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Is there Chaos on the German Labor Market?

Ist der deutsche Arbeitsmarkt chaotisch?

By Michael Neugart*, Berlin

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German labor market, chaos, nonlinear dynamics.

Arbeitsmarkt, Chaos, nichtlineare Dynamiken.

Summary

Evidence on the role of chaotic and nonlinear dynamics on labor markets is mixed. It is unclear whether nonlinear relationships are responsible for the dynamic patterns observed in Europe during the past decades. In this paper, we test German labor market data for the null hypothesis of an i.i.d. process with the BDS test. As several processes including chaotic, nonlinear deterministic, and stochastic linear and nonlinear systems are nested within the alternative hypothesis, time series are whitened with linear and nonlinear filters. Lyapunov exponents and correlation dimensions are applied to the residuals of the filtered time series to test for chaotic dynamics. There seems to be a nonlinear deterministic core to German labor market dynamics. Chaos does not occur.

Zusammenfassung

Die empirischen Evidenzen zu nichtlinearen und chaotischen Dynamiken auf Arbeitsmärkten sind unstimmig. Möglicherweise spielen jedoch Nichtlinearitäten auf den Märkten eine wichtige Rolle für die insbesondere in den letzten Jahrzehnten auf den europäischen Arbeitsmärkten zu beobachtenden Dynamiken. Im folgenden werden Zeitreihen für den deutschen Arbeitsmarkt mit Hilfe des BDS Tests auf Nichtlinearitäten untersucht. Da der Nachweis deterministischer Nichtlinearitäten über den BDS Test nicht direkt erfolgen kann, werden die Daten gefiltert. Dadurch können linear stochastische und nichtlinear stochastische Prozesse als Ursache der Verwerfung der Nullhypothese des BDS Tests ausgeschlossen werden. Mit Hilfe von Lyapunov Exponenten und Korrelationsdimensionen wird versucht, chaotische Dynamiken nachzuweisen. Während nichtlineare deterministische Strukturen einen Teil der Dynamik erklären können, scheinen chaotische Prozesse nicht vorzuliegen.

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1. Introduction

Nonlinear labor market models might be capable of explaining labor market dynamics that linear approaches cannot. In the past, various promising attempts with increasing returns in production (Manning 1990 and Mortensen 1989) or externalities in the matching of unemployed and vacancies (Pissarides 1986) were made yielding multiple equilibria. It was also shown that nonlinear adjustment costs for firms may cause asymmetric cycles (Burgess 1993). Labor market dynamics can become chaotic in models with fixed costs in production and real wage adjustment (Chichilnisky et al. 1995) or when labor supply is backward bending (Bolle and Neugart 1998).

It is well known that in chaotic systems long-run forecasts are impossible. But besides the so-called 'butterfly-effect', nonlinear models have very interesting properties even if dynamics are not chaotic. Incorporating nonlinear supply or demand curves into labor market models paves the way for 'fragile equilibria' (Blanchard and Summers 1988). Economies can be stuck at various non-pareto-optimal equilibria. Some of the equilibria may be locally stable, but none of them will be globally stable. This has interesting policy implications, as a small demand policy budget might suffice to move the economy to a high employment equilibrium. Costs of an expansive policy might be even less considering that it is temporary and no detrimental effects from expectation formations can occur (Pissarides 1986). But it may also be the other way around with an economy that is caught at a local low employment equilibrium that is stable for a comparably large parameter set. One can also think of labor market equilibria where supply and demand curves intersect at very flat angles. In this case, once hit by a negative exogenous shock it will take a very long time for the economy to move back towards its equilibrium. Unemployment will be persistent. Clearly, all these properties fit very well to the facts of European unemployment. Given the latter is really a multiple equilibria problem, knowing more about the local stability properties would enable a framework of thinking about efficient employment policies.

Although a nonlinear approach seems to be promising, only few studies exist testing for nonlinearities and chaos in labor market time series. Most of the evidence gained so far focuses on exchange rates, national products and financial time series. Hsieh (1989) investigated daily foreign exchange rates and found evidence for nonlinear dependence. Kugler and Lenz (1990) confirmed results for weekly exchange rates of the Dollar versus the Swiss Franc, the French Franc, the German Mark, and the Yen from 1979 to 1989. Mizrach (1996) delivered evidence for nonlinearities in daily FF/DM exchange rates from 1987–1992. Finally, Cecen and Erkal (1996) tested exchange rates on an hourly basis from January to July 1986 of the British Pound, the German Mark, the Swiss Franc, and the Japanese Yen in terms of the US-Dollar. They argued that nonlinearities are important for the dynamic behavior of exchange rates, but found little evidence for low-dimensional chaos. Frank, Gencay and Stengos (1988) tested quarterly data of the GNP for West Germany, Italy, Japan and the U.K. The authors found no evidence for chaos, but revealed nonlinear structure for the data of Japan. However, due to a comparatively low number of observations, their results should be interpreted with caution. Scheinkman and LeBaron (1989a) searched for nonlinearities in yearly per capita GNP for the U.S. from 1872 to 1986. Nonlinearities, as they argued, may be due to changes in the variance. Both authors (1989b) also discovered that to a certain extent, variation in U.S. stock returns data come from nonlinearities as opposed to randomness. Hsieh (1991), testing stock returns, indicated that nonlinearities are important in terms of variance changes. However, chaotic dynamics do not apply. Barnett and Chen (1988) referred to monetary aggregates as a possible field of non-linear or chaotic dynamics and showed that highly aggregated monetary demand and supply series have chaotic attractors. Finally, Frank and Stengos (1988) examined Canadian aggregates including unemployment data. To their surprise, the hypothesis of randomness could not be rejected. However, as an uncommon algorithm was used by Frank and Stengos, doubts were raised by Medio (1992) about the validity of their results. Brock and Sayers (1987) found nonlinearities in U.S. quarterly employment and unemployment data from 1950 to 1983 and 1949 to 1982. Unemployment series for the US and the UK were tested by Alogoskoufis and Stengos (1991). Neither the UK sample from 1857 to 1987 nor the data for the US from 1892 to 1987 indicated chaotic dynamics. However, Alogoskoufis and Stengos argue for nonlinearities underlying the unemployment dynamics for the UK, while the US unemployment can best be described by a linear model with ARCH errors. Therefore, on the grounds of empirical tests it seems that chaotic dynamics do not apply to labor markets. However, nonlinear relationships cannot be ruled out. This result is confirmed by the following tests of German labor market data.

We will describe the methods to test for nonlinearity and chaos briefly before applying the tools to the data. Data on employment in the manufacturing sector, the labor cost ratio for manufacturing, monthly hours worked in the mining and manufacturing sector, as well as overall registered unemployment will be tested.

2. Tests for Nonlinearities and Chaos

2.1. Lyapunov Exponent

Chaotic systems are characterized by sensitivity on initial conditions. Trajectories, that are nearby at a specific point in time diverge exponentially as time evolves. When a system is chaotic very small errors in the determination of the initial stage (i. e. due to measurement restrictions) will grow exponentially so that forecasts are impossible in the long run. Lyapunov exponents are a measure for this dynamic property. The higher a positive Lyapunov exponent, the less time passes by until the observations fill the entire defined space. The trajectory will eventually fold back as the system is bounded to a set S (attractor) but will never reach the initial value. A common algorithm to determine the rate by which trajectories diverge was proposed by Wolf et al. (1985). This algorithm is used here. Wolf et al. define a fiducial trajectory that is made out of observations following an initial data point. A second point that is next to the starting value in space is chosen then to calculate the distance between these two trajectories until a threshold value is reached. If the threshold is exceeded, the development of the distance can no longer be regarded as a measurement of the local dynamic properties. Therefore, the fiducial trajectory will be compared to a new trajectory starting from a point with a comparable space orientation. The dominant exponent is finally achieved by averaging the exponential growth rates of all the separating pairs of vectors.

2.2. Correlation Dimension

Grassberger and Proccaccia (1983) propose the correlation dimension as another approach to distinguish random from deterministic systems. Here, a time series has to be transformed into a phase space representation. Vectors of length m located in a m-dimensional phase represent the time series. Under the transformation a time series with N data points

$$\{x_1, x_2, \cdots, x_N\}$$

becomes a matrix

$$X = \begin{pmatrix} X_1 \\ X_2 \\ \cdot \\ \cdot \\ X_{N-(m-1)T} \end{pmatrix}$$

with

$$X_i = (x_1 \; x_{i+T} \cdots x_{i+(m-1)T})$$

The dimension of the reconstructed phase space is m (embedding dimension). M has to be chosen large enough to capture the „true" dynamics of the underlying system. This is why large data sets are needed to achieve reliable results given a comparably high dimensional process. T is called the reconstruction delay. As a rule of thumb T is set equal to the value where the autocorrelation function becomes zero for the first time.[1] Two points in phase space are said to be correlated if they lie within a m-dimensional ball with radius r centered around one of the two vectors in space. Counting these points for every vector in phase-space with a Heavyside function yields the correlation integral

$$C(r,m) = \lim_{T_m \to \infty} \frac{1}{T^2} \sum_{i,j=1}^{T_m} H(r - \|X_i^m - X_j^m\|) \tag{1}$$

with the Heavyside function defined as

$$H(y) = 1 \quad \text{if } y > 0$$

$$H(y) = 0 \quad \text{otherwise} \tag{2}$$

The ratio of the logarithm of the correlation integral and the logarithm of the radius of the ball is the correlation dimension:

$$D(m) = \lim_{r \to 0} \frac{\ln C(r,m)}{\ln r} \tag{3}$$

[1] Another method, based on a nonparametric test, is proposed by *Mizrach* (1996).

Distinguishing between deterministic and stochastic processes is possible by calculating the correlation dimensions for various embedding dimensions m. A correlation dimension which grows with the embedding dimension means that the points of the state vector equally fill the space in which the time series was transformed. In this case, the underlying system is called stochastic. However, if the correlation dimension settles to a specific value and becomes independent for different values of the embedding dimension, the process under investigation is deterministic. This is due to a non-random structure underlying the system. Once the embedding dimension of the system is reached, increasing m will not yield another correlation of the vector points in space as their position follows a deterministic rule. As opposed to a random process, points are not equally distributed in the phase space. The slopes of the correlation integrals are equivalent to the correlation dimensions.

2.3. BDS Test

Testing time series with the BDS-statistics (Brock, Dechert, Scheinkman and LeBaron, 1996) builds on the concept of reconstructing the dynamics of a system in space and calculating the correlation integrals.[2] As a random time series of i.i.d. observations follows the rule

$$C_m \approx C_1(r)^m \tag{4}$$

a test statistic can be written as follows

$$B_{m,T}(r) = \frac{\sqrt{T} \cdot [C_{m,T}(r) - C_{1,T}(r)^m]}{\sigma_{m,T}(r)}. \tag{5}$$

Under the null hypothesis of an i.i.d. process the BDS test follows a standard normal limiting distribution. Intuitively, the correlation integral can be interpreted as the probability that a vector in space lies within a m-dimensional ball with a specific radius r centered around a reference point. If the process is i.i.d. the probability that two points in the m-dimensional space lie next to each other will be equal to the probability of the m-th moment of any two points being close together. In this case the numerator will become null. Only if both probabilities differ as the m-dimensional space is unequally filled with vector points the test statistic will become different form zero. The null hypothesis is then rejected. This is consistent with some type of dependence in the data, such as frequently occurring patterns in the time series that result in a cluster. However, as will be pointed out later, the rejection of the null does not necessarily imply nonlinear deterministic dynamics.

[2] The BDS software was downloaded from:
http://www.ssc.wisc.edu/~blebaron/software/index.html

3. Empirical Findings

3.1. Data

The time series that will be investigated for the (West-)German case are taken from the International Statistical Yearbook.[3] Employment (Figure 1) and the labor cost ratio for the manufacturing sector (Figure 2), monthly hours worked in the mining and manufacturing sector (Figure 3) and registered overall unemployment (Figure 4) will be tested. All time series consist of monthly observations starting at the beginning of the sixties. Compared to the studies on nonlinearities in labor market data already done for Canada, the U.K. or the U.S.[4] the time series are rather long.

This makes robust results more probably as it is important to base calculations of the correlation dimensions on comparably large data set.[5] The time series were searched for unit roots, as the tests for nonlinearity require stationary data. Except for the labor cost data, unit roots could not be rejected (Table 1).

Table 1: Unit root tests

Data:	employment	labor costs
Dickey Fuller t-statistic:[6]	– 2.09 (T,2)	– 3.36 (C,2)
MacKinnon critical values:		
1 %	– 3.99	– 3.45
5 %	– 3.42	– 2.87
Data:	**working hours**	**unemployment**
Dickey Fuller t-statistic:	– 1.91 (T,5)	– 2.72 (T,2)
MacKinnon critical values:		
1 %	– 3.99	– 3.99
5 %	– 3.42	– 3.42

[3] International Statistical Yearbook:

Data	Data Set No.
Employment, manufacturing, in thousands of persons, West Germany	12427708; (1994)
Labour cost, manufacturing, ratio, West Germany	1240302; (1996)
Working hours, mining and manufacturing, in millions, West Germany	12428908; (1994)
Registered unemployment, in thousands of persons, West Germany	12428208; (1994)

[4] *Alogoskoufis/Stengos* (1991), *Brock/Sayers* (1987), *Frank/Stengos* (1988).

[5] The time series are in the range of the small sample size generated by *Barnett* et al. (1997) for their competition of tests for nonlinearity and chaos and showed reasonable results.

[6] In brackekts (...,...): T = constant and trend included in test equation; C = constant included in test equation; Number of lagged difference terms in test equation.

Figure 1: Employment for the manufacturing sector; in thousands of persons from 1960.01–1991.12, West Germany

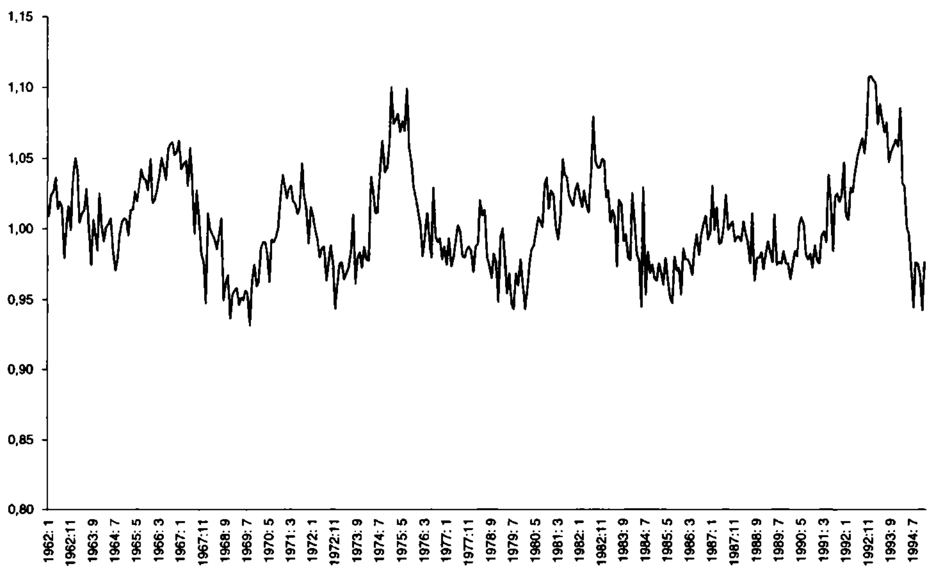


Figure 2: Labor cost ratio for the manufacturing sector from 1962.01–1994.12, West Germany

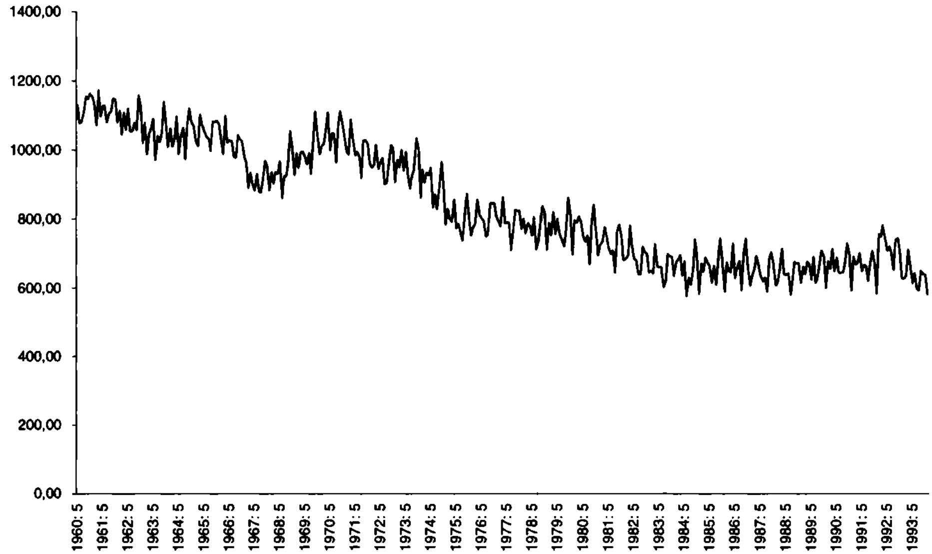


Figure 3: Monthly hours worked; in millions from 1960.05–1993.12, West Germany

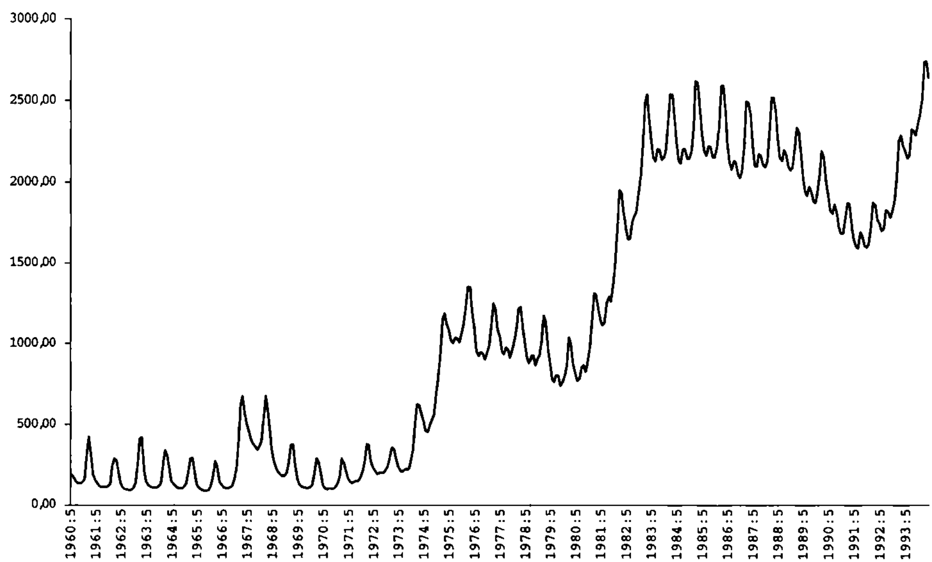


Figure 4: Registered unemployment, in thousands of persons from 1960.05–1994.03, West Germany

Table 2: Tests for linearity in the residuals

Data	employment	labor costs
Box-Pierce:	0.95	0.94
Ljung-Box:	0.90	0.89
Data	working hours	unemployment
Box-Pierce:	0.99	0.33
Ljung-Box:	0.98	0.22

The nonstationary time series were differenced once[7] after the data was seasonally adjusted with a moving average process[8] and logs were taken. With nonstationarities and seasonalities eliminated, stochastic linear and nonlinear underlying systems had to be removed before the BDS test could be applied. This is to be sure that a rejection of the null hypothesis of the BDS test is due to deterministic nonlinear relationships. Otherwise, comparably large test values could not be used to argue for a nonlinear deterministic core in the data which is the necessary condition for chaos.

3.2. Filtering Linear Relationships

The autocorrelation and partial autocorrelation functions were calculated for all four time series up to fifty lags. Based on the values of the autocorrelation and partial autocorrelation functions various models were fitted to the differences of the seasonally adjusted and logged time series. The aim was to eliminate linear relationships as far as possible. As a measure for the goodness of the linear fit the Box-Pierce and Ljung-Box Q-statistics were calculated (Table 2).[9] Both test the hyothesis that all autocorrelations are zero. Values of more than 90 % for the employment, the labor cost, and the working hours data imply little serial correlation. The results on the residuals of the unemployment data are less straight forward but still acceptable. Hence, it was assumed that linear relationships were removed successfully.

3.3. Testing for Nonlinearities

The BDS-test rejected the null hypothesis for the filtered and unfiltered employment series for embedding dimensions from $m = 2 \cdots 10$, although the BDS values are lower for the residuals than for the unfiltered time series (Table 3). This implies that a linear specification cannot capture all the employment dynamics. The residuals hide more information. The same holds true for the dynamics of the working hours and unem-

[7] *Frank/Stengos* (1988) showed that trends should be eliminated by differencing the data in contrast to detrending as the latter might impose structure that could be detected as being chaotic or nonlinear in the following. On the other hand, it should be kept in mind that differencing the data amplifies high frequency noise in relation to low frequencies and the signal to noise ratio deteriorates.

[8] The moving average process covered a whole year and was centred around the current observation. The seasonal factors with which the time series were adjusted had been achieved by taking the mean of the ratios of the moving average process for every month.

[9] The specifications of the linear fits are available on request.

Table 3: BDS tests for employment data

m	Unfiltered data $\sigma = 0.0038$		Residuals of linear fit $\sigma = 0.0029$	
	$r = \sigma$	$r = 2*\sigma$	$r = \sigma$	$r = 2*\sigma$
2	15.05	11.44	6.31	7.27
3	15.98	11.61	6.61	7.03
4	17.68	11.97	7.01	6.96
5	17.48	11.66	6.94	6.72
6	19.49	11.33	6.74	6.55
7	21.72	11.24	6.72	6.49
8	24.54	11.08	6.53	6.38
9	27.80	10.86	6.46	6.24
10	31.76	10.66	6.44	6.19

ployment series (Table 4 and Table 5). Linear specifications do not satisfactorily explain movements of both of these variables. The logged labor cost ratio makes an exemption (Table 6). Here, linear dynamics are given. Hence, we skip labor costs for the tests on chaos as the necessary condition (deterministic nonlinearity) is not fulfilled. As was already indicated, the rejection of the null hypothesis could also be due to nonlinear stochastic processes. Tests on the squared residuals of the linear fits implied conditional heteroscedasticity (ARCH test). However, fits of ARCH and GARCH models to the residuals were not successful. Hence, changing variances were not the stochastic nonlinearities that caused the rejection of the null.

3.4. Is there Chaos?

For the time series where the BDS test rejected the null hypothesis the necessary condition for chaos was fulfilled. Of course, one could argue that the rejection of the null hypothesis for the BDS test does not necessarily imply underlying deterministic nonlinearities. Although ARCH and GARCH models did not explain dynamics in the residuals there might be other stochastic nonlinearities than changing variances being responsible for the dynamic patterns. But as we do not know which stochastic nonlinearities this could be, we have to assume that the null hypothesis of the BDS test was rejected on the grounds of a nonlinear deterministic core. As was already shown, the sufficient condition for chaos which is sensitive dependence on initial conditions can be tested for with Lyapunov exponents. With positive Lyapunov exponents for all three nonlinear time series (Figures 5 to 7) one might be inclined to argue for chaos.[10] Unfortunately, it is impossible to make a clear distinction between a stochastic and a deterministic system when Lyapunov exponents are small. Random noise can cause slightly positive values, too.[11]

[10] The Lyapunov exponents were calculated with the Wolf et al. algorithm at an embedding dimension m = 5. The minimum distance and the threshold value were taken as 2 % and 10 % of the range of the data values respectively. The propagation step size was set to five, so that at every fifth iteration the length of the separation from the fiducial trajectory was measured.

[11] C.f. *Chen* (1993), p. 222.

Table 4: BDS tests for working hours data

m	Unfiltered data $\sigma = 0.0485$		Residuals of linear fit $\sigma = 0.0315$	
	$r = \sigma$	$r = 2^*\sigma$	$r = \sigma$	$r = 2^*\sigma$
2	11.10	11.22	4.49	5.04
3	12.47	9.90	5.16	5.06
4	12.72	9.20	5.44	5.20
5	12.61	8.39	5.61	5.23
6	12.97	7.68	5.42	5.14
7	13.33	7.12	5.24	4.92
8	14.01	6.78	4.66	4.68
9	15.11	6.47	4.02	4.48
10	18.07	6.47	4.00	4.45

Table 5: BDS tests for unemployment data

m	Unfiltered data $\sigma = 0.1074$		Residuals of linear fit $\sigma = 0.0662$	
	$r = \sigma$	$r = 2^*\sigma$	$r = \sigma$	$r = 2^*\sigma$
2	12.29	8.30	10.88	4.86
3	13.73	8.10	12.25	5.78
4	14.00	7.40	13.88	6.50
5	14.13	7.17	15.38	6.95
6	14.74	6.68	17.18	7.25
7	15.30	6.02	19.24	7.42
8	15.89	5.63	22.19	7.56
9	17.05	5.61	26.69	7.87
10	20.74	5.73	32.33	8.34

Table 6: BDS tests for labor cost data

m	Unfiltered data $\sigma = 0.0336$		Residuals of linear fit $\sigma = 0.0166$	
	$r = \sigma$	$r = 2^*\sigma$	$r = \sigma$	$r = 2^*\sigma$
2	40.85	30.97	1.51	2.27
3	46.08	31.24	1.28	1.89
4	52.19	30.95	0.94	1.37
5	60.99	30.76	1.08	1.27
6	73.00	30.83	0.90	1.22
7	89.82	31.16	0.69	1.18
8	111.91	31.66	0.48	1.11
9	142.53	32.36	0.15	1.13
10	184.91	33.22	−0.30	1.07

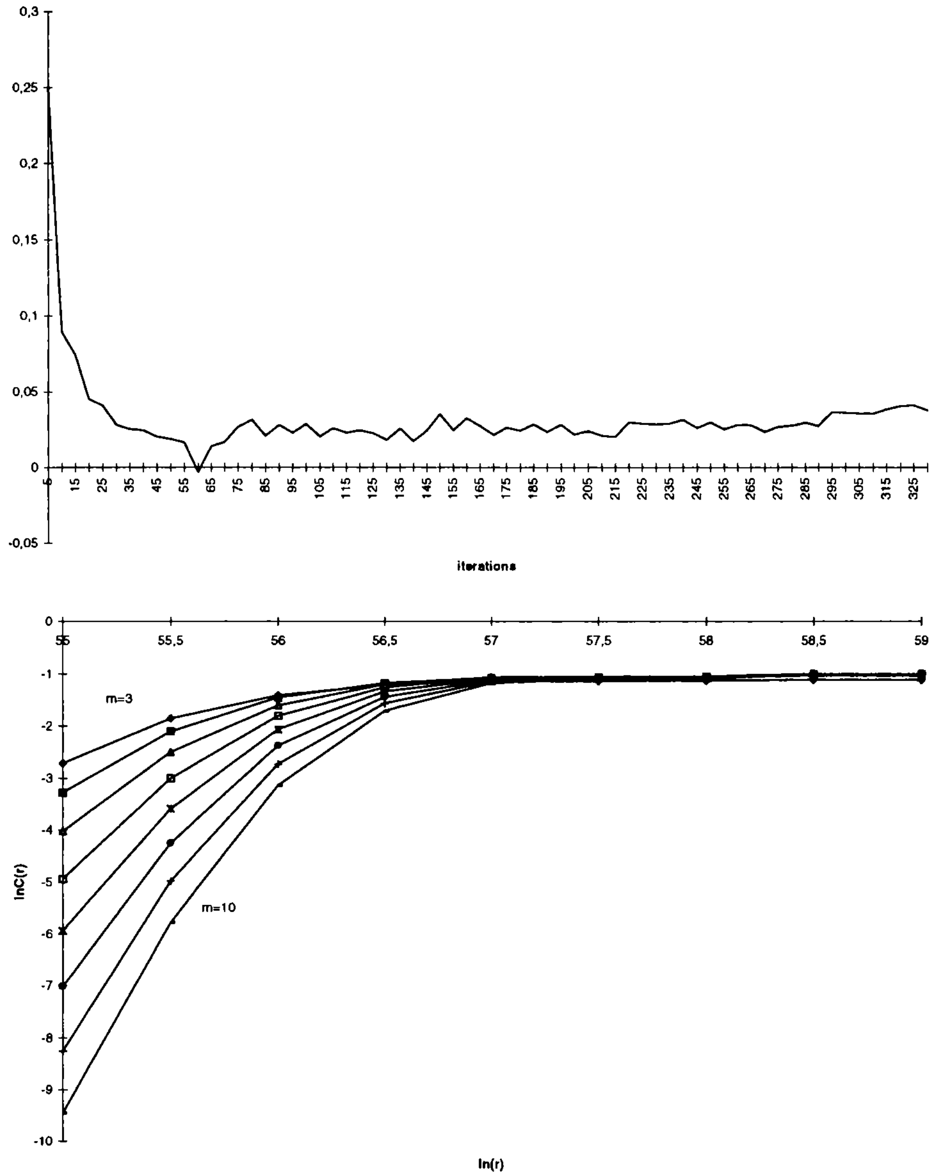
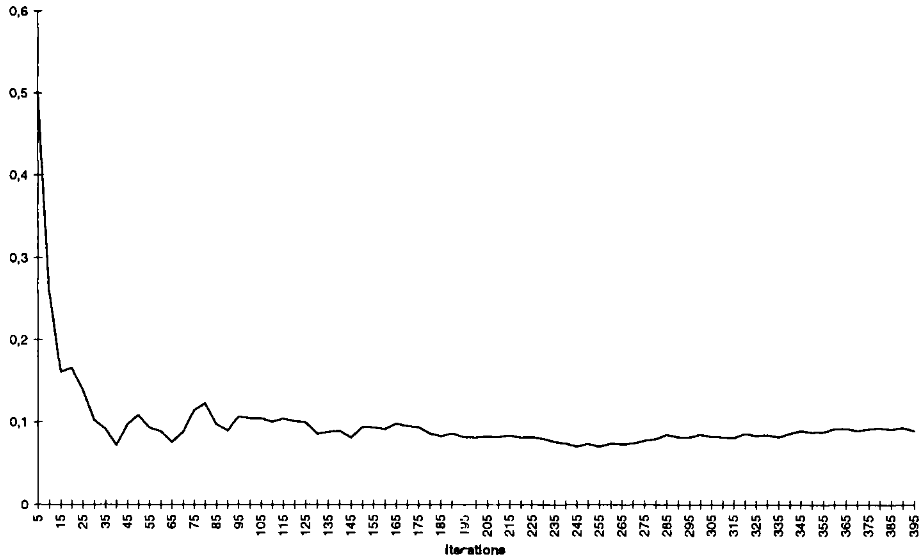


Figure 5: Lyapunov exponent of residuals of linear fit to employment data, m = 5, and correlation dimensions (bottom)



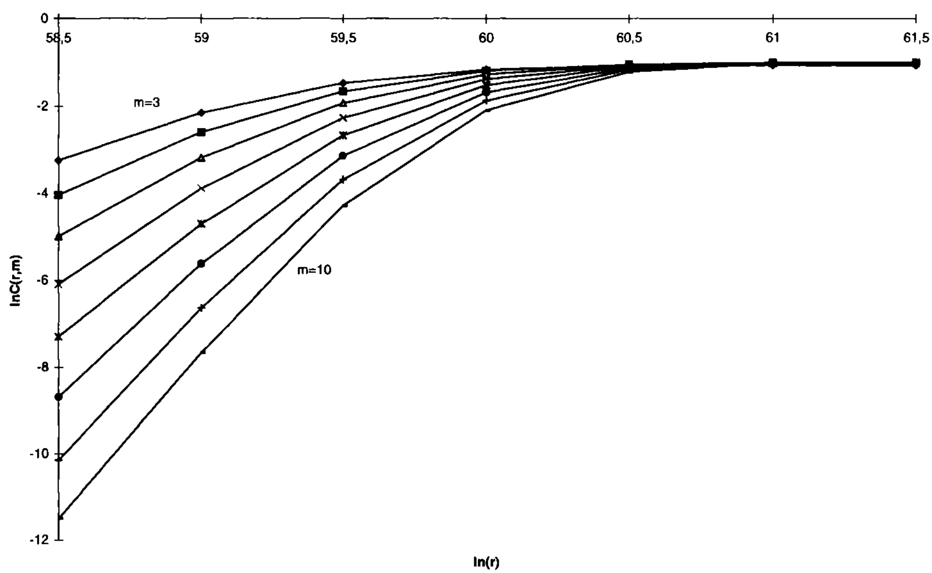


Figure 6: Lyapunov exponent of residuals of linear fit to working hours data, m = 5, and correlation dimensions (bottom)

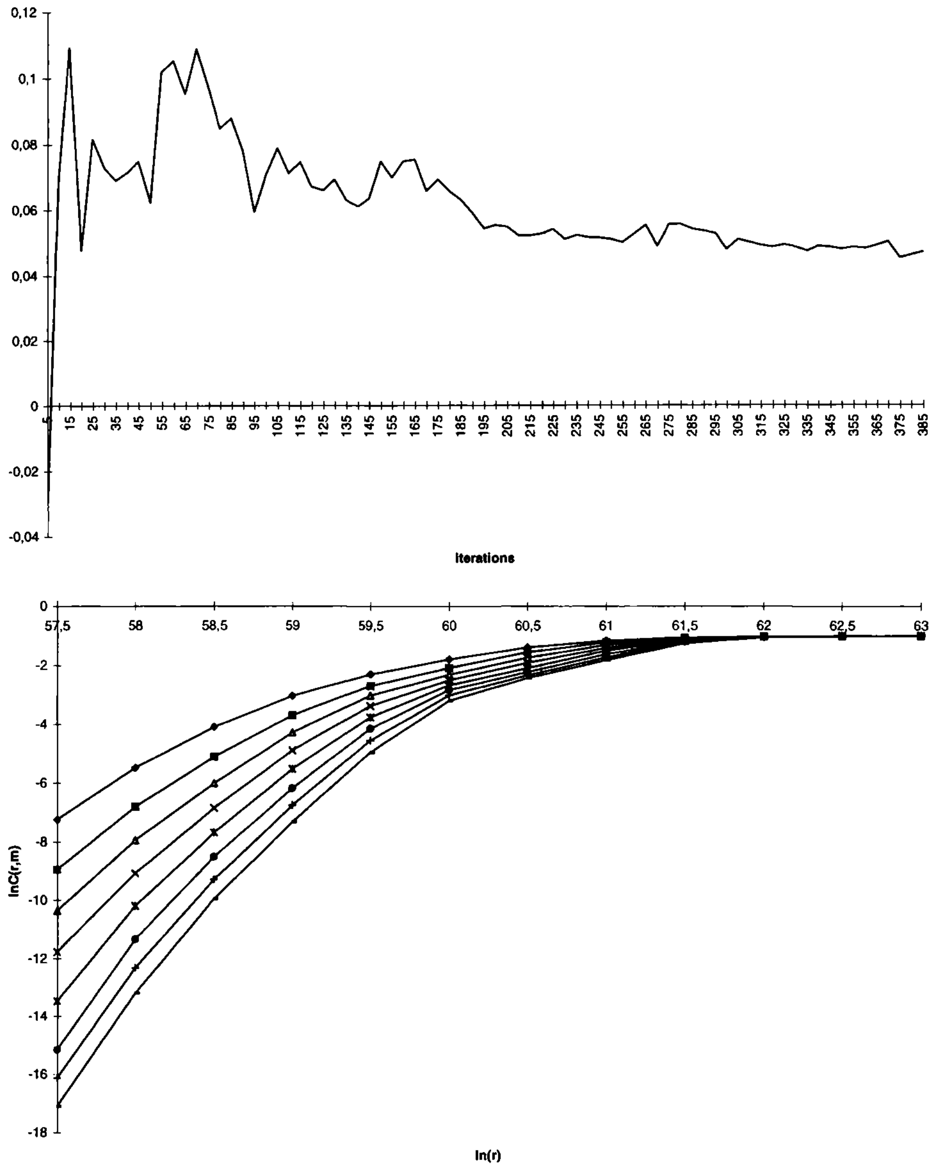


Figure 7: Lyapunov exponent of residuals of linear fit to unemployment data, m = 5, and correlation dimensions (bottom)

Thus, the answer on whether there are chaotic dynamics becomes critically dependent on the quality of the data and the impact on the signal to noise ratio of differencing. It is reasonable to conclude that none of the time series are chaotic. Furthermore, correlation integrals corroborate the result. No saturation level occurs for the correlation dimensions with increasing m as it would happen in the chaotic case.[12] This can be seen from the slopes of the correlation integrals.

4. Conclusion

The nonlinear relationships found for the German data confirm the results of Alogoskoufis and Stengos (1991) for the British unemployment data and the evidence of Brock and Sayers (1988) for U.S. employment and unemployment. Although the capability of the applied tests is certainly limited[13] the empirical results bear important implications for the development of labor market models. There is information in the residuals that linear models do not exploit but could be used in terms of forecasting. It furthermore implies that nonlinear relationships are partly responsible for the labor market dynamics we observe. However, as the BDS-test does not reveal the type of nonlinearity that causes the dynamic patterns we do not know on what kind of nonlinear relationships we have to focus on. A way out is to incorporate potentially important nonlinearities into existing labor market models. The dynamic properties of these models will show whether specific nonlinearities are capable of explaining the facts. If so, these models can be used as a framework of thinking about policy measures that take more sophisticated landscapes, those beyond a single and globally stable equilibrium, into account. Knowing about the stability properties of the current state of an economy may help to economize on the costs of employment policies.

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[12] Actually the correlation integral is supposed to become zero. However, as r is not chosen big enough to capture all points in phase space, the correlation integral reaches the theoretical value only approximately.

[13] Robust results can only be obtained with large sample sizes (*Barnett* et al. 1997). Filtering the data to eliminate linear dependencies might be a further pitfall. Chen (1993, p. 229) showed that the probability density changes under different filters. Hence, the correlation dimension is not invariant under the transformation.

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Michael Neugart, FU Berlin, FB Politische Wissenschaften, Institut für ökonomische Analyse politischer Systeme (WE 2), Ihnestraße 22, D-14195 Berlin.