MEASURING SHOCK PERSISTENCE IN AUSTRIAN EMPLOYMENT AND UNEMPLOYMENT SERIES

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1 Introduction [1]

The rising tide of unemployment which has swept over Europe since the mid-1970s has confronted most European economies with steadily upward ratcheting unemployment rates. But while there are plenty of explanations for the initial lift-off phases, it is the fact that unemployment has remained stubbornly high into the late 1980s that poses a serious challenge to traditional Keynesian or classical theories of macroeconomic fluctuations, since they all share the common presumption that in the medium-run economies would be back to some supply-determined "natural" rate of unemployment. However, there appears to be considerable empirical evidence that the equilibrium rates of unemployment have risen substantially in most European countries and tend to follow actually observed unemployment rates quite closely (see e.g. Coe 1985, Metcalf 1987). This has led to the hypothesis that unemployment may be strongly dependent on its own history, a phenomenon labelled as hysteresis or persistence (for an overview see papers in Cross 1988).

Formally, hysteresis occurs in a system when, in discrete time, the system of differential equations possesses a unit root. Econometric evidence for non-stationarity of economic time series has thus become increasingly popular in the analysis of the hysteresis issue in order to reveal "stylized facts" about the process unter consideration. In their well-known discussion of the striking difference in the behaviour of the U.S. and European labour market series Blanchard & Summers (1986) used estimation results of ARMA-models. Their conclusion about (non)-stationarity of the unemployment rate and the employment series, however, suffered from some lack of statistical reliability. Several other authors have provided test results for the same issue based on the regression theory for integrated processes. The outcome of their investigations is summarized in table 1.

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1) We would like to thank A. Jäger and R. Kunst for helpful comments. The views expressed here are those of the authors and do not necessary correspond to those of the Institute for Advanced Studies or its staff.

Table 1
Tests for Autoregressive Unit Roots;
Unemployment Rate (UR), Employment (LD)

series / specification	country	H_0: unit-root
log UR	U.S.[a]	rejected
UR	U.S.[b]	not rejected
UR, incl.MA(1) term	U.S.[b]	ambigous
log UR	U.S.[c]	in most models not rejected
UR	U.S.[c]	in most models not rejected
log UR	Germany[c]	in most models not rejected
UR	Germany[c]	not rejected
log UR	U.K.[c]	in most models not rejected
UR	U.K.[c]	not rejected
log LD	U.S.[a]	not rejected
log LD	U.S.[b]	not rejected
log LD, incl.MA(1)	U.S.[b]	not rejected

Notes: [a]) Nelson & Plosser (1982); [b]) Schwert (1987); [c])Lai & Pauly (1987); Schwert monthly data, all others annual data; time range: Nelson & Plosser 1890-1970, all others postwar data

At least for the European countries the results of Blanchard & Summers are confirmed. For the unemployment rate of Germany and the U.K. non-stationary models seem adequate. The test results for the U.S. case provide mixed evidence. All studies, however, agree that for the U.S. employment series non-stationarity is strongly suggested.

A related approach has been pursued by Barro (1988). In his model the AR1 coefficient of an ARMA(1,k) model for the unemployment rate is a proxy for the magnitude of the gross turnover rate. A high AR1 therefore implies a low job seperation rate and a low job finding rate, which is in turn interpreted as an indicator for high persistence of the process.

The results for annual unemployment rates of selected countries are given in table 2. The relatively high coefficient for Austria gives rise to the hypothesis that the Austrian unemployment rate may - similar to other European countries - show high persistence.

Table 2
ARMA(1,k) Models of Unemployment Rates

country	time range	AR1 coefficient	S.E.
U.S.	1948-86	0.743	(.142)
Germany	1950-86	0.904	(.057)
U.K	1948-86	1.078	(.058)
Austria	1948-86	0.890	(.061)

Source: Barro (1988) p 33.

Against this background our paper adresses the following two questions:

- First, can the Austrian unemployment rate and employment series be characterized as stationary processes, or are non-stationary models adequate implying that at least some fraction of an innovation is permanent?

- Secondly, if there is in fact evidence for shock persistence, what can be said about the magnitude of its long-run impact?

2 Tests for Autoregressive Unit Roots

We begin discussing the persistence hypothesis for Austrian data by taking a close look at the time series properties of the quarterly unemployment rate (LUR) and the quarterly employment series (LLD) covering the time-span from 1951 to 1986. Both series were transformed to natural logs.

Jäger and Kunst (1988) argue, that quantitative measures of persistence are not robust with respect to different methods of seasonal adjustment. So we applied two different procedures: LURX and LLDX have been obtained by Census X-11 smoothing, whereas LUR4 and LLD4 indicate the results of applying the filter $^1/_4(1+L+L^2+L^3)$, i.e. calculating 4 period averages.

The first 12 autocorrelations (r_k) and partial autocorrelations (α_{kk}) of the levels and the first differences of our variables, shown in table 3, allow a rough characterization. The figures indicate that the levels of the series are highly autocorrelated. They start around 0.98 at lag one and decay only slowly. This is a typical non-stationary behaviour suggesting that differencing is required. Indeed, the autocorrelation of the first differences is much lower.

The high first autocorrelation of ΔLURX suggests the existence of an MA(1) term, a specification that is compatible with the α_{kk}. Assuming an MA(1), however, implies that the autocorrelations r_4 and r_8 significantly differ from zero, indicating that there is still a seasonal component left.

ΔLUR4 might be adequatly represented by an AR(2) model despite of two just significant α_{kk} at lag 9 and 22.

For the employment series AR models of order 1 (LLDX) and 2 (LLD4) are indicated. The X-11 case, again shows a significant partial autocorrelation at lag 8.

Table 3

Sample autocorrelations and partial autocorrelations of quarterly series
Periode 51:1 to 86:4, Number of observations = 144

series	k	1	2	3	4	5	6	7	8	9	10	11	12
LURX	r_k	.975	.944	.915	.884	.845	.802	.756	.710	.676	.638	.597	.559
	α_{kk}	.975	-.171	.067	-.079	-.166	-.068	-.087	-.002	.241	-.152	-.018	.058
LUR4	r_k	.981	.955	.925	.892	.856	.819	.780	.738	.698	.657	.618	.579
	α_{kk}	.981	-.233	-.096	-.052	-.050	-.040	-.060	-.045	.012	-.007	-.005	-.007
LLDX	r_k	.982	.964	.944	.924	.903	.879	.853	.826	.798	.771	.744	.717
	α_{kk}	.982	-.058	-.029	-.015	-.054	-.084	-.058	-.064	-.004	.003	-.004	-.006
LLD4	r_k	.982	.963	.944	.924	.904	.883	.860	.836	.810	.783	.757	.730
	α_{kk}	.982	-.035	-.023	-.018	-.029	-.039	-.047	-.059	-.051	-.030	-.018	-.008
ΔLURX	r_k	.321	.002	.067	.200	.031	-.007	-.061	-.252	-.013	.099	-.089	-.175
	α_{kk}	.321	-.112	.115	.158	-.095	.039	-.105	-.277	.216	.007	-.129	.038
ΔLUR4	r_k	.854	.616	.396	.205	.054	-.046	-.113	-.166	-.154	-.115	-.070	-.000
	α_{kk}	.854	-.419	.031	-.114	-.017	-.008	-.057	-.072	.191	-.094	.049	.109
ΔLLDX	r_k	.519	.330	.286	.301	.175	.133	.063	-.123	-.074	-.061	-.058	-.121
	α_{kk}	.519	.083	.118	.136	-.079	.016	-.068	-.253	.083	-.025	.022	-.015
ΔLLD4	r_k	.912	.755	.577	.403	.257	.142	.043	-.041	-.097	-.116	-.106	-.079
	α_{kk}	.912	-.460	-.066	-.055	.054	-.035	-.103	-.051	.098	.077	.001	-.028

Note: The large sample standard error $T^{-1/2}$ is 0.0833 for the levels and 0.0836 for the fist differences.

We apply two formal test procedures in order to decide whether the series are stationary or non-stationary. Strictly speaking - as explosive cases are neglected - the hypothesis of a distinct class of non-stationary models, which include an autoregressive unit-root, is tested (for a general discussion see Dickey et al. 1986). Both tests rest on the assumption that the data generating process has a sufficient AR representation[2]. The well-known "augmented Dickey Fuller" (ADF) procedure uses the following models:

$$(1) \quad \Delta Y_t = \mu + \alpha\, Y_t + \Sigma\, \beta_j\, \Delta Y_{t-j} + e_t \qquad j = 1,..p$$

$$(2) \quad \Delta Y_t = \mu + \alpha\, Y_t + \Sigma\, \beta_j\, \Delta Y_{t-j} + \delta\, t + e_t$$

In case of a unit root (null hypothesis) the parameter α should not be significantly different from zero, compared to the values of the distribution of α as given in Fuller (1976).

Model (2) sets the null hypothesis of a non-stationary process - in case of j=0 a random walk (with drift) - against the alternative hypothesis of a stationary AR(j), whereas in (3) the alternative is a stationary process around a time trend.

An additional test procedure for unit roots has been provided by Stock and Watson (1986). Again, the null hypothesis is that the process Y_t follows an AR model with exactly one unit root. In more detail Y_t is explained as the sum of a pure random walk W_t and a stationary part S_t. The idea is to determine S_t, subsequently extract W_t and then - by making use of a provided test statistic (SW) - decide wether the result is in fact a random walk. The filter applied on Y_t to remove the stationary component is derived from an AR model of adequate order for $(1-L)Y_t$.

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2) Doubtlessly the finding that many economic time series contain moving average components in general strongly objects to this assumption (see Schwert (1987)).

Both the ADF and the SW depend on fitting appropriate AR polynomials i.e. their significance might depend on the order of lags included. Therefore we tested several specifications, varying the number of lags from 1 to 8, including the models suggested by the inspection of the ACF and PACF [3].

Table 4a shows the results of the tests applied to the levels of the variables under consideration. In case of the unemployment series the null hypothesis of a unit root cannot be rejected regardless of the model - i.e. with or without a trend - and of the seasonal adjustment procedure. For the employment series the results are, however, ambiguous. Especially in case of an autoregressive correction of order 4 the ADF-test rejects the null hypothesis.

The results of the application of the tests to the first differences are reported in table 4b. In all specifications the hypothesis of a unit root is rejected, supporting the hypothesis of an integration of order one - at least for the unemployment rate.

3) According to the usual practice the MA(1) model for ΔLURX is approximated by an autoregressive process of order 1. Additionaly we compared the t-statistic of a ARIMA(1,1,1) for LURX with the critical values provided by Schwert (1987, table 7 and table 10). Again, for a model without a trend, the null hypothesis of a autoregressive unit root can not be rejected.

Table 4a

Tests for autoregressive unit roots, levels

Number of observations = 144

series	k	d^{μ}	d^{τ}	q^{μ}	q^{τ}
LURX	1	-1.522	-0.746	-4.101	-2.465
	2	-1.667	-0.556	-3.934	-1.847
	3	-2.098	-0.911	-5.234	-2.976
	4	-2.672*	-1.478	-7.075	-4.633
	5	-2.031	-1.138	-6.117	-3.873
	6	-2.053	-1.130	-6.861	-3.861
	7	-2.259	-0.956	-6.114	-3.407
	8	-1.812	-0.120	-4.028	-1.217
LUR4	1	-2.258	-1.938	-6.932	-5.326
	2	-1.910	-0.989	-5.239	-3.045
	3	-2.385	-1.236	-6.252	-3.661
	4	-2.463	-0.984	-5.913	-3.027
	5	-1.978	-0.596	-4.988	-2.149
	6	-2.117	-0.572	-5.277	-2.244
	7	-1.998	-0.369	-5.017	-1.886
	8	-1.862	-0.024	-4.537	-1.297
LLDX	1	-1.699	-1.497	-1.715	-5.240
	2	-2.420	-2.027	-2.399	-6.683
	3	-2.821*	-2.617	-2.871	-8.151
	4	-3.846***	-3.905**	-3.561	-9.876
	5	-3.057**	-3.364*	-3.290	-9.815
	6	-2.540	-3.173*	-3.149	-9.564
	7	-2.386	-2.929	-2.886	-9.113
	8	-2.293	-1.991	-2.128	-6.319
LLD4	1	-1.727	-3.881	-3.210	-7.570
	2	-2.073	-2.527	-2.491	-8.040
	3	-2.589*	-2.697	-2.693	-8.067
	4	-3.751***	-3.519**	-3.043	-8.674
	5	-3.364**	-3.369*	-2.955	-8.944
	6	-2.687*	-2.581	-2.476	-7.800
	7	-2.582*	-2.202	-2.212	-6.671
	8	-2.231	-1.846	-1.940	-5.556

Notes: d^{μ},d^{τ} are the Dickey-Fuller test-statistics in a model excluding and including a linear trend; q^{μ},q^{τ} are the respective Stock-Watson test-statistics; *,**,*** indicate the rejection of the null hypothesis of a unit root at a 10%,5%,1% significance level; k is the number of autoregressive corrections

Table 4b
Tests for autoregressive unit roots, first differences
Number of observations = 143

series	k	d^{μ}	d^{τ}	q^{μ}	q^{τ}
LURX	1	-7.576***	-7.874***	-98.482***	-101.73***
	2	-5.779***	-6.219***	-91.335***	-94.762***
	3	-4.594***	-5.179***	-92.136***	-94.507***
	4	-4.735***	-5.523***	-92.762***	-94.822***
	5	-3.753***	-4.302***	-92.288***	-94.794***
	6	-4.077***	-4.700***	-90.457***	-93.781***
	7	-5.259***	-6.423***	-90.367***	-95.075***
	8	-3.681***	-4.735***	-84.094***	-88.406***
LUR4	1	-4.749***	-5.088***	-34.090***	-37.035***
	2	-4.324***	-4.795***	-29.854***	-33.396***
	3	-4.730***	-5.542***	-29.643***	-33.804***
	4	-4.582***	-5.636***	-28.593***	-33.710***
	5	-4.171***	-5.129***	-27.473***	-32.800***
	6	-4.011***	-5.193***	-26.431***	-32.585***
	7	-4.005***	-5.360***	-25.900***	-32.306***
	8	-3.014**	-4.155***	-21.316***	-28.456***
LLDX	1	-5.240***	-5.385***	-61.632***	-63.834***
	2	-4.623***	-4.925***	-61.314***	-63.527***
	3	-4.017***	-4.439***	-62.670***	-64.354***
	4	-4.618***	-5.353***	-65.605***	-66.783***
	5	-3.613***	-4.205***	-64.792***	-66.015***
	6	-3.342**	-3.814**	-62.716***	-64.181***
	7	-4.239***	-4.736***	-57.228***	-59.233***
	8	-3.655***	-4.096***	-65.436***	-67.815***
LLD4	1	-3.916***	-4.094***	-23.719***	-24.899***
	2	-4.117***	-4.400***	-23.222***	-24.683***
	3	-4.400***	-4.861***	-22.904***	-24.774**
	4	-4.400***	-5.195***	-20.819***	-23.444**
	5	-4.056***	-4.861***	-21.034***	-24.012**
	6	-3.928***	-4.594***	-20.432**	-23.113**
	7	-3.662***	-4.272***	-19.176**	-21.810**
	8	-3.028***	-3.413***	-16.329**	-18.601*

Notes: d^{μ},d^{τ} are the Dickey-Fuller test-statistics in a model excluding and including a linear trend; q^{μ},q^{τ} are the respective Stock-Watson test-statistics; *,**,*** indicate the rejection of the null hypothesis of a unit root at a 10%,5%,1% significance level; k is the number of autoregressive corrections

3 Persistence and Shock Response Measures

After having shown that a first essential for persistence - the existence of a AR unit root - cannot be rejected, we provide an assessment of the long-run response of the series to a shock.

As Campbell and Mankiw (1987) showed, first order integration alone is not sufficient for assessing the magnitude of shock persistence. Since the process might follow an ARIMA model, the long-run persistence also depends on the value of the MA coefficients. Therefore, they suggest ARMA modeling for the first differences. Consider the following ARMA representaion of the change in Y_t

$$(3) \qquad \phi(L)\,(1-L)Y_t = \phi(L)\,\Delta Y_t = \theta(L)\,e_t$$

with the moving average representation

$$(4) \qquad \Delta Y_t = \phi(1)^{-1}\theta(L)\,e_t$$
$$= A(L)\,e_t\ .$$

Under the hypothesis that ΔY_t is stationary, $\Sigma\, A_i^2$ is finite implying that the limit of A_i is zero as i goes to infinity. Then a MA representation of the level of the process

$$(5) \qquad Y_t = (1-L)^{-1}\,A(L)\,e_t$$
$$= B(L)\,e_t$$

can be found where the coefficients of B(L) are given by

$$(6) \qquad B_\tau = \Sigma\, A_i \qquad\qquad i=0,..\tau.$$

If Y_t is non-stationary the limit of B_τ for τ going to infinity is not zero and indicates how much an innovation changes a forecast over a long horizon.

After having determined A(L) on the basis of an adequate ARMA model, the values of B_τ for large τ - i.e. the response of $LUR_{t+\tau}$ to an innovation at time t - can be calculated easily. The limit of B_τ is the infinite sum of A_i coefficients, A(L=1), which also can be directly computed.

Though the inspection of the ACF and PACF did not immediately suggest models of higher order, we follow the approach of Campbell & Mankiw and provide the estimation results[4] for ARMA models up to order (3,3) for the first differences of our variables (see tables A1 - A4 in the appendix). First, this proceeding allows to check wether there are more adequate specifications than our initial guesses and secondly, it might be useful to explore how sensitive the quantitative measures of a process' persistence are with respect to different specifications.

In general fitting models for the X-11 adjusted data turned out to be much more difficult than for their 4-period counterparts. (Note the substantial autocorrelation in the residuals of the models for LURX and LLDX.) Compared to the AIC the initial model selections are - by and large - confirmed.

Tables 5a to 5d show the impulse response models for the series under consideration calculated on the basis of the MA representation of the first differences according to equation (6).

In case of the unemployment rate most specifications lead to the result of a long term persistence *greater than one*. The results for LUR4 (table 5a) indicate that a 1 percent innovation in the unemployment rate increases the univariate forecast between 1.2 and 1.7 percent over any predictable horizon for specifications including an AR-term. The shock persistence for pure MA-models, however, is less than 1. The long run results for LURX are quite similar, lying between 1.3 and 1.9 percent.

4) The results have been obtained by the RATS-procedure BOXJENK.

The calculation of the impulse response models for the employment series LLD4 (table 5c) and LLDX (table 5d) yields much bigger figures. Whereas the one-periode shock persistence is quite similar to that of the unemployment rate, the employment series LLD4 shows a long run persistence of 2.6 to 3.8 in models with AR-terms. The respective values for LLDX lie between 2.5 and 4.0 . In view of the ambigous results of the stationarity tests and the unsatisfactory fit of the estimated ARMA-models reported above, one can call in question the reliability of these results.

Table 5a
Model impulse response, LUR4

model p,q	1	2	3	12	20	40	∞
1,0	0.464	0.647	0.804	1.466	1.657	1.730	1.734
1,1	0.552	0.782	0.958	1.457	1.514	1.522	1.522
1,2	0.556	0.800	0.978	1.419	1.454	1.457	1.457
1,3	0.555	0.804	1.001	1.395	1.412	1.413	1.413
2,0	0.551	0.811	0.999	1.214	1.206	1.207	1.207
2,1	0.556	0.813	0.998	1.265	1.263	1.263	1.262
2,2	0.557	0.813	0.998	1.248	1.242	1.242	1.242
2,3	0.551	0.797	0.998	1.183	1.180	1.180	1.180
3,0	0.555	0.816	1.005	1.251	1.246	1.246	1.246
3,1	0.557	0.803	0.985	1.231	1.227	1.227	1.227
3,2	0.528	0.782	0.981	1.131	1.167	1.166	1.166
3,3	0.568	0.817	1.000	1.331	1.342	1.342	1.339
0,1	0.460	0.460	0.460	0.460	0.460	0.460	0.460
0,2	0.530	0.683	0.683	0.683	0.683	0.683	0.683
0,3	0.551	0.747	0.830	0.830	0.830	0.830	0.830

Notes: B_τ, the persistence measure at time τ, equals ΣA_t ($t=0,..\tau$), where A_t are the coefficients of the MA representation A(L) (impulse response function) of the respective ARIMA(p,1,q)-model; the persistence at ∞ is obtained by evaluating this MA Lag-polynomial at A(L=1)

Table 5b
Model impulse response, LURX

model p,q	1	2	3	12	20	40	∞
1,0	1.321	1.424	1.467	1.472	1.472	1.472	1.472
1,1	1.361	1.393	1.396	1.396	1.396	1.396	1.396
1,2	1.359	1.389	1.402	1.410	1.410	1.410	1.410
1,3	1.333	1.367	1.436	1.512	1.513	1.513	1.513
2,0	1.352	1.365	1.330	1.317	1.315	1.317	1.317
2,1	1.360	1.357	1.344	1.344	1.344	1.344	1.344
2,2	1.426	1.431	1.469	1.460	1.456	1.454	1.454
2,3	1.487	1.445	1.535	1.530	1.521	1.512	1.508
3,0	1.371	1.360	1.416	1.508	1.509	1.509	1.509
3,1	1.355	1.346	1.378	1.700	1.739	1.745	1.745
3,2	1.267	1.325	1.451	1.889	1.897	1.895	1.895
3,3	1.301	1.322	1.449	1.766	1.779	1.779	1.779
0,1	1.353	1.353	1.353	1.353	1.353	1.353	1.353
0,2	1.365	1.367	1.387	1.387	1.387	1.387	1.387
0,3	1.440	1.454	1.291	1.291	1.291	1.291	1.291

Notes: B_τ, the persistence measure at time τ, equals ΣA_t ($t=0,..\tau$), where A_t are the coefficients of the MA representation A(L) (impulse response function) of the respective ARIMA(p,1,q)-model; the persistence at ∞ is obtained by evaluating this MA Lag-polynomial at A(L=1)

Table 5c
Model impulse response, LLD4

model p,q	1	2	3	12	20	40	∞
1,0	0.483	0.702	0.905	2.118	2.820	3.539	3.785
1,1	0.577	0.869	1.132	2.456	3.007	3.357	3.409
1,2	0.581	0.902	1.185	2.505	2.975	3.216	3.236
1,3	0.581	0.926	1.270	2.568	2.859	2.942	2.944
2,0	0.587	0.930	1.243	2.415	2.596	2.624	2.624
2,1	0.584	0.928	1.246	2.408	2.534	2.543	2.544
2,2	0.580	0.927	1.247	2.496	2.535	2.550	2.550
2,3	0.582	0.933	1.279	2.419	2.563	2.583	2.583
3,0	0.583	0.929	1.250	2.422	2.546	2.553	2.553
3,1	0.591	0.942	1.267	2.570	2.868	2.970	2.974
3,2	0.554	0.879	1.196	2.379	2.960	3.417	3.521
3,3	0.578	0.918	1.249	2.458	2.773	2.881	2.885
0,1	0.464	0.464	0.464	0.464	0.464	0.464	0.464
0,2	0.552	0.709	0.709	0.709	0.709	0.709	0.709
0,3	0.584	0.842	0.955	0.955	0.955	0.955	0.955

Notes: B_τ, the persistence measure at time τ, equals ΣA_t $(t=0,..\tau)$, where A_t are the coefficients of the MA representation A(L) (impulse response function) of the respective ARIMA(p,1,q)-model; the persistence at ∞ is obtained by evaluating this MA Lag-polynomial at A(L=1)

Table 5d
Model impulse response, LLDX

model p,q	1	2	3	12	20	40	∞
1,0	1.600	1.961	2.178	2.500	2.505	2.505	2.505
1,1	1.433	1.794	2.096	3.262	3.536	3.619	3.621
1,2	1.485	1.783	2.047	3.310	3.783	4.041	4.066
1,3	1.478	1.768	2.043	3.323	3.772	3.997	4.015
2,0	1.524	1.926	2.204	2.829	2.867	2.869	2.869
2,1	1.471	1.819	2.106	3.268	3.576	3.683	3.687
2,2	1.485	1.795	2.078	3.304	3.684	3.845	3.854
2,3	1.500	1.823	2.061	3.307	3.768	4.018	4.018
3,0	1.502	1.804	2.131	3.154	3.324	3.357	3.358
3,1	1.493	1.766	2.069	3.297	3.602	3.701	3.705
3,2	1.535	1.855	2.139	2.801	2.614	2.401	2.661
3,3	1.411	1.842	2.239	3.277	3.717	3.696	3.699
0,1	1.456	1.456	1.456	1.456	1.456	1.456	1.456
0,2	1.568	1.823	1.823	1.823	1.823	1.823	1.823
0,3	1.529	1.808	1.925	1.925	1.925	1.925	1.925

Notes: B_τ, the persistence measure at time τ, equals ΣA_t ($t=0,..\tau$), where A_t are the coefficients of the MA representation A(L) (impulse response function) of the respective ARIMA(p,1,q)-model; the persistence at ∞ is obtained by evaluating this MA Lag-polynomial at A(L=1)

4 Concluding Remarks

Using formal time-series analysis this paper has investigated into persistence properties of the Austrian unemployment rate and employment series. While the results for the employment process are not very clear-out, indicating the rejection of the persistence hypothesis in a number of cases, we have found strong evidence for shock-persistence in the unemployment rate series. Additionally, we have provided an assessment of the magnitude of shock-persistence along the line of Campbell and Mankiw (1987) pointing, in general, towards a long-term persistence greater than one. Loosely speaking, this analysis would suggest that there exist - at least with respect to the rate of unemployment - "good" and "bad" equilibria in the Austrian labour market with the attained equilibrium position being dependent on the history of shocks. Taken at face value, our results also carry the strong implication that you should change your long-run labour market forecast by more than one percent if a one percent innovation occurs.

Obviously, the aggregate time-series analytical approach employed in this paper comes short in identifying the structural reasons why there is persistence in the Austrian unemployment rate. Thus, firm policy conclusions are difficult to draw at this stage of the analysis. The results of our analysis, however, seem to suggest that further research attempts to isolate the determinants of persistence of Austrian unemployment will prove a worthwhile activity.

Appendix

Table A1

Estimated parameters of ARMA-models, $\Delta LUR4$

model p,q	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	S.E.	Q	$\alpha(Q)$	ln AIC
1,0	0.855*						0.02548	52.90	0.01	-7.325
1,1	0.762*			0.445*			0.02351	27.55	0.73	-7.472
1,2	0.728*			0.494*	0.086		0.02353	26.21	0.75	-7.456
1,3	0.676*			0.544*	0.168	0.117	0.02353	22.92	0.90	-7.442
2,0	1.204*	-0.411*					0.02315	26.97	0.76	-7.503
2,1	1.110*	-0.330*		0.113			0.02321	27.46	0.73	-7.483
2,2	1.180*	-0.382		0.048	-0.042		0.02329	26.89	0.76	-7.462
2,3	1.182*	-0.431		0.022	-0.011	0.162	0.02319	21.87	0.93	-7.457
3,0	1.218*	-0.440	0.021				0.02328	26.37	0.78	-7.477
3,1	0.452	0.428	-0.242	0.775*			0.02336	23.06	0.90	-7.456
3,2	2.194*	-1.718*	0.478*	-1.083*	0.294		0.02312	26.60	0.77	-7.462
(3,3)	-0.155*	0.716*	-0.121	1.427*	0.476*	0.945	0.02296	28.40	0.69	-7.462
0,1				0.839*			0.03087	131.68	0.00	-6.941
0,2				1.119*	0.613*		0.02579	64.35	0.00	-7.287
0,3				1.206*	0.782*	0.333*	0.02446	41.85	0.13	-7.379

Notes: A * indicates significance at the 5 percent level; Q is the Ljung-Box test-statistic for serial autocorrelation, $\alpha(Q)$ is the marginal significance level of Q; for specifications in paranthesis no convergence was reached

Table A2

Estimated parameters of ARMA-models, ▲LURX

model p,q	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	S.E.	Q	$\alpha(Q)$	ln AIC
1,0	0.321*						0.07430	50.82	0.02	-5.185
1,1	0.087			0.274*			0.07416	42.77	0.11	-5.174
1,2	0.410			-0.050	-0.117		0.07433	42.66	0.12	-5.156
1,3	0.530			-0.191	-0.149	-0.052	0.07456	42.37	0.12	-5.135
2,0	0.352*	-0.111					0.07417	43.05	0.11	-5.174
2,1	0.093	-0.035		0.266			0.07424	40.97	0.16	-5.158
2,2	-0.765*	0.098		1.191*	0.232*		0.07216	40.62	0.16	-5.201
(2,3)	-0.538*	0.374*		1.026*	-0.153	-0.116	0.06923	44.67	0.08	-5.269
3,0	0.371*	-0.149	0.114				0.07393	38.48	0.23	-5.183
3,1	0.954*	-0.348*	0.164*	-0.598*			0.07327	38.77	0.22	-5.170
3,2	1.423*	-1.045*	0.322*	-1.156*	0.723*		0.07175	37.31	0.27	-5.197
3,3	1.300*	-0.872*	0.196	-0.998*	0.502	0.165	0.07176	33.89	0.42	-5.183
0,1				0.353*			0.07367	42.44	0.12	-5.203
0,2				0.365*	0.021		0.07318	43.67	0.10	-5.201
0,3				0.440*	0.013	-0.162*	0.07377	45.90	0.06	-5.171

Notes: A * indicates significance at the 5 percent level; Q is the Ljung-Box test-statistic for serial autocorrelation, $\alpha(Q)$ is the marginal significance level of Q; for specifications in paranthesis no convergence was reached

Table A3

Estimated parameters of ARMA-models, ▲LLD4

model p,q	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	S.E.	Q	$\alpha(Q)$	ln AIC
1,0	0.933*						0.001662	63.05	0.00	-12.785
1,1	0.898*			0.410*			0.001526	34.19	0.41	-12.942
1,2	0.878*			0.444*	0.122		0.001519	34.32	0.40	-12.937
1,3	0.829*			0.495*	0.279*	0.229*	0.001499	28.66	0.68	-12.949
2,0	1.347*	-0.442*					0.001492	29.97	0.61	-12.986
2,1	1.401*	-0.492*		-0.066			0.001497	29.39	0.64	-12.966
2,2	1.355*	-0.454		-0.034	0.051		0.001501	30.23	0.60	-12.946
2,3	1.065*	-0.227		0.263	0.212	0.194	0.001491	26.08	0.79	-12.945
3,0	1.331*	-0.390*	0.039				0.001501	29.73	0.63	-12.960
3,1	2.105*	-1.468	0.340	-0.741			0.001497	31.23	0.55	-12.951
3,2	2.449*	-2.132*	0.666*	-1.234*	0.460*		0.001477	31.82	0.52	-12.964
3,3	0.863*	-0.359	0.290	0.449	0.582*	0.335*	0.001497	22.66	0.91	-12.922
0,1				0.857*			0.002809	401.20	0.00	-11.735
0,2				1.207*	0.628*		0.002135	220.41	0.00	-12.270
0,3				1.335*	1.033*	0.451*	0.001842	122.70	0.00	-12.551

Notes: A * indicates significance at the 5 percent level; Q is the Ljung-Box test-statistic for serial autocorrelation, $\alpha(Q)$ is the marginal significance level of Q; for specifications in paranthesis no convergence was reached

Table A4

Estimated parameters of ARMA-models, ▲LLDX

model p,q	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3	S.E.	Q	$\alpha(Q)$	ln AIC
1,0	0.600*						0.004722	62.72	0.00	-10.696
1,1	0.834*			-0.401*			0.004659	48.57	0.03	-10.709
1,2	0.884*			-0.398*	-0.130		0.004640	47.75	0.04	-10.703
1,3	0.877*			-0.399*	-0.129	0.021	0.004656	47.05	0.05	-10.682
2,0	0.524*	0.127					0.004711	56.34	0.00	-10.687
2,1	0.986*	-0.118		-0.514			0.004680	47.47	0.05	-10.686
2,2	0.726	0.118		-0.240	-0.161		0.004682	47.01	0.05	-10.671
2,3	0.184	0.617		0.315	-0.387	-0.129	0.004691	47.55	0.05	-10.653
3,0	0.502*	0.050	0.149				0.004685	48.86	0.04	-10.683
3,1	0.750	-0.096	0.145	-0.257			0.004690	46.49	0.06	-10.667
(3,2)	1.660*	-1.709*	0.667*	-1.125*	1.139*		0.004521	63.37	0.01	-10.726
(3,3)	1.574*	-1.649*	0.856*	-1.162*	1.433*	-0.460*	0.004421	49.14	0.03	-10.757
0,1				0.456*			0.005066	109.92	0.00	-10.556
0,2				0.568*	0.255*		0.004861	77.20	0.00	-10.625
0,3				0.529*	0.279*	0.116	0.004853	71.13	0.00	-10.614

Notes: A * indicates significance at the 5 percent level; Q is the Ljung-Box test-statistic for serial autocorrelation, $\alpha(Q)$ is the marginal significance level of Q; for specifications in paranthesis no convergence was reached

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