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# Monthly Estimates for the Portuguese Unemployment Rate*

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**Abstract**

The only data on the unemployment rate currently published by Instituto Nacional de Estatística are the quarterly figures from Inquérito ao Emprego. In periods when the conditions in the labour market are more volatile, this three-month gap in which there is no information about the changes in the unemployment rate can have undesirable consequences. In the absence of better information, the data on the registered unemployment published monthly by Instituto do Emprego e Formação Profissional have been used by Eurostat to obtain monthly estimates of the Portuguese unemployment rate. However, especially in periods of growing unemployment, these estimates have been somewhat unreliable. This paper reports a study carried out in late 2003 investigating the possibility of obtaining better estimates of the Portuguese unemployment rate. The results obtained suggest that, indeed, it was possible to outperform the estimates published by Eurostat at the time.

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## 1. INTRODUCTION

The only data on the unemployment rate currently published by Instituto Nacional de Estatística (INE) are the quarterly figures from Inquérito ao Emprego (IE). In periods where the conditions in the labour market are more volatile, this three-month gap in which there is no information about the changes in the unemployment rate can have undesirable consequences, both at the socioeconomic and political levels. Therefore, there is a need for reliable and more frequent information on the evolution of the unemployment rate.

INE has been working on the possibility of obtaining monthly information on the labour market from the IE data. Indeed, given the way the IE data is gathered, it would be possible to compute monthly estimates of the average unemployment rate in the previous three months. This will certainly be the best way to obtain reliable monthly information on the labour market situation, even if, due to the characteristics of the IE, only three-month moving averages can be obtained. However, until this methodology is fully implemented, the need for monthly information on the unemployment rate remains.

In the absence of better information, the data on the registered unemployment (RU) published monthly by Instituto do Emprego e Formação Profissional (IEFP)[1] is used by Eurostat to estimate the monthly unemployment rate for Portugal.[2] The use of the RU data to forecast the monthly unemployment rate has, however, some important drawbacks. To start with, the RU data is sensitive to administrative decisions, like changes in the unemployment benefit rules, which do not affect the unemployment rate. Moreover, the populations described by the two samples are very different.[3] Finally, the RU data give no information on the active population and therefore they are not

participants in a seminar at Instituto Nacional de Estatística, for the many suggestions and comments that made this work possible. The usual disclaimer applies.

[1] See http://www.iefp.pt/estatisticas/estatdadosmes.htm.

[2] See the "News Releases" on the labour market available here: http://europa.eu.int/comm/eurostat/.

[3] Indeed, the concept of unemployment in the IEFP data is very different from that of IE, and the sampling plans of the two data sets are different. Besides, registration in IEFP is mandatory only for the unemployed who wish to receive unemployment benefits.

enough to estimate unemployment rates. The problems with the use of the RU data to forecast a monthly unemployment rate that is compatible with the IE figures are clearly illustrated by the fact that Eurostat frequently has to revise its forecasts by as much as half a percentage point.[4]

This paper presents the results of an attempt to construct monthly estimates for the Portuguese monthly unemployment rate using the method proposed by Chow and Lin (1971), and data from IE and RU. This study was carried out in late 2003, a time when the Eurostat forecasts of the Portuguese monthly unemployment rate were particularly poor. From January 2004, the level of unemployment in Portugal stabilized at around 6.7 *per cent*. At about the same time, Eurostat changed the method used to obtain the forecasts of the Portuguese monthly unemployment rate, and the results it provides have been adequate since then. Under these circumstances, the need for monthly information on the labour market become less pressing and the method developed here was never used in practice. However, this study shows that the Chow and Lin (1971) method can be successfully used in this context, even in periods when the unemployment rate changes quickly.

This paper is organized as follows. Section 2 briefly presents the Chow and Lin (1971) disaggregation method, as well as some of its extensions. Section 3 describes the implementation of the method, giving details on the information used and on the particular disaggregation methods chosen. Finally, section 4 presents the main results and section 5 summarizes the conclusions of the study.

## 2. THE CHOW AND LIN METHOD[5]

Assume that, given $t$ quarterly values of a time series $\bar{y}$, we want to construct a monthly series $y$ with $m$ observations. Chow and Lin (1971) proposed a general solution to this problem based on the assumption that it is possible to write $y$ as a linear stochastic

[4] This should not be interpreted as a criticism to Eurostat practices, whose methods have to be suitable for producing reasonable results for the entire European Union and not just for a single country.

[5] This section draws heavily on Santos Silva and Cardoso (2001), and can be skipped with little loss of continuity.

function of a set of time series $x$, observed monthly. That is, it is possible to write

$$y = x\beta + \varepsilon, \tag{1}$$

where $\beta$ is a vector of parameters and $\varepsilon$ is a vector of stochastic disturbances with covariance matrix $\sigma^2\Omega$, where $\sigma^2$ is a suitably defined constant.[6]

Let $C$ be a $t \times m$ aggregation matrix that converts monthly series into quarterly series by pre-multiplication. That is, $\bar{y} = Cy$. The form of $C$ depends on the particular type of problem being considered but it can always be written as

$$C = \left[ I \otimes c' | \emptyset \right],$$

where $I$ is an identity matrix of order $t$, $c$ is a $3 \times 1$ vector and $\emptyset$ is a $(m - 3t) \times t$ block of zeros. For example, in the present case, a case of distribution where $\bar{y}$ is the average of the monthly observations of $y$, $c' = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$. Notice that $\emptyset$ is included in $C$ only when $m > 3t$, that is, when we want to construct $y$ for months for which $\bar{y}$, the quarterly average, is not yet available. This is precisely the situation of interest in this study.

Using this notation, the quarterly variable $\bar{y}$ can be expressed as

$$\bar{y} = Cx\beta + C\varepsilon, \tag{2}$$

where $C\varepsilon$ is a vector of random disturbances with covariance matrix $\sigma^2 C\Omega C'$.

Although (1) cannot be estimated directly, estimates of its parameters can be obtained from (2), since the two equations depend on $\beta$, $\sigma^2$ and $\Omega$. Defining $\bar{x} = Cx$ and assuming that $\Omega$ is known, the best linear estimator for $\beta$ is the generalized least squares estimator obtained from (2). That is:

$$\hat{\beta} = \left[ \bar{x}' \left( C\Omega C' \right)^{-1} \bar{x} \right]^{-1} \bar{x}' \left( C\Omega C' \right)^{-1} \bar{y}. \tag{3}$$

In this context, the problem of estimating $y$ is a simple problem of prediction in the context of a linear model with non-spherical disturbances. In fact, from the classical work of Goldberger (1962), it is known that the best linear unbiased predictor for $y$ is given by:

$$\hat{y} = x\hat{\beta} + \Omega C' \left( C\Omega C' \right)^{-1} (\bar{y} - \bar{x}\hat{\beta}). \tag{4}$$

[6] It is assumed that $\Omega$ is normalized in such a way that its trace is $m$.

Equation (4) shows that the predictor for $y$ can be decomposed into two components. The first part, $x\hat{\beta}$, is just an estimate of the conditional expectation of $y$ given $x$. The other is a prediction of the value of the disturbances obtained from the relation between the stochastic components of the observations being predicted and those used in the estimation. This structure of the predictor ensures an important coherency property of the predicted series. In fact, from (4) it is easy to verify that $C\hat{y} = \bar{y}$. That is, the aggregated predicted monthly series coincides with the observed quarterly series. Notice that if $m > 3t$, the last $3t - m$ observations of $\hat{y}$ are not subject to the aggregation restriction since the corresponding quarterly observations are not known.

Naturally, $\Omega$ is not known and a suitable estimator for this covariance matrix has to be found. In practice, the elements of this matrix are defined as functions of a small set of parameters which are estimated together with $\beta$, either by maximum likelihood or by generalized least squares. In their seminal paper, Chow and Lin (1971) started by considering that the errors in (1) are independent and homoskedastic. In this case $\Omega = I$. In the distribution case considered here, this assumption implies that the errors of the quarterly estimation are distributed uniformly by the estimated monthly observations. Naturally, this way of distributing the quarterly residuals by the monthly observations may lead to spurious discontinuities between the last month within a quarter and the first month of the next one.

To overcome this problem, Chow and Lin (1971) suggest that $\Omega$ should be parameterized as the covariance matrix of an $AR(1)$ process of the form $\varepsilon_t = \rho\varepsilon_{t-1} + \xi_t$, where $\xi_t$ is a white noise and $|\rho| < 1$. However, some authors found that this parameterization still leads to estimated series that tend to have artificial blips between the last month of a quarter and the first month of the next one.

Fernández (1981) suggested that a way to minimize this problem is to assume that $\rho = 1$. Of course this is a very strong restriction on the structure of the error process and Litterman (1983) suggested an alternative that amounts to assuming that $\varepsilon_t$ follows an $AR(2)$ process with a unit root. That is: $\varepsilon_t = (1+\alpha)\varepsilon_{t-1} - \alpha\varepsilon_{t-2} + \xi_t$. Pinheiro and Coimbra (1993) have shown that this parameterization of $\Omega$ has an interesting interpretation by viewing $\alpha$ as a roughness penalty, and recommended its use.

More recently, Santos Silva and Cardoso (2001) have shown that it is easy to use this type of disaggregation method when the errors are spherical and (1) is a dynamic model, that is, when the matrix $x$ includes the lagged dependent variable.

Besides the particular version of the Chow and Lin method that is used, this methodology has an additional degree of freedom. Indeed, Salazar, Smith, Weale and Wright (1994) have shown that it is possible to adapt this method to the case in which the dependent variable in (1) is the logarithm of $y$ (see also Pinheiro and Coimbra, 1993). However, in this case, the disaggregation is only an approximation.

Naturally, the quality of the results obtained with this methodology depend on the particular characteristics of the problem being considered. Since no particular version of the Chow and Lin (1971) method is generally superior to its alternatives, any disaggregation exercise requires some experimentation. However, given the multitude of possible combinations between versions of the Chow and Lin method, model specifications and variable transformations, this experimentation can hardly be exhaustive.

When it is not possible to find series related to $y$ that are observed monthly, the simpler temporal disaggregation methods suggested by Boot, Feibes and Lisman (1967) have to be used. It is easy to verify that these methods are special cases of the Chow and Lin (1971) method just described. In fact, the first method suggested by Boot, Feibes and Lisman (1967), the first differences method, corresponds to the Chow and Lin method when $x$ is just a vector of 1's and the errors follow a random walk, as suggested by Fernández (1981). The second method proposed by Boot, Feibes and Lisman (1967), the second differences method, is obtained when $x$ contains a constant and a time trend and the errors follow the $AR(2)$ process suggested by Litterman (1983), with $\alpha = 1$.

It is worth pointing out that most of the disaggregation methods described here are implemented in ECOTRIM (Barcellan, 1994), a software freely available from Eurostat.

## 3. IMPLEMENTATION ISSUES

In this exercise, the implementation of the disaggregation methodology was kept as simple as possible. There are two main reasons for this: first, the method needs to be sufficiently simple to produce results in a timely manner; second, the simplicity and transparency of the method should help the credibility of the results, ensuring that these are in no way manipulated through subjective or discretionary procedures.

An issue that is important to stress is that, as mentioned before, the Chow and Lin (1971) method adopted here permits, not only the disaggregation of a time series subject to the aggregation restriction $C\hat{y} = \bar{y}$, but also, when $m > 3t$, the forecast of the monthly series for periods for which the quarterly average is not yet available. This characteristic is particularly important in the present study since the main objective here is to obtain monthly forecasts for the unemployment rate for months for which the quarterly average data from IE is not available. Naturally, these forecasts do not satisfy the aggregation restriction, and therefore may be incompatible with the quarterly results later available. After the publication of the quarterly figures from IE, monthly estimates of the unemployment rate can be obtained by distribution, imposing the aggregation restriction.

Although the aim here is the estimation of monthly unemployment rates, it is preferable to disaggregate separately the active population and unemployment series. The main reason for this is that, although the difference is generally small, the average of unemployment rates is not an average unemployment rate. Since the figures from IE can be viewed as the average unemployment rate in the quarter, it is not clear which aggregation restriction the estimated monthly series must respect. That is, the vector $c'$ should not be $\begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix}$, and it is not clear how it should be defined. Moreover, the main source of monthly information available is the data on the number of unemployed registered from IEFP, which is a natural indicator to use in the disaggregation of the unemployment data from IE, but not really appropriate for the disaggregation of the unemployment rate. Therefore, the active population and unemployment series were disaggregated separately.

### 3.1. Data sources

Although the RU data published by IEFP is likely to be a good indicator to use in the disaggregation of the unemployment data obtained from IE, the RU data has several drawbacks. Therefore, it is important to consider alternative ways of using this information. One possibility was to use just the data on the number of unemployed registered during the current month, instead of the total number of unemployed currently registered. The main advantage of using the flow rather than the stock of RU is that this variable may be less sensitive to some administrative decisions, being potentially a better indicator of the situation in the labour market. However, this flow is very sensitive, for example, to changes in the rules for access to the unemployment benefit. Moreover, conceptually, it is not very appealing to use a flow variable as an indicator in the disaggregation of a stock. Therefore, the idea of using this flow variable was abandoned.

An alternative way of improving the quality of the RU data could be to try to eliminate some variations caused by purely administrative reasons. However, this idea was not pursued because it could imply the need to correct the RU data for the forecasting period, opening a way for the possible introduction of subjective decisions that could undermine the confidence of the users on the final results.

Besides the IEFP data, other sources could be explored, namely the individual data from the IE itself. However, it was not possible to find any reasonable and simple way of using this information and it was decided to use only the RU data in the disaggregation of the quarterly unemployment figures from IE.

The disaggregation of the quarterly series for the active population is complicated by the lack of any reasonable monthly information about its movements. Indeed, the two possible sources of information (the employment indices and qualitative survey data published by INE) do not currently provide monthly series long enough to be used as regressors in a model for the disaggregation of the active population. In view of this situation, and given that it is much less variable that the number of unemployed, it was decided to disaggregate the active population series using the methods suggested by Boot, Feibes and Lisman (1967), which do not require the use of monthly indicators.

Therefore, the information used here to obtain the monthly forecasts of the unemployment rate is exactly the same that is used by Eurostat.

### 3.2. Seasonal adjustment

Although the seasonal adjustment of time series is often of questionable interest, in the present study it is important to consider this issue for two main reasons. Firstly, it is important to obtain seasonally adjusted estimates of the unemployment rate that can be compared with the figures published by Eurostat, which are also seasonally adjusted. A second reason to use seasonally adjusted data in these exercises is that the disaggregation methods used here are not particularly adequate to deal with seasonal data.

When the quarterly data and the indicators used in its disaggregation exhibit seasonal movements, the seasonality of the disaggregated data is determined by the seasonal pattern of the indicators. However, there is no reason to assume that this is the seasonal pattern of the series to be constructed. Indeed, the estimated model depends only on the relation between the quarterly series to be disaggregated and the quarterly aggregated indicators. Therefore no information on the monthly seasonal patterns is used in the estimation of the model, which therefore cannot be expected to lead to a disaggregated series with the appropriate seasonal pattern. For this reason, the Chow and Lin (1971) method is generally used with seasonally adjusted data.

In the case of the unemployment data from IE and IEFP, it is reasonable to assume that the seasonal pattern of the two series is similar. Therefore, it is acceptable to work with the original, seasonally unadjusted, data. However, for the reasons pointed out above, seasonally adjusted estimates were also obtained. These were produced using the seasonally adjusted series for monthly and quarterly unemployment estimated using DEMETRA 2.0, a software developed by Eurostat. The series for the active population was not adjusted as no significant seasonal patterns were identified.

### 3.3. Choice of disaggregation method

Having defined the data to be used, it is now necessary to choose the particular form of the Chow and Lin (1971) method to be adopted.

The distribution of the IE data can be performed using the RU series which, despite all its pitfalls, should be a reasonable indicator. This has implications for the parameterization of $\Omega$ that is chosen. Indeed, the parameterizations of $\Omega$ proposed by Fernández (1981) and Litterman (1983) imply that the errors in (1) follow a non-stationary process, and so these methods assume that there is no long-run relationship between the series being disaggregated and the indicators that are used. Therefore, despite being known for generally producing good results, these parameterizations of $\Omega$ are not appropriate to disaggregate the quarterly IE data using the RU as an indicator.

Given the drawbacks of the Chow and Lin (1971) method assuming that the errors in (1) are independent and homoskedastic, the decision about the method to use was limited to the choice between the model with $AR(1)$ errors suggested by Chow and Lin (1971) and the dynamic model proposed by Santos Silva and Cardoso (2001).

The results obtained with the dynamic model revealed that the unemployment series has a very strong inertia, leading to a model where the lagged dependent variable has a coefficient close to one and the RU series has a small and statistically insignificant parameter. These characteristics make this model inappropriate for the present study where the main objective is to forecast the number of unemployed individuals. Indeed, with this model, the forecasts would be based on the past behaviour of the series, and the new information on the labour market provided by the RU data would effectively be ignored. Therefore, despite its good statistical properties, the dynamic model was not adopted and the quarterly unemployment data was disaggregated using the static model with $AR(1)$ errors proposed by Chow and Lin (1971), which produces reasonable results.[7]

Given that there is no monthly information that can be used in the disaggregation of the active population data, the disaggregation methods suggested by Boot, Feibes

[7] This model was estimated by maximum likelihood, assuming normality.

and Lisman (1967) were used. After some experimentation, it was concluded that the method that minimizes the squares of the second differences of the disaggregated series tends to significantly over-predict the growth of the active population. Therefore, the method that minimizes the squares of the first differences of the disaggregated series was adopted. With this method, the forecasts of the active population are equal to the value obtained by disaggregation for the last month for which quarterly data is available. Although this is clearly a naïve forecast, it seems reasonable in this specific context, not only because it is used only for very short-term forecasts, but also because the active population is indeed relatively stable.

As an alternative to the Boot, Feibes and Lisman (1967) methods, the dynamic model of Santos Silva and Cardoso (2001) could be used for this disaggregation. However, like the method based on the second differences, this model always predicts a sharp rise of the active population and was, therefore, abandoned. The poor results obtained, both with the dynamic model and with the Boot, Feibes and Lisman (1967) method based on the second differences may be due to the structural break in the active population series in the first quarter of 1998. Although this problem could probably be fixed, this was not attempted because the Boot, Feibes and Lisman (1967) method based on the first differences produces reasonable results and is less arbitrary.

Finally, a decision had to be taken on whether or not to use logarithms. Since the use of logarithms was not essential for the quality of the results, it was decided to work only with the data in levels because the disaggregation of the logged data is only approximated, requiring a second round procedure to distribute the aggregation error.

## 4. MAIN RESULTS

Before presenting the results, it is useful to recall that the IE unemployment data was disaggregated using the $AR(1)$ method of Chow and Lin (1971) (both for the original and seasonally adjusted data), and that the active population series, which does not exhibits significant seasonality, was disaggregated using the first-difference method of Boot, Feibes and Lisman (1967). Given that the objective of this study is to obtain monthly estimates of the unemployment rate, and although the unemployment and active population series were disaggregated separately, only results for unemployment rate are presented and discussed.

To evaluate the quality of the forecasts obtained with the method described above, the following simulation exercise was performed. Starting from the quarterly IE data from 1993 to the fourth quarter of 1999, the monthly forecasts of the unemployment rate were obtained for the first three months of 2000, using the appropriate RU data published by IEFP. Then, this procedure was repeated for every quarter until the third quarter of 2003, the last period for which IE data was available at the time of this study.

Since there are no monthly data on the unemployment rate that can be used to evaluate the forecasts obtained in this exercise, these were aggregated and compared with the IE quarterly data. The results of this exercise, using both the original and the seasonally adjusted data, are displayed in Table 1, together with the IE data. For comparison, the quarterly aggregated monthly forecasts published by Eurostat are also presented.

The results in Table 1 show that the forecasts obtained with the seasonally unadjusted data are somewhat unsatisfactory, but using seasonally adjusted data the results are much better. In particular, the forecasts for this period obtained using the proposed method are generally better than those published by Eurostat, sometimes by a substantial margin. It is important to stress that these results are useful only as a way to evaluate the forecasting ability of the models because, in practice, there is no need to forecast the third month in each quarter. Indeed, at the end of the quarter, data from the IE is available and monthly estimates can be obtained performing the usual distribution of this figure, subject to the aggregation restriction.

Naturally, the objective of this study is to obtain monthly estimates of the unemployment rate, and therefore it is important to evaluate the quality of these forecasts, and not only of their quarterly averages. However, this task faces an insurmountable hurdle. Since there are no monthly data on the unemployment rate, it is not possible to truly evaluate the quality of the monthly forecasts. To bypass this problem, the forecasts obtained without the corresponding quarterly information are compared with the monthly estimates obtained by distribution of the quarterly figure, imposing the aggregation restriction. Of course, this series does not correspond to the true figures for the monthly unemployment rate, but it is the best benchmark available. Table 2 displays the monthly forecasts, both with and without seasonal adjustment, as well as the benchmark data obtained by distribution of the IE figures. For comparison, the monthly forecasts published by Eurostat are also included in this table. The same information is also depicted in Figures 1 and 2.

The results in Table 2 show that, overall, the forecasts obtained with the particular implementation of the Chow and Lin (1971) method used here lead to smaller errors than the forecasts published by Eurostat. This advantage is particularly noticeable when the seasonally adjusted forecasts obtained with the Chow and Lin (1971) method are compared with those from Eurostat, which are also seasonally adjusted. These results, together with those presented in Table 1, clearly suggest that it was possible to obtain monthly forecasts of the unemployment rate that outperformed those that were published by Eurostat during this period.

Table 1: Quarterly aggregated results

| | Original data | | Seasonally adjusted data | | |
|---|---|---|---|---|---|
| Quarter | IE | Forecasts | IE | Forecasts | Eurostat |
| Mar-00 | 4.3 | 4.3 | 4.1 | 4.1 | 4.2 |
| Jun-00 | 3.7 | 4.1 | 3.8 | 4.0 | 4.4 |
| Sep-00 | 3.9 | 3.6 | 4.0 | 3.8 | 4.0 |
| Dec-00 | 3.7 | 4.2 | 3.7 | 4.0 | 4.2 |
| Mar-01 | 4.2 | 4.0 | 4.0 | 3.8 | 4.5 |
| Jun-01 | 3.9 | 4.0 | 4.1 | 4.0 | 4.0 |
| Sep-01 | 4.0 | 3.8 | 4.1 | 4.1 | 4.4 |
| Dec-01 | 4.2 | 4.2 | 4.1 | 4.1 | 4.3 |
| Mar-02 | 4.5 | 4.4 | 4.3 | 4.2 | 4.3 |
| Jun-02 | 4.5 | 4.3 | 4.7 | 4.4 | 4.4 |
| Sep-02 | 5.1 | 4.6 | 5.2 | 5.0 | 4.6 |
| Dec-02 | 6.2 | 6.0 | 6.0 | 5.6 | 5.3 |
| Mar-03 | 6.4 | 6.6 | 6.2 | 6.4 | 6.6 |
| Jun-03 | 6.2 | 6.3 | 6.5 | 6.5 | 7.4 |
| Sep-03 | 6.3 | 6.2 | 6.5 | 6.7 | 7.1 |

Table 2: Monthly estimates

| | Original data | | Seasonally adjusted data | | |
|---|---|---|---|---|---|
| Month | Distribution | Forecasts | Distribution | Forecasts | Eurostat |
| Jan-00 | 4.5 | 4.3 | 4.2 | 4.1 | 4.2 |
| Feb-00 | 4.5 | 4.3 | 4.2 | 4.1 | 4.2 |
| Mar-00 | 4.2 | 4.2 | 4.1 | 4.0 | 4.1 |
| Apr-00 | 3.8 | 4.2 | 3.9 | 4.1 | 4.2 |
| May-00 | 3.6 | 4.1 | 3.8 | 4.1 | 4.5 |
| Jun-00 | 3.6 | 4.0 | 3.8 | 4.0 | 4.4 |
| Jul-00 | 3.9 | 3.6 | 4.0 | 3.8 | 4.3 |
| Aug-00 | 4.0 | 3.6 | 4.1 | 3.8 | 3.8 |
| Sep-00 | 4.0 | 3.7 | 4.0 | 3.8 | 3.8 |
| Oct-00 | 3.8 | 4.2 | 3.8 | 4.0 | 4.1 |
| Nov-00 | 3.7 | 4.3 | 3.7 | 4.0 | 4.1 |
| Dec-00 | 3.7 | 4.2 | 3.7 | 4.0 | 4.3 |
| Jan-01 | 4.1 | 3.9 | 3.9 | 3.7 | 4.4 |
| Feb-01 | 4.3 | 4.0 | 4.0 | 3.8 | 4.5 |
| Mar-01 | 4.2 | 4.0 | 4.1 | 3.8 | 4.6 |
| Apr-01 | 4.0 | 4.1 | 4.0 | 4.0 | 4.0 |
| May-01 | 3.8 | 4.0 | 4.0 | 4.0 | 3.9 |
| Jun-01 | 3.8 | 3.9 | 4.1 | 4.0 | 4.0 |
| Jul-01 | 4.0 | 3.8 | 4.1 | 4.1 | 4.3 |
| Aug-01 | 4.0 | 3.8 | 4.1 | 4.1 | 4.4 |
| Sep-01 | 4.1 | 3.9 | 4.1 | 4.1 | 4.4 |
| Oct-01 | 4.1 | 4.2 | 4.1 | 4.1 | 4.3 |
| Nov-01 | 4.2 | 4.3 | 4.1 | 4.0 | 4.2 |
| Dec-01 | 4.2 | 4.2 | 4.2 | 4.1 | 4.3 |
| Jan-02 | 4.4 | 4.3 | 4.2 | 4.2 | 4.3 |
| Feb-02 | 4.5 | 4.4 | 4.3 | 4.2 | 4.3 |
| Mar-02 | 4.5 | 4.4 | 4.4 | 4.2 | 4.3 |
| Apr-02 | 4.5 | 4.4 | 4.6 | 4.4 | 4.4 |
| May-02 | 4.5 | 4.3 | 4.7 | 4.4 | 4.3 |
| Jun-02 | 4.6 | 4.2 | 4.9 | 4.5 | 4.4 |
| Jul-02 | 4.8 | 4.5 | 5.0 | 4.9 | 4.5 |
| Aug-02 | 5.1 | 4.6 | 5.2 | 5.0 | 4.6 |
| Sep-02 | 5.5 | 4.8 | 5.5 | 5.1 | 4.7 |
| Oct-02 | 5.9 | 5.5 | 5.8 | 5.4 | 4.9 |
| Nov-02 | 6.2 | 5.7 | 6.0 | 5.7 | 5.1 |
| Dec-02 | 6.2 | 5.6 | 6.1 | 5.7 | 5.8 |
| Jan-03 | 6.5 | 6.5 | 6.2 | 6.3 | 6.1 |
| Feb-03 | 6.5 | 6.6 | 6.2 | 6.4 | 6.7 |
| Mar-03 | 6.4 | 6.7 | 6.2 | 6.6 | 7.0 |
| Apr-03 | 6.8 | 6.4 | 6.9 | 6.4 | 7.3 |
| May-03 | 6.0 | 6.3 | 6.2 | 6.5 | 7.5 |
| Jun-03 | 5.9 | 6.2 | 6.3 | 6.6 | 7.3 |
| Jul-03 | 6.1 | 6.1 | 6.4 | 6.6 | 6.9 |
| Aug-03 | 6.2 | 6.1 | 6.5 | 6.7 | 7.0 |
| Sep-03 | 6.5 | 6.4 | 6.6 | 6.8 | 7.4 |

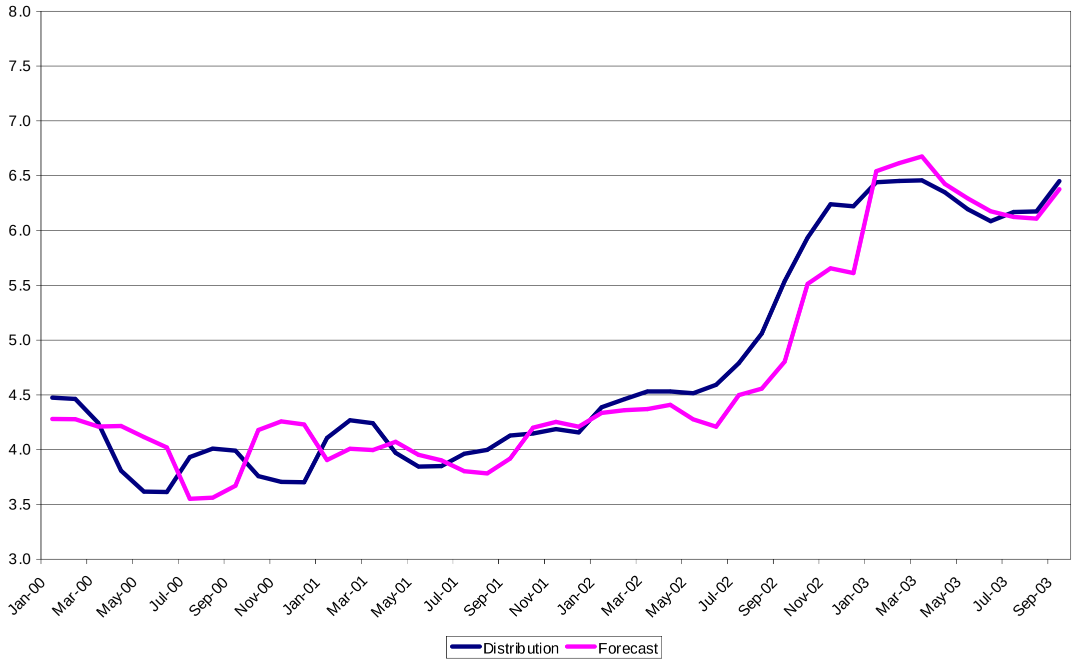


Figure 1: Monthly estimates, seasonally unadjusted data.

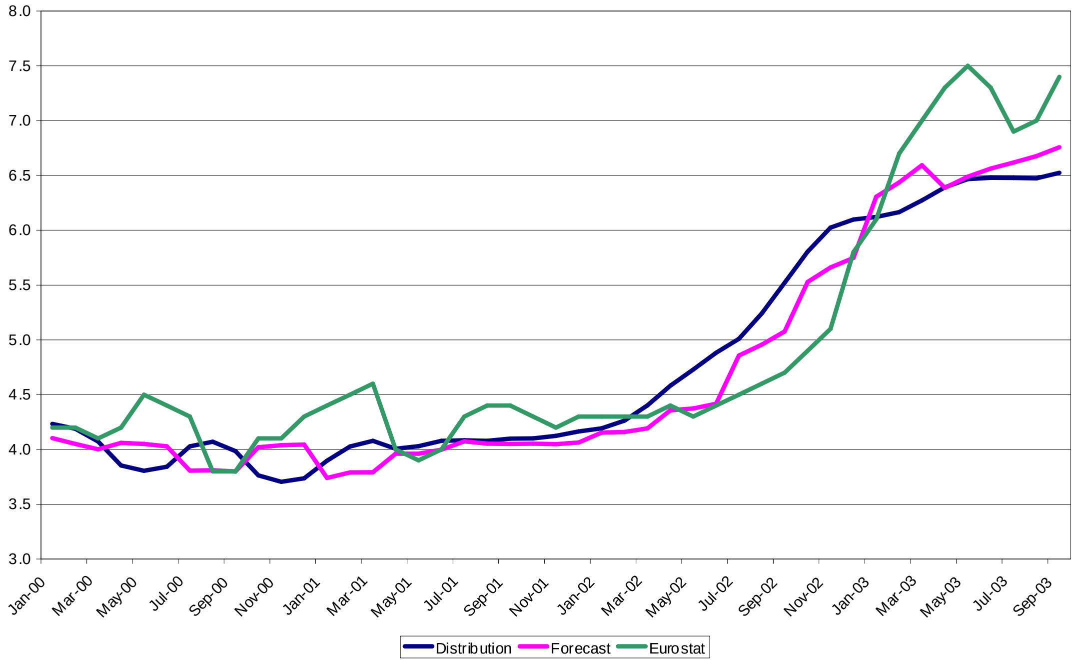


Figure 2: Monthly estimates, seasonally adjusted data.

It is important to notice that, especially since the unemployment started to rise in 2002, the forecasts tend to lag behind the series obtained by distribution of the IE data.

This behaviour may reveal a limitation of the RU data used to forecast the unemployment data: if the unemployed do not register immediately at the unemployment centres, the RU series will be a lagged indicator of the current unemployment. On the other hand, it should be pointed out that the forecast errors tend to be larger, in absolute value, for the last month in each quarter. However, as noted before, these errors are somewhat artificial since, in the third month of the quarter, data form IE is already available and there is no need for forecasts. Therefore, the results for the last month of the quarter are useful to evaluate the forecasting ability of the model, but should not be used in practice.

Finally, as it could be expected from the results in Table 1, with the exception of the first quarter of 2002, the forecasts obtained with seasonally adjusted series are generally better than those obtained with the original data.

## 5. CONCLUSIONS

The main conclusion of this study is that it was possible to obtain monthly forecasts of the unemployment rate for Portugal which generally outperformed those published by Eurostat between 2000 and 2003. Given that the information used is identical, the advantage of the forecasts presented here is entirely due to the use of more appropriate statistical methods. Since 2004, when Eurostat changed the way monthly unemployment rates for Portugal are estimated, the level of unemployment has remained relatively stable. Therefore, it is not yet possible to compare in a meaningful way the performance of the Chow and Lin (1971) technique used here with the method currently used by Eurostat.

Naturally, once monthly information from Inquérito ao Emprego becomes available, the method proposed here will lose some of its appeal. However, the results from Inquérito ao Emprego will not provide monthly estimates of the unemployment rate but only three-month moving averages. Therefore, the Chow and Lin (1971) method, suitably adapted to incorporate the new information, may still be of some use.

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