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ABSTRACT

Illusive Persistence in German Unemployment*

The non-stationarity of many macroeconomic time series has lead to an increased demand for economic models that are able to generate fragile equilibria. For instance, in this literature the natural unemployment rate is allowed to shift over time depending on past unemployment. Actually, many European unemployment series seem to exhibit a unit root or persistence. This view is questioned in the paper using German data on unemployment. A new class of time-series models, the fractionally integrated ARMA model, that allows the difference parameter to take real values, enables the researcher to separate long memory and short memory in the data. It is shown that using this approach the unit root hypothesis is rejected but unemployment exhibits long memory.

JEL Classification: C22, E24 and J64
Keywords: fractional integration, hysteresis, long memory, persistence and unemployment

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Illusive Persistence in German Unemployment

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1 Introduction

The non-stationarity of many macroeconomic time-series has concerned economists in recent years. This finding is especially puzzling for unemployment rates and has also been named hysteresis. The implication of hysteresis is that once the impulses that have caused a change in unemployment disappear, unemployment persists at the level reached during the operation of the shocks. Although hysteresis in its strict form implies a unit root in the level process, some authors also include models which are characterized by shocks that die out slowly. (For some overview of the literature see Cross (1988).) We do not follow this method here, but restrict our attention to hysteresis or persistence of time-series that imply an infinite memory of an impulse.

Blanchard and Summers (1988), for instance, found a large degree of hysteresis in European labour market data. They also regressed unemployment on past unemployment and a time trend and allowed for a moving-average component of the error term, finding that unemployment appears to be non-stationary in Germany, Great Britain and France, whether or not a time trend is included in the regression. This suggests that unemployment should be analysed in the context of the unit root debate and co-integration theory (see Engle and Granger, 1991, among others). Zimmermann (1991) followed this line of research and confirmed the findings of Blanchard and Summers (1988) using the Dickey-Fuller tests in the analysis of age-specific yearly unemployment rates for West German males and females.

On the basis of such findings, Blanchard and Summers (1988) among others have advocated the need for models explaining fragile equilibria. They argued that the recent European experience poses

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a profound challenge to standard Keynesian and classical theories of macroeconomic fluctuations. New theories have to model a situation where, after a shock, unemployment does not return to a stable equilibrium or natural rate, but is dependent upon history. In this framework, the natural rate of unemployment is not constant but shifts over time depending on past unemployment. Theories that are able to explain such behaviour make use of the persistence-effects of a reduced capital stock following a reduction of employment, depreciation effects on human capital or the role of unions. (See Cross, 1988, for references.)

Our paper qualifies this literature. It is known that the existence of long memory in the data may make it difficult to reject the unit root hypothesis. Using West German quarterly unemployment data, we first confirm the inability to reject a unit root on the basis of conventional testing. We then employ a new approach to model time-series, the fractionally integrated ARMA model and find that the unemployment rate does not contain a unit root but exhibits long memory as soon as it is properly analysed. Section 2 introduces the fractionally integrated ARMA models and section 3 discusses its estimation. Section 4 summarizes the empirical findings and section 5 concludes.

2 Persistence and Fractionally Integrated ARMA Models

Recently, there has been substantial interest in the measurement of the permanent component in economic time series. In its early stage, this literature concentrated on determining the long-run effects of a unique shock in the infinite future. If such an impact exists, shocks have been said to be persistent (Campbell and Mankiw, 1987). However, as Diebold and Rudebusch (1989) have pointed out, the effect of a shock on the infinite future is of little importance compared to the adjustment process initiated by it. In this section we strengthen their argument by presenting non-persistent stochastic processes where shocks fade out extremely slowly. These processes are characterized by long memory. A prominent class of such processes is the fractionally integrated ARMA(p, d, q) – short ARFIMA(p, d, q) – model which was independently introduced by Granger and Joyeux (1980) and Hosking (1981). It generalizes the concept of ARIMA(p, d, q) models by allowing the differencing parameter d to take real values instead of restricting it to be an integer.

The ARFIMA(p, d, q) process satisfies the difference equation

$$\alpha(B)\nabla^{d}x_t = \beta(B)\epsilon_t \tag{1}$$

with the disturbance process

$$\{\varepsilon_t\} \sim \mathrm{N}(0, \sigma^2).$$

Using the backshift operator B, the fractional difference operator ∇^d can be written as the infinite power series

$$\begin{aligned}\nabla^d = (1-B)^d &= 1 - dB + \frac{d(d-1)}{2!}B^2 - \frac{d(d-1)(d-2)}{3!}B^3 + \ldots \\ &\quad + (-1)^k \frac{d(d-1)\ldots(d-k+1)}{k!}B^k + \ldots \\ &= \sum_{k=0}^{\infty} (-1)^k \binom{d}{k} B^k = \pi_k B^k. \end{aligned} \tag{2}$$

The binomial coefficients π_k are given by

$$\binom{d}{k} = \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)(-1)^k} = \begin{cases} \frac{d(d-1)(d-2)\ldots(d-k+1)}{k!} & \text{for } k > 0 \\ 1 & \text{for } k = 0 \end{cases}$$

and can be approximated for large k by

$$\pi_k = k^{-d-1}/\Gamma(-d) \quad \text{as } k \to \infty. \tag{3}$$

$\alpha(B) = 1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p$ and $\beta(B) = 1 + \beta_1 B + \beta_2 B^2 + \ldots + \beta_q B^q$ denote the autoregressive and moving average polynomials, respectively. Both these polynomials are assumed to have no common roots, and the roots of the AR-polynomial $\alpha(z)$ and of the MA-polynomial $\beta(z), z \in C$ are assumed to lie outside the unit circle. For $d \in (-0.5, 0.5)$ this process is invertible and causal (see Granger and Joyeux, 1980, Hosking, 1981 and Brockwell and Davis, 1991, (Def. 13.2.2, p. 524, Theorem 13.2.2, p. 525)). To obtain processes with $d \geq 0.5, \nabla^d$ can be obtained by the combination of fractional differencing following equation (2) and integer differencing.

With F_α and F_β denoting the Fourier transforms of $\alpha(B)$ and $\beta(B)$ the spectral density of an ARFIMA(p, d, q) process is given by

$$f(\omega) = \frac{\sigma^2}{2\pi} \frac{|F_\beta(\omega)|^2}{|F_\alpha(\omega)|^2} |1 - e^{-i\omega}|^{-2d}. \tag{4}$$

For $\omega \to 0$ it can be approximated by $\frac{\sigma^2}{2\pi}\left(\frac{F_\beta(0)}{F_\alpha(0)}\right)^2 \omega^{-2d}$. Thus, we obtain for the spectral density at the origin

$$\lim_{\omega \to 0} f(\omega) = \begin{cases} \infty & \text{if} \quad d > 0 \\ 0 & \text{if} \quad d < 0 \end{cases}. \tag{5}$$

This allows to classify the memory properties of the stochastic process y_t that describe the dependence between distant observations by solely looking at the fractional differencing parameter d. From (5) we observe that the limiting behaviour of the spectral density is discontinuous as d changes its sign. Whereas for positive d it approaches infinity thus causing aperiodic long cycles it reaches zero for negative d which is sometimes referred to as intermediate memory (see Brockwell and Davis, 1991 (p. 520)).

In the time domain ARFIMA processes for $d \neq 0$ are characterized by a hyperbolic decaying autocovariance function

$$\varrho(\tau) \sim C\tau^{2d-1} \qquad \text{as } \tau \to \infty, \tag{6}$$

where $C > 0$. (See Brockwell and Davis, 1991 (Theorem 13.2.2, pp. 525-526) for proofs.) Thus, in comparison to the autocovariance function of traditional ARMA models, the autocovariance function of stationary ARFIMA processes declines much slower. This also holds for the parameters of the infinite MA-representation of such a process. This can be seen by applying the approximation of the power series expansion (3) to the inverted filter ∇^{-d}. Moreover, in the time domain the property of long memory corresponds to an autocovariance function that is not absolutely summable. An explicit formula for computing the autocovariance function of an ARFIMA(p, d, q) process was derived by Sowell (1992). This procedure involves the calculation of the hypergeometric function if the AR-part is non-zero.

Now, we can show that long memory processes with $0 < d < 1$ exhibit no persistence in the definition of Campbell and Mankiw (1987). They measure persistence by the cumulative impulse response $c = \psi(1) = \sum_{u=0}^{\infty} \psi_u$ where the parameters ψ_u are the coefficients in the MA-representation of the first difference x_t of the time series y_t under investigation

$$x_t = \nabla y_t = \psi(B)\varepsilon_t, \quad \{\varepsilon_t\} \sim N(0, \sigma^2). \tag{7}$$

Then, our claim can be stated as:

$$c = \left\{ \begin{array}{r} \infty \\ b, b > 0 \\ 0 \end{array} \right\} \quad \text{for} \quad d \left\{ \begin{array}{c} > \\ = \\ < \end{array} \right\} 1. \tag{8}$$

The second line is a standard result. The first and third line follow directly from the behaviour of the spectral density $f_x(\omega)$ of the integer-differenced process $\nabla^D x_t = \nabla^D \nabla y_t$, $D = d-1$, at the origin since from equation (5) it follows that

$$f_x(0) = \left\{ \begin{array}{c} \infty \\ 0 \end{array} \right\} \quad \text{for} \quad D \left\{ \begin{array}{c} > \\ < \end{array} \right\} 0 \quad \text{or} \quad d \left\{ \begin{array}{c} > \\ < \end{array} \right\} 1, \text{ respectively.} \tag{9}$$

By using the relationship $f_x(0) = \frac{\sigma_\varepsilon^2}{2\pi}[\psi(1)]^2$, one obtains (8).

However, this finding is of no practical relevance as the impact of a shock fades out extremely slowly for these processes. This can be seen from Table 1 which shows finite cumulative responses $c_k = \sum_{j=0}^{k} \psi_j$ for various k and $d < 1$. This observation can be explained by the hyperbolically decaying parameters of the infinite MA-representation corresponding to an fractionally differenced process instead of the exponential decline of the MA-parameters corresponding to an ARMA specification. Table 1 contains an example by comparing the c_k for AR(1) processes with $\alpha_1 = 0.1$ and $\alpha_1 = 0.9$ and ARFIMA(0,d,0) processes with $d = 0.1$ and $d = 0.9$, respectively.

Table 1
Finite cumulative responses for selected Short and Long Memory Processes

c_k	α_1	d				α_1
	0.9	0.9	0.5	0.2	0.1	0.1
c_0	1.000	1.000	1.000	1.000	1.000	1.000
c_1	0.900	0.900	0.500	0.200	0.100	0.100
c_2	0.810	0.855	0.375	0.120	0.055	0.010
c_3	0.729	0.827	0.313	0.088	0.039	0.001
c_4	0.656	0.806	0.273	0.070	0.030	0.000
c_5	0.591	0.790	0.246	0.059	0.024	0.000
c_{10}	0.431	0.740	0.176	0.034	0.013	0.000
c_{100}	0.000	0.590	0.057	0.005	0.002	0.000
c_{1000}	0.000	0.469	0.018	0.000	0.000	0.000
c_{10000}	0.000	0.373	0.006	0.000	0.000	0.000
c_{100000}	0.000	0.296	0.002	0.000	0.000	0.000

This result provides additional evidence that an analysis of the permanent component requires the application of a sequence of finite cumulative impulse responses c_k and not simply the calculation of the cumulative impulse response c as it might give a completely misleading picture. In addition, it stresses the importance of a reliable estimation of the fractional differencing parameter d.

3 Estimation of ARFIMA(p, d, q) processes

Most conveniently one estimates $d = D+1$ with the semiparametric least square regression model introduced by Geweke and Porter-Hudak (1983). This method has been applied by Diebold and Rudebusch (1989) in their analysis of the permanent component in US unemployment rates. However, this approach has been critized by Sowell (1990a) for its sensitivity to short-run components which cannot be handled by the Geweke/Porter-Hudak method. He makes the case for the maximum likelihood method that allows for the simultaneous estimation of short and long run parameters and for which efficiency has been proven for certain values of the fractional differencing parameter d (see e.g. Robinson, 1990). Since Sowell (1992) has introduced a numerical method for the calculation of the autocovariance function of an ARFIMA(p, d, q) process the exact time domain likelihood can be computed.

In addition, two approximative frequency domain maximum likelihood methods are available: the Whittle estimator (1951) and its approximation. As both are used in our analysis they will be described in some detail. Let θ denote the parameter vector which is to be estimated. Following the presentation of Fox and Taqqu (1986), the key element of both methods is the approximation of the inverted covariance matrix $\Sigma^{-1}(\theta)$ of the stochastic process by an expression in the frequency domain $A_T(\theta)$ where each element $[A_T(\theta)]_{jk}$ is given by

$$\frac{1}{2\pi}\int_{-\pi}^{\pi}\frac{1}{g(\omega;\theta)}e^{i(j-k)\omega}d\omega$$

and $g(\omega;\theta) = \frac{2\pi}{\sigma^2}f(\omega;\theta)$. Assuming normality and approximating $\det(\Sigma) \sim (\sigma^2)^T$, minimization of the likelihood function leads to the estimator of the white noise variance

$$\tilde{\sigma}_T^2 = \frac{(X-\mu)'A_T(\theta)(X-\mu)}{T}. \tag{10}$$

Minimizing (10) then gives the parameter estimates $\tilde{\theta}$. If one further uses the empirical autocovariance function $\tilde{\gamma}(\tau) = \frac{1}{T}\sum_{j=1}^{T-|\tau|}(x_{j+|\tau|} - \bar{x})(x_j - \bar{x})$, one obtains

$$\tilde{\sigma}_T^2(\theta) = \sum_{\tau=-T+1}^{T-1}\frac{1}{2\pi}\tilde{\gamma}(\tau)\int_{-\pi}^{\pi}\frac{1}{g(\omega;\theta)}e^{-i\tau\omega}d\omega. \tag{11}$$

On the basis of the periodogram

$$I_T(\omega) = \frac{1}{2\pi}\sum_{\tau=-T+1}^{T-1}\tilde{\gamma}(\tau)e^{-i\tau\omega}$$

an alternative representation of (11) is given by

$$\tilde{\sigma}_T^2(\theta) = \int_{-\pi}^{\pi} \frac{I_T(\omega)}{g(\omega;\theta)} d\omega. \tag{12}$$

which is known as the Whittle estimator. Dahlhaus (1989) has shown its asymptotic efficiency.

As the numerical integration of the fraction containing the periodogram in (12) is cumbersome and possibly inaccurate, Tschernig (1992) provides an alternative computation method of the Whittle estimator that avoids the integration of the periodogram. It is based on the representation (11) which allows to make use of Sowell's (1992) method to compute the autocovariance function of an ARFIMA(p, d, q) process.

Although this method is exact, this algorithm still requires the computation of various hypergeometric functions if the MA-part is not zero. A simpler solution to the integration problem in (11) is to approximate the integral by the sum over the Fourier frequencies $\omega_u = 2\pi u/T$. This leads to the approximative Whittle estimator

$$\hat{\sigma}_T^2(\theta) = \frac{2\pi}{T} \sum_{u=1}^{T-1} \frac{I_T(\omega_u)}{g(\omega_u;\theta)}. \tag{13}$$

For this estimator Robinson (1990) sketched a way to prove asymptotic efficiency. Based on Monte Carlo simulations, Tschernig (1992) has shown that in small sample estimation the approximative Whittle estimator in general performs rather well compared to the Whittle estimator if the true mean is not known. Cheung (1990) and Cheung and Diebold (1990) come to similar conclusions in a comparison of the approximative Whittle estimator and the exact maximum likelihood method. Thus, we use the approximate Whittle estimator (13) and control for a possible estimation bias by reestimating the selected specification with the Whittle estimator (11).

4 Empirical Results

For studying the permanent component in (West) German unemployment, we choose the seasonally adjusted quarterly unemployment rate of the civil labour force published from the OECD main economic indicators for the period from 1962:I to 1989:IV. Beginning with traditional tools of analysing the long run impact of disturbances, we conduct the augmented Dickey and Fuller (1981) tests. In selecting the correct lag specification, we follow the procedure suggested by Campbell and Perron (1991). The maximum lag length is chosen to be $k = 10$

and the specification is selected for which the t-value of the last lag is significant at the 5%-level. Then one obtains the following regressions for the augmented Dickey-Fuller testing procedure where the t-values are denoted in brackets

$$\begin{array}{lllllllll} \nabla y_t = & -0.0375 y_{t-1} & - & 0.0361 & + & 0.0035t & - & 0.7981 \nabla y_{t-1} \\ & [-3.15] & & [-1.04] & & [2.91] & & [13.69] \end{array}$$

$$\Phi_2 = 3.57 \quad \Phi_3 = 4.97 \quad DW = 1.86 \quad R^2 = 0.64 \tag{14}$$

and

$$\begin{array}{llllll} \nabla y_t = & -0.0055 y_{t-1} & - & 0.0361 & - & 0.7842 \nabla y_{t-1} \\ & [-1.17] & & [-1.44] & & [13.05] \end{array} \tag{15}$$

$$\Phi_1 = 1.04 \quad DW = 1.76 \quad R^2 = 0.61$$

Thus, the presence of a unit root cannot be rejected and the German unemployment rate seems to be characterized by non-stationarity as well as by a positive cumulative impulse response c. Investigating $d = 2$, we find that this hypothesis is clearly rejected at the 1%-level. However, the former results may be spurious if one takes Sowell's (1990b) result into account that the existence of long memory in the data may make it difficult to reject the unit root hypothesis. Therefore, we next apply the ARFIMA model to the data.

As the maximum likelihood methods discussed in the previous section allow for the simultaneous estimation of the long and short memory component of a stationary time series, we include in our set of alternatives the nested sequences of ARFIMA$(p, 0, q)$ and ARFIMA(p, d, q) models with the length of the AR and MA polynomial varying between 0 and 4. For model selection we apply the Akaike Information Criterion (AIC) as its performance is superior to the Schwarz criterion if the true process exhibits simultaneously long and short run memory (Tschernig, 1992).

Since the maximum likelihood estimation of ARFIMA processes requires stationarity, we difference the data once in order to eliminate the unit root that cannot be rejected and analyse $x_t = \nabla y_t$. However, taking the first differences often induces overdifferencing, e.g. a vanishing spectral density at the origin such that a traditional ARIMA(p, d, q) model, $d \in N$, must be misspecified. This is also true for the first differences of the quarterly German unemployment rates as the periodogram in Figure 1 suggests. By applying specifications that allow for fractional integration, this misspecification is avoided and overdifferencing is no longer an issue. Applying the estimation and selection procedure described above leads to the following estimates:

$$\begin{array}{cccccccc} (1 & - & 1.651B & + & 0.689B^2) & \nabla^{-0.817}x_t & = & \varepsilon_t \\ & & (0.188) & & (0.167) & (0.243) & & \\ & & [8.785] & & [-4.123] & [-3.355] & & \end{array} \tag{16}$$

$$\tilde{\sigma}_\varepsilon^2 = 0.024 \quad AIC = -408.225$$

where the numbers in parentheses and brackets denote the standard errors and t-values for the null of the parameters being zero, respectively. All parameters are significant from zero on the 1%-level.

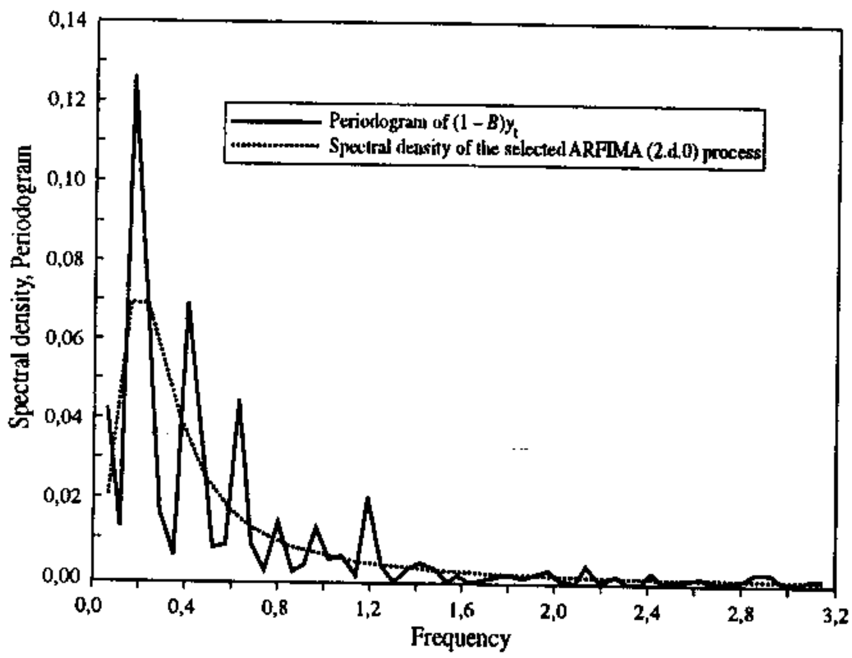

Figure 1: Quarterly German Unemployment Rate (seas. ad.)

In particular, the hypothesis $D = 0$ or $d = 1$ is rejected which clearly contradicts the acception of the unit root by the unit root tests and the estimate of the integration parameter of the series in levels $d = 0.183 = D + 1 < 1$ is plausible. Consequently, the German unemployment rates exhibit long memory, but the point estimate of $d = 0.183$ implies a stationary long memory process in the levels. As a consequence, unemployment rates show no persistence in the definition of Campbell and Mankiw (1987) which contrasts the results of Blanchard and Summers (1988) and Zimmermann (1991). Following the analysis in section 2, shocks nevertheless disappear extremely slowly if $d > 0$. This result is confirmed by the finite cumulative responses c_k for various k in Table 2 as c_k is smaller $1.0e^{-3}$ not before $k = 100000$.

Table 2

Finite cumulative responses for the seasonally adjusted quarterly German unemployment rate based on an ARFIMA(2, d,0) specification with $\alpha_1 = 1.651$, $\alpha_2 = -0.689$, $d = 0.187$

c_0	c_1	c_2	c_3	c_4	c_5	c_6	c_{10}
1.000	1.834	2.447	2.855	3.091	3.188	3.179	2.577
c_{20}	c_{30}	c_{40}	c_{50}	c_{100}	c_{1000}	c_{10000}	c_{100000}
0.939	0.427	0.300	0.243	0.129	0.019	0.003	0.000

Moreover, Table 2 demonstrates that a shock reaches its largest effect in the 5th quarter which indicates a considerable adjustment process. It then is three times as large as the initial effect. Beginning with the 6th quarter, the impact slowly declines as the shock still maintains a quarter of its initial impact after 12.5 years.

These conclusions are stable. As Figure 1 shows, the estimated spectral density fits the periodogram of the first differences very well. Moreover, the parameter estimates remain basically the same if the Whittle estimator (11) is applied. We then obtain

$$\begin{array}{ccccccc} (1 & - & \underset{[8.697]}{\underset{(0.189)}{1.640B}} & + & \underset{[-4.104]}{\underset{(0.166)}{0.681B^2}}) & \nabla^{\underset{[-3.337]}{\underset{(0.240)}{-0.801}}} x_t & = \varepsilon_t \end{array} \tag{17}$$

$$\tilde{\sigma}_\varepsilon^2 = 0.024 \quad AIC = -408.568$$

Nevertheless, some qualifications are necessary. First, one cannot test the null hypothesis that $\alpha_1 + \alpha_2 = 1$ as this would imply non-stationarity. However, the point estimate $\alpha_1 + \alpha_2 = 0.962$ should not be interpreted as evidence for a non-stationary AR-part since $\alpha_1 + \alpha_2 = 1$ would cause the spectral density to approach infinity at the origin which clearly contradicts the periodogram estimate in Figure 1. Second, although the periodogram of the level series shows a sharp peak at the origin and thus indicates a positive d, one cannot reject the null hypothesis that $D = -1$ or equivalently $d = 0$ for which hypothesis the t-value is given by 0.753. Both remarks indicate that one cannot exclude the possibility of a negative bias in $\tilde{d}$ which is compensated by a positive estimation bias for α_1. In fact, the Whittle estimator (11) is known for its negative bias for $\tilde{d}$ (Cheung, 1990). As a consequence, it is not possible to obtain a rejection of the null hypothesis $d = 0.5$ against the alternative of stationarity ($d < 0.5$). Indeed, the corresponding t-value is given by -1.304 and stationarity of the level series is not statistically significant at the 5%-level though the unit root can clearly be rejected. This also suggests that the finite cumulative responses of Table 2 might be underestimated. Third, there might be problems caused by the seasonal adjustment of the data. Based on Monte Carlo evidence Ghysels (1990) concludes that seasonal adjustment filters likely induce higher persistence in the time series although Wolters (1992) presents a counter-example using German output and employment data.

5 Conclusion

Investigating West German quarterly unemployment using the conventional Dickey-Fuller testing procedure, we were unable to reject non-stationarity. However, employing the ARFIMA approach, we find an autoregressive part in the first differences that has a sum of lagged coefficients that is close to unity but we also estimate a long memory parameter of -.82. This indicates that the series is stationary in the levels although the unemployment rate shows long memory. Thus, shocks die out extremely slowly despite a persistence of zero in the definition of Campell and Mankiw (1987) and shocks reach a peak after 5 quarters. The conclusion is that persistence in German unemployment is illusive and the consequence of an inadequate statistical treatement of the data. Similar conclusions may hold for other European countries. This qualifies the need for models explaining fragile equilibria as was advocated for instance by Blanchard and Summers (1988). However, we have to face the fact that this result is achieved by the existence of long-memory so that adjustments in the data are very slow. Here, the theories developed in the hysteresis debate are still of much use.

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