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EMPLOYMENT AND BUSINESS CYCLE ASYMMETRIES: A DATA BASED STUDY

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ABSTRACT

Does the magnitude of a trough in employment differ from the magnitude of a peak in employment, and is the time employment spends in rising from a trough to a peak longer than the time spends in falling from a peak to a trough? In this paper we measure the "asymmetry of magnitudes" and the "asymmetry of durations" of seven US postwar employment series. The series are detrended using the Hodrick–Prescott filter prior to the analysis. Appropriate measurements of the two types of asymmetry are the skewness of the detrended series and the skewness of the first differenced detrended series, respectively. Monte Carlo and bootstrapping procedures are used to evaluate the significance levels. Five out of seven series show negative skewnesses in levels as well as in first differences. The skewnesses of "magnitudes" and "durations" of US aggregate employment are significant, and yield –0.50 and –0.60 respectively.

In the second part of the paper a nonlinear AR model is derived from the theory of Hermitian type polynomials that have the potential to realize stochastic asymmetric self-sustained oscillations. In contrast with the standard linear AR model, the nonlinear AR model, fitted to the employment series, accurately generates the two types of asymmetry.

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"It was clear that, while it was being built, the architect was constantly in conflict with the owner's tastes. The architect was a pedant and was in favour of symmetry."

Nikolai Gogol
Dead Souls, 1842

1. INTRODUCTION

Half a century ago several economists were well aware of the importance of "asymmetry of durations", that is the fact that time economies spend in rising from a trough to a peak importantly differs from time economies spend in falling from a peak to a trough[2]. After a long period of torpor, the notion has revived that typical nonlinear phenomena of economic time series such as irreversibility and asymmetries cannot be explained by linear time series models, and may be important issues. Recently, postwar US unemployment has been found to show considerable asymmetry of durations over the business cycle[3].

Basically, business cycles may demonstrate two types of asymmetry. The second type of business cycle asymmetry is characterized by the fact that on average the magnitude of a trough differs from the magnitude of a peak. In a recent paper Sichel (1989) provided evidence for the presence of "asymmetry of magnitudes" in quarterly postwar U.S. unemployment series, real GNP, and industrial production.

Since labor supply does not show asymmetry over time (cf. DeLong and Summers, 1986), it is to be expected that time series of employment data exhibit asymmetric cyclical movements as well. This paper investigates asymmetric dynamic properties of seven postwar US employment series. The series are US aggregate employment, white male employment, white female employment, nonwhite male employment, nonwhite female employment, professional employment, and nonfarm laborers. Theories of asymmetric adjustment costs and heterogeneous workers displacement predict that cyclical moves substantially differ between different employment categories[4].

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[2] See, for example, Keynes (1936), Kaldor (1940), Goodwin (1951), Hicks (1951), and Burns and Mitchell (1946).

[3] See, for example, Neftçi (1984), DeLong and Summers (1986), Falk (1986), Stock (1987), and Hamilton (1989).

[4] See Pfann and Palm (1989), Pfann and Verspagen (1989), and Pfann (1990) on asymmetric adjustment costs of heterogeneous labor in the Netherlands and the U.K., and Rogerson (1990) on heterogeneous labor in U.S. business cycle models.

Measuring asymmetry over the cycle is not straightforward. Nonstationarity of the series should be appropriately removed before a statistical procedure can sensibly be applied. In stead of first differencing or linear detrending, the natural procedure for filtering the data is the Hodrick Prescott filter. The HP filter removes the time dependency of the series mean but does not affect its cyclical behavior. Then the skewnesses of the detrended series and the skewness of the detrended series in first differences can be computed in order to measure the asymmetry of magnitude and the asymmetry of durations, respectively. To account for serial correlation and distributional nonnormality Monte Carlo and bootstrapping simulation procedures have been used for the evaluation of the marginal significance levels. The results of this exercise are presented in section 2.

Section 3 of the paper is concerned with the derivation of an appropriate nonlinear AR model. Ozaki (1982, 1984) introduced a nonlinear model for the statistical analysis of time series from general nonlinear random vibrations and explained asymmetric phenomena using the model. The model is a parametric specification of the dynamics of the characteristic roots of an autoregressive model. Hermitian type polynomials that have the potential to realize stochastic asymmetric self-sustained oscillations form the basis of the nonlinear AR model. In section 4 a simple approximation of Ozaki's exponential AR model is fitted to the seven US employment series. Special attention is paid to the nonlinear model's ability to endogenously generate asymmetry of magnitudes and asymmetry of durations. The asymmetries that result from a simulation exercise including the marginal significance levels are presented. In section 5 conclusions are drawn.

2. MEASURING ASYMMETRY

In this section the skewnesses are calculated from seven postwar quarterly US employment data series. Source of the basic data is the US Household Survey data bank. US aggregate employment, US white male employment, US white female employment, US nonwhite male employment, and US nonwhite female employment run from 1954.I to 1990.IV. Due to a breakdown in the definitions of US professional employment and US nonfarm laborers after 1982, these series only run from 1958.I to 1982.IV. All series are seasonally adjusted. First, the series are detrended using the Hodrick Prescott filtering procedure that leaves unaltered the so called business cycle facts. The HP filtering procedure is described in Prescott (1986). Figures 1a to 7a display the actual and trend employment. Figures 1b to 7b show the deviations from trend of the seven employment series.

DeLong and Summers (1986) pointed out that the natural way to infer about possible asymmetry is to compute the series frequency distribution coefficient of skewness. The coefficient of skewness is given in Snedecor (1956)

$$\hat{SK} = \frac{m_3}{\sqrt{m_2^3}}. \tag{2.1}$$

where m_2 and m_3 are the second and third centered moments of the series x_t, respectively. A negative skewness indicates a distribution with more than half its observations above the mean. Negative skewness in the detrended series implies that the magnitude of troughs exceeds the magnitude of peaks. Negative skewness in the first differenced detrended series points at relatively more time spent in rising from a trough to a peak than time spent in falling from a peak to a trough.

Figures 1c to 7c and figures 1d to 7d present the filtered employment series frequency distributions in levels and in first differences respectively. Optical inspection of these figures show that US aggregate employment, US white male employment and US nonwhite female employment levels are negatively skewed (asymmetry in magnitudes). Moreover, US aggregate employment, US white male employment, and US nonwhite male employment first differences demonstrate negative skewesses, directing at asymmetry in durations.

The estimated coefficients of magnitudes are presented in table 2.1, and show that five out of seven employment series are negatively skewed in levels. Only US nonfarm laborers show a positive coefficient of asymmetry in magnitudes, whereas US nonwhite male employment has practically zero skewness. Table 2.2 presents the coefficients of asymmetry of durations. Again, five out of seven employment series are negatively skewed in first differences. Only US white female employment shows a positive coefficient of asymmetry in durations, whereas the asymmetry of durations of US nonfarm laborers is practically zero.

Due to the serial correlation in the data the following Monte Carlo procedure has been obtained to compute the marginal significance levels of the coefficients of asymmetry. The basic, unfilterded data are fitted to the two linear AR models which are most commonly applied to employment series. Model 1 is an AR(1) model in first differences plus a constant. Model 2 is an AR(2) model in levels with a constant term and a linear trend[5]. The fitted models have been used to generate 2 x 1,000 artificial series for the sample period assuming that the shocks are normally distributed with zero mean and variance equal to the estimated variance of the two models. The 2 x 1,000 series were then HP filtered, and from the deviations from the trend coefficients of asymmetry were computed. The calculated standard deviations of the skewnesses were used to compute the marginal significance levels of the coefficients of asymmetry. Notice that this procedure has been suggested by DeLong and Summers (1986) with only one essential difference. Removing the nonstationarity from the basic data as well as from the artificial series is done by HP filtering.

To account for the effects of possible nonnormality in the residual errors of model 1 and model 2, we also report the marginal significance levels computed from the following bootstrapping exercise. Again the fitted models 1 and 2 have been used to generate 2 x 1,000 artificial series for the sample period. Now, the

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[5] Model 1: $\Delta x_t = \alpha_{00} + \alpha_1 \Delta x_{t-1} + \epsilon_{1t}$,
Model 2: $x_t = \beta_{00} + \beta_0 t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \epsilon_{2t}$,
where the α's and β's are constant parameters, and ϵ_{1t}, ϵ_{2t} are iid random shocks.

shocks added to the series are randomly selected from the vectors of residual errors, ϵ_1 and ϵ_2. Next, the 2 x 1,000 series were HP filtered, and from the deviations from the trend coefficients of asymmetry were computed. The generated vectors of the skewnesses were used to compute the marginal significance levels of the coefficients of asymmetry.

[Table 2.1 & Table 2.2]

The results in table 2.1 show that the three series that showed negative asymmetry of magnitudes by optical inspection, US aggregate employment, US white male employment, and US nonwhite female employment, are indeed significantly skewed to the left at the 5% level, when the random shocks are assumed to be normally distributed. However, in exception of nonwhite female employment, the p-values rise beyond the level of statistical significance as soon as the assumption of normality in the errors is abandoned.

The results presented in table 2.2 show that the three series that exhibited optically negatively skewed frequency distributions in first differences, US aggregate employment, US white male employment, and US nonwhite male employment are indeed found to be significantly skewed to the left at the 5% level in the Monte Carlo simulation. Moreover, although the p-values tend to be bigger, for these three series the significance of the parameter of asymmetry of duration remains below 10% after assuming nonnormality in the errors.

By and large, US aggregate employment and US white male employment show significant coefficients of asymmetry of magnitudes and asymmetry of durations, meaning that troughs of these series are more severe than the peaks, whereas the time these series generally spend in falling to a trough is considerably smaller than the time spend in rising from a trough to a peak. US nonwhite female employment is also inclined to experience more severe troughs than peaks, but the time falling to a trough exceeds the time rising to a peak. Finally, peaks and troughs of US nonwhite male employment are of the same magnitude. Falling-to-a-trough time of nonwhite male employment, however, is signifigantly shorter than rising-to-a-peak time.

Moreover, we conclude that the asymmetry of magnitudes is mainly due to unexpectedly large innovations in the economic system. This implies that the maintained hypothesis of normality of the errors when analyzing the standard linear dynamic models of employment gives rise to biased parameter estimates. Asymmetry of durations, however, is not caused by nonnormal random shocks, but appears to be structurally present in the data. In order to account for the skewnesses present in the employment series, in the next section we put forward a nonlinear AR model that endogenously generates asymmetry of magnitudes and asymmetry of durations.

3. A NONLINEAR AUTOREGRESSIVE MODEL FOR EMPLOYMENT DATA

Nonlinear phenomena of economic time series such as irreversibility and asymmetry cannot be explained by linear time series models. In this section we derive a nonlinear AR model that has the property of generating asymmetric cycles. Ozaki (1982) introduced a nonlinear model for the statistical analysis of time series from general nonlinear random vibrations and explained asymmetric phenomena using the model. The derivation of the model has been based on the parametrization of the dynamics of the damping force $g_1(x)x'$ or the restoring force $g_2(x)x$ in the general second order Van der Pol differential equation

$$x'' + g_1(x)x' + g_2(x)x = \epsilon(t) \tag{3.1}$$

where $\epsilon(t)$ is an external force. The model parametrizes the dynamics of the characteristic roots of a nonlinear autoregressive model. Hermitian type polynomials that have the potential to realize stochastic asymmetric self-sustained oscillations form the basis of Ozaki's exponential AR model

$$x_t = (\phi_1 + f_1(x_{t-1})e^{-\gamma x_{t-1}^2})x_{t-1} + (\phi_2 + f_2(x_{t-1})e^{-\gamma x_{t-1}^2})x_{t-2} + \epsilon_t \tag{3.2}$$

where $f_i(x_{t-1})e^{-\gamma x_{t-1}^2}$, (i = 1,2) are Hermitian type polynomials with

$$f_i(x_{t-1}) = \pi_0^{(i)} + \pi_1^{(i)}x_{t-1}, \quad (i = 1,2).$$

If the order of the Hermitian type polynomials is taken to be odd the nonlinear AR model will induce asymmetry of durations (cf. Ozaki (1982)).

The theory of adjustment costs proves useful in providing an economic notion of the exponential AR model (3.2). As a rule, linear dynamic employment schedules are derived from a structural model, where the quadratic function

$$h_1(\Delta x_t) = \tfrac{1}{2}\lambda_1\Delta x_t^2, \quad \Delta x_t = x_t - x_{t-1}, \tag{3.3}$$

gives rise to the dynamics of the employment equation, with x_t being employment at period t. An optimizing employer minimizes the costs of employment input over time. This yields a linear decision rule, because $\partial h_1(\Delta x_t)/\partial x_t = \lambda_1 \Delta x_t$ (cf. Sargent (1978)). By nature, the cyclical dynamics generated by the linear-quadratic model are symmetric. A quadratic adjustment costs function implies marginally equivalent hiring costs and firing costs.

Alternatively, an adjustment costs model that takes into account differences between hiring costs and firing costs has been put forward by Pfann and Verspagen (1989). The idea of asymmetric adjustment costs has been analyzed in an optimizing agent economy with heterogeneous labor by Pfann and Palm (1989), who applied the model to data of the U.K. and Netherlands manufacturing sectors. In both papers convincing evidence was found for asymmetry in employment equations. The asymmetric adjustment costs function is as follows.

$$h_2(\Delta x_t) = \tfrac{1}{2}\lambda_1 \Delta x_t^2 + \lambda_2 \Delta x_t + e^{-\lambda_2 \Delta x_t} - 1, \tag{3.4}$$

where λ_1, λ_2 are constant parameters. Note that if $\lambda_2=0$ then $h_1(\Delta x_t)=h_2(\Delta x_2)$, which means that hiring costs equals firing costs. Note also that if $\lambda_2<0$ hiring costs exceed firing costs, which implies that the employment adjustment speed to a peak being lower than the employment adjustment speed to a trough (cf. Pfann and Palm, 1989). Consequently, the dynamics of the asymmetric employment schedule are caused by

$$\partial h_2(\Delta x_t)/\partial x_t = \lambda_1 \Delta x_t + \lambda_2(1 - e^{-\lambda_2 \Delta x_t}),$$

which is closely related to the Hermitian polynomial type of functions given in equation (3.2), since

$$\lambda_1 \Delta x_t + \lambda_2(1 - e^{-\lambda_2 \Delta x_t}) = (\phi_0 + (\pi_0 - \lambda_2 x_{t-1}) e^{-\lambda_2 x_{t-1}^2}) x_{t-1} + \Re(x_t, x_{t-1}),$$

where ϕ_0, π_0 are constant parameters, and $\Re(x_t, x_{t-1})$ is a restterm that contains Taylor type polynomials of x_t, x_{t-1}.

Taking the second order Taylor series expansion of the Hermitian type polynomials of equation (3.2) around $x_{t-1}=0$, and eliminating the even powers of x_{t-1}, restricting $\pi_0^{(1)} = \pi_1^{(1)} = \pi_0^{(2)} = 0$, we obtain the following nonlinear AR model

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \alpha_3 x_{t-1} x_{t-2} + \alpha_4 x_{t-1}^3 x_{t-2} + \alpha_5 (x_{t-1} - x_{t-2})^3 , \tag{3.5}$$

where $\alpha_1 = \phi_1$, $\alpha_2 = \phi_2$, $\alpha_3 = \pi_1^{(2)}$, $\alpha_4 = -\gamma\pi_1^{(2)}$, and α_5 being constant parameters. The fifth term in equation (3.5) is added to control for the inaccuracy of the second order Taylor series approximation of equation (3.2). Ozaki (1982) shows that if $\pi_1^{(2)} > \pi_1^{(1)}$, which in our model means $\pi_1^{(2)} > 0$, the cycle generated by equation (3.2) spends more time in rising to a peak, than time spend in falling to a trough, causing asymmetry of durations. The parameter γ in equation (3.2) acts as a scaling factor, measuring the intensiveness of the fluctuations. By and large, $\pi_1^{(2)}$ can be interpreted as the parameter that measures the marginal difference between hiring costs and firing costs, or rather $\pi_1^{(2)} = -\lambda_2$. Thus, the parameter α_3 is expected to be positive and the parameter α_5 is expected to be negative iff the asymmetry (skewness) of durations is negative. Moreover, the parameter α_4 is expected to be negative iff the asymmetry (skewness) of magnitudes is negative. In the next section the empirical contents of model (3.5) will be investigated.

4. NONLINEAR EMPLOYMENT EQUATIONS

Table 4.1 presents the results of the traditional linear model that is commonly used for the estimation of employment series. This model is as follows.

$$x_t = \alpha_{00} + \alpha_0 t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \mu_{1t} \, . \tag{4.1}$$

where x_t is employment at period t, α_i, (i=00, 0, 1, 2), are constant parameters, and μ_{1t} are normally distributed shocks to the economic system.

[Table 4.1]

Basically, all regressions show stationary second order difference equations. Only white male employment show residual autocorrelation at a 5% level, but not at a 1% level. Consequently, the linear model would have been an acceptable model. Or, according to Blanchard and Fisher (1989, op cit. page 7):

> *"For the postwar United States, however, the assumption that major economic variables follow linear (or loglinear) stochastic processes does not appear too strongly at variance with the data."*

To show that this statement may not be as true as it appears, the following nonlinear AR model was fitted to the seven employment series.

$$x_t = \alpha_{00} + \alpha_0 t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \alpha_3 x_{t-1} x_{t-2} + \alpha_4 x_{t-1}^2 x_{t-2} + \alpha_5 (x_{t-1} - x_{t-2})^3 + \mu_{2t} \, . \tag{4.2}$$

where α_i, (i=00, 0, 1, .. , 5) are constant parameters, and μ_{2t} are normally distributed shocks to the economic system. Note that model (4.1) is nested in model (4.2) restricting $\alpha_3=\alpha_4=\alpha_5=0$. Results are presented in table 4.2.

[Table 4.2]

Table 4.2 shows that the nonlinear AR model (4.2) outperforms the linear AR model

(4.1) for the series that are both negatively skewed in levels and in first differences, and that the results in general corroborate with the findings in the previous section. The additional parameters α_3 and α_4 are significantly different from zero at the 1% level, and have the expected signs for the series that show negative skewnesses. Also α_5 has the expected sign in all the cases except nonfarm laborers, but only comes in significant for aggregate employment and nonwhite female employment. Moreover, the standard errors of the regression have decreased substantially. The linear AR model appears to be more appropriate only for US nonfarm laborers, which is the only series that is positively skewed in levels and hardly shows any skewness in first differences. From the discussion in the previous section, these findings imply indeed that in five out of seven cases more time is spent in rising to a peak, than time is spent in falling to a trough, wheras for all series but US nonfarm laborers the magnitude of troughs exceeds the magnitude of peaks.

[Table 4.3]

Table 4.3 presents the results of a comparison between the nonlinear model and the linear model through imposing the restrictions $\alpha_3=\alpha_4=\alpha_5=0$ simultaneously. Again, we find that the nonlinear model suits all employment series except US nonfarm laborers better than the linear model. Consequently, the nonlinear AR model encompasses the standard linear model for the employment series that show business cycle asymmetries.

Table 4.4 and table 4.5 present the skewnesses and marginal significance levels that have been computed as a result from the average of a Monte Carlo simulation and a bootstrapping simulation of 1,000 draws with the length of the sample size. Every simulation round a series x_t was computed. After HP filtering the artificially generated series x_t the skewnesses were computed. The asymmetry of magnitudes given in table 4.4 and the asymmetry of durations given in table 4.5 are the means of the simulated skewnesses. The reported Monte Carlo skewnesses are purely generated by the nonlinear AR model, whereas the bootstrapping skewnesses are a combination of skewnesses generated by the nonlinear AR model and skewnesses incurred by the remaining nonnormality in the residual errors.

From table 4.4 it can be seen that the asymmetry of magnitudes apparent in the data can be largely accounted for by the nonlinear AR model even if the distribution of residual errors is assumed to be normal. The model mimics the signs of the asymmetry exactly right. The simulated asymmetries of magnitudes do not significantly differ from the asymmetry in the real data in either the Monte Carlo simulation or the bootstrapping simulation.

[Table 4.4 & Table 4.5]

Table 4.5 shows that the nonlinear AR model does indeed generate asymmetries of durations for all the series. Only for nonfarm laborers the signs are wrong, although in this case the p-values show that this is just a futility. For the three employment series that show significant negative asymmetry of durations, that is aggregate employment, white male employment, and nonwhite male employment, the p-values show, however, that the model is not completely able to capture the asymmetry. Nevertheless, also for these series the nonlinear AR model does much better in generating asymmetry of durations than the standard linear model. There is just one exception, the p-value that results from bootstrapping nonwhite male employment is higher for the linear model than for the nonlinear model.

5. CONCLUSIONS

This paper establishes the stylized facts that for postwar US employment (a) the magnitude of a trough in employment exceeds the magnitude of a peak in employment, and (b) the time employment spends in rising from a trough to a peak is longer than the time spends in falling from a peak to a trough. The asymmetric dynamic properties of seven US postwar employment series have been examined. From computing simply the skewness of the detrended series, using the Hodrick Prescott filtering procedure, and the skewness of the detrended series in first differences, we get a notion of the cyclical asymmetries that are present in the data. We argue that time series of employment data show basically two types of business cycle asymmetry. The fact that on average the magnitudes of troughs differ from the magnitudes of peaks is called "asymmetry of magnitudes". The fact that time economies spend in rising from a trough to a peak differs from the time spend in falling from a peak to a trough is defined as "asymmetry of durations". Simulation exercises are performed to compute the significance levels of the coefficients of asymmetry. US aggregate employment and US white male employment are subject to significant asymmetry of magnitudes as well as significant asymmetry of durations.

We find convincing evidence that the asymmetry of magnitudes is mainly due to unexpectedly large innovations in the economic system. This implies that the maintained hypothesis of normality of the errors when analyzing the standard linear dynamic models of employment gives rise to biased parameter estimates. Asymmetry of durations, however, is not caused by nonnormal random shocks, but appears to be structurally present in the data.

In the second part of the paper, a nonlinear AR model is put forward and estimated in order to capture the asymmetries present in the data. The nonlinear AR model outperforms the standard linear model for the series that show negative skewnesses. The linear AR model appears to be more appropriate for only US nonfarm laborers, which is the only series that is positively skewed in levels and hardly shows any skewness in first differences. From the results presented in the paper it is fair to say that asymmetry is an important feature in employment data, especially at the aggregate level. Therefore it is a sensible recommendation to take this kind of nonlinearity into account in future research that considers employment to be an essential economic variable.

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Table 2.1: Coefficients of Asymmetry of Magnitudes and Significance Levels of Seven US Employment Series

EMPLOYMENT	PERIOD	ASYMMETRY of MAGNITUDES	MONTE CARLO p-values Model 1	Model 2	BOOTSTRAPPING p-values Model 1	Model 2
Aggregate	54.I - 90.IV	-0.490	0.049	0.048	0.340	0.364
White Male	54.I - 90.IV	-0.768	0.006	0.004	0.232	0.252
White Female	54.I - 90.IV	-0.239	0.186	0.182	0.160	0.176
NonWhite Male	54.I - 90.IV	-0.0001	0.498	0.497	0.484	0.436
NonWhite Female	54.I - 90.IV	-0.568	0.021	0.013	0.024	0.044
Profesionals	58.I - 82.IV	-0.345	0.123	0.106	0.288	0.316
Laborers	58.I - 82.IV	0.133	0.303	0.299	0.360	0.388

Table 2.2: Coefficients of Asymmetry of Durations and Significance Levels of Seven US Employment Series

EMPLOYMENT	PERIOD	ASYMMETRY of DURATIONS	MONTE CARLO p-values Model 1	Model 2	BOOTSTRAPPING p-values Model 1	Model 2
Aggregate	54.I - 90.IV	-0.604	0.003	0.002	0.056	0.068
White Male	54.I - 90.IV	-0.702	0.000	0.000	0.048	0.048
White Female	54.I - 90.IV	-0.138	0.229	0.264	0.248	0.224
NonWhite Male	54.I - 90.IV	-0.372	0.036	0.027	0.088	0.096
NonWhite Female	54.I - 90.IV	0.147	0.249	0.213	0.264	0.252
Profesionals	58.I - 82.IV	-0.273	0.128	0.122	0.188	0.188
Laborers	58.I - 82.IV	-0.009	0.495	0.495	0.436	0.428

Table 4.1: The Linear AR Model Fitted to the Employment Series*

Employment	α_{00}	α_0	α_1	α_2	R^2	s.e.	AR(4)
Aggregate	1.445	0.011	1.538	-0.563	0.999	0.366	3.90
	(2.39)	(2.33)	(22.06)	(-8.16)			
White Male	1.066	0.004	1.468	-0.498	0.999	0.175	11.78
	(2.19)	(2.26)	(20.35)	(-6.95)			
White Female	0.256	0.004	1.109	-0.124	0.999	0.178	3.86
	(2.25)	(1.98)	(12.95)	(-1.45)			
NonWhite Male	0.034	0.001	1.188	-0.199	0.998	0.054	5.08
	(0.78)	(1.37)	(14.41)	(-2.39)			
NonWhite Female	0.024	0.001	1.032	-0.045	0.999	0.050	2.84
	(1.38)	(2.09)	(12.28)	(-0.54)			
Professionals	0.424	0.006	1.075	-0.106	0.998	0.193	8.44
	(1.45)	(1.67)	(10.73)	(-1.04)			
Laborers	0.349	0.002	0.735	0.159	0.961	0.100	0.64
	(2.14)	(1.90)	(7.22)	(1.57)			

* Asymptotic t-values are given within parentheses.
s.e. denotes the standard error of the OLS regression.
AR(4) is a $\chi^2(4)$ distributed statistic testing for fourth order residual autocorrelation.

Table 4.2: The Nonlinear AR Model Fitted to the Employment Series*

Employment	α_{00}	α_0	α_1	α_2	α_3	α_4	α_5	R^2	s.e.
Aggregate	21.28	0.030	1.556	-1.154	0.004	-0.081	-0.231	0.999	0.351
	(3.47)	(3.62)	(13.26)	(-7.10)	(3.22)	(-3.13)	(-2.90)		
White Male	33.61	0.011	0.868	-1.739	0.029	-2.171	-0.586	0.999	0.169
	(2.93)	(3.73)	(3.27)	(-3.95)	(2.68)	(-2.54)	(-1.34)		
White Female	3.945	0.015	1.094	-0.471	0.008	-1.382	-0.722	0.999	0.168
	(2.76)	(2.54)	(7.43)	(-2.93)	(2.92)	(-3.13)	(-1.35)		
NonWhite Male	2.651	0.004	0.764	-0.981	0.139	-0.593	-8.034	0.998	0.052
	(4.03)	(3.91)	(4.21)	(-4.40)	(3.76)	(-3.39)	(-0.92)		
NonWhite Female	1.017	0.005	0.593	-0.226	0.079	-0.433	9.411	0.999	0.047
	(3.10)	(3.07)	(4.51)	(-1.39)	(3.23)	(-3.40)	(2.52)		
Professionals	14.66	0.045	0.433	-1.088	0.045	-0.012	-0.496	0.999	0.176
	(4.62)	(4.48)	(2.02)	(-4.26)	(4.01)	(-3.34)	(-0.78)		
Laborers	1.216	0.001	0.436	-0.249	0.156	-1.997	1.686	0.959	0.101
	(0.36)	(1.59)	(0.50)	(-0.19)	(0.39)	(-0.52)	(0.69)		

* Asymptotic t-values are given within parentheses.
s.e. denotes the standard error of the NLLS regression.
For presentational convenience α_4 has been scaled by 10^{-6} for the first 3 series and by 10^{-3} for the last 4 series.

Table 4.3: The Nonlinear Model versus the Linear Model

Employment	$H_0: \alpha_3 = \alpha_4 = \alpha_5 = 0$	p-value
Aggregate	$F(3,139) = 5.327$	0.002
White Male	$F(3,139) = 3.411$	0.019
White Female	$F(3,139) = 3.924$	0.010
NonWhite Male	$F(3,139) = 5.586$	0.001
NonWhite Female	$F(3,139) = 6.563$	0.000
Professionals	$F(3, 91) = 7.046$	0.000
Laborers	$F(3, 91) = 0.433$	0.730

Table 4.4: Asymmetry of Magnitudes and Significance Levels from Simulating the Estimated Nonlinear AR Model

EMPLOYMENT	PERIOD	Skewness (Real Data)	MONTE CARLO Skewness (Model 4.2)	MONTE CARLO p-value (Model 4.2)	BOOTSTRAPPING Skewness (Model 4.2)	BOOTSTRAPPING p-value (Model 4.2)
Aggregate	54.I - 90.IV	-0.490	-0.433	0.296	-0.458	0.384
White Male	54.I - 90.IV	-0.768	-0.682	0.268	-0.700	0.272
White Female	54.I - 90.IV	-0.239	-0.114	0.184	-0.166	0.296
NonWhite Male	54.I - 90.IV	-0.0001	-0.026	0.436	-0.017	0.432
NonWhite Female	54.I - 90.IV	-0.568	-0.278	0.140	-0.257	0.163
Profesionals	58.I - 82.IV	-0.345	-0.172	0.224	-0.278	0.356
Laborers	58.I - 82.IV	0.133	0.049	0.344	0.080	0.400

Table 4.5: Asymmetry of Durations and Significance Levels from Simulating the Estimated Nonlinear AR Model

EMPLOYMENT	PERIOD	Skewness (Real Data)	MONTE CARLO Skewness (Model 4.2)	MONTE CARLO p-value (Model 4.2)	BOOTSTRAPPING Skewness (Model 4.2)	BOOTSTRAPPING p-value (Model 4.2)
Aggregate	54.I - 90.IV	-0.604	-0.346	0.096	-0.332	0.100
White Male	54.I - 90.IV	-0.702	-0.297	0.061	-0.293	0.080
White Female	54.I - 90.IV	-0.138	-0.081	0.392	-0.107	0.388
NonWhite Male	54.I - 90.IV	-0.372	-0.051	0.044	-0.073	0.056
NonWhite Female	54.I - 90.IV	0.147	0.293	0.296	0.258	0.328
Profesionals	58.I - 82.IV	-0.273	-0.074	0.180	-0.092	0.204
Laborers	58.I - 82.IV	-0.009	0.038	0.432	0.003	0.456

FIGURE 1a: US AGGREGATE (point) & TREND (solid) EMPLOYMENT

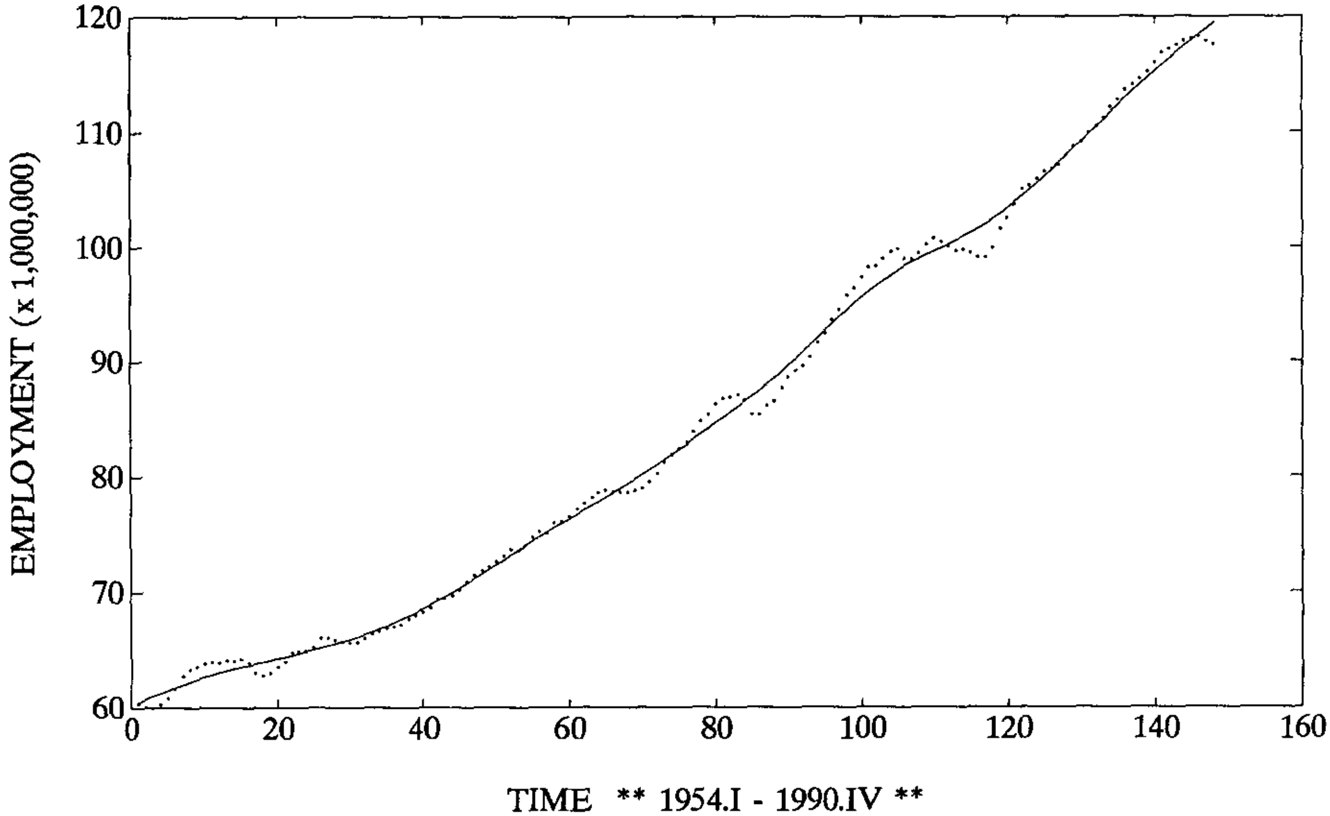


FIGURE 1b: DEVIATIONS FROM TREND OF US AGGREGATE EMPLOYMENT

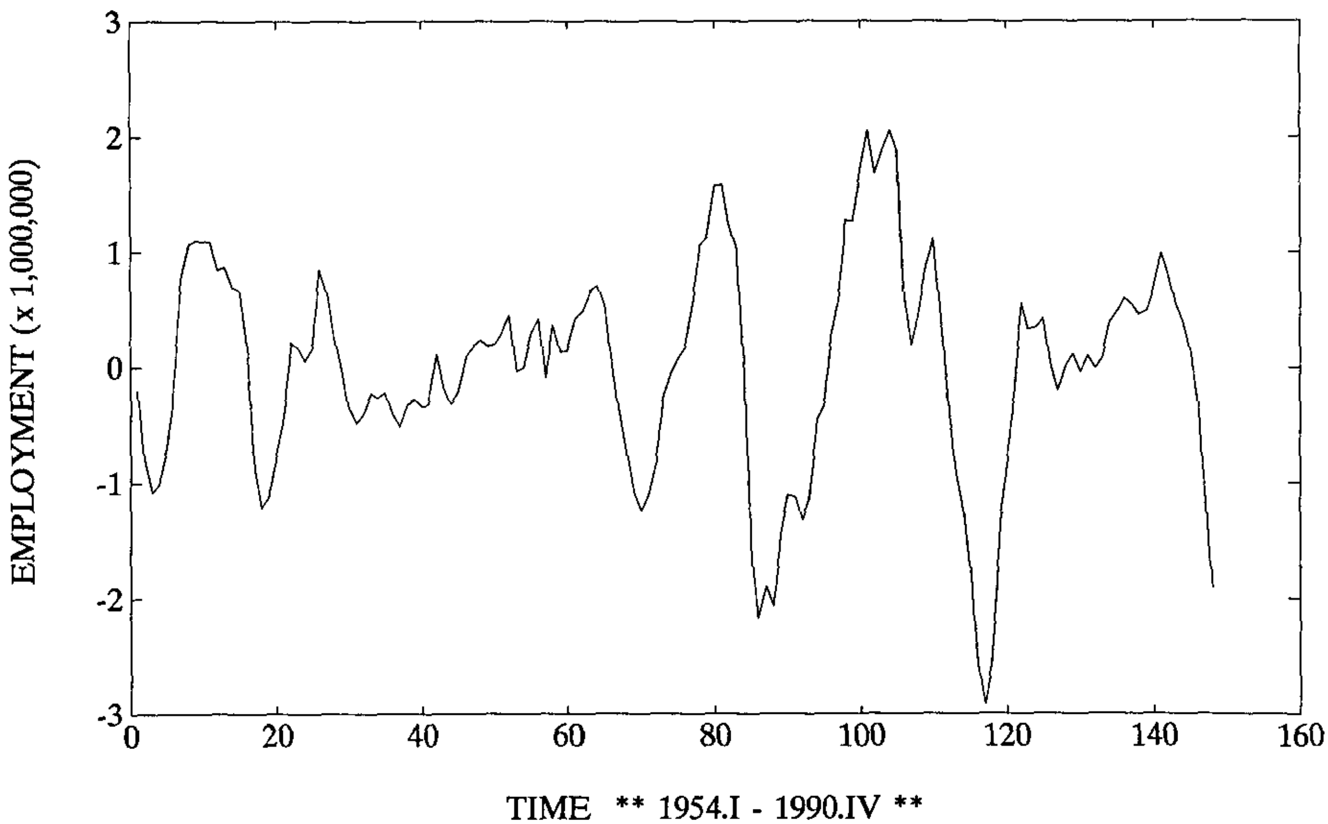
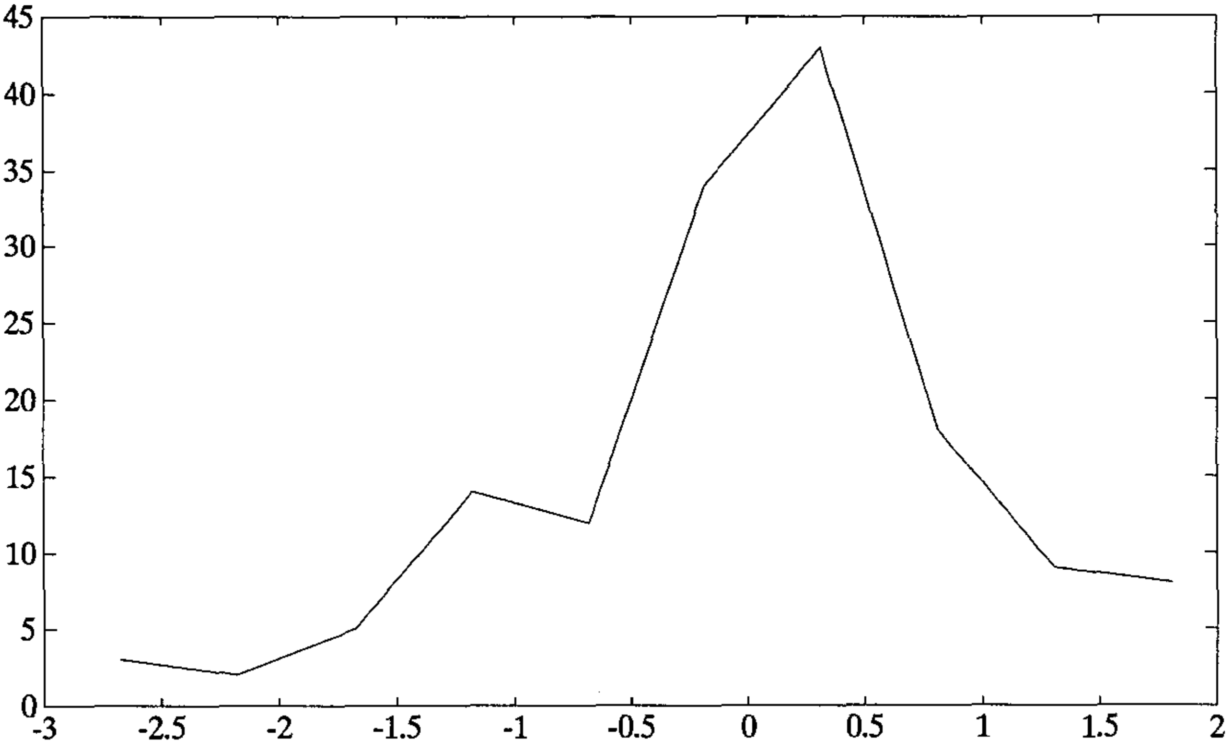


FIGURE 1c: FREQUENCY DISTRIBUTION OF US AGGREGATE EMPLOYMENT

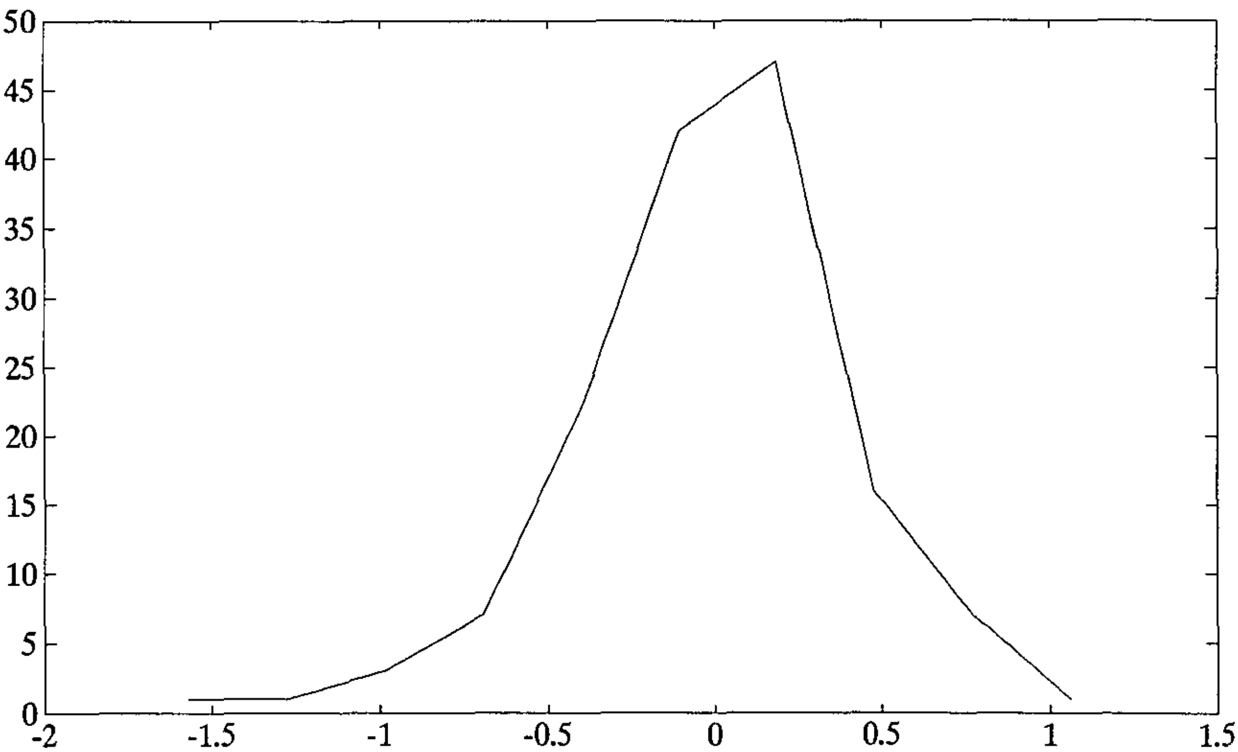
NUMBER OF QUARTERS



DEVIATIONS FROM TREND OF US AGGREGATE EMPLOYMENT (x 1,000,000)

FIGURE 1d: FREQUENCY DISTRIBUTION OF US AGGREGATE EMPLOYMENT

NUMBER OF QUARTERS



FIRST DIFF DEVIATIONS FROM TREND OF US AGGREGATE EMPLOYMENT

FIGURE 2a: US WHITE MALE (point) & TREND (solid) EMPLOYMENT

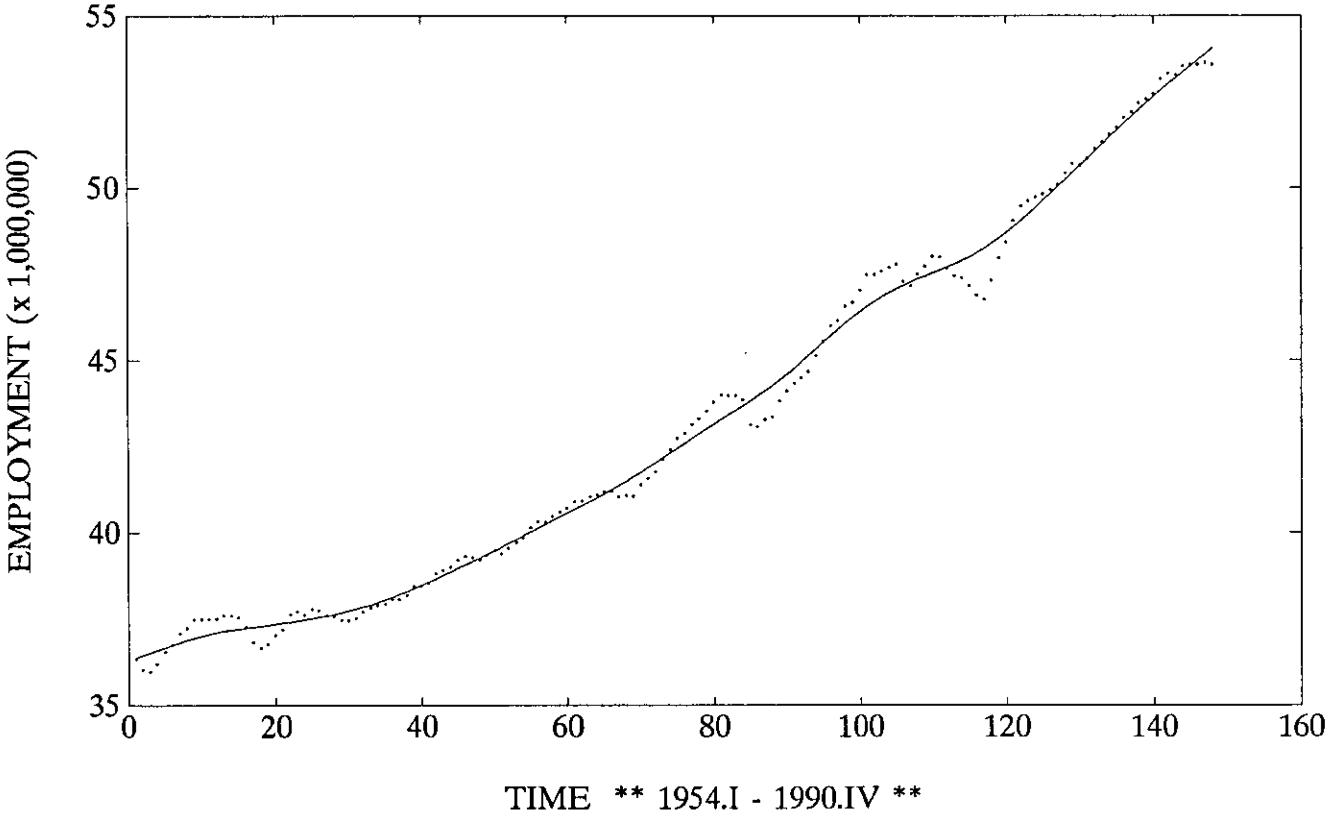


FIGURE 2b: DEVIATIONS FROM TREND OF US WHITE MALE EMPLOYMENT

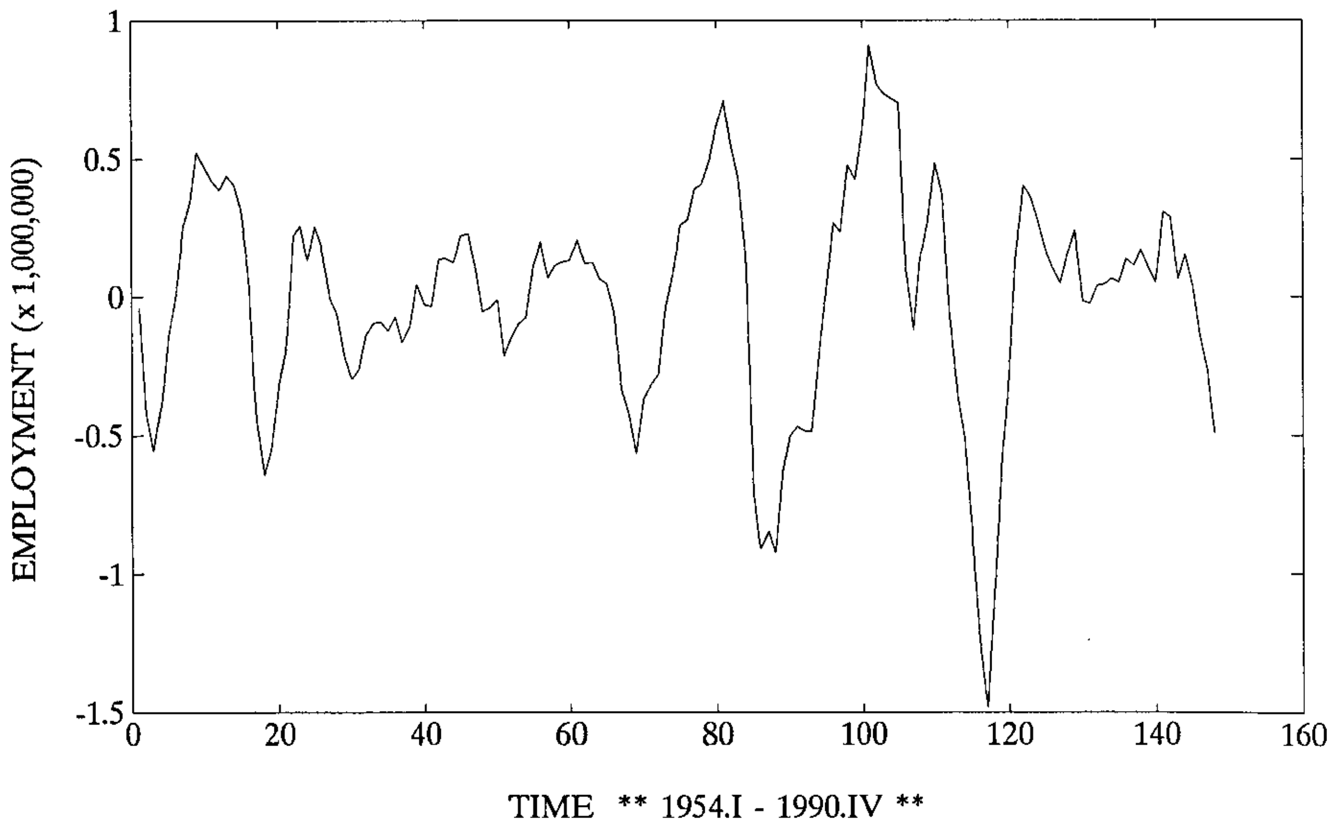


FIGURE 2c: FREQUENCY DISTRIBUTION OF US WHITE MALE EMPLOYMENT

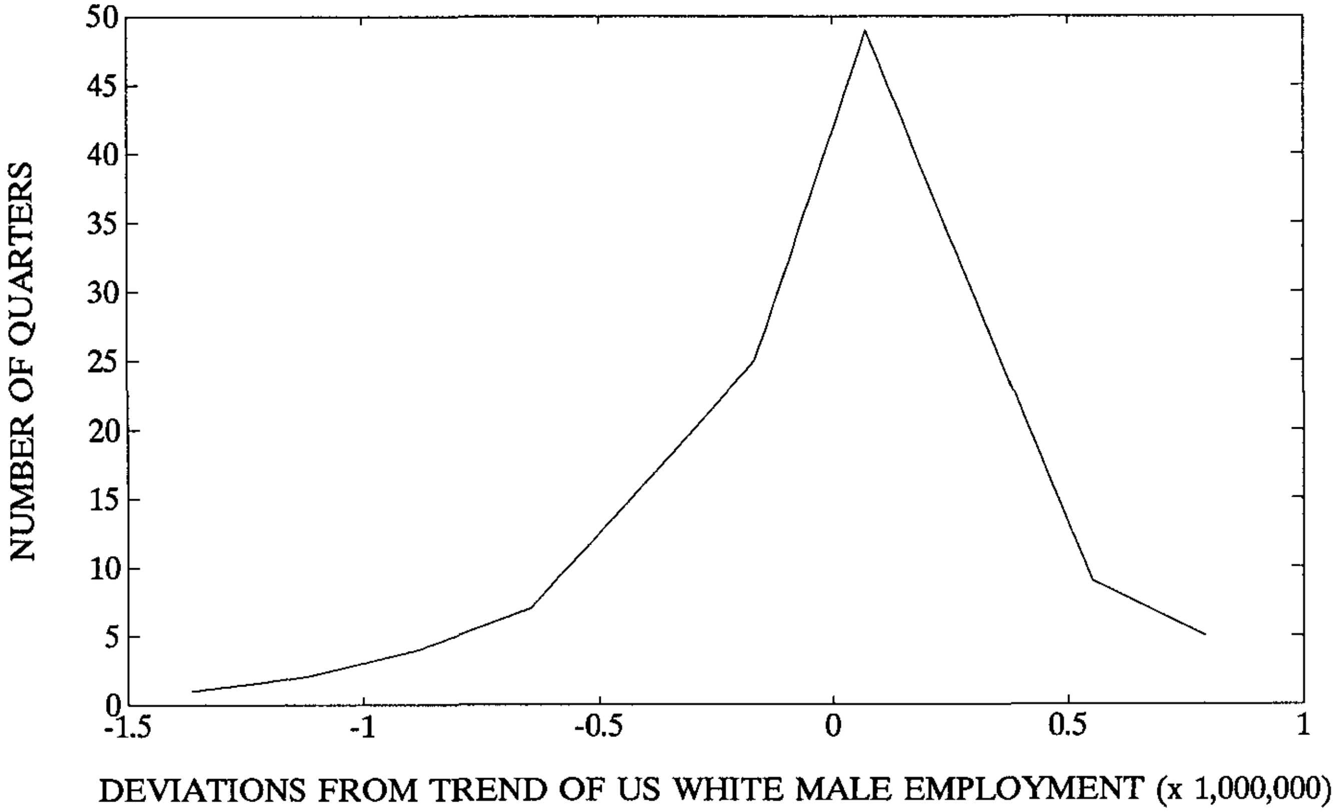


FIGURE 2d: FREQUENCY DISTRIBUTION OF US WHITE MALE EMPLOYMENT

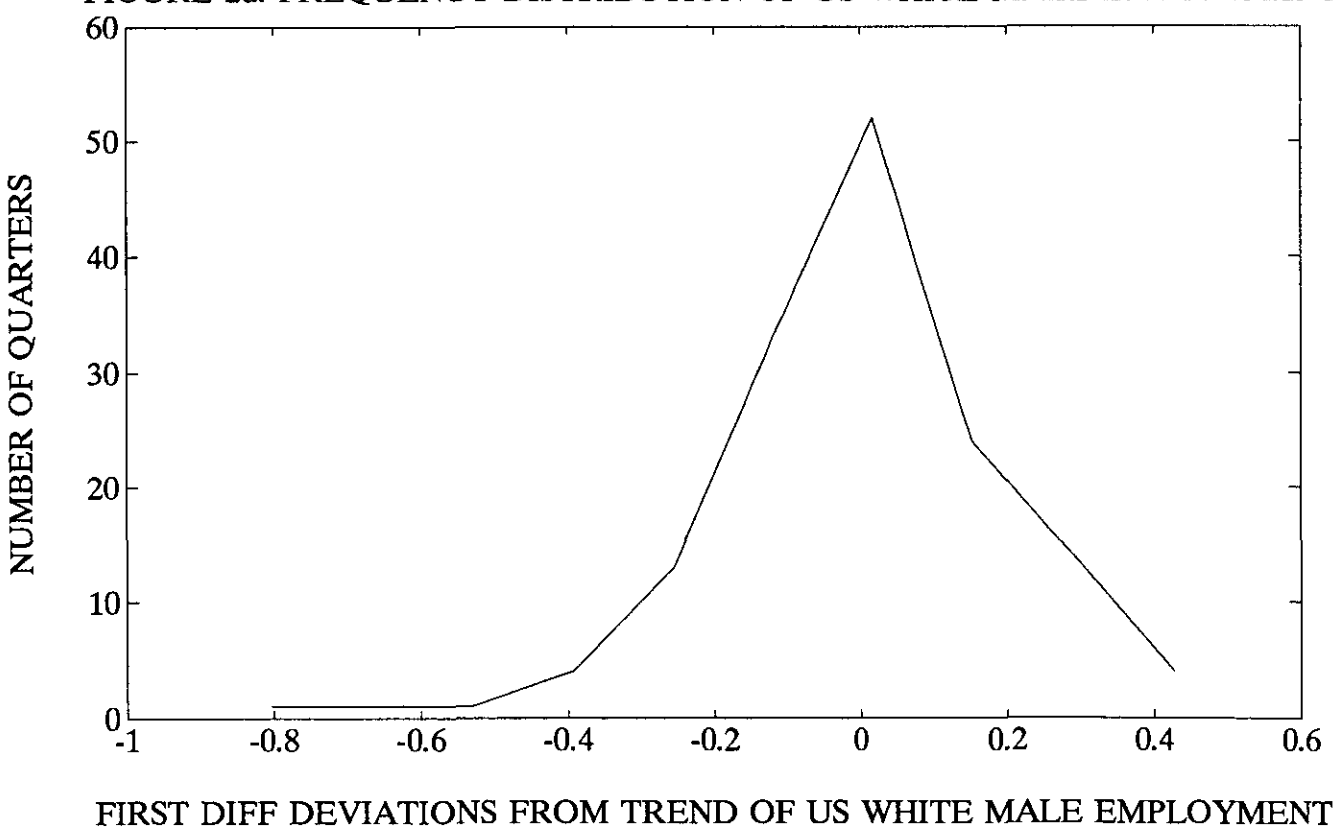


FIGURE 3a: US WHITE FEMALE (point) & TREND (solid) EMPLOYMENT

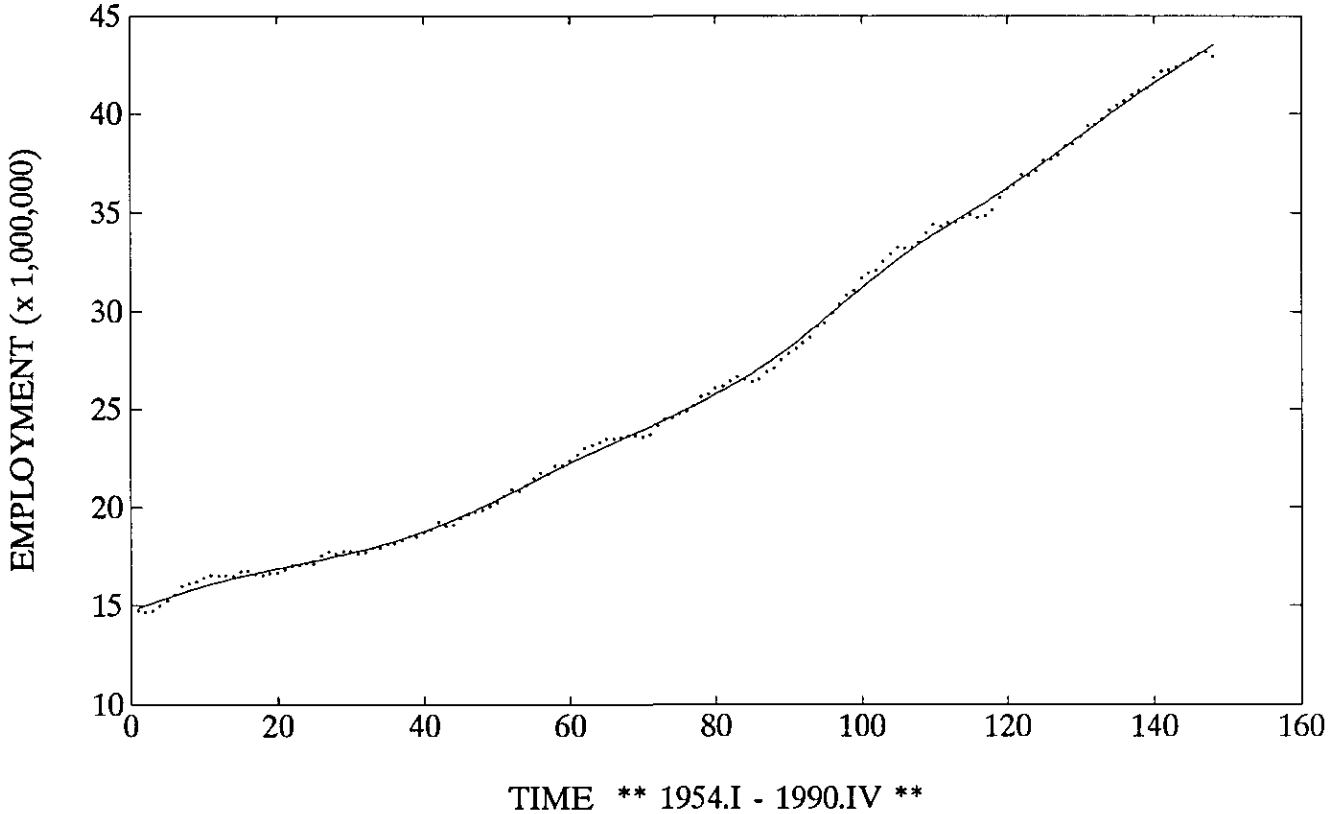


FIGURE 3b: DEVIATIONS FROM TREND OF US WHITE FEMALE EMPLOYMENT

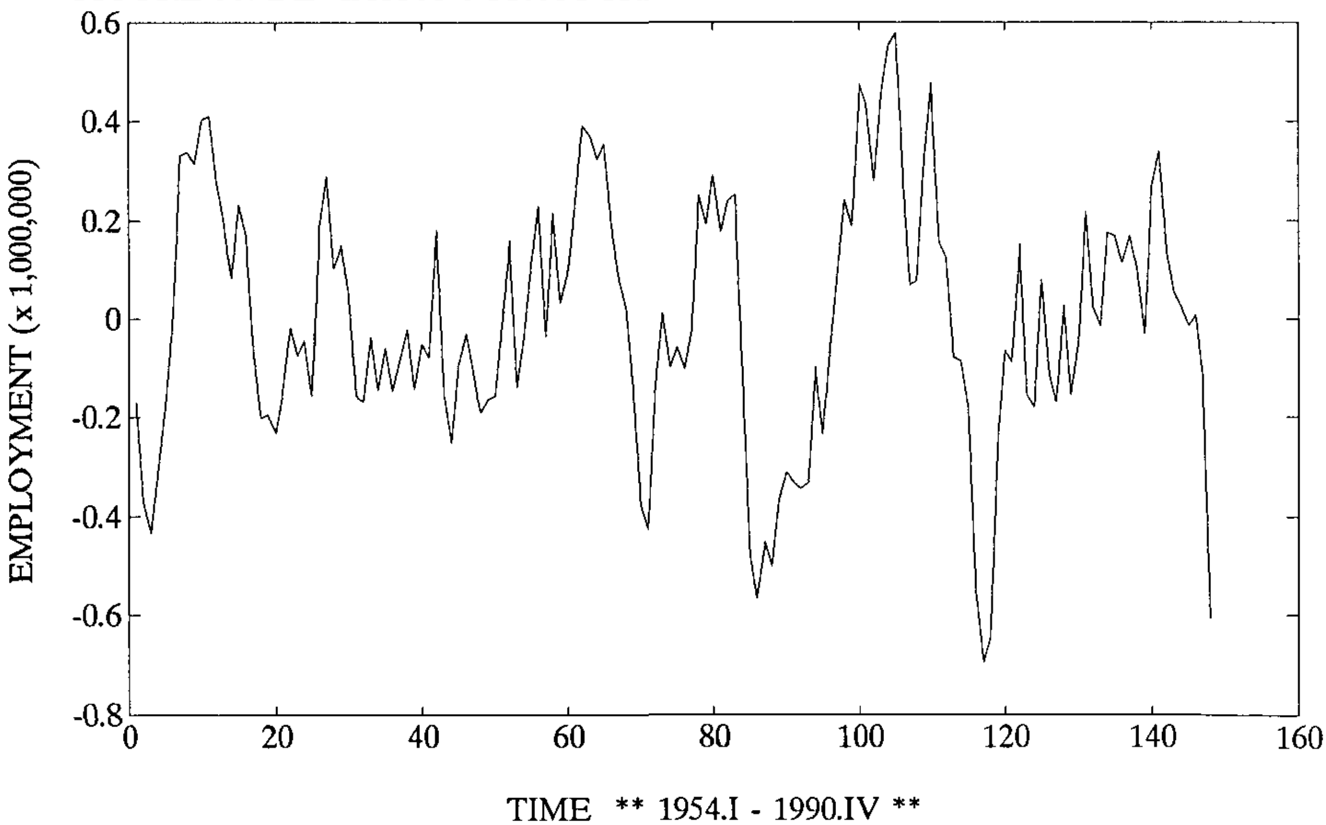
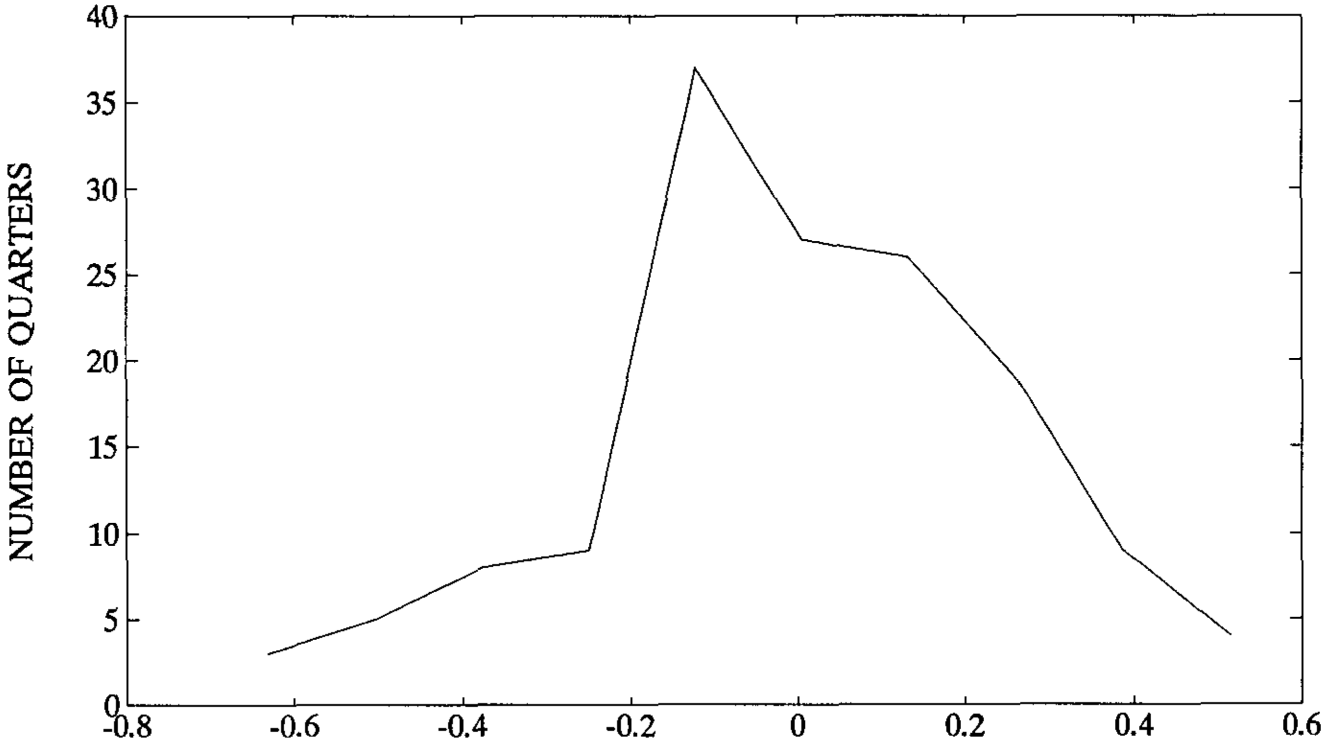
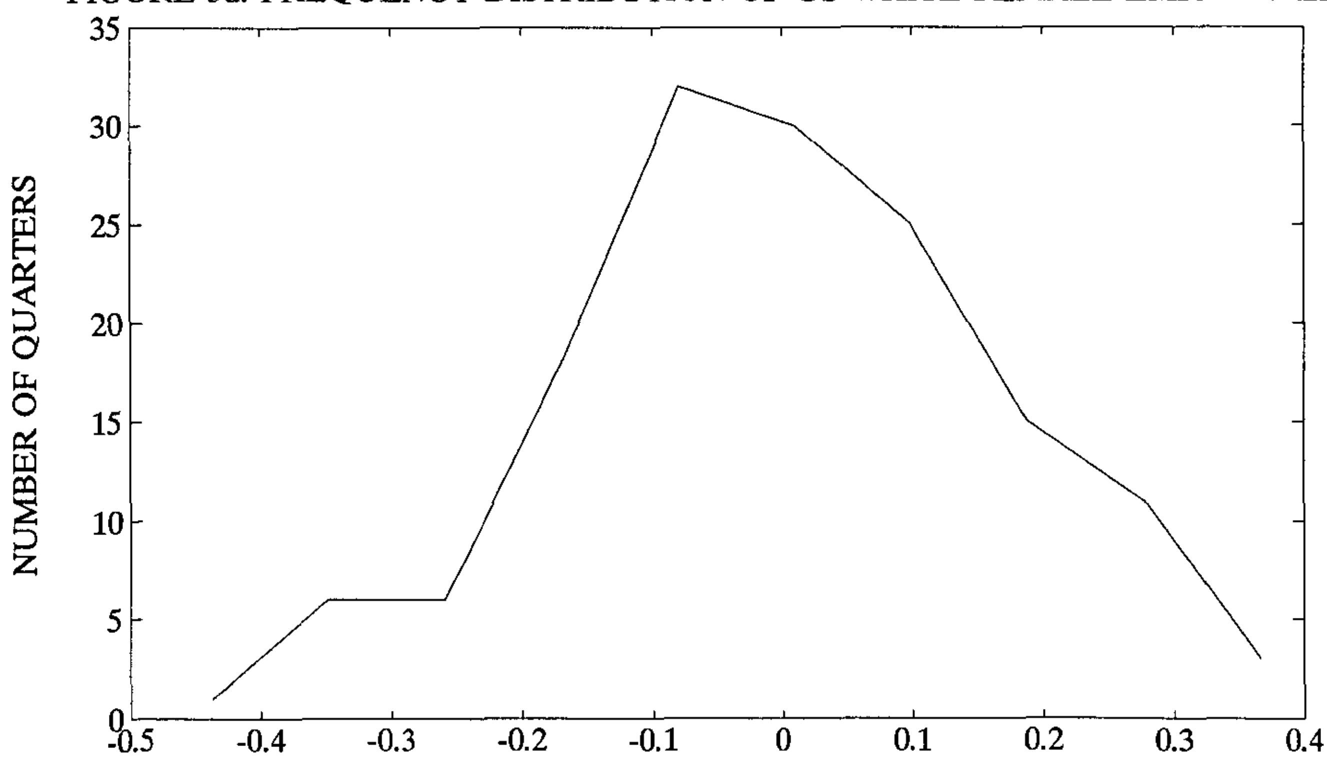


FIGURE 3c: FREQUENCY DISTRIBUTION OF US WHITE FEMALE EMPLOYMENT



DEVIATIONS FROM TREND OF US WHITE FEMALE EMPLOYMENT (x 1,000,000)

FIGURE 3d: FREQUENCY DISTRIBUTION OF US WHITE FEMALE EMPLOYMENT



FIRST DIFF DEVIATIONS FROM TREND OF US WHITE FEMALE EMPLOYMENT

FIGURE 4a: US NONWHITE MALE (point) & TREND (solid) EMPLOYMENT

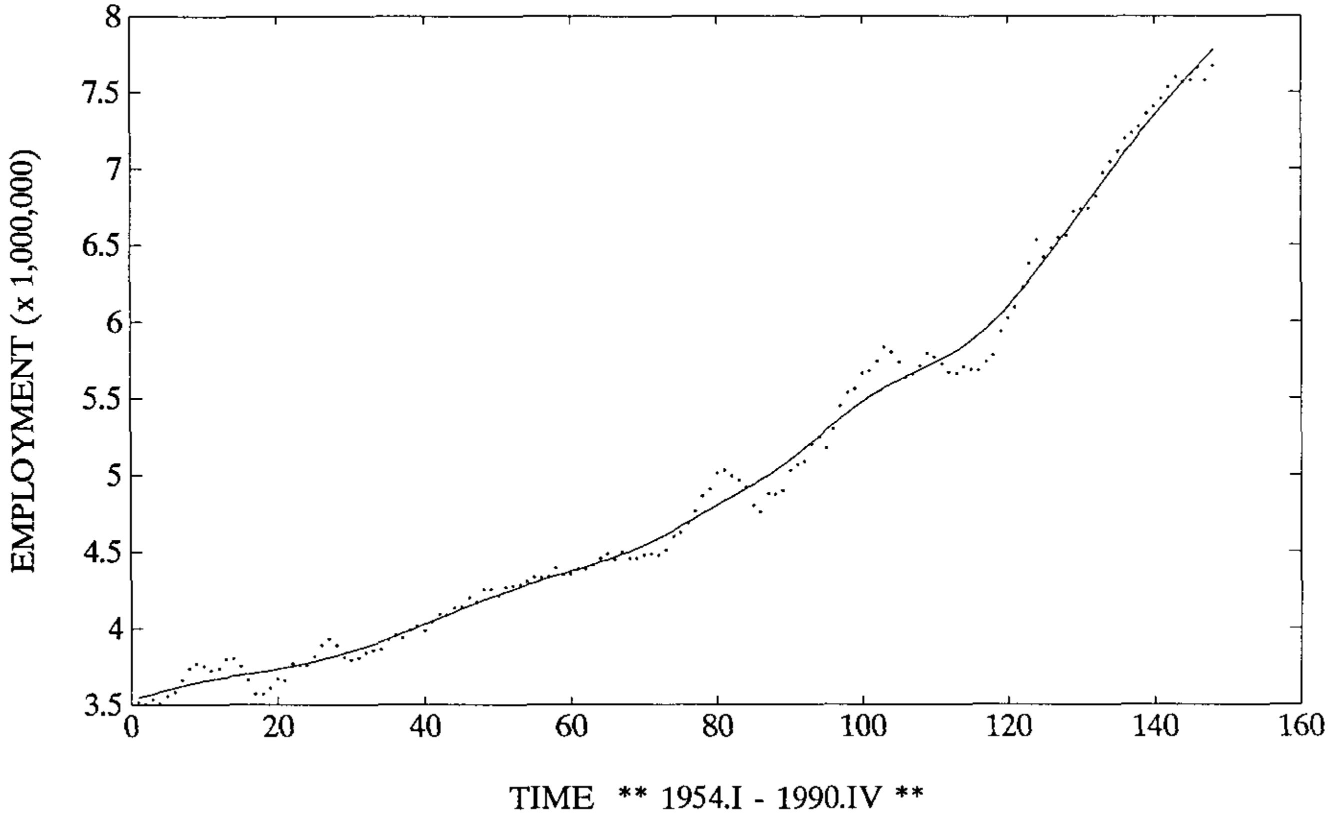


FIGURE 4b: DEVIATIONS FROM TREND OF US NONWHITE MALE EMPLOYMENT

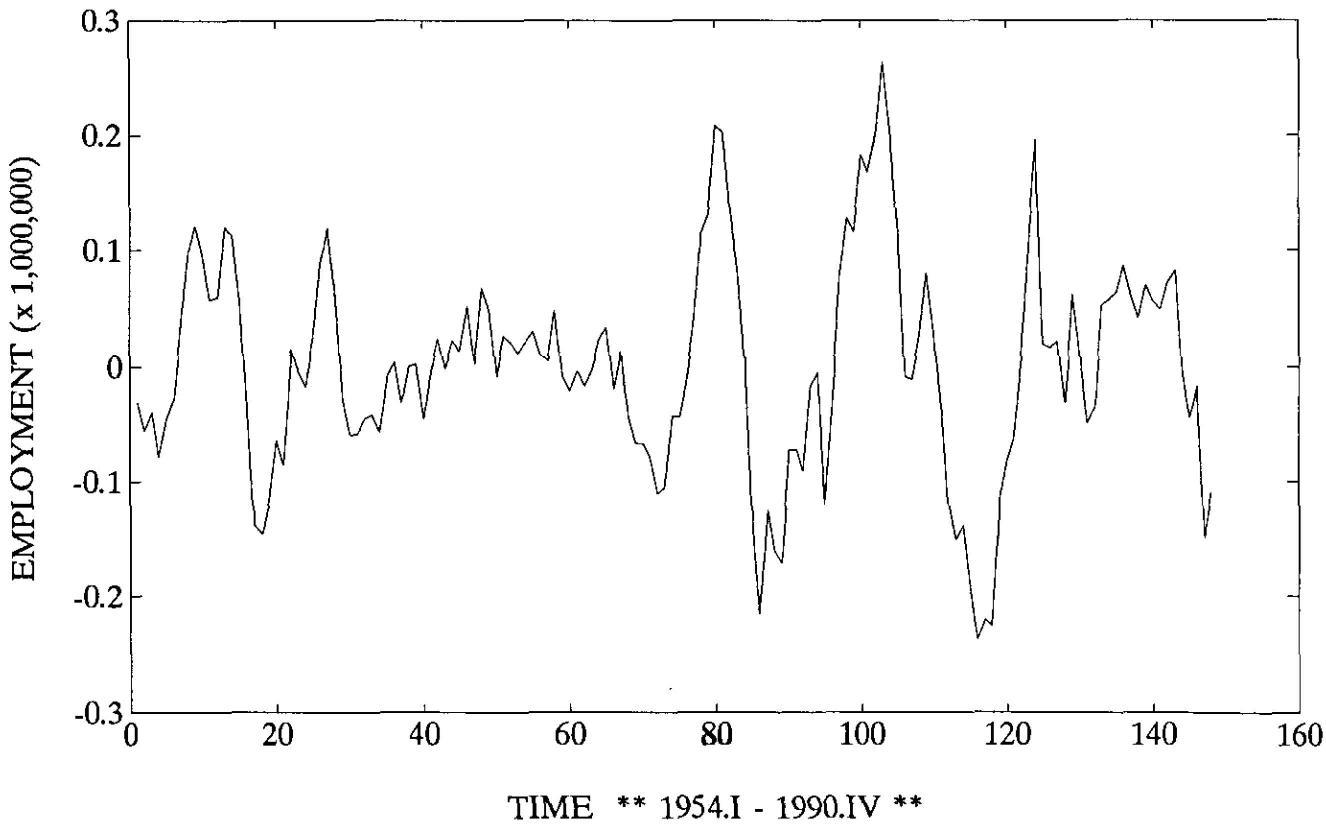


FIGURE 4c: FREQUENCY DISTRIBUTION OF US NONWHITE MALE EMPLOYMENT

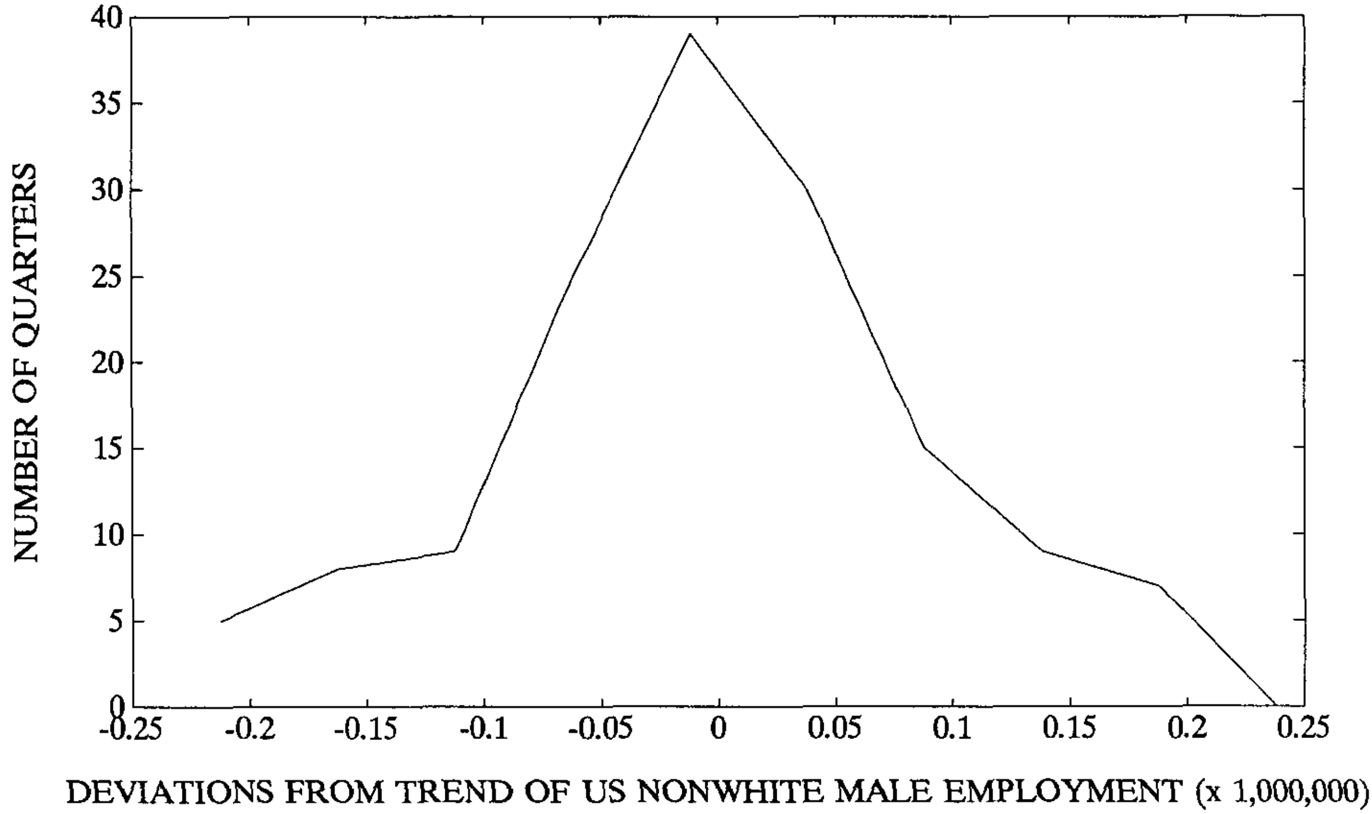


FIGURE 4d: FREQUENCY DISTRIBUTION OF US NONWHITE MALE EMPLOYMENT

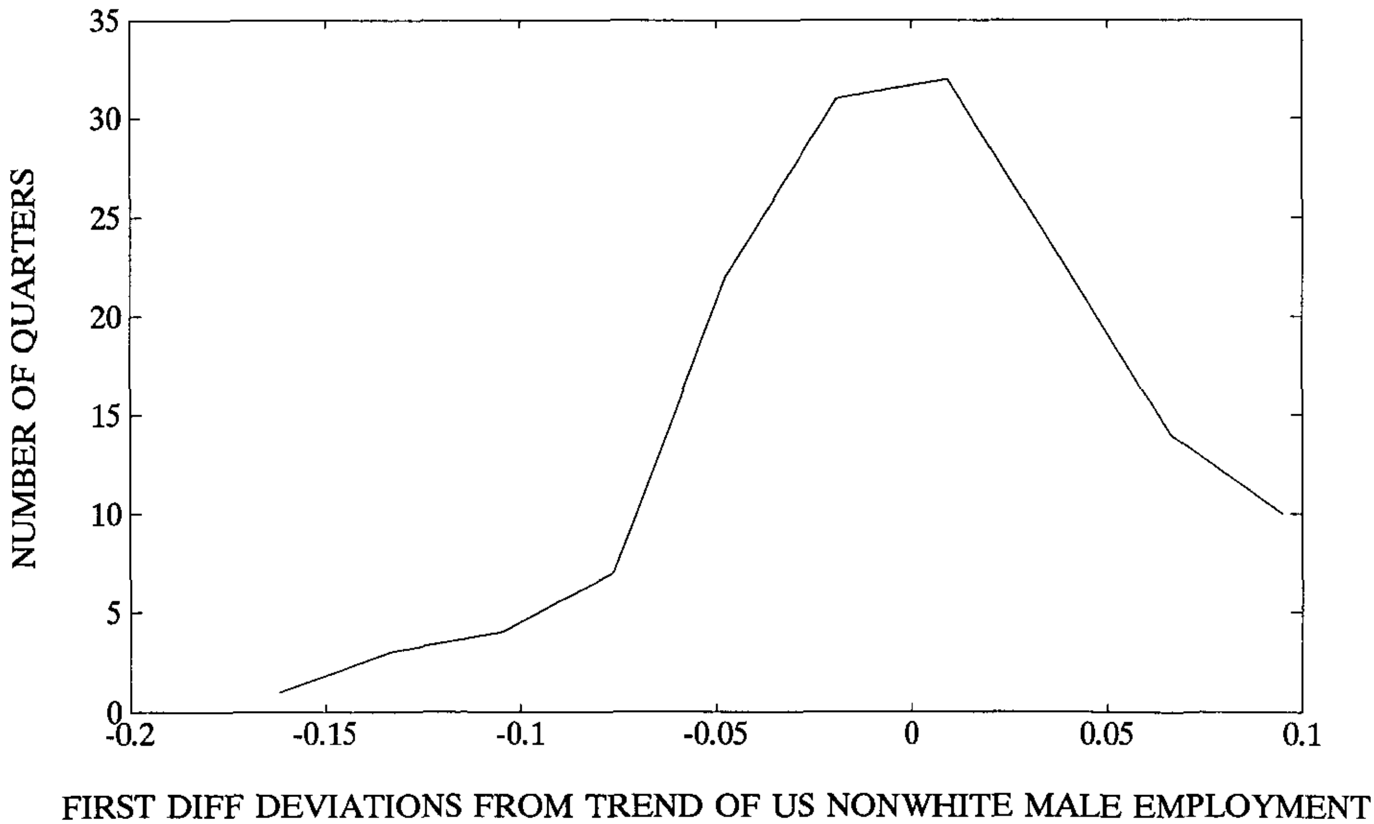


FIGURE 5a: US NONWHITE FEMALE (point) & TREND (solid) EMPLOYMENT

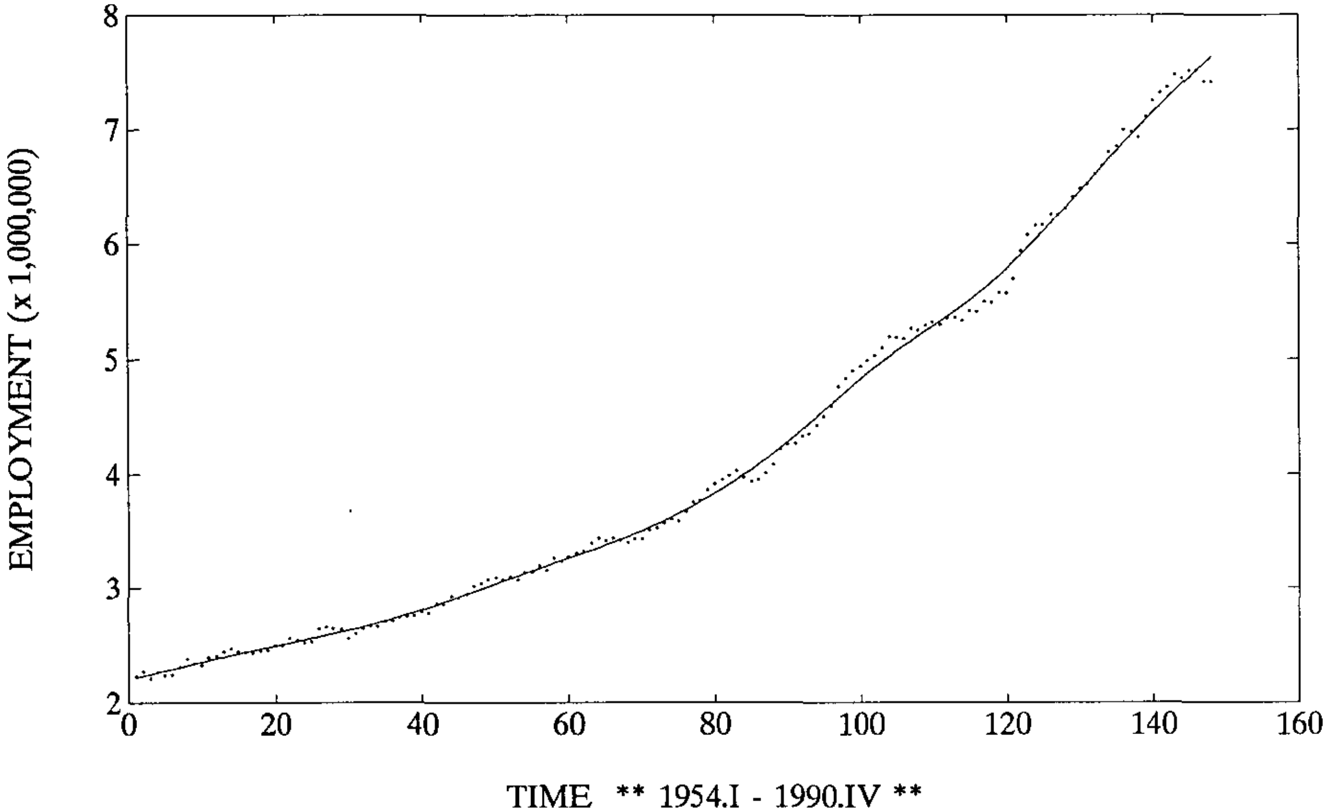


FIGURE 5b: DEVIATIONS FROM TREND OF US NONWHITE FEMALE EMPLOYMENT

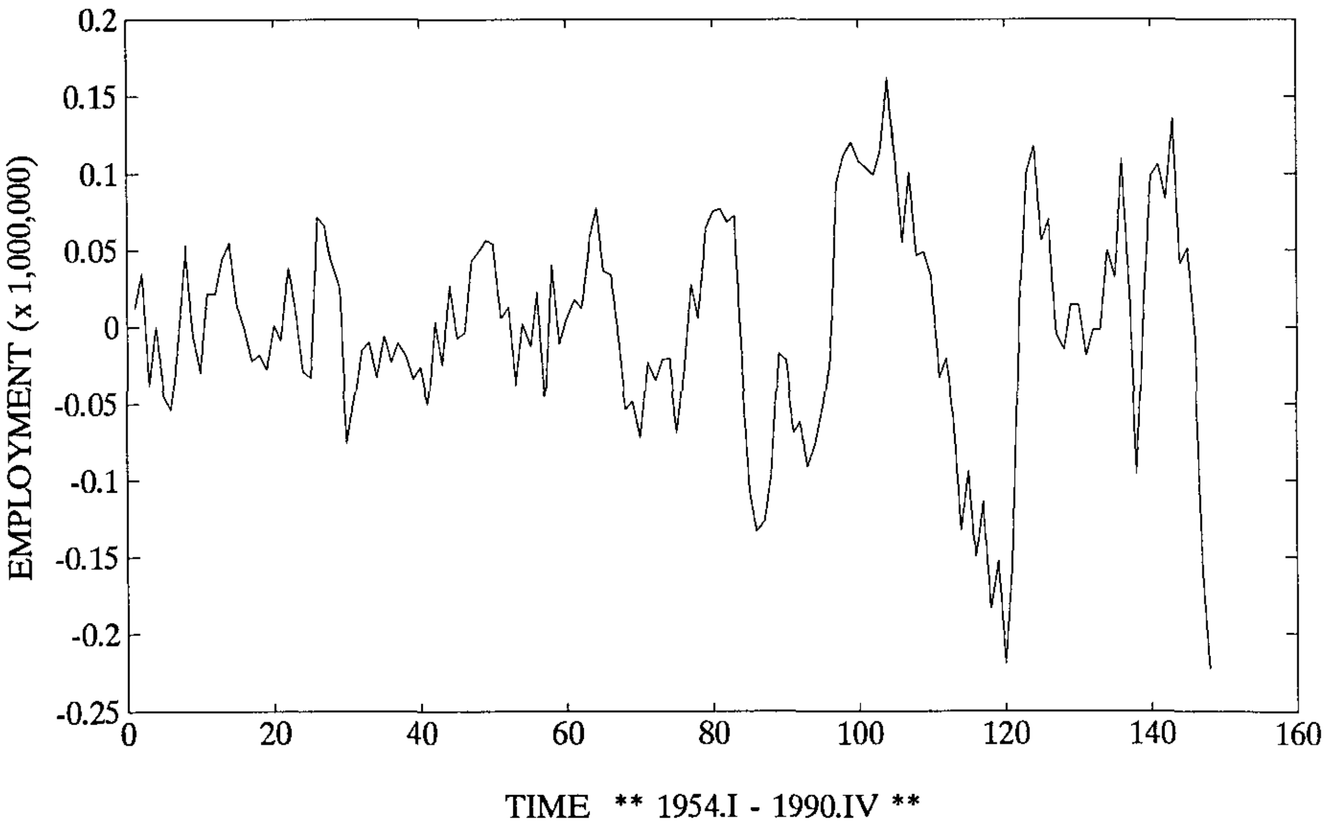
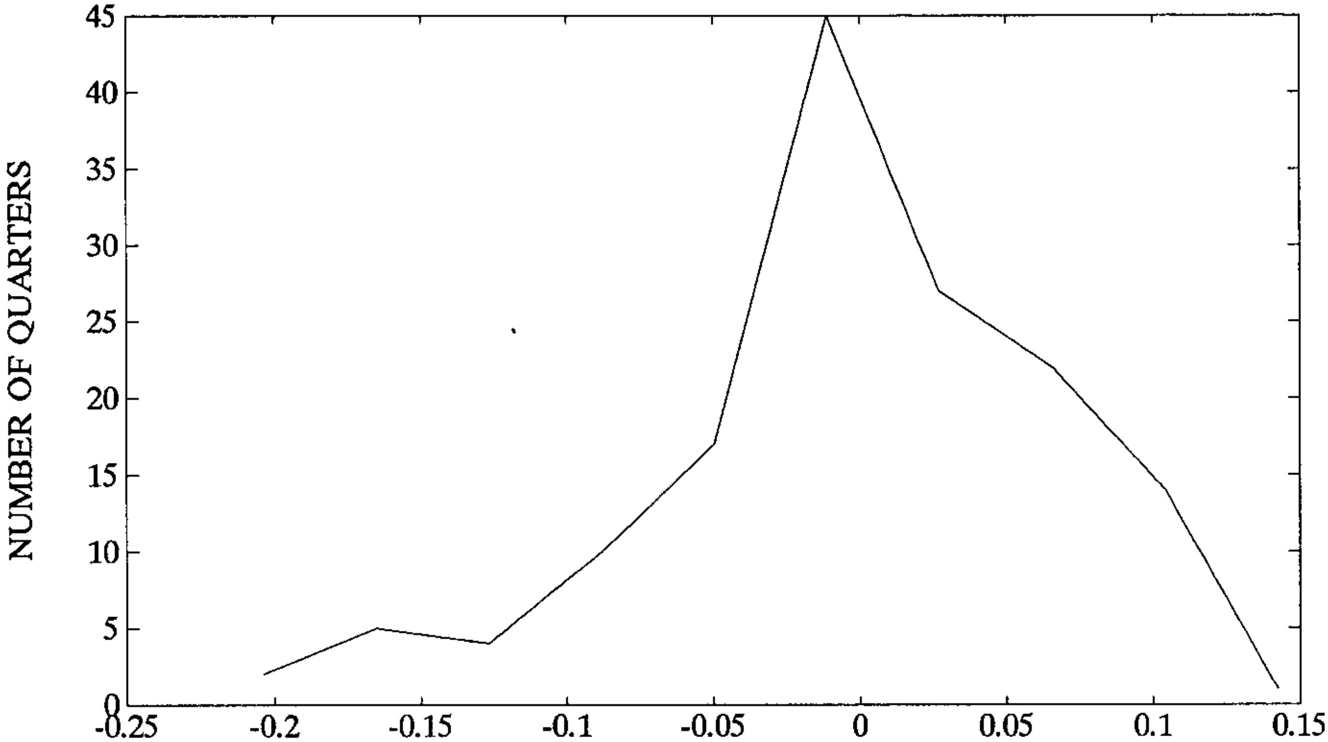
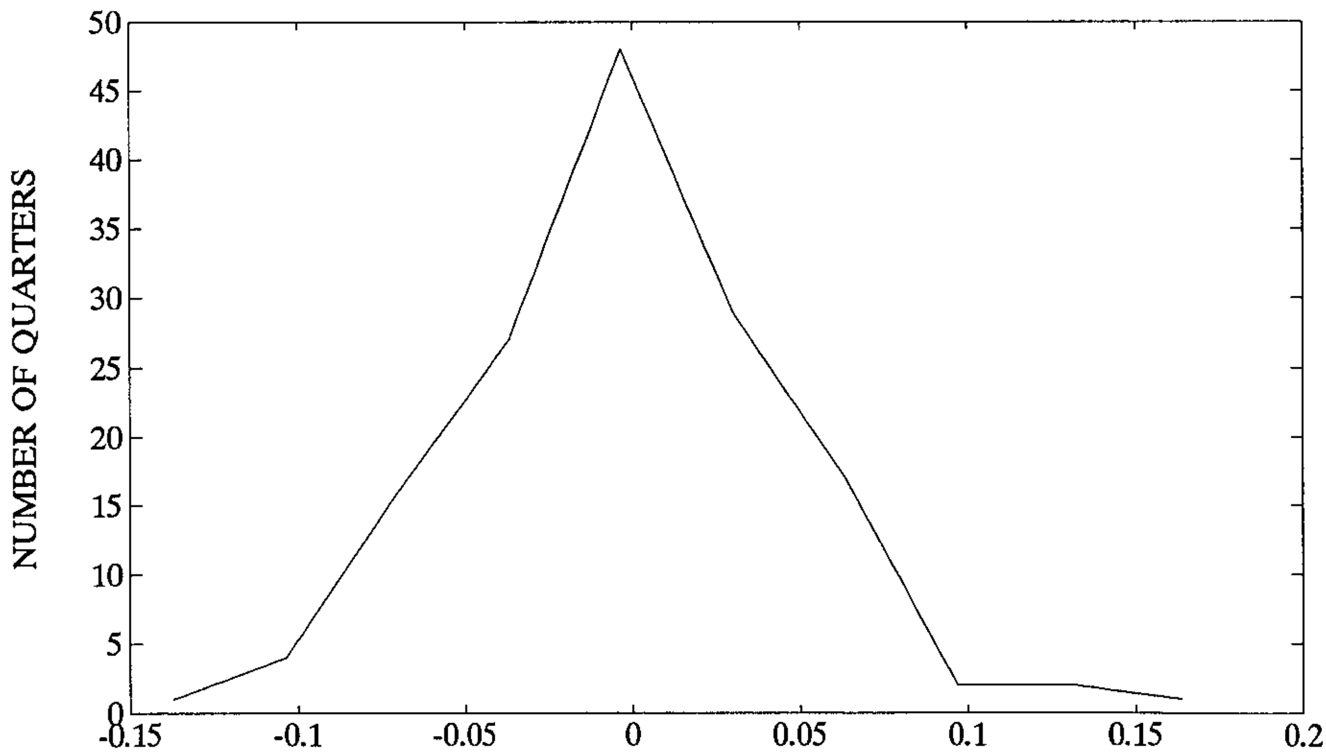


FIGURE 5c: FREQUENCY DISTRIBUTION OF US NONWHITE FEMALE EMPLOYMENT



DEVIATIONS FROM TREND OF US NONWHITE FEMALE EMPLOYMENT (x 1,000,000)

FIGURE 5d: FREQUENCY DISTRIBUTION OF US NONWHITE FEMALE EMPLOYMENT



FIRST DIFF DEVIATIONS FROM TREND OF US NONWHITE FEMALE EMPLOYMENT

FIGURE 6a: US PROFESSIONAL (point) & TREND (solid) EMPLOYMENT

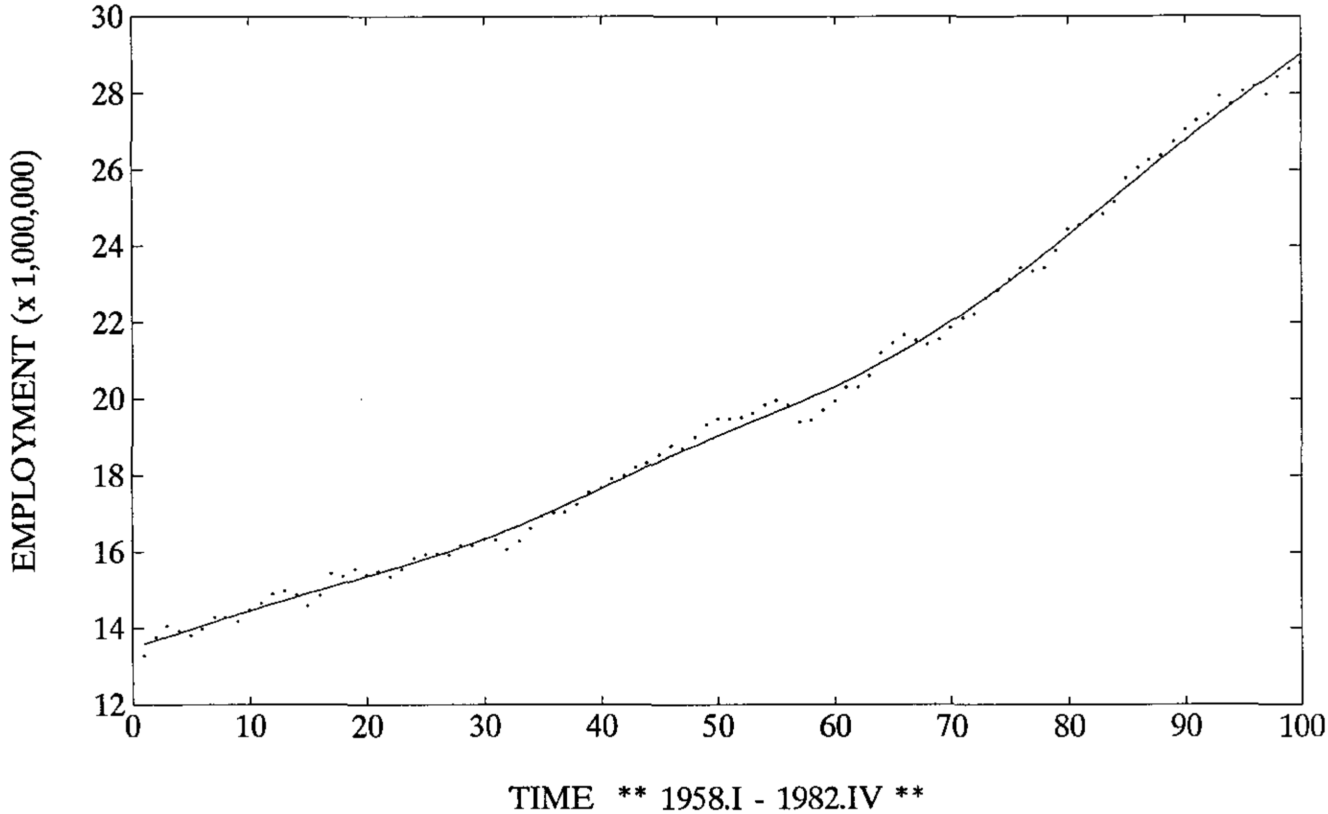


FIGURE 6b: DEVIATIONS FROM TREND OF US PROFESSIONAL EMPLOYMENT

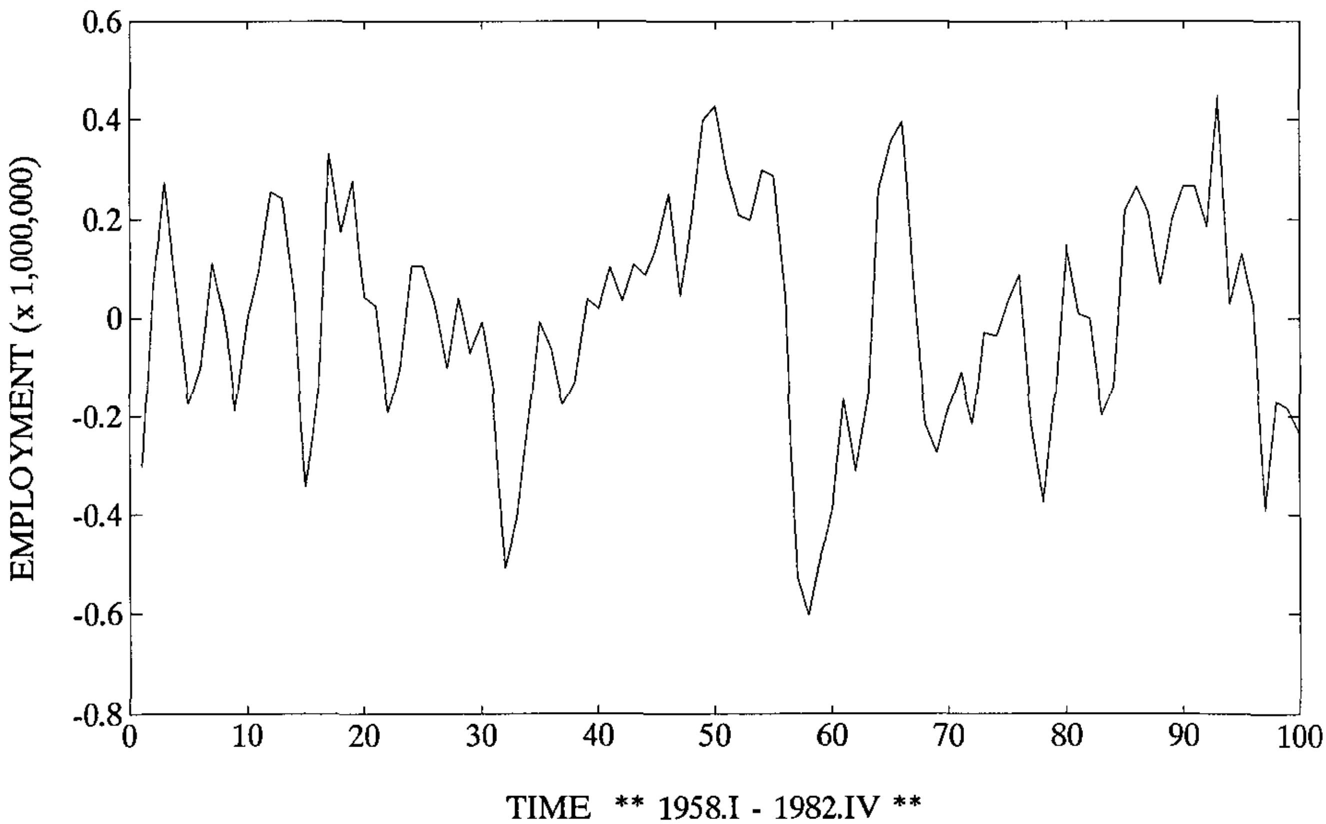


FIGURE 6c: FREQUENCY DISTRIBUTION OF US PROFESSIONAL EMPLOYMENT

FIGURE 6d: FREQUENCY DISTRIBUTION OF US PROFESSIONAL EMPLOYMENT

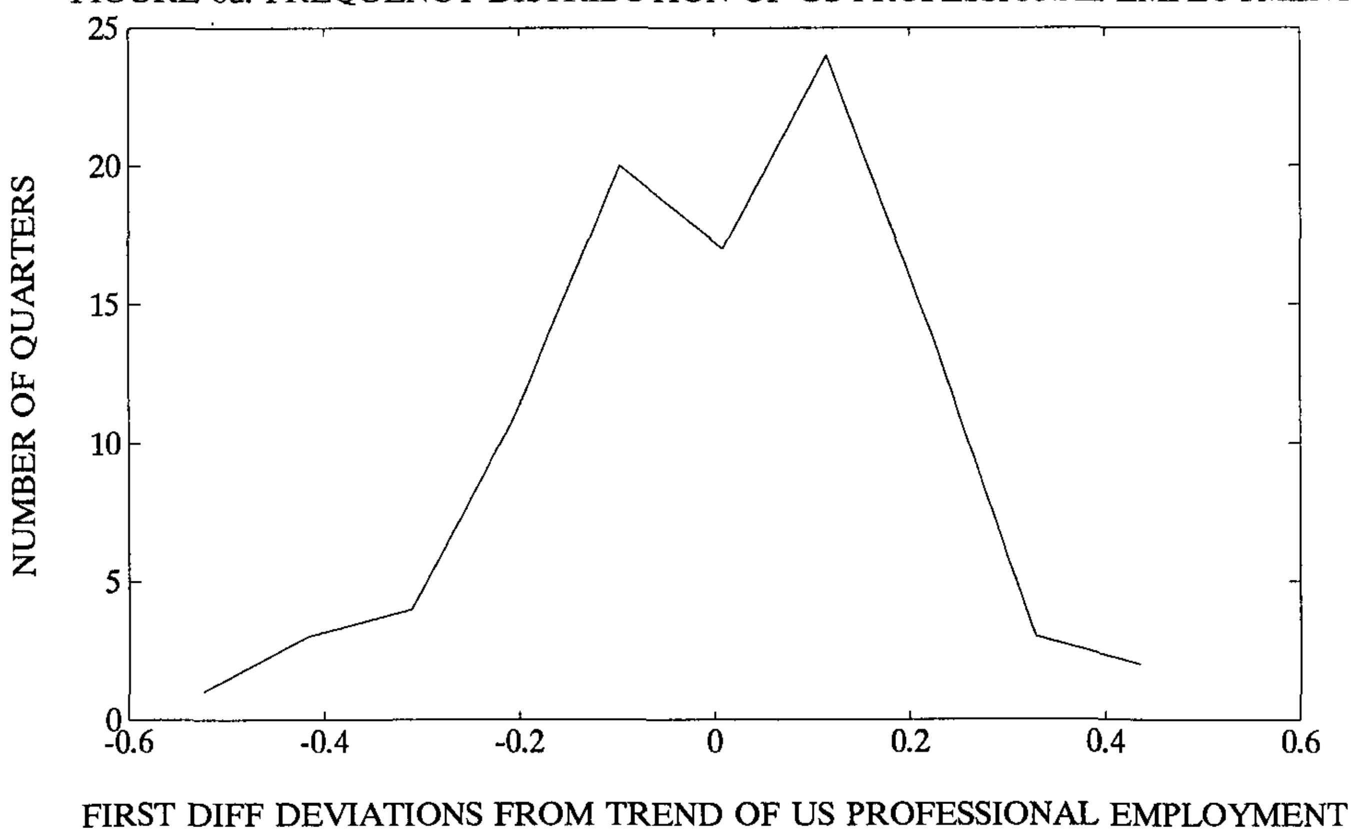


FIGURE 7a: US NONFARM (point) & TREND (solid) LABORERS

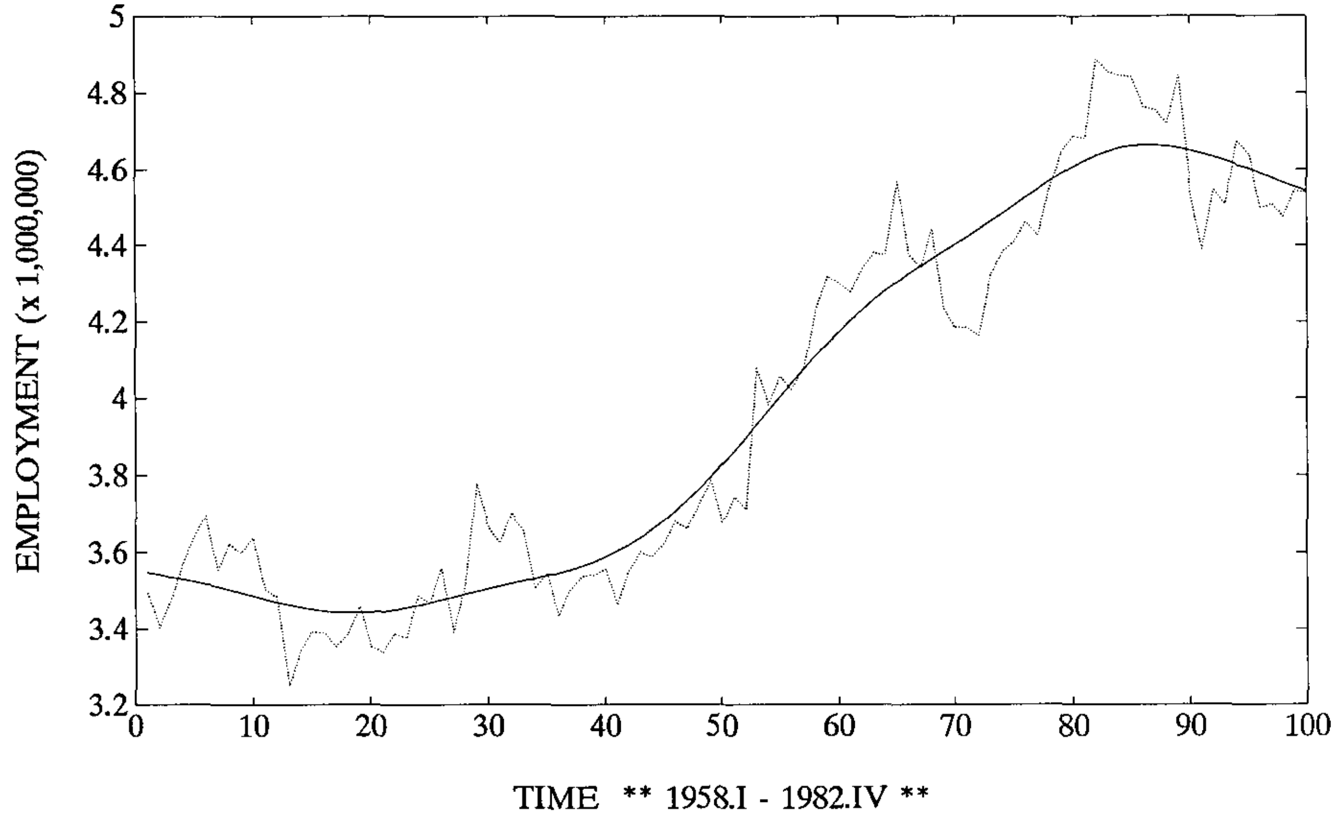


FIGURE 7b: DEVIATIONS FROM TREND OF US NONFARM LABORERS

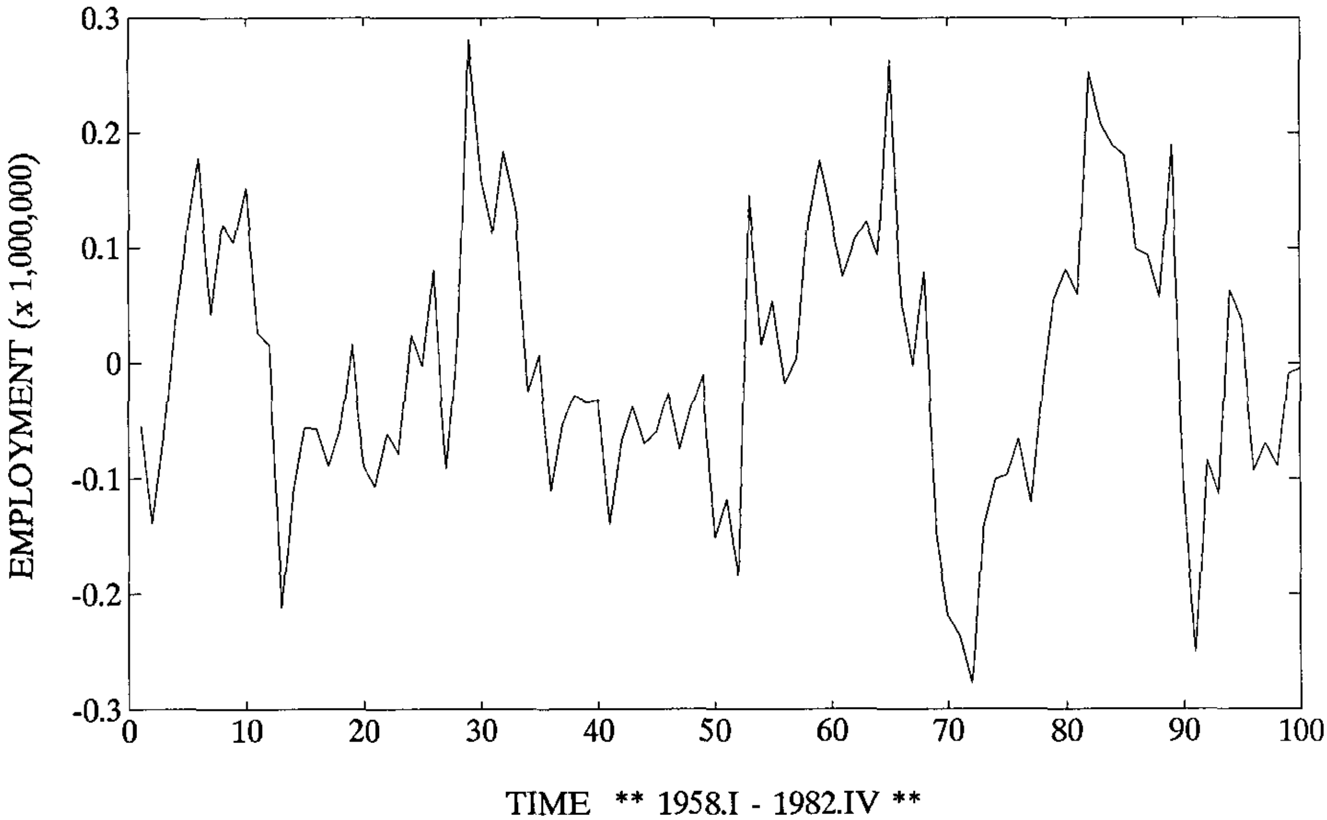


FIGURE 7c: FREQUENCY DISTRIBUTION OF US NONFARM LABORERS

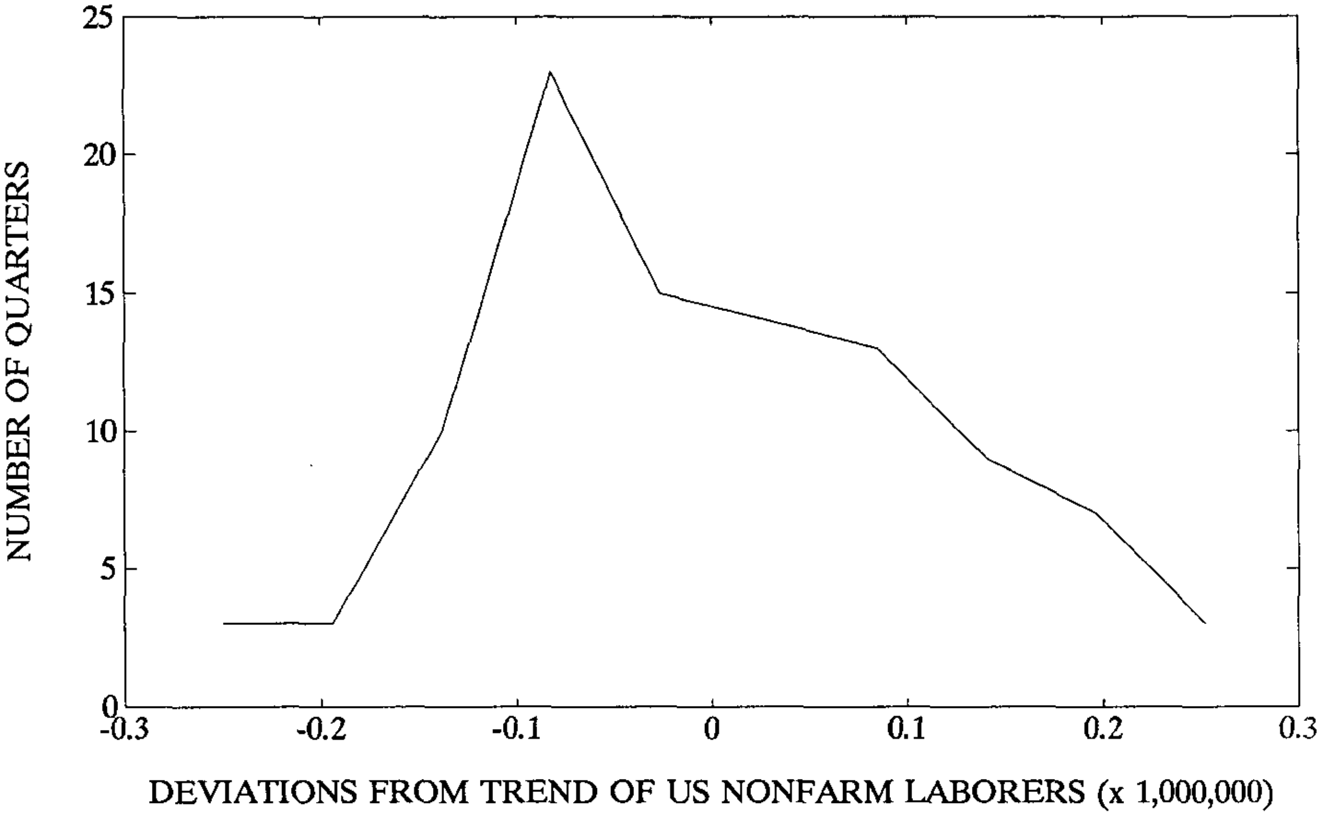


FIGURE 7d: FREQUENCY DISTRIBUTION OF US NONFARM LABORERS