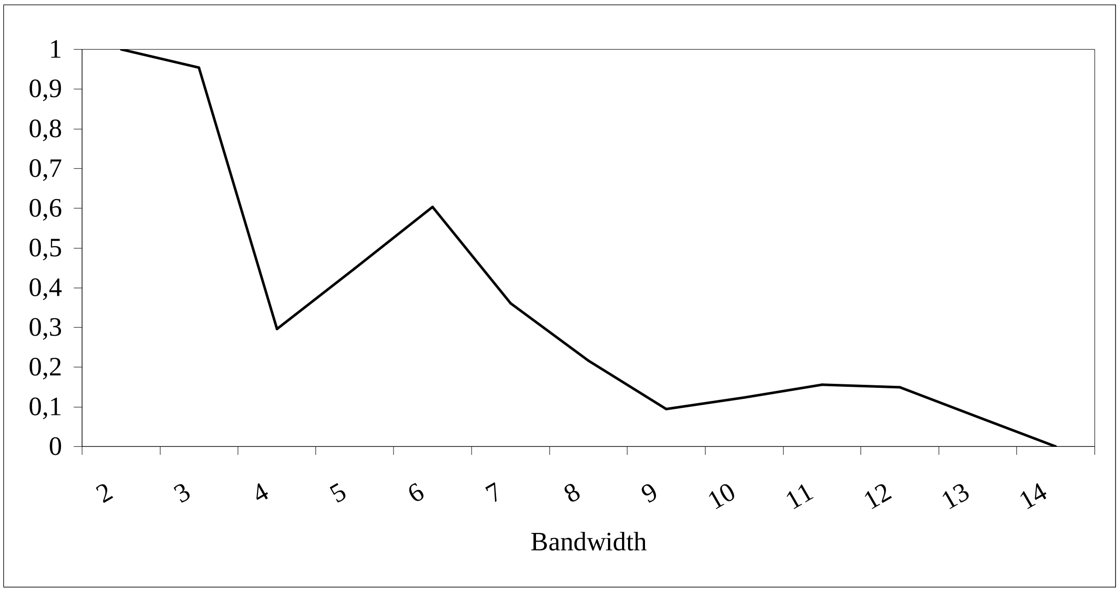

Figure 7. Estimation of the memory parameter at frequency 42 ($\hat{d}_{42}$).

The fact that a series of prices is stationary in a general economic context in which inflation is moderate but positive hints at the profitability problem faced by the agents who are paid those prices. Note that the fact that inflation in Spain in the period under analysis shows a long or even infinite memory (Arteche, 2007) means that the general level of prices (measured by the consumer price index) shows greater persistence than a I(1) series, which in turn means that shocks are indeed passed on permanently to general prices. Moreover, feedback results in the effects of those shocks intensifying over time. From the viewpoint of fishermen, profitability would increase in the long term if the increases suffered regularly in the prices of production factors could be passed on to the price at source. This would go at least some way towards solving the profitability problem from which this fishery has suffered for over ten years, which fishermen attempt to palliate by landing catches well over the allocated TAC, thus endangering the biological sustainability of the stock.

The next step in the analysis is to filter series x_t at the frequencies where a significant memory parameter is found, i.e. 0 and 28. This new series is denoted by y_t and is obtained as follows: $y_t = (1-L)^{0.40}(1-2L\cos 0.2417 + L^2)^{0.28} x_t$.

To check for any deterministic seasonal component, y_t is regressed on two dummy variables in sine-cosine form that reflect the seasonal cycles: $D_{1,t} = \left(\sin(\omega_{28}t), \cos(\omega_{28}t)\right)$ and $D_{2,t} = \left(\sin(\omega_{42}t), \cos(\omega_{42}t)\right)$, for $t = 1,...,T$. The variable that represents the four-month cycle ($D_{2,t}$) was found to be significant at 5% while the one representing the half-year cycle ($D_{1,t}$) was not, so a reduced regression was carried out (this time only on the variable associated with the four-month cycle, as shown in Table 3), saving the residuals, denoted as z_t, which represent a series clear of persistence. Figure 8 shows the periodogram of z_t, in which both the seasonal peaks and at frequency zero have disappeared. Moreover, the ACF for z_t shown in Figure 9 also shows behaviour typical of an I(0) process, with autocorrelations that drop rapidly towards zero.

Table 3. Estimation of the deterministic seasonal component.

Variable	Coefficient	Standard deviation	t-statistic	P-value
$\sin(\omega_{42}t)$	0.0122433	0.016105	0.7602	0.44737
$\cos(\omega_{42}t)$	0.0851162	0.0159586	5.3336	<0.00001

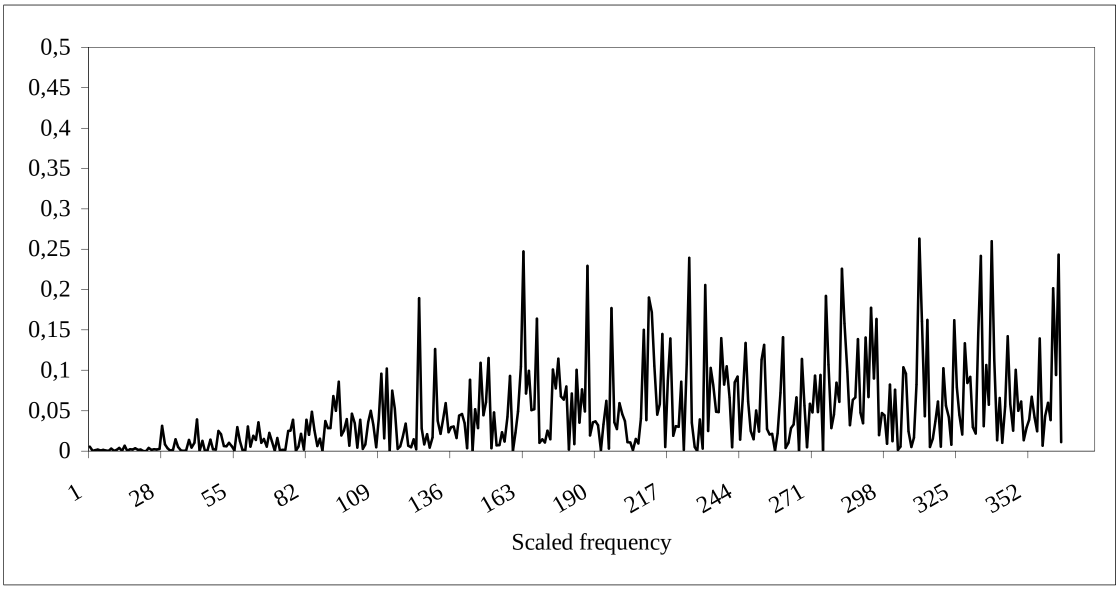

Figure 8. Periodogram of z_t .

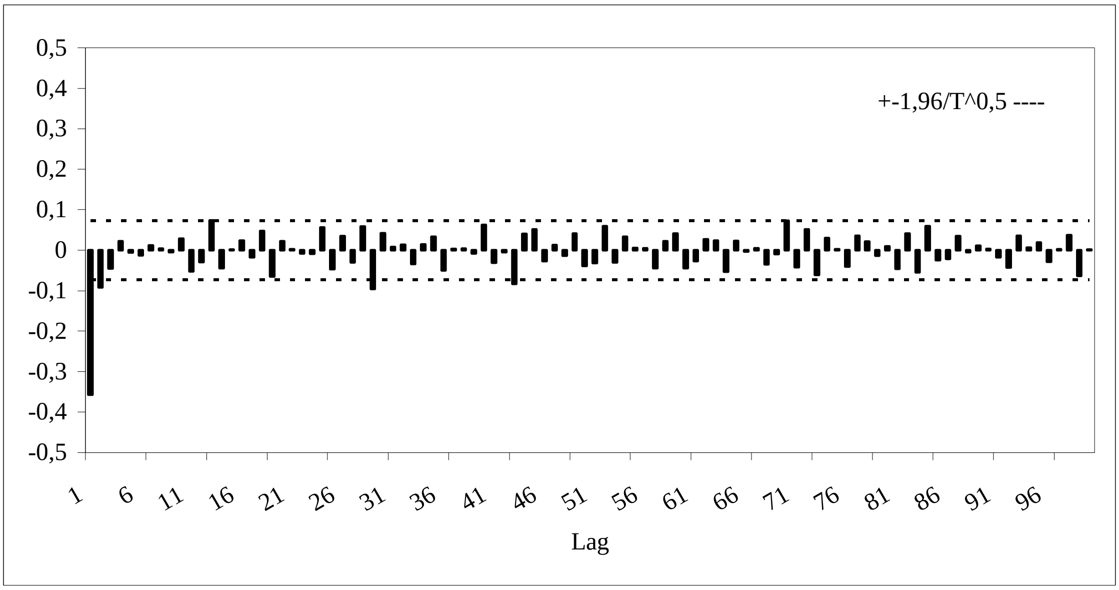

Figure 9. ACF of z_t.

4.2 *Proposition & Estimation of the ARMA(p,q) Model*

Once a I(0) series is obtained, a Box-Pierce test is run on the first 100 lags of z_t. The null hypothesis of no correlation is rejected for the various lags (with p-values always below 0.001)[12], indicating that the series shows some time-dependence (short memory), which can be modelled via an *ARMA(p,q)* model. Various *ARMA(p,q)* models are proposed and the most parsimonious of those which fit best is chosen. To decide what model best fits the series, the significance of the parameters and whether or not the series is turned into white noise are considered, along with conventional selection criteria such as the Akaike information criterion (AIC), Schwarz's Bayesian information criterion (BIC) and the Hannan-Quinn criterion (HQC). Based on these arguments, the model selected is *ARMA(1,1)*, an estimation of which is presented in Table 4.

Table 4. Estimation of the *ARMA(1,1)* model.

Variable	**Coefficient**	**Standard deviation**	**t-statistic**	**P-value**
ϕ_1	0.257476	0.0482234	5.3392	<0.00001
θ_1	-0.840767	0.0271463	-30.9716	<0.00001

The Box-Pierce test on the residuals from the *ARMA(1,1)* model reveals that the series shows no linear time-dependence, and that it therefore behaves as white noise (the

[12] Note that the rejection of the null hypothesis of no correlation is grounded mainly in the first two autocorrelations.

lowest p-value for a time frame of up to 100 lags is 0.72). This can also be seen through the periodogram shown in Figure 10 where, as occurs in white noise processes, no peaks stand out and all cycles contribute similarly to the variance of the series. Finally, Figure 11 shows the ACF for those residuals, with autocorrelations which are within (or very close to) the no significance bands, which is a further indication of the absence of linear time-dependence.

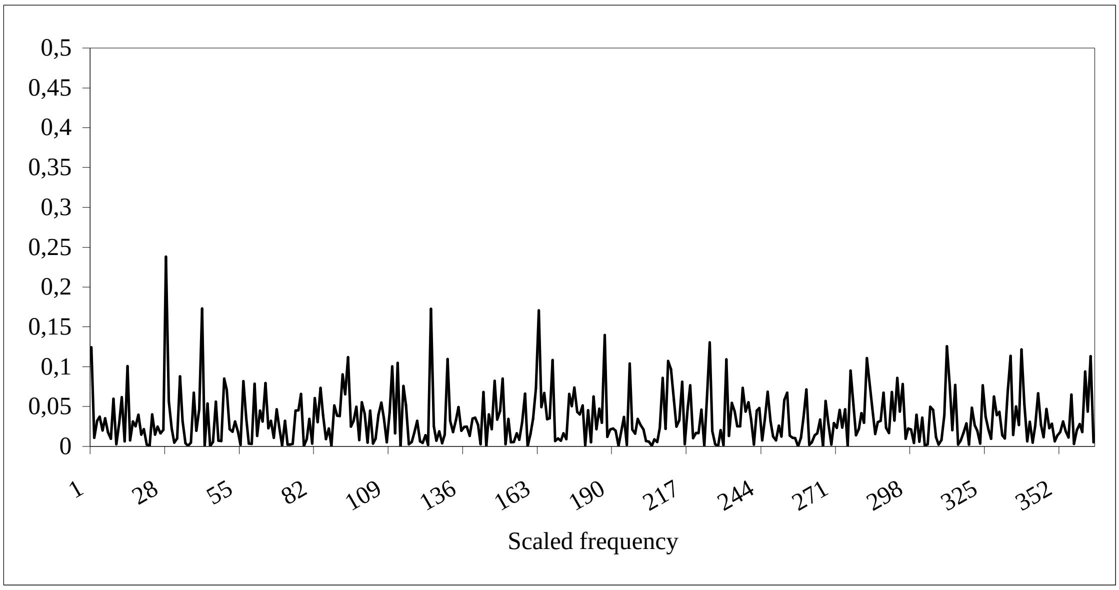

Figure 10. Periodogram of the residuals of the *ARMA(1,1)* model.

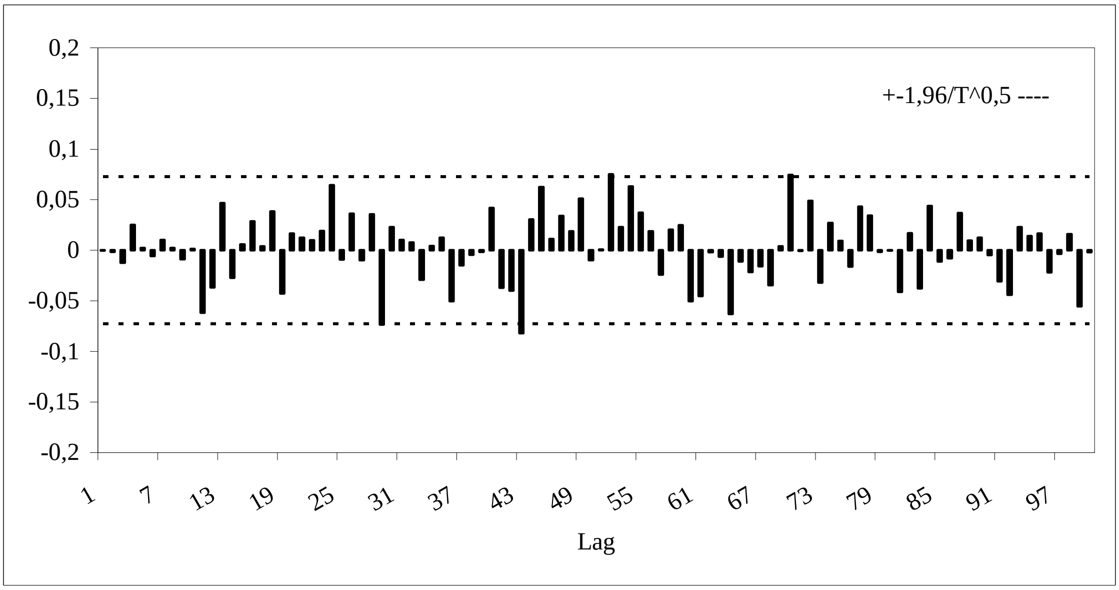

Figure 11. ACF of the residuals of the *ARMA(1,1)* model.

Thus, the final model selected for the logs of the price series analysed is:

$$(1-0.26L)z_t = (1-0.84L)\varepsilon_t \tag{14}$$

where $z_t = (1-L)^{0.40}(1-2L\cos 0.2417 + L^2)^{0.28}x_t - 0.01\sin(0.3625t) - 0.08\cos(0.3625t)$

4.3 Calculating the IRF

Once (14) was proposed as the model for explaining the behaviour of the series analysed, the disturbance effect of a random unitary shock on the model was calculated to determine its duration and learn the extent to which fishermen were able to pass on the effect to their prices. Such shocks may be caused by the following, among other factors:

- Variations in production costs. One of the main problems affecting the fishing industry in general and the mackerel fishery in particular is the considerable increase in fuel prices, as fuel may account for up to 50% of total operating costs (Source: AZTI-Tecnalia DB).
- Downturns in catches. Drops in mackerel catches in recent years have been due mainly to the introduction of a catch control system or quota per fisherman per day, to increased competition between fleets, to changes in TAC, etc.

The analysis is run by defining the IRF of series x_t. For a model such as that proposed in (14), this is calculated as the sequence of coefficients of the following polynomial:

$$\pi(L) = (1-L)^{-0.40}(1-2L\cos 0.2417 + L^2)^{-0.28}\frac{1-0.84L}{1-0.26L} \tag{15}$$

Figure 12 shows the IRF for a time-frame of 156 weeks (3 years). A slow convergence towards zero can be observed, with fluctuations dominated by the half-year cycle. Among other things, this indicates that a change in prices due to a random shock is unsustainable in the long term and will fade away over time. This result evidences the need to strengthen the power of fishermen in the future, since shocks currently have only a transitory (albeit long-lasting) effect on selling prices in ports, in contrast to the permanent effect that they have on general price levels. Moreover, following the paper by Cheung and Lai (2000), the half-life of shocks is calculated to be 0.78 weeks (5.46 days), which gives a measure of their persistence. However, this measure should be treated with caution, especially in series with long memories, because, as pointed out by

Murray & Papell (2005), when shocks do not decline at a constant rate it is advisable to observe the IRF as a whole rather than any particular measure.

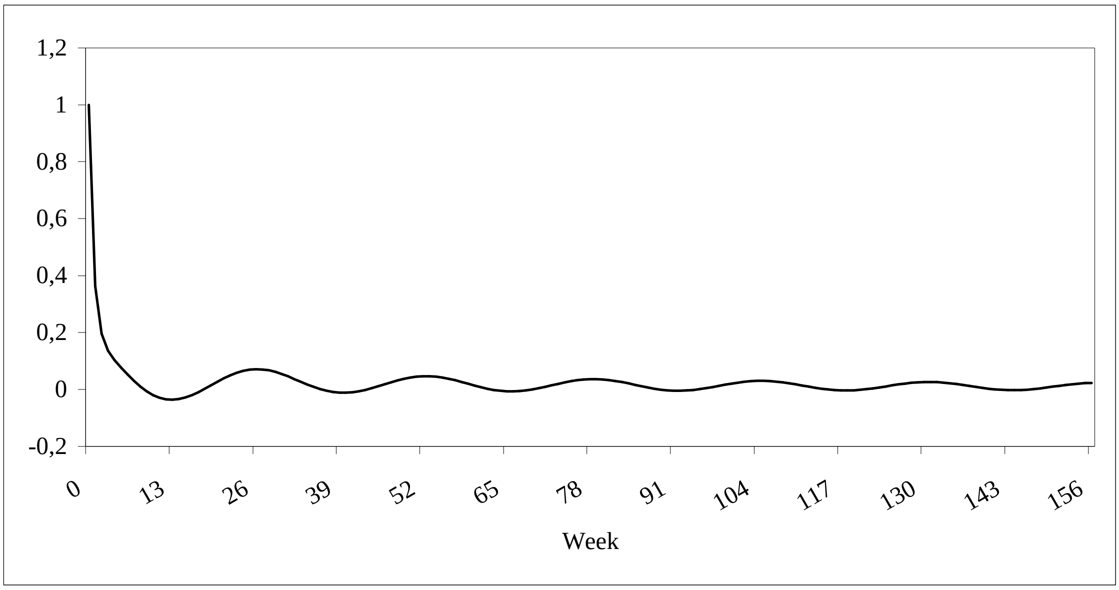

Figure 12. IRF of x_t .

5 Conclusions

The low profitability from which almost all European fishing markets are suffering has given rise to a major social problem, especially in those areas with a high dependency on fishing. A case in point is that of mackerel prices at Basque ports, which have remained more or less the same (and unusually low) in recent years in spite of continual increases in costs. This seriously compromises both the profitability of this important subsector and the biological sustainability of the stock fished. The key factors affecting mackerel include the number of vessels fishing the stock, the behaviour and strategies of fishermen themselves, the auction system used to set prices at ports and the quota-based catch control systems introduced in recent years.

To identify the process that governs the behaviour of prices over time and analyse the ability of fishermen to pass the impact of the shocks that they suffer on to prices, a cyclical ARFIMA model is estimated. This model fits the data better than a conventional ARIMA and is more flexible, since it reflects the exact degree of persistence of stochastic components at any frequency. In this specific case two persistent stochastic cycles are found: the long-term cycle at frequency zero and the half-year cycle. As a result an $ARFIMAC(1,1)\times(0,0.40)\times(0.2417,0.28)$ model is proposed. The IRF for this model indicates, among other things, that the possible repercussions of production cost variations on prices disappear over time, showing them to be unsustainable in the long term. This shows how little power producers have: for instance they cannot pass on to prices at source any of the increases that have taken place in oil prices in recent years. As a result attempts to solve the successive crises that have hit the sector have been based on a policy of one-off subsidies, but this is only a short-term measure that does not solve the problem once and for all. In recent years the public authorities and the industry itself have therefore begun to consider other policies of a more structural nature which can bring about a more favourable situation for fishermen, i.e. which may lead to permanent increases in prices in the face of any increases in production costs. In that context, a scheme was piloted during the 2008 inshore campaign that involved a system of voluntary daily quotas per crew per vessel as a complement to the TAC, with a view to limiting mackerel catches. In the wake of that experiment, in 2009 the whole fishery was managed with that quota system, which was made compulsory for all Spanish fleets. Alternatively, based on successful experiments in other regions (where first-sale prices have increased), the application of other methods could be considered, such as sales through electronic dockside markets and fish sale/purchase agreements. However, these systems have not always produced positive results and are rejected by some of the agents involved in the auction process in the internal market of the Basque Country. Rejection is indeed not confined to the Basque Country but is widespread throughout European ports. This is the main reason why the Dutch auction system continues to predominate in Europe.

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References

Abeysinghe, T., 1991. Inappropriate use of seasonal dummies in regression. Econ. Lett. 36, 175-179.

Abeysinghe, T., 1994. Deterministic seasonal models and spurious regressions. J. Econometrics 61, 259-272.

Andel, J., 1986. Long-memory time series models. Kybernetica 22, 105-123.

Arteche, J., 2002. Semiparametric robust tests on seasonal or cyclical long memory time series. J. Time Ser. Anal. 23, 251-285.

Arteche, J., 2007. The analysis of seasonal long memory: the case of Spanish inflation. Oxford B. Econ. Stat. 69, 749-772.

Arteche, J., Robinson, P.M., 2000. Semiparametric inference in seasonal and cyclical long memory processes. J. Time Ser. Anal. 21, 1-25.

Chan, N.H., Terrin, N., 1995. Inference for unstable long-memory processes with applications to fractional unit root autoregressions. Ann. Stat. 23, 1662-1683.

Chan, N.H., Wei, C.Z., 1988. Limiting distributions of least squares estimates of unstable autoregressive processes. Ann. Stat. 16, 367-401.

Cheung, Y.W., Lai, K.S., 2000. On the purchasing power parity puzzle. J. Int. Econ. 52, 321-330.

Cheung, Y.W., Lai, K.S., 2001. Long memory and nonlinear mean revision in Japanese yen-based real exchange rates. J. Int. Money Financ. 20, 115-132.

Compés, R., 1994. Mecanismos de Coordinación y Competitividad: la subasta de frutas de la Almunia (Zaragoza). Rev. Estud. Agrosoc. 168, 295-322.

Gadea, M.D., Mayoral, L., 2006. The persistence of inflation in OECD countries: a fractionally integrated approach. Int. J. Cent. Bank. 2, 51-104.

Gil-Alaña, L.A., Robinson, P.M., 2001. Testing of seasonal fractional integration in UK and Japanese consumption and income. J. Appl. Econom. 16, 95-114.

Giraitis, L., Leipus, A., 1995. A generalized fractionally differencing approach in long memory modelling. Liet. Matem. Rink. 35, 65-81.

Gordon, D.V., Hannesson, R., 1996. On prices of fresh and frozen cod fish in European and U.S. markets. Mar. Resour. Econ. 11, 223-238.

Gordon, D.V., Salvanes, K.G., Atkins, F., 1993. A fish is a fish is a fish? Testing for market linkages on the Paris fish markets. Mar. Resour. Econ. 8, 331-343.

Granger, C.W.J., 1966. The typical spectral shape of an economic variable. Econometrica 34, 150-161.

Gray, H.L., Zhang, N.F., Woodward, W.A., 1989. On generalized fractional processes. J. Time Ser. Anal. 10, 233-257.

Gray, H.L., Zhang, N.F., Woodward, W.A., 1994. On generalized fractional processes- a correction-. J. Time Ser. Anal. 15, 561-562.

Hannan, E.J., 1963. The estimation of seasonal variation in economic time series. J. Am. Stat. Assoc. 58, 31-44.

ICES, 2009. Report of the Working Group on Widely Distributed Stocks. ICES Document, CM 2009/ACOM, Copenhagen.

Jiménez-Toriribio, R., García-del-Hoyo, J.J., 2006. Evidence of market price leadership in the Spanish red seabream value chain-Implication for fisheries management. Fish. Res. 81, 51-59.

Murray, C.J., Papell, D. H., 2005. The purchasing power parity puzzle is worse than you think. Empir. Econ. 30, 783-790.

Robinson, P.M., 1994. Efficient tests of non-stationarity hypotheses. J. Am. Stat. Assoc. 89, 1420-1437.

Robinson, P.M., 1995. Gaussian semiparametric estimation of long-range dependence. Ann. Stat. 23, 1630-1661.

Setäla, J., Laitinen, J., Virtanen, J., Saarni, K., Nielsen, M., Honkanen, A., 2008. Spatial integration of freshwater fish markets in the Northern Baltic Sea area. Fish. Res. 92, 196-206.

Taqqu, M.S., Teverovsky, V., 1996. Semi-parametric graphical estimation techniques for long-memory data. Lect. Notes Stat. 115, 420-432.