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Fábio Augusto Reis Gomes

Cleomar Gomes da Silva

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Fábio Augusto Reis Gomes
Corresponding author
Affiliation: Ibmec São Paulo
Address: Rua Quatá, 300, sala 422, Vila Olímpia. São Paulo - SP, Brasil CEP: 04546-042 (Professor Fábio Gomes).
Phone: (011) 4504-2776
E-mail: FabioARG@isp.edu.br

Cleomar Gomes da Silva
Affiliation: Getulio Vargas Foundation, São Paulo School of Economics and Center for Research in International Economics
Address: Rua Nestor Pestana 44 apto 51, São Paulo - SP, Brasil CEP: 01303-010
Phone: (031) 3825-1290
E-mail: cleomargomes@gvmail.br

Abstract:

This article makes use of Auto-Regressive-Fractionally-Integrated-Moving-Average (ARFIMA) models to examine the unemployment persistence of different labor forces in the Greater Metropolitan Area of Sao Paulo, Brazil. To this purpose, not only is the region's open unemployment rate analyzed but it is also disaggregated by gender, age, color and position within the household. The period ranges between January/1985 and December/2005 and, despite showing heterogeneous orders of integration, the results lie between 0.5 and 1, in general. This is an indication that the unemployment rates in Sao Paulo are non-stationary but still mean-reverting. The only two series which can be considered to be exceptions to the general case are those related to workers aged between 15 and 17 and workers over 40. Both of them are neither stationary nor mean-reverting. Therefore, all disinflation policies performed by the Brazilian policymakers in the last two decades have impacted Sao Paulo's labor force distinctively, with a heavier burden on young adults and older generations.

1 Introduction

The Greater Sao Paulo Metropolitan Area is one of the five most populous places in the world. According to the 2006 estimate released by IBGE, the Brazilian Bureau of Geography and Statistics, the region has a population of around 19 million people in its 55 municipalities and the city of Sao Paulo itself has a population of over 11 million. Therefore, it accounts for about 10% of the total Brazilian population. Such magnitude has made unemployment in the region be always an important issue, especially in the last two decades. And this is due to many factors, such as a series of failed economic stabilization plans in the 1980s and in the beginning of the 1990s.

The implementation of the *Real Plan*, in 1994, can be considered to be the turning point in the Brazilian economy, once it was the first stabilization package that really managed to bring down inflation in the country. Nonetheless, Brazilian policymakers opted to keep an appreciated fixed exchange rate, which culminated in serious consequences to the trade balance account, level of international reserves and unemployment rates as well. All of these factors together, and a deep international crisis, forced the country to adopt a flexible exchange rate in 1999. Shortly after the exchange rate depreciation, the Brazilian central bank adopted an inflation targeting regime so as to build credibility on its intention to fight inflation and put the country back on the track. Nevertheless, maintaining inflation under control has meant keeping high interest rates, which have been preventing the country from growing and the unemployment rates from decreasing.

Theoretically, NAIRU and Hysteresis are the two main hypotheses related to the explanation of unemployment and its persistence. Friedman (1968) and Phelps (1968) proposed the Natural Rate Hypothesis, arguing that real variables determined their own behavior and, consequently, they could not be influenced permanently by nominal variables, such as inflation. As a result, unemployment would converge to its natural rate in the long run, meaning that it should be a non-integrated process, I(0), with transitory shocks. On the other hand, Blanchard & Summers' (1986) showed that the insider's bargaining power in wage-setting implied that aggregate employment followed a random walk with a drift. In this case, unemployment rate would be an integrated process, I(1), and any shocks to the series would shift unemployment equilibrium permanently from one level to another. This persistence is what defines the so-called Hysteresis phenomenon.[1] In other words, perturbations affecting unemployment can be either transitory (NAIRU) or permanent (Hysteresis) and the degree of persistence they generate is a key determinant of the costs of disinflation.

As far as econometrics is concerned, the two theories stated above can be evaluated by means of unit root tests, in which the researcher estimates the order of integration 'd' of the series.[2] However, this methodology imposes that 'd' assumes an integer value, i.e., unemployment is either I(0) or I(1), and discards the possibility of a non-integer parameter. Auto-Regressive-Fractionally-Integrated-Moving-Average (ARFIMA) models account for this matter. Besides allowing for fractionally integrated parameters, this methodology helps to overcome the well-known problem of low power of traditional unit roots. ARFIMA models are also able to jointly model short-run and long-run dynamics of unemployment, which makes possible the estimation of useful impulse-response functions.

For the reasons mentioned above, there has been a growing number of literature concerned about unemployment persistence. For instance, Koustas & Veloce (1996) make use of ARFIMA models to assess output and unemployment persistence for Canadian and American data. Both exhibit higher persistence in Canada when compared

[1] Other sources of hysteresis are: *i)* deterioration of skills, i.e., unemployed workers are unable to update their skills and, consequently, have their probabilities of finding a new work reduced even when demand is recovered; *ii)* labor-force attachment, i.e., individuals who are unemployed for long periods may adjust their standard of living to a lower level and/or may even get used to the joblessness situation and so the labor supply decreases permanently (Romer, 2001).

[2] See Neudorfer *et al*. (1990), Mitchell (1993), Jaeger & Parkinson (1994), Song & Wu (1998), Arestis & Mariscal (1999), Camarero & Tamarit (2004), Clement *et al*. (2005) and Gomes & Gomes (2006).

to the USA. Mikhail *et al*. (2006) revise the Canadian aggregate unemployment case using a Bayesian ARFIMA model and find evidence that persistence is stronger than previously reported by Koustas & Veloce (1996). Gil-Alana (2001a) analyzes USA, Germany, France, Italy and the UK. His results indicate more persistence in unemployment rates of Great Britain and France, when compared to Germany and the USA. In another paper, Gil-Alana (2001b) studies the unemployment evolution of nineteen countries (Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Netherlands, Ireland, Italy, Japan, Norway, Portugal, Spain, Sweden, Switzerland, UK, USA). In this case, his results point out that the order of integration of most countries is higher than one, the exceptions being the USA, Japan, Austria, Italy and Canada. Gil-Alana & Henry (2003) analyze unemployment in UK and find that the order of integration of unemployment for the country is higher than 0.5 but smaller than 1, which means that it is non-stationary but with a mean-reverting behavior. Tolvi (2003) uses ARFIMA models to study the unemployment persistence of different labor forces in Finland, finding less persistence in the series for females and young people than for the entire labor force and males.

The empirical literature revised above shows us that the research on the topic has been mainly focused on developed countries instead of emerging market economies, such as Brazil. In an attempt to fill this gap, our main goal in this article is to use ARFIMA methodology to estimate unemployment persistence of different labor forces in the Greater Sao Paulo.[3] Thus, besides analyzing the region's open unemployment rate, we disaggregate it by gender, age, color and position within the household. For the period ranging between January/1985 and December/2005, most of the fractionally integrated parameters lie between 0.5 and 1, indicating non-stationarity but mean-reversion in the series. The exceptions are workers aged between 15 and 17 and workers

[3] The option for Sao Paulo, instead of Brazil as a whole, is due to the existence of a more complete data set for this region.

over 40, whose results showed neither stationarity nor mean reversion. It means that economic policies in Brazil will have long-lasting effects, specially, for those aged 15 to 17 and over 40.

The remainder of the paper is organized as follows. Section 2 presents the econometric methodology. Section 3 presents the data. Section 4 summarizes the results and section 5 concludes the article.

2 Econometric Methodology

Define $X_{i,t} = 1$, if individual i is unemployed in period t and $X_{i,t} = 0$, otherwise. Thus, if $i = 1,..., N$, aggregate unemployment can be defined as an aggregation of a panel data information of the kind:

$$u_t = \sum_{i=1}^{N} X_{i,t} / N \tag{1}$$

As usual, suppose that $X_{i,t}$ follows a Markov Process with transition probabilities given by:

$$\begin{bmatrix} p_{e,e}^{t} & p_{u,e}^{t} \\ p_{e,u}^{t} & p_{u,u}^{t} \end{bmatrix} \tag{2}$$

where $p_{s,k}^{t}$ is the probability of changing from regime s to regime k in period t, and e refers to being employed while u refers to being unemployed[4]. The probabilities depend on t due to aggregate shocks, such as those coming from monetary policy. Finally, if for each period the Markov Process is ergodic, then:

$$u_t = \sum_{i=1}^{N} X_{i,t} / N \to E\left(X_{i,t}\right) \tag{3}$$

[4] Obviously, these probabilities depend on individual characteristics. But, as we are working with aggregate data, we are modeling a type of representative agent for each labor force group. Therefore, the assumption that probabilities do not depend on *i* makes sense.

where $E\left(X_{i,t}\right) = p_{e,u}^{t} + p_{u,u}^{t}$ is the probability of becoming unemployed plus the probability of continuing unemployed.

By applying the ARFIMA methodology we are implicitly modeling the probability above, with special interest in measuring its degree of persistence. Therefore, suppose that $\{u_t, t = 1,2,...,T\}$ is the observed unemployment time series that follows the model:

$$(1-L)^{d}\, u_t = e_t \tag{4}$$

where e_t is a covariance stationary process and d can be any real number. If this the case, the operator (1 - L)$^{-d}$ can be represented by the filter:

$$(1-L)^{-d} = \sum_{j=0}^{\infty} l_j L^j \tag{5}$$

where ?$_0$ = 1 and $l_j = (1/j!)(d+j-1)(d+j-2)(d+j-3)\cdots(d+1)(d)$.

Consequently,

$$u_t = (1-L)^{-d}\, e_t = l_0 e_t + l_1 e_{t-1} + l_2 e_{t-2} + \cdots \tag{6}$$

Notice that ‘d’ plays a central role in explaining the impact of past shocks on u_t. In fact, if e_t is a white noise, equation (6) is a direct representation of the impulse response functions of u_t. Whilst the impulse-response coefficients for a stationary ARMA procedure decay geometrically, the ARFIMA process in equation (6) implies a slower (hyperbolic) decay. Because of this feature, fractionally integrated processes can be useful in modeling time series with long memory.

In the ARFIMA framework[5], the higher the order of integration of the series, the higher its persistence will be. In fact, if 0 = d = 0.5, the series is stationary and mean-reverting. If 0.5 < d = 1, the series is non-stationary but still mean-reverting (the effects of shocks are long-lasting). Finally, when 'd' = 1, the series is non-stationary and non-mean-reverting (Gil-Alana, 2001a).

In order to estimate the parameter 'd' we apply the Nonlinear Least Squares Method (NLS), which is sometimes referred to as the Approximate Maximum Likelihood Method.[6] The NLS estimator is based on the maximization of the following likelihood function:

$$\ell_N\left(d,\Phi,\Theta\right) = -\frac{1}{2}\log\left(\frac{1}{T}\sum_{i=1}^{N}\tilde{e}_t\right) \tag{7}$$

where the residuals $\tilde{e}_t$ are obtained by applying the ARFIMA(p, d, q) to u_t and the vectors Φ and Θ represent the p autoregressive and the q moving-average parameters, respectively.[7]

3 Data

The data used in the analysis are the seasonally adjusted monthly unemployment rates of different labor forces in the Greater Metropolitan Area of Sao Paulo. The time series are the following: *i)* male; *ii)* female; *iii)* white; *iv)* non-white; *v)* head of the household; *vi)* other members of the household; *vii)* workers aged 15 to 17, 18 to 24, 25 to 39 and over 40; *viii)* aggregate open unemployment rate. The data were obtained from SEADE – Fundação Sistema Estadual de Análise de Dados, which is the State of

[5] The reader may refer to Granger & Joyeux (1980) and Hosking (1981) for a complete understanding of the fractionally integrated models.
[6] As the series to be examined seem to be non-stationary, the Exact Maximum Likelihood methodology is not suitable because it is seriously downward biased for values of 'd' close to 0.5 and larger than 0.5. But with the sample sizes used in this paper, the NLS estimation does not suffer from these biases and it is more suitable for our examination.
[7] The econometric package used for the estimations is Doornik & Ooms' (2001) OxMetrics and the numerical method used to maximize the likelihood function is BFGS.

Sao Paulo Bureau of Statistics[8] and the sample period ranges from 1985:01 to 2005:12, giving a total of 252 observations.

Figure 1 shows the evolution of unemployment in the Sao Paulo Metro Area. Compared to the aggregate open unemployment, the rates of unemployment of other members of household, female and nonwhite workers are higher. On the other hand, male, white and head of household workers have lower rates. Figure 2 shows the rates of unemployment of different age groups of workers. Again, compared to the aggregate open unemployment rate, youngsters have higher unemployment rates than older workers. Hence, what the two figures suggest is that the *Real Plan* did not have a negative effect on employment until the end of 1995. From then on, there was an increase in unemployment, which lasted until the end of 1998. From the beginning of 1999, the period of adoption of a flexible exchange rate followed by the implementation of an inflation targeting regime, unemployment rates showed some decrease up to the end of 2000, and after that became instable again.

Insert Figure 1

Insert Figure 2

Table 1 helps us to analyze unemployment behavior more carefully. It reports the unemployment mean and growth rates considering full and sub samples of the series. Looking at the full sample, unemployment amongst youngsters aged between 15 and 17 is the highest, followed by workers aged between 18 and 24 and other members of household. On the other hand, the head of household's unemployment rate is the lowest, which is expected once these workers have a higher opportunity cost of waiting for a better job offer when they do lose their jobs. As for workers over 40 years of age, their rate of unemployment is low as well because they are very experienced, which increases their marginal product. In addition to that, those who are eventually

[8] Available at www.seade.gov.br.

unemployed might feel that it will be hard to find a new job and, thus, they simply abandon the formal sector and look for something else in the informal economy or as entrepreneurs. White workers have a lower rate of unemployment than non-whites, which is more likely due to the former ones having more years of formal education and, therefore, having higher human capital accumulation. Finally, the unemployment rate of males is much lower than of females, and the reason for that probably being that unemployed women might decide to leave the work force and perform home-based jobs, for instance.

As for the sub-samples, they were divided taking into consideration the beginning of the *Real Plan* and the implementation of the inflation targeting system. In all cases the average unemployment rate increased from one period to another. Given the Phillips Curve Theory, this is an expected (and undesirable) result, once these two economic policies implemented were all aimed at controlling inflation, and they were successful in doing so. Comparing the period 1985:01-1994:06 (sub-sample 1) to the period 1994:07-1998:12 (sub-sample 2), the series exhibiting the largest growth rates were Age 40+ (58.43%) and Head of Household (48.77%). And comparing sub-sample 2 with sub-sample 3 there was a decrease in the growth rates in relation to the previous comparison. Age 40+ (28.97%), Age 18-24 (25.56%) and Age 15-17 (23.97%) are the ones that showed the highest growth rates. The last column on Table 1 compares the period before the implementation of the *Real Plan* with the period after the introduction of the inflation targeting system. The unemployment growth rate related to workers aged 40 or more (over 100%) calls our attention once it is almost as double as the growth rate related to open unemployment.

Insert Table 1

Figure 3 shows a scatter plot of each unemployment rate in January/1985 against December/ 2005 rates, i.e., it compares the first and last observations of each series. The plots show a positive correlation between initial and final values, and, therefore, persistence might be the case for the rates of unemployment in Sao Paulo.

Insert Figure 3

4 Results

First of all, it is advisable to plot the sample autocorrelations and investigate them carefully. They are reported, in levels and in first differences, on Table 2. In levels, the values begin at 0.98 or 0.99 and then decay very slowly. In fact, at lag 18 all of them are around 0.74, which is very high. There is no doubt this slow decay shown in the autocorrelations is consistent with a non-stationary process. In first differences, all of the series show some significant autocorrelations at the first lags and in the majority of the other lags.

Insert Table 2

As a benchmark, we start by estimating ADF, PP and KPSS[9] unit root tests for all series (Table 3). Using a 10% level of significance, the ADF estimations reject the unit root hypothesis only for workers aged 15-17 and aged 18-24 whereas all PP estimations reject the same hypothesis, except for age 40+, male and head of household. Kwiatkowski, Phillips, Schmidt & Shin (1992) see a drawback to testing unit root as a null hypothesis once this null is usually accepted unless there is strong evidence against it. In other words, ADF and PP-type tests have lower power to make a distinction between unit root and near unit root processes.[10] As a result, the authors propose a unit root test (KPSS) in which the null hypothesis is stationarity against an alternative hypothesis of non-stationarity. The KPSS results indicate that at a level of significance of 10% there is rejection of the null for all series, except for workers aged 15 to 17 and

[9] See Dickey & Fuller (1979), Phillips & Perron (1988) and Kwiatkowski, Phillips, Schmidt & Shin (1992). As opposed to the others, the latter imposes stationarity under the null.
[10] In fact, regarding fractionally integrated processes, Diebold & Rudebusch (1990) show that ADF tests can mistakenly lead to the conclusion that a time series is non-stationary.

18 to 24. As a final remark regarding unit root tests, it is obvious that they are unable to provide evidence on the true order of integration of the series once they usually show opposite results, especially ADF and PP estimations. Therefore, a fractionally integrated process can be the case.

Insert Table 3

In order to estimate the ARFIMA (p, d, q) by means of the NLS methodology, we allow *p* and *d* to be lower than or equal to 3, which generates 16 different models for each series. We then use the Schwarz Information Criterion to select the most suitable model for each type of labor force examined. These selected models and the 'd' parameters of all estimations performed are reported on Tables 3 and 4, respectively. Looking at the overall estimations, it is clear that most of the calculated 'd' lie between 0.5 and 1, which is a characteristic related to non-stationarity but mean-reversion.

The analysis of the open unemployment rate in Sao Paulo shows that, apart from the first two estimations, all others do not vary a lot, ranging $0.74 < d < 0.89$, which means that the series is non-stationary but mean-reverting. Taking our selection criteria into account, the series can be characterized as an ARFIMA (0, 0.782, 2) model (Table 3). For the rates of unemployment related to color, we notice that the behavior of 'd' is quite similar to the open unemployment rate (Table 4). When the best models are chosen, the whites and non-whites time series can be defined as an ARFIMA (0, 0.685, 2) and an ARFIMA (1, 0.715, 2), respectively. Therefore, both parameters are fractionally integrated, non-stationary but mean-reverting (Table 3).

For the question whether there is difference in unemployment persistence when the position of the worker within the household is accounted for, both head of household, ARFIMA (0, 0.794, 3), and other members of household, ARFIMA (0, 0.729, 2), can be characterized as a long memory process, non-stationary but mean-reverting. When the assessment is on the rates of unemployment related to gender, males and females behave quite similar to the open unemployment rate as well, i.e., apart from the first two estimations, all others have ‘d’ parameters varying between 0.54 and 0.90, which describe both series as non-stationary but mean-reverting (Table 4). When we look at the best models selected (Table 3), the unemployment rate of males can be defined as an ARFIMA (0, 0.660, 2) whilst female’s rate is best characterized as an ARFIMA (0, 0.685, 2). Despite having their ‘d’ close to each other, the latter seems to be a bit more persistent and, therefore, it can take longer to recover.

Finally, turning our attention to the rates of unemployment related to age groups, the first relevant comment is that ‘d’ varies considerably in this case. For the age range in which most of the work force is employed (between 18 and 39 years of age) the behavior of the series resembles that of an open unemployment rate. In spite of that, the overall ‘d’ is a little higher, and so is unemployment persistence for this age range (Table 4). Regarding the selection of the most suitable models, the rates of unemployment of workers 18 to 24 and 25 to 39 can be defined as ARFIMA (0, 0.834, 3) and ARFIMA (0, 0.821, 3), respectively (Table 3).

However, results change considerably when we analyze the unemployment rates of youngsters between 15 and 17 and older workers (over 40). In these two cases, the two best models are ARFIMA (0, 1.292, 3) and ARFIMA (0, 1.266, 3), respectively, which means that both are neither stationary nor mean-reverting (Tables 3 and 4). Besides that, some other points are worth mentioning. Firstly, contrary to the results above, all unit root tests reported on Table 3 indicate stationarity for workers 15 to 17. On the other hand, for workers 40 and over the tests suggest non-stationarity, which is in line with the ARFIMA results. Secondly, we are able to show that the level of a time series and its persistence are two different things. By looking at Figure 2 and Table 1, one could conjecture that the series related to workers 40+ is non-persistent, once it has the lowest mean of the unemployment rates. And this is not what is reported when the

ARFIMA methodology is applied. As mentioned previously, there might be several reasons related to such behavior. For instance, unemployed workers over 40 might prefer not to look for a new job as it would be very hard to get a new position as least as good as the old one. As a result, either they stay collecting unemployment benefits or they abandon the formal sector and look for something else in the informal sector or as entrepreneurs. As for youngsters 15 to 17, the ARFIMA result makes sense once workers at this age are usually unskilled, which makes very difficult for them to get into the labor market.

Figures 4 and 5 report the impulse response functions for each one of the selected models shown on Table 3. We plotted 120 periods, which correspond to 10 years.[11] Looking first at the open aggregate unemployment rate, we see that 70% of a one-time shock to the series still remains even after 10 years. This indicates persistence but mean reversion. As for the impulse responses related to the rates of unemployment of different age groups, we notice that, as expected, Age 15-17 and Age 40+ show explosive behavior. On the other hand, Age 18-24 and Age 25-39 do not show explosive behavior but about 70% and 50% of their respective disturbances remain after 10 years.

Figure 5 reports results for gender, color and position within the household. Males unemployment rate is slightly less persistent than females, as reported by the small difference between the 'd' of each series. Unemployment related to whites is less persistent than that related to non-whites, and the same comparison applies to head of household and other members of household. Thus, altogether, it seems safe to say that impulse responses related to age-related unemployment rates are more persistent than the others and, as a result, they tend to be more important in determining unemployment in Sao Paulo.

Insert Figure 4

[11] We made use of Baum's (2000) code for the calculations of the impulse response functions.

Insert Figure 5

5 Final Remarks

In this article we examined the persistence phenomenon in the rates of unemployment of different labor forces in the Greater Metropolitan Area of Sao Paulo by means of ARFIMA models. Not only did we analyze the region's open unemployment rate but we also disaggregated it by gender, age, color and position within the household.

The overall results show that the majority of the unemployment rates analyzed show orders of order of integration between 0.5 and 1, which is a signal of a long-memory process, non-stationarity but mean-reversion. Workers aged between 15 and 17 and over 40 are the exceptions once their rates of unemployment are neither stationary nor mean reverting.

In terms of economic policy, our findings show that all the economic decisions made by the Brazilian policymakers in the past twenty years have had an impact in Sao Paulo's labor force, and it is a good picture of what has happened to unemployment in Brazil as a whole. There is no doubt that young adults and older generations are the ones that paid, and will continue to pay, the highest price for a long time. Hence, disinflation policies are important and necessary but their negative impacts should also be cared for.

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References

Arestis, P., & Mariscal, I. (1999). Unit roots and structural breaks in OECD unemployment, *Economic Letters*, 65(2), 149-156.

Baum, C. F. (2000). FRACIRF: Stata module to compute impulse response function for fractionally-integrated time-series. Boston College Dept. of Economics, *Statistical Software Component Series No. S414004*. Available at: http://ideas.repec.org/c/boc/bocode/s414004.html.

Blanchard, O. & Summers, L. (1986). Hysteresis and the European unemployment problem. In S. Fischer (ed.), *NBER Macroeconomics Annual*. Cambridge: MIT Press.

Camarero, M., & Tamarit, C. (2004). Hysteresis vs. natural rate of unemployment: new evidence for OECD countries, *Economic Letters*, 84(3), 413-417.

Clement, J., Lanaspa, L., & Montanés, A. (2005). The unemployment structure of the US States, *The Quarterly Review of Economics and Finance*, 45, 848-868.

Dickey, D.A. & Fuller, W.A. (1979). Distribution of the estimators for auto-regressive time series with a unit root, *Journal of the American Statistical Association*, 74, 427-431.

Diebold, F.X. & Rudebusch, G.D. (1991) On the power of Dickey-Fuller tests against fractional alternatives, *Economics Letters*, 35(2), p. 155-160.

Doornik, J. A. & Ooms, M. (2001). A package for estimating, forecasting and simulating Arfima Models: Arfima package 1.01 for Ox. *Nuffield College – Oxford Discussion Paper*. Available on line at: http://www.faculty.econ.northwestern.edu/faculty/spady/econ498/Ox/arfima/arfima.pdf

Friedman, M. (1968). The role of monetary policy, *American Economic Review*, 58, 1-17.

Gil-Alana, L. A. (2001a). The persistence of unemployment in the USA and Europe in terms of fractionally ARIMA models, *Applied Economics*, 33, 1263–9.

Gil-Alana, L. A. (2001b). Measuring unemployment persistence in terms of I(d) statistical models, *Applied Economics Letters*, 8(12), 761-63.

Gil-Alana, L. A. & Brian Henry, S. G. (2003). Fractional integration and the dynamics of UK unemployment, *Oxford Bulletin of Economics and Statistics*, 65, 2.

Gomes, Fábio A.R. & Gomes, C. (2006). Hysteresis versus natural rate of unemployment in Brazil and Chile, *Applied Economics Letters*. Forthcoming.

Granger, C. W. J. (1980). Long memory relationships and the aggregation of dynamic models, *Journal of Econometrics*, 14, 227-38.

Granger, C. W. J. and Joyeux, R. (1980) An introduction to long memory time series and fractional differencing, *Journal of Time Series Analysis*, 1, 15-29.

Hosking, J. R. M. (1981) Modeling persistence in hydrological time series using fractional differencing, *Water Resources Research*, 20, 1898-908.

Jaeger, A., & Parkinson, M. (1994). Some evidence on hysteresis in unemployment rates, *European Economic Review*, 38(2), 329–342.

Koustas, Z. and Veloce, W. (1996). Unemployment hysteresis in Canada: an approach based on long-memory time series models, *Applied Economics*, 28, 823–31.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series are non stationary? *Journal of Econometrics*, 54, 159-178.

Mikhail, O., Eberwein, C. J. & Handa, J. (2005). Testing for persistence in aggregate and sectoral Canadian unemployment, *Applied Economics Letters*, 12, 893–898.

Mikhail, O., Eberwein, C. J. & Handa, J. (2006). Estimating persistence in Canadian unemployment: evidence from a Bayesian ARFIMA, Applied Economics, 38 (15), 1809-1819.

Mitchell, W. F. (1993). Testing for unit roots and persistence in OECD unemployment, *Applied Economics*, 25(12), 1489–1501.

Neudorfer, P., Pichelmann, K., & Wagner, M. (1990). Hysteresis, NAIRU and long-term unemployment in Austria, *Empirical Economics*, 15(2), 217–229.

Phelps, E. (1968). Money-wage dynamics and labor-market equilibrium, *Journal of Political Economy*, 76(4), 678-711.

Phillips, P.C.B. & Perron, P. (1988). Testing for a Unit Root in Time Series Regression, *Biometrika*, 75, 335-346.

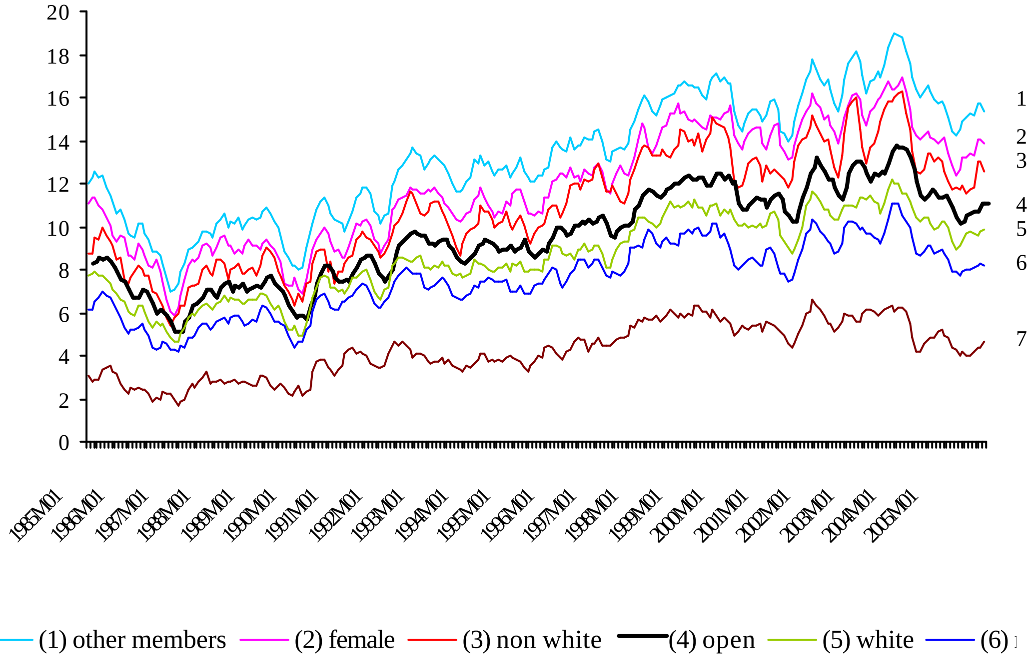
Romer, D. (2001). *Advanced Macroeconomics*. 2nd. ed. New York: McGraw-Hill/Irwin.

Song, F. M. & Wu, Y. (1998). Hysteresis in unemployment: Evidence from OECD countries, *The Quarterly Review of Economics and Finance*. 38(2), 181-192.

Tolvi, J. (2003) Unemployment persistence of different labor force groups in Finland, *Applied Economics Letters*, 10, 455–458.

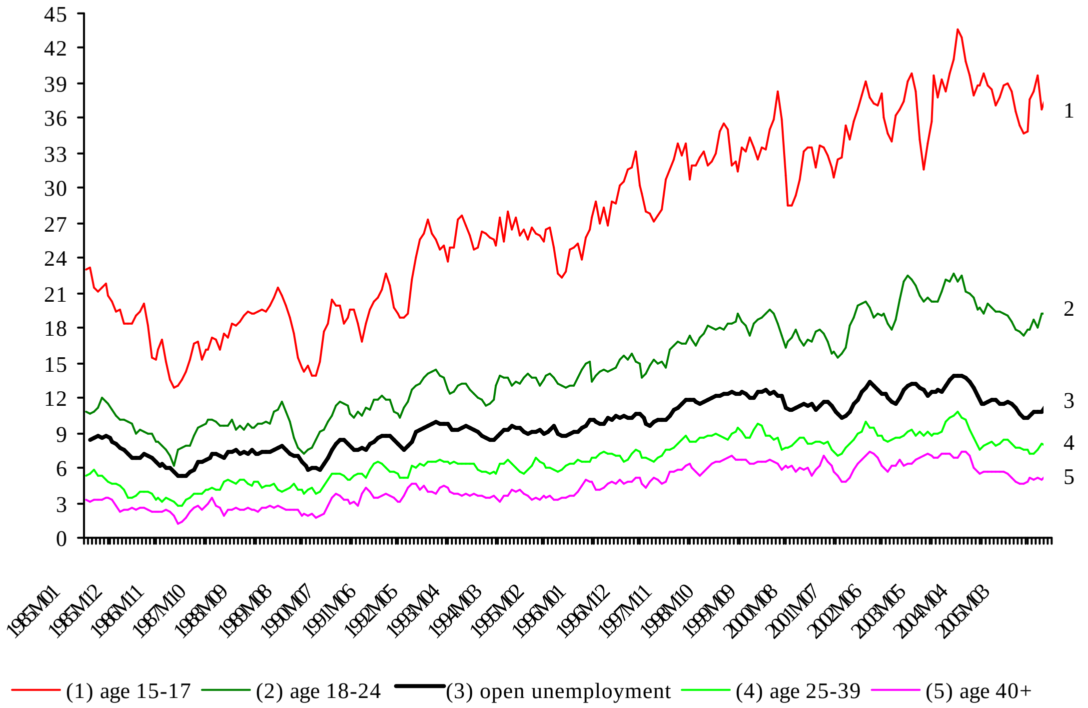
Figures and Tables

Figure 1 - Seasonally Adjusted Unemployment Series (1985:01 – 2005:12)



Source: Seade

Figure 2 - Seasonally Adjusted Unemployment Series (1985:01 – 2005:12)



Source: Seade

Figure 3 – Seasonally Adjusted Unemployment Series:

January 1985 versus December 2005

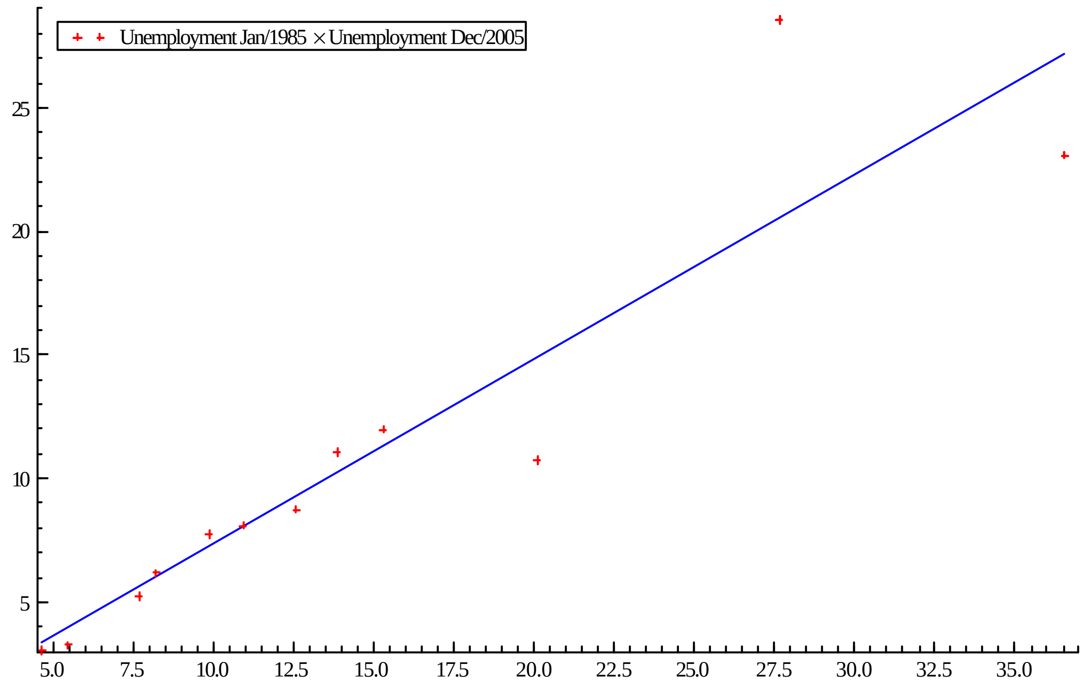


Figure 4: Impulse Response Functions I

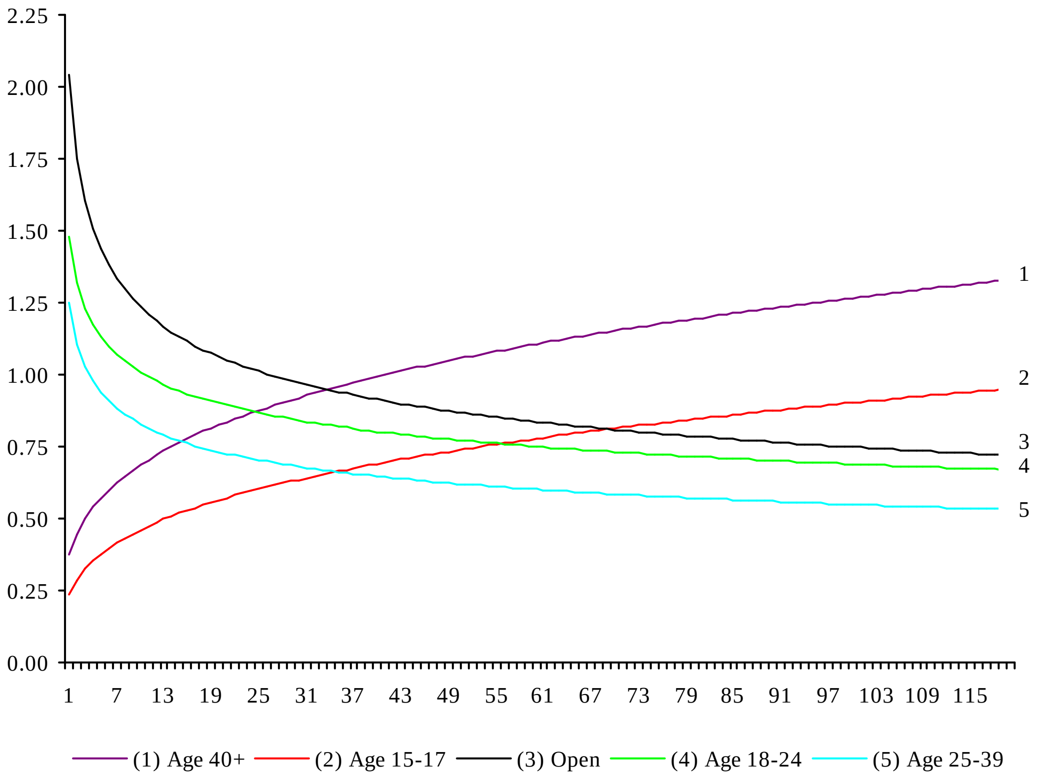


Figure 5: Impulse Response Functions II

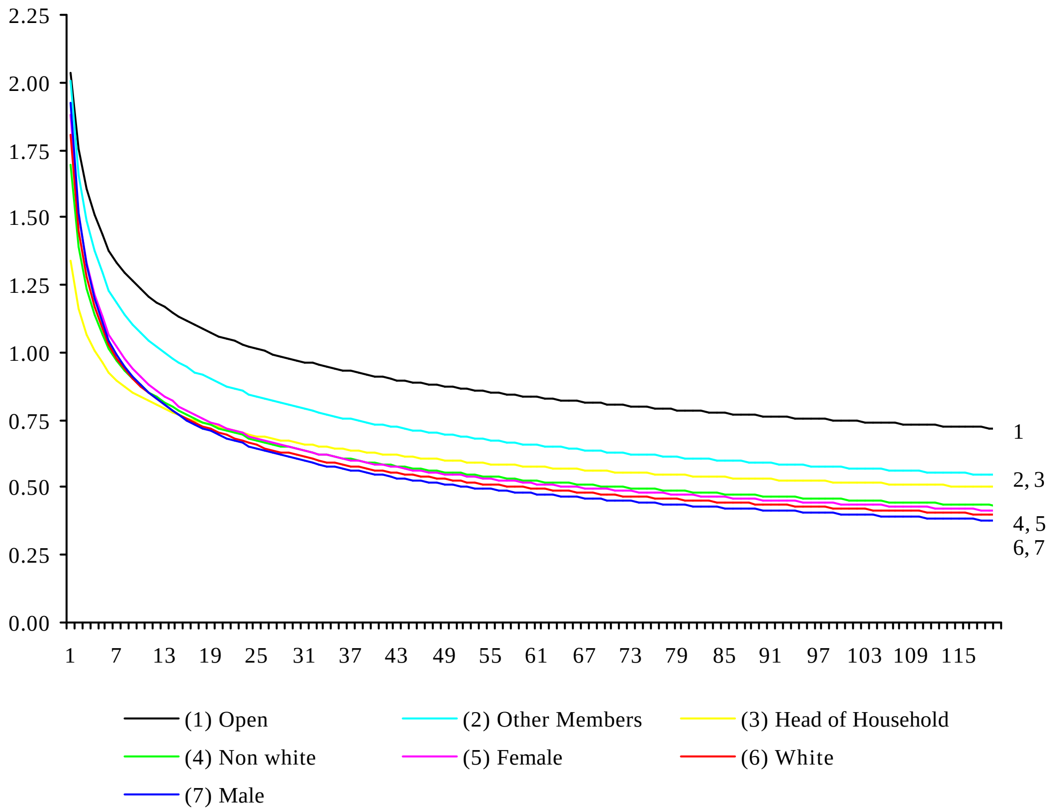


Table 1 - Seasonally Adjusted Unemployment Series: Descriptive Statistics

Unemployment Series	Mean				Growth Rate		
	Whole Sample 1985:01 to 2005:12	Sub Sample 1 1985:01 to 1994:06	Sub Sample 2 1994:07 to 1998:12	Sub Sample 3 1999:01 to 2005:12	Sub Sample 1 to Sub Sample 2 (%)	Sub Sample 2 to Sub Sample 3 (%)	Sub Sample 1 to Sub Sample 3 (%)
Open	9.39	7.45	10.02	11.62	34.50	16.04	56.07
Age 15-17	27.29	20.17	28.95	35.89	43.51	23.97	77.91
Age 18-24	14.41	10.66	15.14	19.02	42.10	25.56	78.42
Age 25-39	6.63	4.97	7.17	8.55	44.37	19.12	71.98
Age 40+	4.44	3.02	4.78	6.16	58.43	28.97	104.33
White	8.58	6.90	9.11	10.50	31.99	15.18	52.03
Non white	10.92	8.60	11.72	13.54	36.31	15.54	57.49
Male	7.56	6.13	8.16	9.10	33.12	11.58	48.54
Female	11.87	9.46	12.56	14.68	32.75	16.91	55.20
Head of household	4.22	3.14	4.68	5.39	48.77	15.25	71.45
Other members	13.26	10.71	14.02	16.23	30.92	15.83	51.64

Source: Seade

Table 2 - Sample autocorrelations of the series in level

	Series										
Lags	Open	Age 15-17	Age 18-24	Age 25-39	Age 40+	Male	Female	White	Non White	Head	Other Members
1	0.99	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.98	0.98	0.99
2	0.97	0.96	0.97	0.96	0.95	0.95	0.97	0.97	0.95	0.95	0.97
3	0.95	0.93	0.94	0.94	0.93	0.92	0.94	0.94	0.92	0.92	0.94
4	0.93	0.92	0.93	0.92	0.91	0.89	0.92	0.92	0.9	0.89	0.92
5	0.91	0.91	0.91	0.9	0.9	0.87	0.91	0.9	0.88	0.88	0.9
6	0.9	0.9	0.9	0.89	0.89	0.85	0.89	0.89	0.86	0.86	0.89
7	0.88	0.89	0.89	0.88	0.88	0.83	0.88	0.88	0.85	0.86	0.87
8	0.88	0.88	0.89	0.87	0.88	0.83	0.88	0.87	0.85	0.85	0.87
9	0.87	0.88	0.88	0.86	0.88	0.83	0.87	0.87	0.85	0.85	0.86
10	0.87	0.87	0.88	0.86	0.87	0.83	0.87	0.86	0.85	0.84	0.86
11	0.86	0.86	0.87	0.85	0.86	0.82	0.86	0.85	0.84	0.83	0.86
12	0.85	0.86	0.86	0.84	0.85	0.81	0.85	0.84	0.83	0.81	0.85
13	0.84	0.84	0.85	0.82	0.83	0.79	0.84	0.82	0.82	0.8	0.83
14	0.82	0.83	0.84	0.8	0.82	0.77	0.82	0.8	0.8	0.78	0.81
15	0.8	0.81	0.82	0.79	0.8	0.75	0.8	0.79	0.78	0.76	0.79
16	0.78	0.79	0.8	0.77	0.79	0.72	0.78	0.77	0.75	0.75	0.77
17	0.76	0.78	0.78	0.75	0.77	0.7	0.77	0.75	0.73	0.73	0.75
18	0.75	0.77	0.77	0.74	0.76	0.67	0.75	0.73	0.72	0.71	0.74

Table 2 (cont) - Sample autocorrelations of the series in first difference

	Series										
Lags	Open	Age 15-17	Age 18-24	Age 25-39	Age 40+	Male	Female	White	Non White	Head	Other Members
1	0.43	0.10	0.22	0.14	0.17	0.39	0.32	0.27	0.27	0.16	0.37
2	0.25	0.14	0.21	0.11	0.10	0.14	0.12	0.19	0.16	0.15	0.20
3	-0.11	-0.41	-0.22	-0.27	-0.42	-0.19	-0.25	-0.21	-0.21	-0.25	-0.17
4	-0.04	-0.09	-0.12	-0.01	0.00	-0.06	-0.07	-0.03	-0.08	-0.07	-0.01
5	-0.16	-0.10	-0.10	-0.02	-0.15	-0.10	-0.07	-0.12	-0.11	-0.11	-0.13
6	-0.29	-0.04	-0.21	-0.19	-0.06	-0.28	-0.17	-0.21	-0.32	-0.25	-0.24
7	-0.29	0.02	-0.10	-0.09	-0.12	-0.27	-0.09	-0.14	-0.14	-0.06	-0.27
8	-0.13	-0.02	-0.10	-0.10	0.06	-0.17	-0.08	-0.08	-0.07	-0.02	-0.12
9	-0.04	-0.04	-0.03	0.01	0.04	-0.01	-0.03	0.03	0.04	0.06	-0.04
10	0.10	-0.09	0.02	0.09	0.05	0.12	-0.04	0.01	0.03	0.06	0.05
11	0.15	0.07	0.04	0.05	0.07	0.12	0.13	0.15	0.05	0.09	0.14
12	0.29	0.10	0.11	0.12	0.07	0.20	0.21	0.15	0.17	0.05	0.28
13	0.23	0.21	0.15	-0.01	0.04	0.16	0.19	0.16	0.15	0.04	0.23
14	0.09	0.05	0.18	0.07	-0.03	0.12	0.01	-0.01	0.14	-0.08	0.09
15	-0.07	-0.02	-0.05	-0.06	-0.05	0.00	-0.06	-0.06	0.01	0.04	-0.07
16	-0.14	-0.14	-0.05	0.02	0.01	-0.06	-0.09	-0.03	-0.09	0.04	-0.14
17	-0.23	-0.19	-0.20	-0.05	-0.09	-0.12	-0.17	-0.16	-0.20	0.04	-0.21
18	-0.26	-0.08	-0.13	-0.06	0.04	-0.21	-0.18	-0.13	-0.28	-0.07	-0.25

Table 3 - Unit Root Tests and ARFIMA Models

Series	Unit Root/Stationarity Tests			ARFIMA chosen by SC criterion					
	H_0: (d=1) Unit Root		H_0: (d=0) Stationarity	d	MA(1)	MA(2)	MA(3)	AR(1)	Const
	ADF	PP	KPSS	(sd)	(sd)	(sd)	(sd)	(sd)	(sd)
Open	-2,246	-3.269***	0.141***	0.782	0.729	0.685	-	-	8,670
				(0.055)	(0.055)	(0.047)			(0.853)
Age 15-17	-4,245*	-4.301*	0.118	1,292	-0.100	0.030	-0.718	-	25,354
				(0.100)	(0.082)	(0.048)	(0.046)		-2,047
Age 18-24	-3,692**	-4.056*	0.102	0.834	0.458	0.503	-0.293	-	11,534
				(0.094)	(0.113)	(0.099)	(0.103)		-2,138
Age 25-39	-2,426	-3.501**	0.152**	0.821	0.434	0.371	-0.377	-	5,819
				(0.114)	(0.129)	(0.120)	(0.112)		-1,178
Age 40+	-2,018	-3.006	0.156**	1,266	0.056	0.041	-0.761	-	3,943
				(0.132)	(0.103)	(0.072)	(0.065)		(0.666)
White	-2,621	-3.197***	0.141***	0.685	0.721	0.672	-	-	8,112
				(0.051)	(0.060)	(0.053)			(0.627)
Non white	-2,176	-3.247***	0.148**	0.715	0.938	0.842	-	-0.289	9,298
				(0.062)	(0.049)	(0.042)		(0.093)	(0.892)
Male	-2,225	-2.982	0.156**	0.660	0.857	0.771	-	-	6,423
				(0.050)	(0.049)	(0.049)			(0.492)
Female	-2,529	-3.542**	0.153**	0.685	0.775	0.711	-	-	11,613
				(0.049)	(0.051)	(0.044)			(0.838)
Head of household	-1,706	-2.987	0.193**	0.794	0.494	0.443	-0.368	-	2,682
				(0.105)	(0.123)	(0.118)	(0.112)		(0.704)
Other members	-2,590	-3.525**	0.124***	0.729	0.771	0.741	-	-	12,938
				(0.051)	(0.047)	(0.043)			(0.949)

Note: *i*) ADF, PP and KPSS stand for Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin, respectively. *ii*) Estimations with constant and linear trend. *iii*) ADF's lagged first differences chosen by the Schwarz Information Criterion. *iv*) PP and KPSS use Bartlett Kernel with the Newey-West Bandwith. *v*) *, **, *** mean rejection of H_0 at 1%, 5% and 10%, respectively; *vi*) Standard deviation in parenthesis.

Table 4 - ARFIMA(p, d, q): Estimation of 'd'

Model	'd'										
(p,q)	**Open**	**Age 15-17**	**Age 18-24**	**Age 25-39**	**Age 40+**	**Male**	**Female**	**White**	**Non White**	**Head**	**Other Members**
(0,0)	1.370	-	1.154	1.054	1.044	1.304	1.230	1.197	1.180	1.080	1.301
(0,1)	1.182	0.888	1.039	0.932	0.893	1.057	1.021	1.056	-	0.952	1.115
(0,2)	**0.782**	0.599	0.672	0.584	0.584	**0.660**	**0.685**	**0.685**	0.615	0.573	**0.729**
(0,3)	0.826	**1.292**	**0.834**	**0.821**	**1.266**	0.748	0.782	0.813	0.760	**0.794**	0.786
(1,0)	0.743	0.754	0.767	0.742	0.713	0.714	0.733	0.697	0.673	0.710	0.713
(1,1)	0.748	0.745	0.768	0.725	0.713	0.684	0.728	0.719	0.685	0.707	0.719
(1,2)	0.827	0.706	0.768	0.699	0.691	0.727	0.752	0.785	**0.715**	0.697	0.776
(1,3)	0.768	0.278	0.822	-0.171	-	0.746	0.542	0.470	0.749	-0.230	0.665
(2,0)	0.770	0.774	0.821	0.746	0.712	0.667	0.755	0.777	0.697	0.715	0.751
(2,1)	0.754	0.771	0.808	0.725	0.763	0.799	0.755	0.795	0.728	0.727	0.716
(2,2)	0.812	0.745	-	0.805	0.696	0.775	0.779	0.813	0.777	0.815	0.797
(2,3)	0.790	-	0.606	-	-	-	0.633	0.733	0.672	0.534	0.862
(3,0)	0.892	0.933	0.864	0.928	1.041	0.852	-	0.914	0.811	0.828	0.938
(3,1)	0.815	0.909	0.865	0.870	0.909	0.787	0.901	0.847	0.764	0.789	0.840
(3,2)	0.751	0.773	0.780	0.771	0.792	0.704	0.796	0.761	0.712	0.728	0.799
(3,3)	0.770	-	1.504	-	0.403	0.890	-	-	-	1.247	0.840

Notes: Method: NLS (BFGS numerical derivatives). Some models did not converge and, consequently, the result was not reported.
Sample: 1985:01- 2005:12 (252 observations)