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ASYMMETRIC EMPLOYMENT CYCLES AT THE FIRM LEVEL: A DYNAMIC LABOR DEMAND MODEL AND SOME EMPIRICAL EVIDENCE*

GUSTAVO GONZAGA

SETEMBRO 1993

* This paper is a condensed version of chapters 2 and 3 of my doctoral dissertation at the University of California at Berkeley. I would like to thank William Dickens, David Romer, Andy Rose, and Bryan Lincoln for their many comments and suggestions. I claim total responsibility for any remaining (non-Gaussian) errors.

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1 Introduction

A necessary requirement of any theoretical model is that it be able to explain to a reasonable degree of approximation observed empirical phenomena. It has been found by many analysts that labor market time series seem to display some salient features, often related to asymmetric cycles. This paper proposes modifying traditional dynamic labor demand models in order to make them better suited for the task of capturing these observed special features of labor market time series.

In this paper, it is shown how slight modifications to the standard dynamic labor demand model can generate asymmetric employment cycles. More specifically, it is assumed that the maximizing firm faces *asymmetric* employment adjustment costs when determining its optimal labor input level.[1] The model shows that this asymmetry in the turnover cost parameter induces an asymmetric employment cycle. The reduced form found resembles a nonlinear model which is well-known for its ability to explain asymmetric cycles: a threshold autoregressive (TAR) model with two regimes and a switching-regime index that reflects the past history of employment changes.[2] If turnover costs are asymmetric, the firm will change its labor input in any period in a way that depends on whether employment was rising or falling in the previous period.

Why would it be expected that this model would provide a better fit of employment cycles? A well known fact in macroeconometric research is that traditional models of the business cycle are not capable of producing nonlinear reduced forms. In general, nonlinear models or asymmetric shocks are needed to generate asymmetric cycles, since stationary Gaussian linear ARMA models are incapable of generating them. Unless one assumes that the stochastic disturbance terms in these models are drawn from asymmetric probability distributions (thus, non-Gaussian), they are not suited for fitting data exhibiting strong asymmetry. This point has been made by several authors, including Blatt (1980), Wecker (1981), Tong (1990), Neftci (1984), and Brock and Sayers (1988). The main lesson from this debate is that, in the absence of asymmetric stochastic shocks, these models do not fit well the observation of some nonlinear phenomena often found in economic time series, such as time irreversibility and asymmetric limit cycles.

On the other hand, as mentioned above, empirical studies of asymmetries and nonlinearities tend to find that labor market variables are asymmetric and nonlinear (see, for instance, Neftci (1984), DeLong and Summers (1986), and

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[1] Pfann and Verspagen (1989) and Jaramillo *et al.* (1991) provide some evidence that employment adjustment costs are in fact asymmetric in Dutch and Italy manufacturing sectors, respectively. Nickell (1986) in his comprehensive survey of dynamic labor demand models stresses the implausibility of symmetric employment adjustment costs.

[2] The threshold autoregressive model was first proposed by Tong (1978) and further discussed by Tong and Lim (1980) and Tong (1990).

Brock and Sayers (1988)).[3] This paper uses quarterly U.S. airline industry data at the firm level between 1959 and 1977 in order to assess empirically the presence of asymmetries and nonlinearities in microeconomic employment cycles.[4]

The strategy of the empirical exercise of this paper is to search for asymmetries in each of the series (each pair of firm-worker category) in the data set. Standard asymmetry and nonlinearity tests are performed, showing that in fact about half of the series appear asymmetric.

These findings would go against using linear models when studying firm employment cycles. However, the traditional dynamic labor demand model (*a la* Sargent (1978) and Nickell (1986)) still used in most studies is linear. I thus argue that better forecasts can be obtained with nonlinear models of the threshold autoregressive (TAR) type when employment turnover costs are asymmetric.

In fact, I attempt to fit the threshold autoregressive (TAR) model to each of the series in the airline sample. I find that the TAR model reduces the residual variance substantially (compared to the linear model) in about half of the series.

The paper is organized as follows. The next section proposes a dynamic labor demand model with asymmetric adjustment costs assuming a quadratic structure and a two-state Markov environment. Section 3 discusses qualitative evidence about the size and structure of employment adjustment costs in the U.S. airline industry. Section 4 describes the data. Section 5 tests whether the employment growth series are asymmetric or not, by computing skewness coefficients. Section 6 applies several linearity tests available in the literature to the data. Section 7 then fits the threshold autoregressive (TAR) nonlinear model to each series and compares it to the linear model. Finally, section 3.8 concludes.

2 A Dynamic Labor Demand Model with Asymmetric Adjustment Costs

In a recent paper, Caballero and Engel (1993) defined a hazard employment adjustment function as the relation linking the probability a firm adjusts its labor input in a given period to the magnitude of the deviation from the optimum. They noted that in the standard partial adjustment equation derived from a dynamic labor demand model with symmetric quadratic adjustment costs, this hazard function is constant. Moreover, they show how a piecewise constant hazard function which takes different values depending on whether the firm's deviation from the optimum is positive or negative can generate an asymmetric aggregate employment cycle. In this sub-section, I show how a firm's piecewise hazard function can be derived from a standard dynamic labor demand maximization setup once the possibility of asymmetric employment adjustment costs is considered.

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[3] See Sichel (1989) for opposite findings, though.

[4] The reason I choose to study employment behavior in the airline industry is the availability of an extremely rich data set. Belonging to a heavily regulated industry between 1938 and 1978, airlines were required to report a substantial amount of statistical information to the regulating agency, the Civil Aeronautics Board (CAB), including labor practices. The data are disaggregated by category of worker for each firm, are available at a relatively high frequency (quarterly), and include employment, wages and activity variables (revenues).

The intertemporal firm's profit maximization problem in discrete time is:

$$(1) \quad Max\ E_t \left\{ \sum_{i=0}^{\infty} \beta^i \left[R(Z_{t+i}, N_{t+i}) - W_{t+i} N_{t+i} - C(x_{t+i}) \right] \right\}$$

where E_t denotes expectations formed at time t; $0<\beta<1$ is a real discount factor assumed to be constant for analytical simplicity; R(.) is the firm's real operating revenue function, which is assumed to be increasing and concave in N_t, the employment level; Z_t is a shock to the general state of the firm's business conditions as in Bertola (1990) and Burgess (1992);[5] W_t is the real wage rate taken as given by the firm; C(.) is the adjustment cost function; and x_t represents employment changes.[6]

In this paper, the model is solved assuming a convex (quadratic) structure for C(.) and a linear-quadratic revenue function. Contrary to previous partial-adjustment models, however, I allow for the possibility of asymmetric adjustment costs, introducing a cost of firing parameter (α_f) that can be different from a hiring cost parameter (α_h). Note that the symmetric adjustment cost case is nested in this approach - obviously, in the symmetric case, $\alpha_f=\alpha_h$.[7]

A simple dynamic environment is assumed - a two-state Markov world in which each state is totally defined by the value of a technology parameter Z_t (Z_G is observed in the good state and Z_B in the bad state, $Z_G>Z_B$). The probability of persisting in each state is given by π_i, where i=G,B index each state.

$C(x_t)$ is given by:

$$(2) \quad C(x_t) = \frac{1}{2}\alpha_h 1_{[x_t\geq 0]} x_t^2 + \frac{1}{2}\alpha_f 1_{[x_t<0]} x_t^2$$

where $1_{[.]}$ is the indicator function and all other terms have been previously defined.

The real operating revenue function is given by:

$$(3) \quad R(Z_t, N_t) = Z_t N_t - \frac{1}{2} b N_t^2$$

where Z_t can be viewed as an additive shock to marginal product of labor at time *t* and *b* is a technology parameter as in Sargent (1987).

The modeling strategy is to derive one Euler equation for each of 2 regimes: one in which employment is rising at time *t* ($x_t>0$) and another in which

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[5] Burgess (1992) models $\{Z_t\}$ as a vector of forcing variables affecting profits such as capital stock, technical progress, world trade shocks, and competitiveness.

[6] An alternative to the competitive dynamic labor demand model above is the efficient contract model in which firms and unions maximize a joint utility function. Card (1986a), however, found no evidence that an efficient contract model outperforms the competitive model for mechanics in the airline industry.

[7] Gonzaga (1993) also studies the linear (asymmetric) cost of adjustment structure. In this paper, however, the intention is to compare the standard partial adjustment model with an "asymmetric partial-adjustment" model.

employment is decreasing at time t ($x_t < 0$). An asymmetric employment cycle will result whenever the speed of adjustment (the coefficient on lagged employment) is different across these two regimes.

Assume first that the firm is hiring new workers at time t ($x_t > 0$), *i.e.*, that the firm is in regime 1.[8] The Euler equation when $x_t > 0$ ($Z_t = Z_G$) is given by:

$$(4)\quad M(Z_G, N_t) - W_t - \alpha_h(N_t - N_{t-1}) + \pi_G \beta \alpha_h (N_{t+1} - N_t) + \\ + (1-\pi_G)\beta\alpha_f(N_{t+1} - N_t) = 0$$

where M(.,.) is the marginal revenue function.[9] When R(.) is given by (3), $M(Z_t, N_t) = Z_t - bN_t$. After rearranging terms, (4) can be rewritten as a second-order linear difference equation:

$$(5)\quad \{\beta\pi_G\alpha_h + \beta(1-\pi_G)\alpha_f\}N_{t+1} + \\ + \{-b - \alpha_h - \beta\pi_G\alpha_h - \beta(1-\pi_G)\alpha_f\}N_t + \alpha_h N_{t-1} = W_t - Z_G$$

Defining $C_G = \pi_G \alpha_h + (1-\pi_G)\alpha_f$, $\phi_G = -(\beta + \alpha_h/C_G + b/C_G)$, $\mu_G = \alpha_h/C_G$, and denoting L as the lag operator, I get:

$$(6)\quad \beta\left(1 + \frac{\phi_G}{\beta}L + \frac{\mu_G}{\beta}L^2\right)N_{t+1} = \frac{W_t - Z_G}{C_G}$$

Note that if $\alpha_h = \alpha_f$, then $C_G = \alpha_h = \alpha_f$ and $\mu_G = 1$, in which case equation (6) collapses into the familiar form found in Sargent (1978), which is the basis for deriving the partial adjustment result. In other words, equation (6) nests the standard symmetric quadratic adjustment cost structure extensively studied in the dynamic labor demand literature. The only innovation here is to allow for the possibility of asymmetric adjustment costs.

Note also that when $\alpha_h = \alpha_f = 0$, then $bN_t = W_t - Z_G$, which is the standard static maximization condition for employment determination (real wage equals marginal revenue in each period).

The reciprocals of the roots of this second order difference equation are:

$$(7)\quad \lambda_G = \frac{-\phi_G \pm \sqrt{\phi_G^2 - 4\beta\mu_G}}{2\beta}$$

It can be shown that the term inside the square root is greater than zero for

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[8] I assume that this occurs when the economy is in the good state G. This is consistent with the relevant Euler equation when $x_t > 0$, as shown below.

[9] Note that when $x_t > 0$, and by substituting in equation 4,

$$Z_G > bN_t + W_t - \beta E_t[C'(x_{t+1})] = A$$

One can show by symmetry that $Z_B \leq A$ when $x_t \leq 0$. Therefore, the maximization procedure proposed here can be applied since the two relevant Euler equations are independent from each other (see Jaramillo *et al.* (1991)).

reasonable values of the parameters b, β, and a_h, which implies that the two roots are real. I experimented solving equation (7) for some special interesting cases and for a range of reasonable parameter values. In most situations, I obtained $0<\lambda_{G1}<1<\lambda_{G2}$, as in Sargent (1978), which permits one to rewrite equation (6) by operating on both sides of it with the forward inverse of $1-\lambda_{G2}$ to get:[10]

$$(8)\quad N_{t+1} = \lambda_{G1} N_t - \frac{\lambda_{G1}}{C_G \mu_G} \sum_{i=0}^{\infty} \left(\frac{1}{\lambda_{G2}}\right)^i E_{t+1} \left(W_{t+1+i} - Z_{t+1+i}\right)$$

Note that this condition should hold for each period $t+j+1$ whenever the economy is hiring at $t+j$ ($x_{t+j}>0$), $j=0,1,...$

Assuming that employers' expectations about $\{W_t\}$ and $\{Z_t\}$ are formed rationally, the last term in equation (8) can be substituted for contemporaneous and lagged values of these two variables. For example, if W_{t+1} is well represented by an autoregressive process of order 1 plus a constant k, with $\rho<1$ as the AR parameter, then $E_t W_{t+i} = \rho^i W_t + ik$. Substituting this back into equation (8), I get for each period $t+j+1$:[11]

$$(9)\quad N_{t+j+1} = K_G + \lambda_{G1} N_{t+j} - \frac{\lambda_{G1}}{C_G \mu_G} \left(\frac{W_{t+j+1}}{1-\frac{\rho_w}{\lambda_{G2}}} - \frac{Z_{t+j+1}}{1-\frac{\rho_z}{\lambda_{G2}}} \right)$$

The equation above shows explicitly how the parameter λ_{G1} determines the speed of employment adjustment whenever the economy is in this regime (whenever $x_{t+j}>0$). It is similar to the standard partial adjustment labor demand equation, but the difference here is that it is valid only when the economy is in regime 1.

One can show by symmetry that the following partial adjustment equation is valid when the firm is in the other regime, *i.e.*, when the firm is firing at time t ($x_t<0$):

$$(10)\quad N_{t+j+1} = K_B + \lambda_{B1} N_{t+j} - \frac{\lambda_{B1}}{C_B \mu_B} \left(\frac{W_{t+j+1}}{1-\frac{\rho_w}{\lambda_{B2}}} + \frac{Z_{t+1+j}}{1-\frac{\rho_z}{\lambda_{B2}}} \right)$$

Comparing the two previous equations, it is observed that the speed of employment adjustment differs across the two states of the economy, as long as $\pi_G \neq \pi_B$ and $a_h \neq a_f$. The pair of equations above constitutes a Threshold Autoregressive (TAR) multivariate model in levels:

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[10] For details on this step, the reader is referred to Gonzaga (1993). See also Sargent (1987), page 203.

[11] I assumed here that $\{Z_t\}$ also follows an AR(1) process. In general, if both {Wt} and {Zt} follow an AR(p), several lags of these two variables should be added to equation (9). K_G is a constant.

$$(11)\quad N_t = \begin{cases} a_0^{(1)} + a_1^{(1)} N_{t-1} + \sum_{i=0}^{1} b_i^{(1)} W_{t-i} + \sum_{i=0}^{1} c_i^{(1)} Z_{t-i} + \epsilon_t^{(1)}, & if\ x_{t-1} > 0 \\ a_0^{(2)} + a_1^{(2)} N_{t-1} + \sum_{i=0}^{1} b_i^{(2)} W_{t-i} + \sum_{i=0}^{1} c_i^{(2)} Z_{t-i} + \epsilon_t^{(2)}, & if\ x_{t-1} \le 0 \end{cases}$$

In this paper, I compare this model with the standard partial adjustment model in terms of their abilities to fit firm level employment data. The partial adjustment model (as in Sargent, 1978) specification is:

$$(12)\quad N_t = a_0 + \lambda N_{t-1} + \sum_{i=0}^{1} \alpha_i W_{t-i} + \sum_{i=0}^{1} \beta_i Z_{t-i} + \epsilon_t$$

Note that the partial adjustment model is nested in the TAR representation in levels given by equation 11, being observed there when the AR coefficients and the variances of the error terms are the same in both regimes.

The model thus produces a simple piecewise reduced form for employment (a TAR representation) which is capable of generating an asymmetric cycle that fits the basic features observed by most labor market series analysts.

In sum, this section showed how an asymmetric employment cycle can be generated from a standard convex dynamic labor demand model once one drops the unrealistic assumption of symmetric labor turnover costs.

3 Adjustment Costs in the U.S. Airline Industry - 1959-77[12]

This section presents some informal evidence on the size of hiring and firing costs faced by firms in the airline industry for each class of workers studied in this paper.[13] The discussion framework is one in which firing costs are assumed to depend mainly on the effectiveness of labor unions' activity through the introduction of provisions regarding monetary compensation for breach of contract, dismissal payments, and layoff advance notices. Hiring costs, on the other hand, are assumed to increase with the level of skillness required for each category of workers. In general, hiring costs include costs of advertising, interviewing, screening and training new workers; and the cost of intrawork transfers (see Piore, 1986).

It has been suggested by many authors that pilots carry relatively high employment adjustment costs (see, for instance, Williams (1991)). On the hiring side, costs are inflated by expensive ground and flight training. On the firing side,

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[12] Quarterly data was collected by the Civil Aeronautics Board (CAB) only for the period 1959-1977.

[13] The U.S. airline industry in the period studied here (1959-1977) was characterized by strict government regulation, the presence of some strong craft unions, and by a high concentration rate. See Gonzaga (1993) for a description of the main features of the U.S. airline industry under the regulated period.

costs are also large due to the high degree of pilots' unionization.[14] One should also expect an almost complete idiosyncratic labor market for pilots with a low voluntary turnover rate, since seniority rewards regarding wages and work conditions are substantial and are not transferrable across carriers (see Cappelli, 1987).

Seniority rewards also exist for flight attendants but are less steep. Hiring costs are lower, since training costs are not so expensive. On the firing side, flight attendants did not have their own independent union until 1975 when the Association of Flight Attendants (AFA) was created. As a consequence, flight attendants were not able to obtain wage gains comparable to those made by pilots and mechanics during most of the regulated period. Low firing costs should thus be expected, since their bargaining power was not very high during most of the period of analysis.

Mechanics have arguably the highest degree of bargaining power in the airline industry. Their skill requirements are large, seniority rewards are not so steep, there is a high demand for them outside the airline industry, and their main union, the International Association of Machinists (IAM), was highly centralized and effective throughout the regulated period (see Cappelli, 1987). In fact, both hiring and firing costs should be expected to be large. Williams (1991) found that labor hoarding for mechanics seems to be high.

4 The Data

One of the main weaknesses of the empirical literature on asymmetric employment cycles has been the sparse use of firm level data, which is clearly preferable since aggregation tends to obscure movements at the microeconomic level, usually removing asymmetries. The problem is to find firm level data that is frequent enough to avoid temporal aggregation bias and that span a period of time containing a reasonable number of complete business and firm specific cycles.

Some European countries recently started to collect firm level employment data in response to the increasing demand for a better analysis of the "Eurosclerosis" phenomenon (see Bertola and Bentolila, 1990). However, most of this new data is annual. For more frequent data, either the span is too short or there is no information on real wages, sales, or revenues.[15]

The data set used in this paper consists of quarterly observations on employment, wages and total operating revenues for 19 U.S. airline companies between 1959 and the first quarter of 1977.[16] I collected employment (total

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[14] The Air Line Pilot Association (ALPA), created in the 1930s, represented the union workers with the highest salaries by 1959 (see Cremieux, 1992).

[15] Gavosto and Sestito (1992), for instance, explored a huge monthly firm level data set available from the Italian social security agency, INPS. However, the data misses information on production variables and wages are only available at an annual frequency.

[16] I should note that a sub-set of the data used in this chapter was explored by Card (1986), and by Hamermesh (1992). They both used data for mechanics in

number of employees) and wages (average payroll per employee, excluding fringe benefits) variables for three categories of workers: pilots and copilots, flight attendants, and maintenance mechanics.[17] As shown in the previous section, these categories represent a wide dispersion in terms of adjustment costs, which implying a dispersion in employment adjustment behavior for each type of worker.

The source of the data are the Form 41 reports that airlines were required to file with the defunct Civil Aeronautics Board - CAB. The labor variables were found in the Form 41's Schedule P-10, which was filed quarterly until 1977:1.

Total operating revenues data was collected from Air Carrier Financial Statistics (several issues), a CAB serial publication. It consists of the sum of transport revenues and subsidies. Only data on domestic operations were considered, since most workers in some categories (like pilots) are not reported in international operations. I use the quarterly U.S. Implicit Price Deflator to convert nominal wages and total operating revenues into real values.

Some filters were applied to the employment and wage data before analysis. I collected information on strikes and other labor-management problems that resulted in total or partial suspension of operations for some airline in the period considered. Whenever employment numbers dropped considerably in any of these periods, they were removed from the data set.[18] I also include strike dummies in the linear and nonlinear model regressions.

One problem with the data should not be overlooked. Cremieux (1992) reported that the wage numbers taken from Schedules P-10 are based on the last two weeks of the quarter. That could bias the results since I do not consider any variation in wages along the quarter. Therefore, the wage variables used in this analysis should be viewed as proxies to the actual salaries received in each period.

5 Skewness and Other Summary Statistics

In this section, I begin the search for nonlinearities in each series in the airlines data set by computing some conventional measures of asymmetries.

The empirical strategy is based on DeLong and Summers (1986). Employment growth is defined as in Davis and Haltiwanger (1990)[19]:

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seven trunk airlines between 1969 and 1976. Card (1986) compared the performance of a dynamic efficient contract model to the standard partial adjustment labor demand model by Sargent (1978), finding that neither model successfully explained the relationship between wages and employment in the data. Hamermesh (1992) showed that including fixed adjustment costs in a dynamic labor demand model produced better results when compared to the nested partial adjustment model.

[17] Table 1 gives the names and codes of the 19 air carriers in the data set, and the types of workers available for each airline.

[18] For more details on data sources and procedures, see Gonzaga (1993).

[19] The reason for using this definition rather than a standard employment growth rate is that the latter induces asymmetry, while the former should be

$$(13)\quad DN_t = \frac{(N_t - N_{t-1})}{\frac{1}{2}(N_t + N_{t-1})}$$

I compute skewness coefficients for this measure of employment growth for each series (each pair of firm-worker category in the airline data set). In Gonzaga (1993), I show that removing a linear trend and seasonal effects do not alter significantly the results reported here.[20] Skewness coefficients are defined as in Kendall and Stuart (1969):

$$(14)\quad Sk = \frac{T^2}{(T-1)\,(T-2)} * \frac{m_3}{s^3}$$

where T is the total number of observations, and m_3 and s are, respectively, the third centered moments and the standard deviation of the series under analysis (employment growth as defined above). A zero skewness coefficient implies a symmetric series (roughly, it implies that negative employment changes are not significantly different than positive changes). A positive skewness coefficient - a distribution skewed to the right - indicates asymmetry, being observed when the median is below the mean (roughly, it implies that positive changes are larger than negative changes).

Table 2 contains summary statistics for the measure of employment growth (DN_t) defined above for pilots, flight attendants and mechanics in each airline. As expected from the discussion in Section 3, I find that flight attendants' employment growth vary more than for other categories in almost every airline (see the fourth column of Table 2). Note also how employment growth standard deviation is much higher for all categories in small and seasonal carriers compared to the large trunk carriers.[21]

The second column of Table 3 presents skewness coefficients of employment growth for each series. However, to examine the statistical significance of these skewness coefficients, one has first to test for serial correlation in the employment growth variables. Kendall and Stuart (1969) showed that when there is no serial correlation the skewness coefficients are normally distributed with standard errors given by $((6T)/(T-1)(T-2))^{1/2}$. When there is serial correlation, however, there are no available test statistics in the literature. The conventional approach in these circumstances is to compute sampling skewness

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symmetrically distributed between -2 and 2 for a symmetric series.

[20] In Gonzaga (1993), I removed a linear deterministic trend, since the span for each series is not too long (18 years). In future work, I intend to use alternative trend-cycle decomposition methods to check the robustness of the results obtained here. I also note that taking logs does not significantly affect the results.

[21] Gavosto and Sevisto (1992) also observed this negative size effect on employment growth variability for Italian firms in the INPS sample.

standard deviations based on a simple Monte Carlo simulation procedure proposed by DeLong and Summers (1986). This procedure was recently used by Pfann (1991) and Choi (1991), and is fully described in Gonzaga (1993).

The third column of Table 3 shows marginal significance values (p-values) for the second column skewness coefficients. They are based on one-tailed normal distribution with standard errors as given in Kendall and Stuart (1969), *i.e.*, assuming no serial correlation. The fourth column presents p-values of Box-Pierce Q statistics testing for up to 4^{th} order serial correlation. These Q statistics should follow a chi-square distribution with 4 degrees of freedom. A p-value of 5% in this column, for example, means that the null hypothesis of zero serial correlation is rejected at the 5% significance level. Finally, the fifth column presents p-values based on the Monte Carlo procedure described above (300 replications and an AR(4) are used for each series).

Note that the p-values from the Monte Carlo simulation do not differ much from p-values assuming Kendall and Stuart's distribution - no serial correlation - when serial correlation is in fact rejected by the Q-test at a 10% or less margin of significance, which reassures the validity of the procedure used here.

Therefore, to count how many series are significantly skewed, I use Table 3 third column p-values for each of the series that appears not to be serially correlated at the 10% significance level (based on fourth column Q statistics p-values), and the fifth column p-values for the remaining series. I find that 30 out of 57 series are significantly positively skewed at the 10% level (28 at the 5% level), while eight series are negatively skewed at the 10% level (7 at the 5% level). So most series - 38 out of 57 - are found to be asymmetric.

According to the labor demand model derived in section 2, this can be indicating that adjustment costs are asymmetric, with downward adjustment costs being in most of the cases larger than upward adjustment costs. Alternatively, it can be indicating that forcing variables (real wages and real revenues) are asymmetric, or still that shocks to these variables are asymmetric.

To test whether the observed asymmetries are coming from asymmetries of forcing variables, I study the residuals from the standard partial adjustment regression due to Sargent (1978) - equation 12 of section 2 - applied to each of the series in the sample.

Gonzaga (1993) presents the estimation methods and results. Most of the coefficients have the expected signs, with coefficients on lagged employment corresponding to values typically found in the empirical literature (see Hamermesh, 1993). Here, however, I present only the results from the analysis of asymmetries in the residuals from the linear model.

As in Table 3, Table 4 presents skewness coefficients, p-values assuming zero serial correlation of the residuals, and Q-statistics' p-values for serial correlation of up to 4^{th} order. Most of the series appear to be serially uncorrelated (zero serial correlation is rejected for only 9 series at the 5% level).

Examination of the p-values from the third column (no serial correlation) suggests that 20 series are significantly positively skewed at the 5% level, while 12 series present significant negative skewness at the 5% level. Therefore, even controlling for movements in forcing variables, 32 out of 57 series seem to be asymmetric.[22] This is very damaging to the class of linear labor demand models. It is either indicating that the disturbance term in the partial adjustment equation (12) is asymmetric (thus, non-Gaussian), or that employment adjustment is asymmetric (thus, nonlinear). If the latter is true, one should use a nonlinear model like the one developed in section 2.

Summing up the findings of this section, I showed that most of the untransformed employment growth series seem to be asymmetric - 38 out of 57 series. Then, I tested whether this apparent asymmetry remained after controlling for movements in forcing variables typically used in labor demand models. The analysis of the residuals from a standard partial adjustment model showed that 32 series still appear asymmetric.

To conclude this section, I note that the existent analysis of asymmetries in employment adjustment in the literature usually performed only the first exercise above (the study of the employment growth series) and applied it to aggregate data.[23] Replicating this exercise here to firm level data in fact confirmed their previous findings of asymmetries for most of the series in the sample studied.

However, I moved one step further. I checked the residuals from a standard linear labor demand model and found that most of them also appear asymmetric. In order to distinguish whether this asymmetry is coming from a departure from Gaussianity in the error term or from linearity in the model structure, I perform more rigorous nonlinearity tests. This is the topic of the next section.

6 Nonlinearity Tests

In this section, I apply several nonlinearity tests to the employment series studied above. In the analysis below, a process $\{x_t\}$ is defined to be linear in mean with respect to the information set spanned by Z_t if:

$$(15) \quad P[E(x_t \mid Z_t) = Z_t' \theta^*] = 1 \quad , \quad for\ some\ \theta^* \in \mathbb{R}^k .$$

as in Lee *et al.* (1993) - note that Z_t may contain lagged values of x_t..

The condition above - linearity in mean - is the null hypothesis in all tests described below.[24] Most of the nonlinearity tests consist of examining whether the residuals of a linear AR model are orthogonal to some transformation of the dependent variable. In case they are not, the null hypothesis (of linearity in mean) is rejected. All tests are described in Gonzaga (1993). I used Tsay's (1991) mnemonics for each test: ORI-F is the original Tsay's (1986) F test, AUG-F is

[22] Note that the number of negative skewness increased significantly compared to the previous table. Now 12 series seem to be skewed to the left - compared to 8 in the previous table. That is probably indicating that some of the positive skewness in the previous analysis was coming from positive asymmetries in the forcing variables.

[23] See, for instance, DeLong and Summers (1986) and Pfann (1991).

[24] Note that a time series exhibiting ARCH is linear in mean according to condition above.

Luukkonen *et al.* (1988) augmented F test, TAR-F is Tsay's (1989) test, CUSUM is Petruccelli and Davies (1986) test.

Table 5 displays the results of the application of the nonlinearity tests described in the appendix to the airlines data set. It uses log first-differenced series.[25]

All series were log first-differenced to make them stationary. If the series were non-stationary, then one can show that the arranged autoregression tests would be biased in the direction of rejecting linearity. This is because both the TAR-F and the CUSUM tests are based on the white noise distribution of the standardized predictive residuals under the null of linearity. When unit roots are present, however, these residuals are not white noise.

In fact, I could not reject non-stationarity for most of the series in the sample (Augmented Dickey-Fuller (ADF) tests fail to reject unit roots for all but three series), while ADF tests rejected unit roots for all log first-differenced series.

Table 5 suggests that most log first-differenced series appear to be linear. Linearity is rejected at the 10% level for 12, 9, 13, and 16 (out of 57) series when ORI-F, AUG-F, TAR-F, and CUSUM tests are respectively used. This is in fact much less nonlinearity (thus much less asymmetry) than what is suggested by the skewness analysis of the previous section.

However, these results should be taken with caution. A Monte Carlo simulation presented in Gonzaga (1993) showed that these tests are not very powerful when the AR parameters and the error variances are not very far apart from each other across regimes, which could very well be the case for most of the series in this sample.

The results from the previous section, nonetheless, pointed to more nonlinear series than found by the nonlinearity tests. As mentioned above, this is possibly due to coefficients being too close to each other across regimes. The next section, thus, estimates the TAR model proposed in section 2. It then tests whether one can reject equality of coefficients across regimes.

7 Fitting the TAR Model

In this section, I fit the threshold autoregressive (TAR) nonlinear model suggested in section 2 to each series in the airlines sample and compare it to the traditional partial adjustment labor demand model *a la* Sargent (1987). I use a simple procedure proposed by Tsay (1989) and used in Potter (1991).

The Tsay (1989) procedure for estimating a TAR model consists of four steps. First, one should choose the order of the AR, p, of the time series under analysis. This is usually done by studying the partial autocorrelation function or by using the Akaike Information Criterion (AIC).[26] Second, calculate the statistic TSAY2 described in the appendix for each arranged AR of order p and delay parameter $d \epsilon S$. Then, select d_p such that:

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[25] The results are not significantly sensible to the log specification, nor to removing linear trends and seasonal effects.

[26] The first step automatically determines the set of possible threshold lags $S = \{1,\ldots,p\}$. I used below the AIC to determine the AR order p.

$$(16)\quad TSAY2(p, d_p) = \underset{d \in S}{MAX} \{TSAY2(p, d)\}$$

The third step consists in selecting the threshold values r_i, $i = 1,\ldots,k$. This is done by analyzing scatterplots of various statistics (such as t-ratios and standardized predictive residuals) against the threshold values as described in Tsay (1989). Finally, refine the model by computing AIC for the two sets of regressions to determine the final AR order in each regime.

Since the theoretical model of section 2 includes other variables, I choose a different strategy for the first two steps. The multivariate model from our analysis of section 2, equation (11), is fitted here. I also set arbitrarily $d = 1$. The model is thus:

$$(17)\quad N_t = \begin{cases} a_1^{(1)} N_{t-1} + \sum_{i=0}^{1} b_i^{(1)} W_{t-i} + \sum_{i=0}^{1} c_i^{(1)} R_{t-i} + \epsilon_t^{(1)}, & if\ DN_{t-1} > r \\ a_1^{(2)} N_{t-1} + \sum_{i=0}^{1} b_i^{(2)} W_{t-i} + \sum_{i=0}^{1} c_i^{(2)} R_{t-i} + \epsilon_t^{(2)}, & if\ DN_{t-1} \leq r \end{cases}$$

a linear multivariate model for each regime, with the switch given by the employment rate of change last period.

The choice of the single threshold r is done by applying the rolling window technique (see Potter (1991) and Tsay (1989)). Scatterplots of the t-ratios of recursive estimates of the coefficients in the arranged regression above against the size of the threshold variable are studied. The intuition of this technique is that if the series is linear (if the series does not show a break across regimes) then the t-ratios should converge smoothly to its asymptotic value. On the other hand, if in fact the coefficients change across regimes, then there should be a jump in the t-ratios as soon as observations from the second regime start coming in.

For each and every series in the sample, I in fact observe this jump for values of the threshold variable between -0.01 and 0.01 (see Gonzaga, 1993). Since the value of zero is suggested by the theoretical model, I set the threshold at this level for all series.

I then fit equation (17) for each regime defined by the threshold being greater or less than zero. The results and methods are ommitted here to save space - see Gonzaga, 1993, for a complete description. The results show that the estimates of the coefficients on lagged employment seem to differ across regimes indicating that employment adjusts differently in contractionary periods (when $DN_t < r$) compared to expansionary periods ($DN_t > r$).

To test how this nonlinear model compares to the linear model (without regime-switching) estimated in section 4, I compute residual variances for both models for all series - as suggested by Potter (1991) - and Chow F-tests of equality of the coefficients across the two regimes in the nonlinear model. The results are in Table 6. The first column after the series names show the combined error variance for the regressions in the TAR model. The second column presents the error variance for the linear model. The third column measures the percent change of residual variances when comparing the nonlinear model and the linear model.

The result is that the nonlinear model residual variance is significantly lower than in the linear model (in one case, 34% lower) for almost half of the series in the airlines sample. Residual variances drop more than 10% (5%) in the nonlinear model for 19 (27) series in the sample.

The Chow F-test confirms these findings. It rejects equality of the coefficients across regimes - defined by the sign of lagged employment changes - in 23 series at the 10% significance level (16 series at the 5% level).

Caution should be exercised here, since I am not correcting for the possible non-stationarity of the series in levels. In future research, I intend to run the regressions in first-differences and allow for possible cointegration between the variables in the model.

Summing up, I showed that the TAR model fits the data better than the traditional partial adjustment model for about half of the series in the airline data set. This reinforces the findings of section 5 that about half of the series appear asymmetric. Since the traditional partial adjustment linear model is incapable of generating an asymmetric employment cycle, contrary to the TAR nonlinear model proposed here, this result does not come as a surprise.

I thus argue that the TAR nonlinear labor demand model should replace the standard linear model in empirical work that attempts to explain employment cycles at the firm level whenever asymmetric labor adjustment costs are present.

8 Summary

In this paper, I studied the phenomenon of asymmetric employment cycles at both the theoretical and empirical levels.

On the theoretical side, I proposed modifying the standard dynamic labor demand models by introducing the assumption of asymmetric employment adjustment costs, while keeping the assumption of a quadratic structure. The major finding was that the assumption of asymmetric turnover costs produced asymmetric employment cycles. The reduced form for employment obtained in the quadratic asymmetric adjustment cost version of the model is a threshold autoregressive (TAR) multivariate model, which nests the standard linear employment equation as a special case. The TAR model is nonlinear and capable of generating asymmetric cycles.

On the empirical side, I studied the behavior of 57 microeconomic employment series from the U.S. airline industry. Section 5 showed that firm employment cycles for the three categories of workers studied - pilots, flight attendants, and mechanics - looked asymmetric in most firms. The analysis of the residuals of a linear labor demand regression revealed that 32 out of 57 series still appear asymmetric after controlling for movements in forcing variables. However, more general nonlinearity tests failed to reject linearities in more than 80% of the series, a result that could be associated with the low power of most of these tests.

In section 7, I then fitted the multivariate nonlinear TAR model developed in section 2 to each series and compared its performance to the standard multivariate partial adjustment labor demand model without a switching-regimes condition. The results indicated that the TAR model explained the data better than the traditional partial adjustment model for about half of the series studied - the residual variance dropped by more than 5% in 27 out of 57 series.

I then concluded that the TAR model proposed in this paper should replace the standard linear model for fitting employment cycles at the firm level whenever adjustment costs are suspected to be asymmetric.

TABLE 1

FORM 41 - SCHEDULE P10								
		ACCOUNTS						
AIRLINES	CODE	21	23	5524	25	6226.3	6426.3	28.1
American Airlines	AA	X	X	X	X	X	-	X
Aloha Airlines	AQ	X	X	X	X	-	X	-
Alaska Airlines	AS	X	X	X	X	-	X	-
Braniff	BN	X	X	X	X	X	-	X
Continental	CO	X	X	X	X	X	-	X
Delta	DL	X	X	X	X	X	-	X
Eastern Airlines	EA	X	X	X	X	X	-	X
Frontier	FL	X	X	X	X	-	X	-
Hawaiian Airlines	HA	X	X	X	X	X	-	-
National	NA	X	X	X	X	X	-	X
North Central	NC	X	X	X	X	X	-	X
Northwest	NW	X	X	X	X	-	-	X
Ozark	OZ	X	X	X	X	-	X	-
Piedmont	PI	X	X	X	X	-	-	-
Southern	SO	X	X	X	X	-	X	-
Texas International	TT	X	X	X	X	-	-	X
TWA	TW	X	X	X	X	X	-	X
United Airlines	UA	X	X	X	X	X	-	X
US AIR (Allegheny)	US	X	X	X	X	X	-	-
Western	WA	X	X	X	X	X	-	X

Notes: Accounts - 21 - General Management
23 - Pilots and Co-Pilots
5524 - Flight Attendants
25 - Mechanics
6626.3 and 6426.3 - Passenger Handling
28.1 Trainees and Instructors

TABLE 2

SUMMARY STATISTICS - EMPLOYMENT GROWTH - US AIRLINE INDUSTRY ORIGINAL SERIES						
Series	Usable Observ.	Mean	Standard Deviation	Skewness	Maximum Value	Minimum Value
AAE_P	72	0.008367	0.05257	-0.4467	0.1745	-0.1881
AAE_FA	72	0.02023	0.04251	0.2699	0.1664	-0.1120
AAE_M	72	0.004587	0.02947	-1.141	0.06276	-0.1061
ASE_P	65	0.02233	0.1935	0.7458	0.6263	-0.3961
ASE_FA	65	0.03308	0.2699	0.4533	0.7160	-0.6667
ASE_M	65	-0.001557	0.1506	-2.649	0.2268	-0.7961
BNE_P	72	0.01011	0.04051	0.7258	0.1543	-0.1117
BNE_FA	72	0.02363	0.05165	0.6397	0.1863	-0.08604
BNE_M	72	-0.001168	0.06122	-1.674	0.1423	-0.2889
COE_P	70	0.02010	0.04600	0.4689	0.1382	-0.06734
COE_FA	66	0.03536	0.07020	0.7246	0.2609	-0.1565
COE_M	65	0.007557	0.03290	0.1518	0.08796	-0.06565
DLE_P	72	0.02001	0.03609	2.248	0.2112	-0.05278
DLE_FA	72	0.03057	0.05084	-0.02402	0.1863	-0.1505
DLE_M	72	0.01498	0.03503	0.8923	0.1551	-0.1230
EAE_P	70	0.01180	0.05849	4.295	0.4075	-0.1366
EAE_FA	70	0.01742	0.04794	0.08699	0.1541	-0.1211
EAE_M	70	0.009433	0.03388	0.8228	0.1567	-0.08492
FLE_P	70	0.01727	0.07577	2.821	0.4407	-0.1176
FLE_FA	42	0.02992	0.1093	0.3327	0.2564	-0.1605
FLE_M	68	0.01790	0.09061	2.183	0.5106	-0.3078
HAE_P	70	0.009541	0.1570	-0.07729	0.3881	-0.4460
HAE_FA	70	0.01677	0.1549	-0.4618	0.4103	-0.5660
HAE_M	70	0.0009563	0.09363	0.2566	0.3881	-0.3012
NAE_P	63	0.01096	0.06702	-0.7107	0.1629	-0.2248
NAE_FA	63	0.02487	0.06542	-0.08960	0.2163	-0.1744
NAE_M	63	-0.005442	0.07698	-2.818	0.1742	-0.4366

TABLE 2
(Continued)

Series	Usable Observ.	Mean	Standard Deviation	Skewness	Maximum Value	Minimum Value
NCE_P	72	0.008886	0.04426	0.2407	0.1389	-0.1314
NCE_FA	68	0.01460	0.05494	1.154	0.2222	-0.1289
NCE_M	72	0.006587	0.03724	0.2190	0.1713	-0.1644
NWE_P	61	0.02088	0.05593	-2.064	0.1306	-0.2623
NWE_FA	61	0.02998	0.05525	-1.553	0.1894	-0.2449
NWE_M	61	0.008562	0.03775	-0.4174	0.1607	-0.1684
OZE_P	70	0.01063	0.04771	-0.1024	0.1299	-0.1602
OZE_FA	70	0.01788	0.05960	0.04366	0.1368	-0.1124
OZE_M	70	0.01799	0.04883	0.3634	0.1425	-0.09548
PIE_P	68	0.01374	0.03955	1.218	0.1721	-0.08511
PIE_FA	68	0.02404	0.07523	1.336	0.3407	-0.1206
PIE_M	68	0.01372	0.05388	1.337	0.2387	-0.1330
SOE_P	72	0.01905	0.06555	0.5240	0.2109	-0.1949
SOE_FA	72	0.02732	0.09080	0.6036	0.3333	-0.1987
SOE_M	72	0.009249	0.08755	0.9873	0.4079	-0.2642
TIE_P	70	0.01388	0.07055	4.139	0.4673	-0.07813
TIE_FA	70	0.02249	0.07556	2.771	0.4444	-0.09091
TIE_M	68	0.005257	0.1090	-0.004600	0.4955	-0.3846
TWE_P	72	0.007260	0.03015	-0.2924	0.07914	-0.07224
TWE_FA	70	0.01905	0.07279	-0.1003	0.1672	-0.1263
TWE_M	72	0.008628	0.03428	-0.06635	0.09079	-0.07575
UAE_P	72	0.01200	0.04951	6.769	0.3971	-0.04543
UAE_FA	72	0.02592	0.08091	4.499	0.5812	-0.1206
UAE_M	72	0.01067	0.08001	4.143	0.5256	-0.1740
USE_P	70	0.02681	0.08722	3.166	0.4599	-0.1075
USE_FA	70	0.03462	0.09056	1.651	0.4393	-0.1509
USE_M	70	0.02882	0.08938	1.628	0.3985	-0.1709
WAE_P	68	0.02795	0.08841	2.552	0.5256	-0.1659
WAE_FA	68	0.02903	0.05643	0.2171	0.1927	-0.1413
WAE_M	68	0.01973	0.04590	0.6635	0.1484	-0.1080

TABLE 3

EMPLOYMENT GROWTH - US AIRLINE INDUSTRY ORIGINAL SERIES				
Series	Skewness Coefficient	P-Value Skewness No Ser.Corr.	P-Value Q-Statistic for Ser.Corr.	P-Value Skewness Monte Carlo
AAE_P	-.4467225	0.06485	.096402 *	0.06785 *
AAE_FA	.2698900	0.17998	.428803	0.17446
AAE_M	-1.140951	0.00000	.023116 **	0.00000 **
ASE_P	.7457691	0.00824 **	.522741	0.00752
ASE_FA	.4532543	0.07250	.000895 **	0.03955 **
ASE_M	-2.648621	0.00000 **	.850140	0.00000
BNE_P	.7258472	0.00690	.000136 **	0.00621 **
BNE_FA	.6397441	0.01500 **	.263765	0.01283
BNE_M	-1.674065	0.00000 **	.546452	0.00000
COE_P	.4688862	0.05853	.001203 **	0.06334 *
COE_FA	.7245938	0.00942	.004161 **	0.01332 **
COE_M	.1517944	0.31275	.009240 **	0.31841
DLE_P	2.247685	0.00000 **	.823907	0.00000
DLE_FA	-.0240238	0.46753	.756150	0.46585
DLE_M	.8923182	0.00123 **	.649628	0.00075
EAE_P	4.294520	0.00000 **	.991652	0.00000
EAE_FA	.0869943	0.38561	.954177	0.38768
EAE_M	.8228019	0.00297 **	.829883	0.00606
FLE_P	2.821267	0.00000 **	.161263	0.00000
FLE_FA	.3326673	0.19804	.492576	0.17062
FLE_M	2.183101	0.00000 **	.147188	0.00000
HAE_P	-.0772949	0.39807	.032811 **	0.39251
HAE_FA	-.4618091	0.06135	.000007 **	0.05244 *
HAE_M	.2565733	0.19557	.408881	0.19367
NAE_P	-.7106802	0.01229 **	.645190	0.03207
NAE_FA	-.0895979	0.38843	.970377	0.40281
NAE_M	-2.818289	0.00000 **	.626874	0.00000

TABLE 3
(Continued)

Series	Skewness Coefficient	P-Value Skewness No Ser.Corr.	P-Value Q-Statistic for Ser.Corr.	P-Value Skewness Monte Carlo
NCE_P	.2406685	0.20716	.000000 **	0.15905
NCE_FA	1.154093	0.00000 **	.489536	0.00000
NCE_M	.2189858	0.22881	.413894	0.22379
NWE_P	-2.063821	0.00000 **	.523312	0.00000
NWE_FA	-1.552648	0.00000 **	.380657	0.00000
NWE_M	-.4173786	0.09713	.045891 **	0.13569
OZE_P	-.1024348	0.36603	.453323	0.37631
OZE_FA	.0436558	0.44199	.663696	0.44350
OZE_M	.3634086	0.11225	.516300	0.12163
PIE_P	1.217596	0.00003 **	.708136	0.00002
PIE_FA	1.335712	0.00000 **	.592849	0.00003
PIE_M	1.337422	0.00000	.018850 **	0.00005 **
SOE_P	.5240428	0.03774 **	.134118	0.02638
SOE_FA	.6036170	0.02031	.064473 *	0.02367 **
SOE_M	.9873205	0.00040 **	.487653	0.00075
TIE_P	4.138791	0.00000 **	.351384	0.00000
TIE_FA	2.770926	0.00000 **	.410650	0.00000
TIE_M	-.0046000	0.49396	.841318	0.49406
TWE_P	-.2923826	0.16067	.000038 **	0.17792
TWE_FA	-.1002997	0.36872	.000000 **	0.36273
TWE_M	-.0663469	0.41097	.305483	0.40985
UAE_P	6.769470	0.00000 **	.957936	0.00000
UAE_FA	4.498574	0.00000 **	.164791	0.00000
UAE_M	4.143164	0.00000 **	.275850	0.00000
USE_P	3.165788	0.00000 **	.985995	0.00000
USE_FA	1.650890	0.00000 **	.703804	0.00000
USE_M	1.628040	0.00000 **	.932381	0.00000
WAE_P	2.552302	0.00000 **	.772346	0.00000
WAE_FA	.2170929	0.23740	.338167	0.24644
WAE_M	.6634750	0.01447 **	.159477	0.01696

Notes: Skewness p-values are based on one-tailed normal distribution.
(**) Significant at the 5% level; (*) Significant at 10%, but not at 5%.
"0.00000" indicates that the corresponding p-value is less than 0.00001.

TABLE 4

US AIRLINE INDUSTRY RESIDUALS FROM LINEAR MODEL			
Series	Skewness Coefficient	P-Value Skewness No Ser.Corr.	P-Value Q-Statistic for Ser.Corr.
AAE_P	-.7871186	.8517395E-02 **	.2946920
AAE_FA	-.9966980	.8643142E-03 **	.2944631
AAE_M	-1.288539	.1656531E-04 **	.2463430E-01 **
ASE_P	1.987716	.1645903E-09 **	.7650885E-01 *
ASE_FA	.0797705	.7975725	.1540600E-01 **
ASE_M	-1.095386	.4282276E-03 **	.5817973
BNE_P	.3811440	.1960864	.5580289E-01 *
BNE_FA	.3224103	.2741452	.1816657
BNE_M	-.9282492	.1641221E-02 **	.8112933
COE_P	-.1320593	.6865291	.8085805
COE_FA	1.180779	.3080526E-03 **	.2406435
COE_M	-.1436032	.6607719	.7227184E-01 *
DLE_P	2.977043	.5656646E-23 **	.1490874
DLE_FA	-1.324231	.7069365E-05 **	.2270868
DLE_M	1.351400	.4567296E-05 **	.8592046
EAE_P	3.867567	.3176209E-37 **	.8033189
EAE_FA	-.8701911	.3631677E-02 **	.7594226
EAE_M	-.2451426	.4125828	.1768925
FLE_P	.9090587	.2388528E-01 **	.4858976
FLE_FA	.1868710	.6423856	.3657623E-01 **
FLE_M	.3254490	.4186727	.1288015
HAE_P	.3613251	.2271698	.3604050
HAE_FA	.3652936	.2221065	.9286477
HAE_M	1.320090	.1023124E-04 **	.1689749
NAE_P	.3727037	.2384362	.9335170
NAE_FA	.1438853	.6490189	.6632571
NAE_M	-2.336780	.1451784E-12 **	.4472988

TABLE 4
(Continued)

Series	Skewness Coefficient	P-Value Skewness No Ser.Corr.	P-Value Q-Statistic for Ser.Corr.
NCE_P	.4649797	.1380805	.4653103E-01 **
NCE_FA	.0293988	.9252977	.9385459
NCE_M	1.192662	.1424929E-03 **	.1891610
NWE_P	-.9897780	.2082449E-02 **	.9016626
NWE_FA	-.8759051	.6448298E-02 **	.8628962
NWE_M	-1.174542	.2593652E-03 **	.4538100E-02 **
OZE_P	.3692348	.2171587	.6762724
OZE_FA	.4765564	.1111989	.9354557
OZE_M	.3864566	.1964679	.1109111
PIE_P	.8919262	.3320967E-02 **	.7003976
PIE_FA	.0456909	.8804322	.9353803
PIE_M	-.1359557	.6544518	.4201633E-01 **
SOE_P	1.222266	.5724674E-04 **	.5103232
SOE_FA	.9619288	.1541202E-02 **	.8772975
SOE_M	.3211756	.2903485	.8367572
TIE_P	1.303074	.1787453E-04 **	.1133222
TIE_FA	.9616683	.1545753E-02 **	.7729097
TIE_M	-.7085812	.1966107E-01 **	.9082762
TWE_P	.7157197	.1674775E-01 **	.2393750E-02 **
TWE_FA	.2147959	.4728023	.2101422E-01 **
TWE_M	.1557463	.6026723	.5372026
UAE_P	3.677436	.1044066E-34 **	.5366955
UAE_FA	.0004143	.9988785	.3809738
UAE_M	2.564284	.3387958E-17 **	.8189134E-01 *
USE_P	1.520771	.5539903E-06 **	.8863462
USE_FA	.6947265	.2218753E-01 **	.8425481
USE_M	.6900369	.2310444E-01 **	.6764354
WAE_P	1.068688	.4343558E-03 **	.8399238E-01 *
WAE_FA	.2964144	.3291437	.2432755
WAE_M	.3853739	.2045453	.6057923E-02 **

Note: Skewness p-values are based on one-tailed normal distribution.

TABLE 5

EMPLOYMENT GROWTH - US AIRLINE INDUSTRY DETRENDED SEASONALY ADJUSTED SERIES (FIRST-DIFFERENCES) P-VALUES				
Series	ORI-F	AUG-F	TAR-F	CUSUM
AAE_P	0.6139	0.8309	0.1705	0.7805
AAE_FA	0.4197	0.6540	0.4638	0.0730
AAE_M	0.1018	0.1960	0.1257	0.0114
ASE_P	0.2238	0.3899	0.6955	0.8769
ASE_FA	0.6095	0.7575	0.5253	0.7663
ASE_M	0.1719	0.5633	0.0237	0.1671
BNE_P	0.0033	0.0445	0.3289	0.0294
BNE_FA	0.6261	0.6880	0.6720	0.5081
BNE_M	0.3769	0.1042	0.0733	0.3288
COE_P	0.6966	0.8845	0.8309	0.3170
COE_FA	0.6835	0.9048	0.7452	0.4617
COE_M	0.1211	0.2287	0.1457	0.0323
DLE_P	0.1069	0.3681	0.2858	0.6583
DLE_FA	0.2634	0.4989	0.8021	0.7859
DLE_M	0.0067	0.0051	0.0002	0.0000
EAE_P	0.6444	0.9513	0.8665	0.3481
EAE_FA	0.9372	0.3643	0.2007	0.1220
EAE_M	0.3407	0.4498	0.4964	0.5288
FLE_P	0.3476	0.3368	0.8433	0.3242
FLE_FA	0.7561	0.6339	0.6839	0.2917
FLE_M	0.8770	0.6060	0.6768	0.1608
HAE_P	0.0357	0.1056	0.2193	0.1475
HAE_FA	0.0445	0.1190	0.0200	0.0238
HAE_M	0.0319	0.0909	0.9908	0.8814
NAE_P	0.4526	0.7338	0.9335	0.9987
NAE_FA	0.1357	0.0544	0.1948	0.3754
NAE_M	0.4876	0.8163	0.9893	0.6685

TABLE 5
(Continued)

Series	ORI-F	AUG-F	TAR-F	CUSUM
NCE_P	0.1079	0.1095	0.0819	0.7474
NCE_FA	0.2145	0.4827	0.4551	0.8683
NCE_M	0.7772	0.8961	0.7084	0.8591
NWE_P	0.4106	0.5049	0.6927	0.6448
NWE_FA	0.0087	0.0633	0.0000	0.6367
NWE_M	0.0000	0.0013	0.0000	0.0829
OZE_P	0.6374	0.8888	0.6161	0.8061
OZE_FA	0.1883	0.4122	0.3479	0.2368
OZE_M	0.8488	0.9096	0.4920	0.0196
PIE_P	0.7778	0.6502	0.6329	0.5967
PIE_FA	0.6766	0.5235	0.0066	0.1570
PIE_M	0.7563	0.8880	0.1322	0.5966
SOE_P	0.2306	0.3700	0.2653	0.0548
SOE_FA	0.4779	0.6877	0.5450	0.6058
SOE_M	0.1334	0.0281	0.1222	0.0112
TIE_P	0.1752	0.1907	0.0000	0.0004
TIE_FA	0.0983	0.1578	0.0026	0.0158
TIE_M	0.0010	0.0027	0.8904	0.0031
TWE_P	0.8003	0.8013	0.4848	0.8212
TWE_FA	0.7906	0.9155	0.3558	0.0280
TWE_M	0.5283	0.8089	0.5536	0.7894
UAE_P	0.6138	0.8953	0.0963	0.7628
UAE_FA	0.2626	0.5448	0.8357	0.6296
UAE_M	0.0952	0.1682	0.5179	0.0307
USE_P	0.9090	0.8822	0.7919	0.7539
USE_FA	0.4051	0.7699	0.9254	0.5264
USE_M	0.7541	0.7084	0.9066	0.4660
WAE_P	0.1010	0.2333	0.3977	0.7004
WAE_FA	0.0364	0.0844	0.0173	0.0153
WAE_M	0.0917	0.2093	0.3013	0.1956

Note :"0.00000" indicates that the corresponding p-value < 0.00001.

TABLE 6

COMPARING THE NONLINEAR AND LINEAR MODELS
RESIDUAL VARIANCES

Series	Residual Variances Nonlinear	Linear	(NL/L)	CHOW p-value
AAE_P	9631.1	10710.9	-10.08	.073 *
AAE_F	13619.5	14560.1	-6.46	.152
AAE_M	25818.2	28425.0	-9.17	.088 *
ASE_P	141.1	141.4	-.20	.432
ASE_F	223.1	247.5	-9.87	.097 *
ASE_M	221.0	274.9	-19.64	.013 **
BNE_P	679.3	719.0	-5.52	.174
BNE_F	1047.2	966.7	8.33	.952
BNE_M	4167.9	3947.2	5.59	.819
COE_P	641.4	588.8	8.94	.947
COE_F	1470.9	1312.3	12.08	.987
COE_M	1066.0	1068.7	-.26	.430
DLE_P	4802.0	4690.8	2.37	.600
DLE_F	12041.1	13854.9	-13.09	.033 **
DLE_M	6337.5	6213.4	2.00	.574
EAE_P	13055.4	17786.3	-26.60	.001 **
EAE_F	13174.4	13969.8	-5.69	.178
EAE_M	25738.0	24864.9	3.51	.668
FLE_P	472.4	576.3	-18.02	.012 **
FLE_F	139.1	138.1	.71	.475
FLE_M	966.1	1460.8	-33.87	.000 **
HAE_P	52.1	52.8	-1.34	.365
HAE_F	80.8	79.8	1.27	.520
HAE_M	222.0	235.0	-5.51	.184
NAE_P	518.6	513.8	.94	.492
NAE_F	1439.5	1374.3	4.75	.696
NAE_M	2201.1	2669.3	-17.54	.027 **

TABLE 6
(Continued)

Series	Residual Variances Nonlinear	Linear	(NL/L)	CHOW p-value
NCE_P	199.4	180.5	10.50	.996
NCE_F	75.5	73.4	2.79	.602
NCE_M	196.0	201.2	-2.62	.294
NWE_P	1555.6	1888.4	-17.63	.029 **
NWE_F	1873.0	2301.9	-18.63	.023 **
NWE_M	1094.1	1400.6	-21.89	.012 **
OZE_P	113.0	116.9	-3.31	.269
OZE_F	67.2	92.5	-27.38	.001 **
OZE_M	239.8	250.2	-4.14	.234
PIE_P	72.0	75.7	-4.76	.220
PIE_F	57.5	71.6	-19.68	.010 **
PIE_M	298.0	296.9	.36	.463
SOE_P	115.7	135.8	-14.83	.024 **
SOE_F	83.2	100.3	-17.07	.016 **
SOE_M	182.7	174.9	4.48	.737
TIE_P	122.2	150.4	-18.72	.010 **
TIE_F	72.1	80.3	-10.18	.074 *
TIE_M	521.4	587.9	-11.32	.063 *
TWE_P	3019.9	3291.1	-8.24	.101
TWE_F	45694.1	45916.8	-.48	.413
TWE_M	26650.8	26606.8	.17	.451
UAE_P	9122.6	10086.2	-9.55	.076 *
UAE_F	50537.7	50365.2	.34	.463
UAE_M	281285.7	278042.9	1.17	.517
USE_P	1289.4	1645.8	-21.66	.005 **
USE_F	616.1	631.2	-2.39	.316
USE_M	1522.0	1669.9	-8.86	.103
WAE_P	1520.4	1482.1	2.59	.598
WAE_F	2169.7	2423.6	-10.48	.078 *
WAE_M	1871.2	1807.2	3.54	.658

Note: (**) Rejects that coefficients are equal across regimes at the 5% level; (*) Rejects it at 10%, but not at 5%.

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