Universidad Nacional de La Plata

Departamento de Economía
Facultad de Ciencias Económicas
Universidad Nacional de La Plata

Quinto Seminario Internacional sobre Finanzas Federales

La Plata, 2 de junio de 2000

Wage determination in Argentina: An econometric analysis with methodology discussion

Sebastián Galiani (UTDT)

Wage determination in Argentina: An econometric analysis with methodology discussion

Sebastián Galiani

Wolfson College, University of Oxford
and Universidad and Instituto Torcuato Di Tella

Abstract: Micro evidence on the relationship between wages and unemployment has been provided recently in a series of contributions by Blanchflower and Oswald (1994, 1995). They argue for the existence of a wage curve linking local wages to local unemployment. They claim the relationship to be static. They also claim that the unemployment elasticity of pay is –0.1 across-countries. They claim that this shows that countries exhibit the same degree of wage flexibility.

In this paper we study wage determination in Argentina. We believe that both regional and national factors affect wage setting. Thus, we also favor the modelization at the regional level of aggregation. However, we show that a regional wage two-way fixed effects error component model does not identify the effect of aggregate variables on wages though it controls for them. Thus, the claim that the estimated unemployment elasticity of pay in this model provides a good measure of wage flexibility may be misleading.

We propose a three-step estimator that may identify the whole set of parameters of interest in a wage equation. That is, we propose a statistical procedure that may consistently estimate the coefficients of both local and aggregate variables that affect wage setting.

We reject the existence of a static wage curve in favor of a dynamic regional wage equation. Additionally, we tentatively favor an error correction mechanism representation instead of a Phillips curve type representation for the common time series component of the regional wages.

Keywords: Local and aggregate determinants of wages, three-step procedure, Phillips curve, error correction mechanism and Argentina.
JEL classifications: C2, E24 and J30.

March, 1999

This paper has benefited greatly from the comments of my supervisor, Steve Nickell. I also thank R. Di Tella, Andrew Oswald and seminar participants at the University of San Andres. Needless to say, all remaining errors are my own.

Email: Sebastian.Galiani@wolfson.ox.ac.uk

1. Introduction

Real wage responsiveness to unemployment is a key issue in macroeconomic analysis. A higher degree of wage flexibility implies, *ceteris paribus*, a lower equilibrium unemployment rate (see, e.g., Bean, 1994, Blanchard and Katz, 1997, Layard et al., 1991 and Pissarides, 1990).

Much of the early empirical work analyzing the relationship between wages and unemployment was based on country time-series data (see, e.g., Alogoskoufis and Manning, 1988, Bean et al., 1986, Layard et al., 1991 and Newell and Symons, 1985). Recently, in a couple of very important contributions, Blanchflower and Oswald (1990, 1994) shifted the emphasis more to the use of micro data sets. They use repeated cross-sectional data on individuals in a range of countries to examine the wage-unemployment relationship. They find that in any given region, if local unemployment rises, wages fall *ceteris paribus.*[1] Thus, they use the variability of wages and unemployment across-regions and time to estimate the impact of the latter on the former. Moreover, they claim that the relationship between wages and unemployment is static, that is, that any change in local unemployment exercises all its impact on local wages during a year. They call this negative relationship between local wages and local unemployment the wage curve. Finally, they argue that the unemployment elasticity of pay is around –0.1 for an important range of countries. Thus, for example, an increase in local unemployment from five to six percent (i.e. a 20 percent rise) in any given year will reduce local wages by two percent, *ceteris paribus.*

[1] Of course, contrary to the claims of Blanchflower and Oswald (1995), this finding does not challenge at all the Harris-Todaro (1970) model.

Both the lack of dynamic adjustment of wages and the apparently homogeneous unemployment elasticity of pay have aroused many debates. Card and Hyslop (1997), Bell (1997a), Bell (1997b) and Blanchard and Katz (1997) present convincingly evidence that shows that there is a high degree of persistence in regional wages. Thus, it is plausible to conclude that the best specification for a regional wage equation is one that assumes a dynamic adjustment of wages. However, there is no consensus in the literature about the degree of autoregression displayed by regional wages and why there exists such autocorrelation in the first place. Hence, as Blanchard and Katz (1997) argue, more research on this topic is desirable.

Additionally, those authors also show that the short-run elasticity of pay is significatively lower than –0.1.[2] Furthermore, comparing Bell's papers one also find that both short and long run elasticities of pay differ greatly between United States and United Kingdom. However, some of the reported long run elasticities of pay are not very different from –0.1.

In this paper we pay another look at the estimation and interpretation of dynamic regional wage equations using the Argentine household survey for the period 1990-1997. There are some other reasons that justify the exercise. First, it is germane to evaluate, in well-specified models, whether or not there is variability in the estimated unemployment elasticity of pay across-countries. This is quite relevant because it is often argued that countries have different wage setting institutions which in turn lead to more or less wage rigidity and hence, *ceteris paribus*, to different equilibrium unemployment rates. However, as we argue in section 2, this issue is subtler than has been recognized in the wage curve literature. The point is that if aggregate variables influence wage determination at the regional level (i.e. aggregate unemployment), their impact is not identified in models that include time dummy variables. Thus, the comparison of the estimated coefficients of the elasticity of pay in these models does not provide a cross-country comparison of the degree of wage flexibility. To circumvent the lack of identification of the parameters associated with the aggregate variables in regional wage equations, we propose a three-step procedure that identifies the impact of both local and aggregate variables on local wage determination. This constitutes a methodological contribution to the literature.

Additionally, some authors argue that what matters for equilibrium unemployment determination is not the unemployment elasticity of pay but the unemployment semi-elasticity of pay (see, e.g., Layard et al., 1991, chapter 9). The reason for this is the following: as the equilibrium unemployment rate gets higher and higher, excess unemployment becomes less and less effective at reducing wage pressure. If this were the case, the countries with higher equilibrium unemployment rates are still the ones that have the lower unemployment semi-elasticity of pay, that is, the ones that have the lower wage flexibility, given that all of them are supposed to have the same unemployment elasticity of pay.

Second, Blanchflower and Oswald (1995) celebrates Hoddinott (1993) estimate of a wage curve for Cote d'Ivore because it was the first estimate of the local unemployment elasticity of pay for a developing country. We agree that more work has to be done exploring the information available outside the OECD countries and this paper does that.

[2] Indeed, some of the elasticities of pay reported by Blanchflower and Oswald (1994), Table 9.1, are quite different from –0.1. Additionally, Teulings and Hartog (1998) rightly point out that the model specification

Finally, the last decade has seen some dramatic changes in the Argentine economy. After stagnating during the high inflation of the 1980s, GDP growth took off in the 1990s following the launch of a major stabilization and structural reform program. Among its reforms, the program included a substantial trade liberalization package as well as a wide-ranging privatization program. During this period both employment and the labor force grew rapidly until 1993 when employment started to slow down and unemployment began to rise. This increase accelerated during 1994 and by 1995, a year of economic depth slump, unemployment reached an unprecedented 18.4 percent. Since 1996, however, it has been falling fast and by the end of 1998 it was 12.4 percent. Thus, it is interesting to look at the data in this particular context.

The paper is organized as follows: in section 2 we analyze some important methodological issues. In section 3 we present the data in some detail and estimate dynamic regional wage equations that identify the effect of both local and aggregate variables on local wages for Argentina. Finally, in section 4, we present the conclusions of the paper.

under which these coefficients are estimated differ and hence they are not strictly comparable.

2. Some methodological considerations

Blanchflower and Oswald (1994) merge several cross-sections of data on individuals that reside in different regions of a country and estimate the coefficients of the conditional expectation of the logarithm of wages. They condition individual wages on a set of demographic controls, region fixed effects, time effects and the logarithm of the regional unemployment rates. They call this conditional expectation the wage curve.

Given the structure of the data available, they are not able to condition on the past level of individual wages. However, there is much evidence, coming from individual panel data analysis that shows that individual earnings are autocorrelated, although they present huge variance (see, e.g., Abowd and Card, 1989, Dickens, 1996 and Moffit and Gottschalk, 1993). Note that even the existence of a low level of positive autocorrelation in both individual wages and regional unemployment would bias upward the absolute value of the unemployment elasticity of pay coefficient if the estimation does not condition on the past level of wages. Therefore, given that national representative data bases are cross-sectional data, we believe that the parameter of interest is only identified at the regional level, that is, by estimating conditional regression functions of regional wages.

Additionally, efficiency wage or wage bargaining theories suggest that wage setting depends on reservation wages, labor productivity and the state of the labor market (see Layard et al., 1991). Blanchard and Katz (1997, 1999) argue that the reservation wage is likely to depend on both productivity and lagged wages. Moreover, Card (1990) decomposes real wage changes during the course of a contract into intended and unintended components using Canadian contract data. He finds that both changes in real wages over the course of the previous contract have similar effects on wages in the next contract. Blanchard and Katz (1997) conclude that Card's (1990) results suggest that the actual own lagged wage plays a direct role in wage determination and it is not only just a proxy for some other variables, like productivity, which matter in wage determination and are correlated with the lagged wage. Certainly, the lagged wage may play its role through the reservation wage as suggested by Blanchard and Katz (1997, 1999).

Hence, to estimate our wage equations, we first follow Blanchard and Katz (1997) and estimate dynamic regional wage two-way fixed effects error component equations in two-steps. This procedure is useful because it permits us to control for the impact of changes in demographic factors on the change in wages before identifying the effect of regional unemployment on regional wages. This two-step approach is also usually recommended to deal with the problem of random group or cluster effects in the data (see, e.g., Dickens and Katz, 1986). But the reason for estimating the model in two steps is the identification of the parameter of interest. Canziani (1997) presents evidence that shows that once regional fixed effects are controlled for, there is no evidence of clusters in the error structure of the wage curves he estimates. In any case, there are others alternative estimators to the two-step approach we follow here to deal with the random group effects (see, e.g., Huber, 1967 and Moulton, 1986).

Blanchflower and Oswald (1994) themselves estimate a dynamic regional model using regional-cells data and find little autocorrelation on this specification. However, some papers have suggested that this result was driven by the data used and by the presence of measurement errors in the dependent variable which, as it is well known, turns out to be pervasive in the estimation of dynamic models (see Bell, 1997a).

Finally, we have to address a very important point related to the interpretation of the parameter of interest in (dynamic) regional wage two-way fixed effects error component equations. Although Blanchflower and Oswald (1994, 1995) claim that the unemployment elasticity of pay coefficient measures the degree of wage flexibility of a country, this is not quite right. Letting aside whether it is the unemployment elasticity or the semi-elasticity of pay what matters in the determination of equilibrium unemployment, suppose that the true wage setting function relates regional wages to aggregate productivity or national wages, and both regional and national unemployment. Then, a dynamic regional wage two-way fixed effects error component model will estimate the local unemployment elasticity of local pay. This will be different from the national unemployment elasticity of national pay. The difference between these two measures of wage flexibility may arise from an attempt by unions to set similar wages in all regions or because relative conditions matter in wage determination.

Let equation (1) below be the estimated wage equation, where w measures the logarithm of local wages, u measures the logarithm of local unemployment, μ_i denotes the region effect and λ_t denotes the time effect.

$$\mathrm{w}_{it} = \varphi\,\mathrm{w}_{it-1} - \beta\, u_{it} + \lambda_t + \mu_i + \varepsilon_{it} \tag{1}$$

Note that λ_t is region-invariant and it accounts for any time-specific effect that is not included in the regression. Thus, if the wage setting at the local level is affected by the national unemployment rate, this effect will be accounted for the year fixed effects included in the regression function (1).

Alternatively, one can try to account for the region-invariant effects on local wages including aggregate variables in a dynamic one-way fixed effects error component model. However, to be successful, this exercise requires that the estimated regression function control for all the aggregate variables that affect local wages. This may be a difficult thing to do. Indeed, it is here that the virtue of using panel data resides, a virtue emphasized by Blanchflower and Oswald (1994). One can control for all the aggregate effects without the necessity of measuring them, a difficult task, particularly, whenever there are unobservable region-invariant effects. For example, suppose that although unemployment benefits are constant during the period studied and are the same across regions, the number of insider workers, that is, those workers who have a higher probability of getting benefits if they were fired, changes during the period studied. Then, the effect of unemployment benefits on wage determination becomes difficult to control for in a one-way fixed effects error component regression function but not in a two-way fixed effects error component regression function.

Thus, to conclude this section, we shall say that the identifiable parameter in a dynamic regional wage two-way fixed effects error component model is an interesting one. Obviously, it is a very useful parameter to know in the analysis of regional economics. Additionally, if national variables do not affect regional wage setting much, the estimation of a regional wage equation will provide a good measure of wage flexibility at the national level. Finally, and more important, it may be possible, although difficult, to identify both measures of wage flexibility estimating a dynamic regional wage equation. We discuss this issue in section 3.4 below where we propose a three-step procedure to identify the impact of both local and aggregate variables on wage setting.

3. A dynamic wage equation

3.1 Analysis of the regional wage data

In this section, we use data from the household survey to estimate a regional dynamic wage equation for Argentina for the period 1990-1997. During this period, the household survey sampled the population of the main twenty-five urban agglomerates of Argentina. Here, we denote them regions. The household survey is conducted twice per year (in May and October). Hence, we have sixteen cross-sections available. Unfortunately, there were no data tapes available for most regions before the 1990's, a period characterized by high inflation and recession. This reduces the time dimension of our sample and imposes some restrictions in the analyses we can do. Additionally, the content of information in the data tapes change during the period studied. This also restricts us in the analysis.

The household survey is conducted by the Argentine National Institute of Statistics and Census (INDEC). The household survey uses a typical stratified (by regions) two-stage sampling design.[3] Its administration is decentralized by regions. During the period studied, there are some missing regions' data tapes. Additionally, the survey was not conducted in two regions once during the period studied. In terms of the panel of regions we construct, we consider the missing observations as ignorable and

[3] Clusters are randomly selected with probability proportional to the number of households they contain. The same number of households is selected from each cluster, producing a self-weighting design. There is a post-sampling re-weighting of family units, to correct by differential response rates by sampling clusters.

pursue the analysis with the remaining unbalanced panel. We believe it to be justified in that these observations are missed for administrative reasons.

In the regions the survey is conducted, its coverage is virtually complete. We focus the analysis only on employees who report monthly earnings and have only one job. Thus, we exclude from the sample, self-employed, owner-managers, unpaid workers and employees with more than one job. The usable cross-section sample size is over twenty thousand for every wave of the survey. In addition, we also conduct the analysis excluding females from the sample since there is some evidence that the wage response to local unemployment may differ by gender (see, e.g., Janssens and Konings, 1998). Additionally, female participation has changed substantially over the period and this may introduce some difficulties for inference.

For reasons we discussed in the previous section, we proceed in three-steps. In the first-step, we estimate a conditional expectation function for different measures of individual earnings (monthly and hourly). Then, in the second-step we use the regional expected wages to estimate dynamic regional wage two-way fixed effects error component equations. Finally, in the third-step we identify the impact of aggregate variables on regional wages.

The survey provides information on individual monthly earnings. Individuals report their earnings in the month before the survey is conducted. Individuals also report total hours worked. We use individual hours worked in their main occupation during the survey reference week to compute earnings per hour in a straightforward way.

We conduct the analysis using both monthly and hourly individual earnings. On the one hand, it can be argued that the hourly wage is the right price of labor at a point in time and it should be preferred. On the other hand, earnings per hour are likely to be more error prone than monthly earnings (see Bound et al., 1994).[4] Thus, there are reasons for conducting the analysis using both earnings measures. Finally, it is also worth noting that Card (1995) argues that Blanchflower and Oswald (1994) introduce in their analysis of the relationship between regional earnings and regional unemployment an extraneous negative correlation. This occurs because they use individual annual wages as a measure of the price of labor and those states that have low annual wages are likely to be states were workers have not worked a full-year due to unemployment. This correlation is of no interest because it tells us nothing about the relationship between the price of labor and unemployment, and much about the relationship between weeks worked and unemployment. Although our measure of monthly earnings would not introduce such an extraneous negative correlation between earnings and unemployment, still, it is possibly that the unemployment elasticity of pay reflects both responsiveness of wage rates to unemployment and to hours worked per week. This possibility reinforces the necessity to conduct the analysis using both measures of earnings.

We assume, as it is usual in the literature, that the earnings conditional expectation function is linear in the parameters, and hence we condition the logarithm of the individual earnings on a set of regional dummy variables, a set of industry affiliation dummy variables, a set of dummy variables capturing the educational attainment of the individual and a quadratic polynomial in potential experience. We allow all coefficients except the coefficients of the regional dummies to differ by gender. While these are by no

[4] They show, using the panel of income dynamics validation study that earnings per hour are less reliable reported than annual earnings. They also show that biases in estimating earnings functions are relatively small but still our concern here is due to the possible inference difficulties introduced by this type of bias in the estimation of dynamic models.

means an exhaustive set of controls, we know that they are the most important explanatory variables in standard cross-section wage equations. What is more, the proportion of the variance of the individual earnings that is explained by this set of controls is extremely high. The coefficient of determination is on average 0.9. This high statistic is explained by the huge variation existent in regional earnings, which is captured in the regressions by the regional dummy variables. Thus, our estimates of the regional dummies are extremely precise.

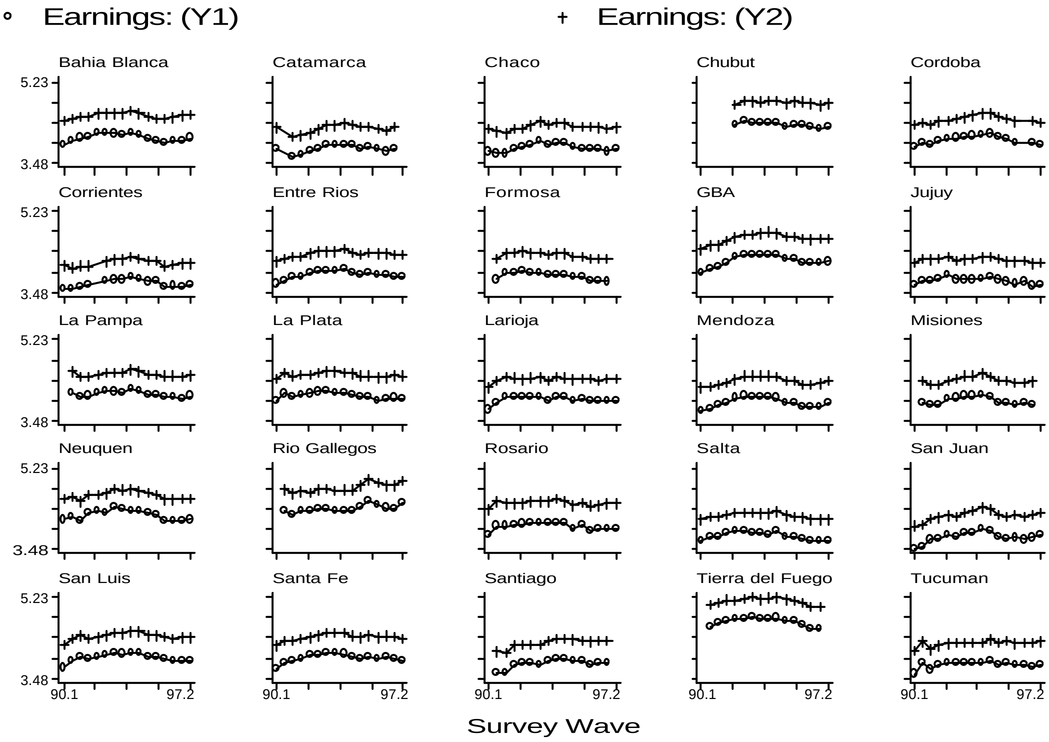
Solon et al. (1994) shows that the true procyclicality of real wages is normally obscured in aggregate time series analysis due to the existence of a composition bias. They show that aggregate statistics are constructed in a way that gives more weight to low-skill workers during expansions than during recessions. We believe the set of estimated regional dummy variables provides us with a regional wage statistic that does not suffer from composition bias. Indeed, as long as we have enough observations, we consistently estimate the parameters of the conditional expectation function. However, if the correlation of the observable and unobservable characteristics of the individuals is altered in any cyclical way, then, it may be the case that our statistics would also suffer from composition bias.

Finally, there is an additional minor point to be considered when estimating the regional wages. To illustrate it, suppose that instead of a polynomial in potential experience, we fit a spline on it to the data. Then, to estimate the set of regional dummies, a typical procedure would be to restrict one coefficient per set of dummy variables but the regional ones to be zero. This procedure estimates a full set of regional dummies. Note, however, that these estimates do not provide us with an estimation of the expected regional earnings. Still, these estimates are appropriate statistics whenever the parameters of interest in the second-stage analysis are not the common time-effects across regions. However, if we were interested in modeling these common time-effects, then, the expectation of the regional earnings should be the statistics used, at least that an specific demographic group were the focus of the research. Hence, instead of constraining one coefficient per set of dummy variables to be zero in the estimation of the conditional expectation function, we constraint the sum of each set of dummy variables (except, of course, the coefficients of the regional dummies) to be zero transforming appropriately the regional dummies so that the fitted value of the equation is not altered at all. Note that the difference between these estimates of the regional dummies in every period t and any other estimate of them is, say, k_t, a common time-effect. In that way, the coefficient of every regional dummy in a cross-section estimates the expected level of the logarithm of earnings in the region while the coefficients of the other dummy variables estimates the expected difference of the earnings of a particular group of individuals to the regional mean (see Suits, 1984).

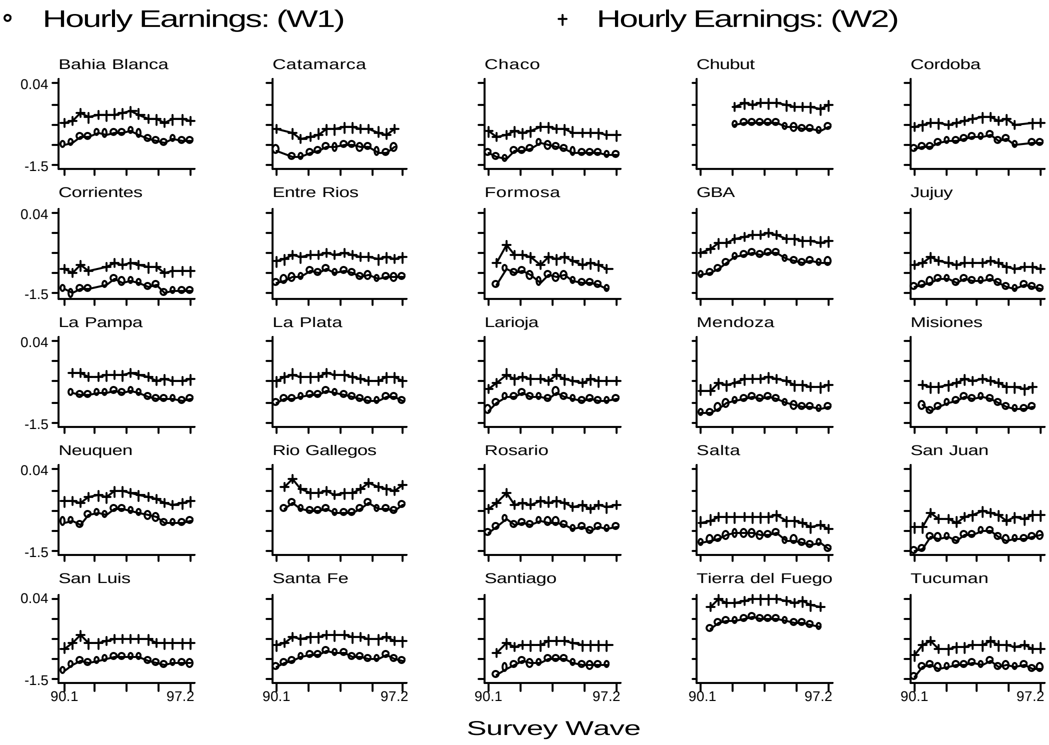
Instead of a spline in potential experience we fit a polynomial on it. This allows us to derive two alternative statistics of regional expected earnings. The regional expected level of earnings and the regional expected level of earnings of a new entrant to the labor market. The comparison of both the trend and the cyclical change between these two statistics is of potential interest. To evaluate the former statistic, we compute the quadratic polynomial in potential experience in every region for every time period fixing both the level of potential experience by gender and a the gender composition at the regional means of these variables in the sample studied. Given the small variation that exists among regions in these weights, there is no practical difference in considering that the two estimations of the regional dummies adopted here only change them compared to any other estimate by a common year effect.

In what follows, $Y1_{it}$ ($W1_{it}$) is the expected real monthly (hourly) earnings of a new entrant in region i at period t while $Y2_{it}$ ($W2_{it}$) is the expected real monthly (hourly) earnings in region i at period t. Figures 3.1 and 3.2 show these statistics. Several patterns are worth noting. First, there are huge regional differences in earnings. Roughly, earnings increase as one moves geographically from the North regions to the South regions. Note that every panel in both figures has the same scale. Second, there are no apparent important differences in their trends. Third, after real earnings increased at the beginning of the sample period, they decreased, particularly after unemployment started to increase. For example, if we analyze the unweighted average of the male statistics, we obtain the following stylized facts: the four statistics increase from the beginning of the period studied until the first wave of the survey in 1994, although most of the increase has taken place before 1993. The unweighted average monthly earnings of the new entrants increased between 1990 and 1994 by thirty percent and then decreased twelve percent while the same statistic for the average worker increased twenty-two percent before it decreased eight percent. The hourly wages increased twenty-eight (seventeen) percent and then decreased fifteen (ten) percent respectively. What is more, the four statistics have at the end of the period studied the same values they had at the end of 1991 in spite of the huge increase in labor productivity during the same period. It is worth noting that the wages of the new entrants first increased more than the average wages and then also decreased more. See both Bils (1985) and Beadury and DiNardo (1991) for some

Figure 3.1
Earnings by Region

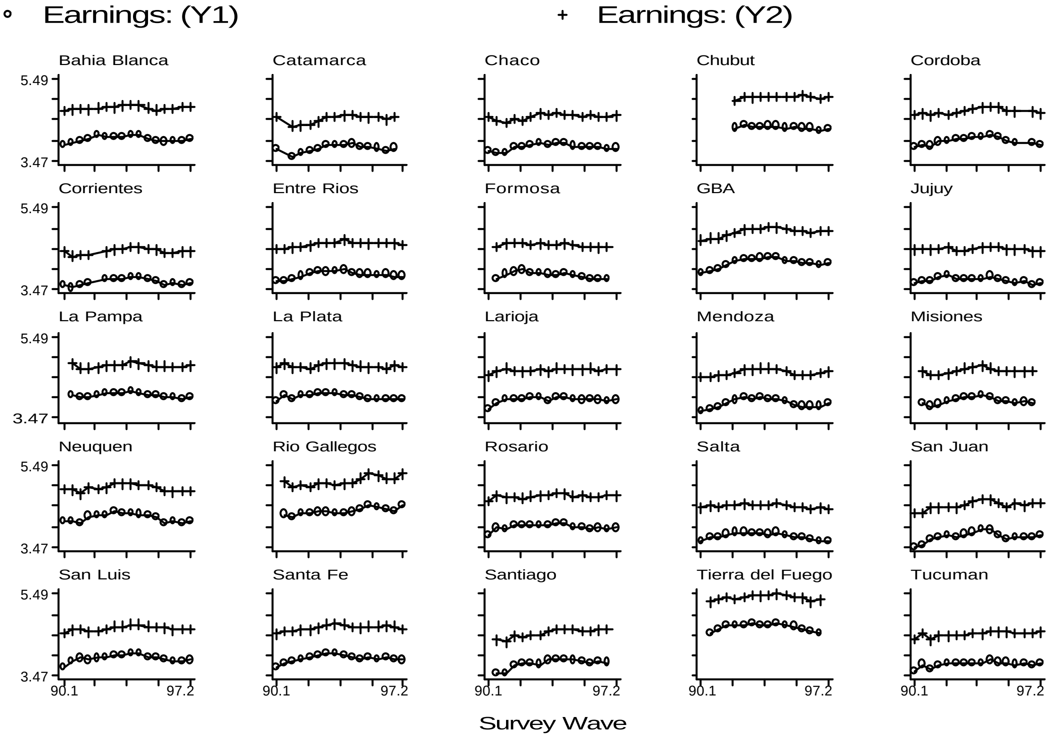


Real Monthly Earnings by Region

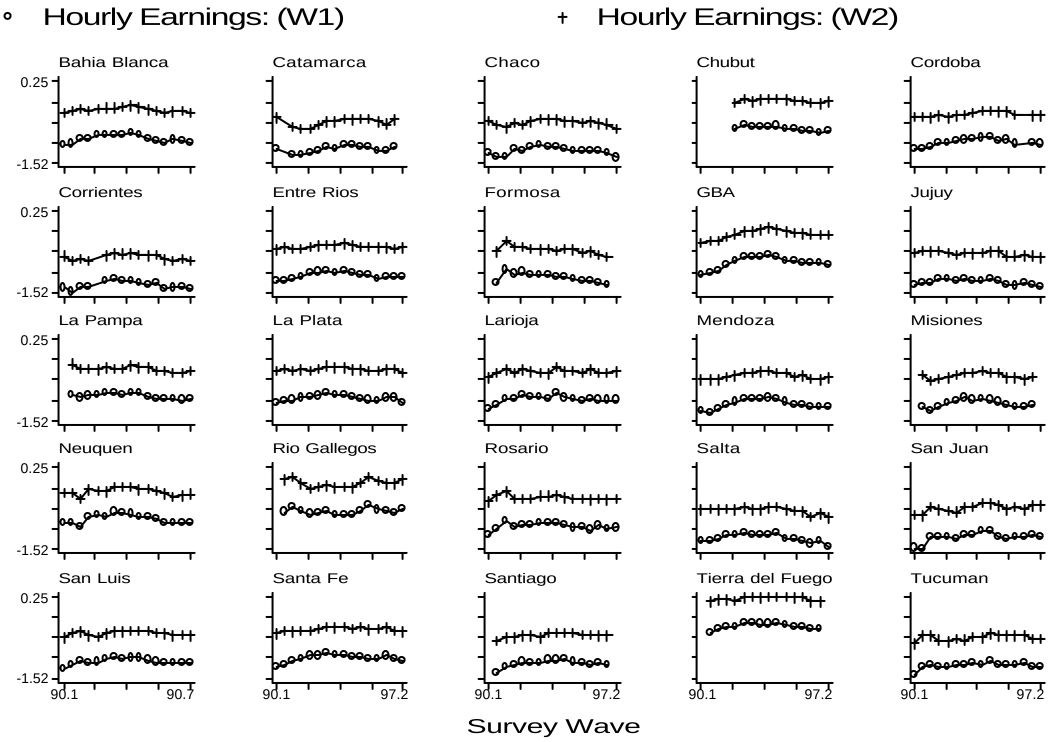


Real Hourly Earnings by Region

Figure 3.2
Male Earnings by Region



Real Monthly Earnings by Region: Males



Real Hourly Earnings by Region: Males

evidence that shows that the wages of the new employees are more sensitive to the cycle than the wages of the insiders workers. Fourth, the differences in earnings between an average experienced worker and a new entrant to the labor market are wider and apparently most affected by the cycle for males than for the whole population.

Finally, it is worth noting the following issues. We estimate the cross-sectional conditional expectation functions by the method of least squares, that is, we do not use sampling weights.[5] We ignore the observations with missing values and estimate the conditional expectation function using the remaining usable observations. In this case, there are no compelling reasons to pursue another route.[6] Additionally, we exclude, in every wave of the survey, some observations of individuals that report extremely high number of hours worked per week. In any case, none of the results of this paper would be changed at all if we had not excluded these observations.

3.2. Dynamic regional wage equations

Generically, we adopt a dynamic specification for our empirical model and postulate a dynamic two-way fixed effects error component model of the form:

$$y_{it} = \varphi\, y_{it-1} - \beta(\mathrm{L})\, u_{it} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (2)$$

[5] It is not obvious whether or not there is a case in which their use is recommended (see DuMouchel and Duncan, 1983 and Kish and Frenkel, 1974). If the population is homogenous, both the weighted and the least squares estimators are consistent but the latter estimator is more efficient in its class and hence it is preferred. In any case, in this sample, there are no statistically significant differences in the estimates obtained.

[6] Note, for example, that regression imputation would make not difference in this case an it seems to be more appropriately than the hot deck method used by the US Census Bureau (see, e.g., Lillard et al., 1986).

where y_{it} is any of our regional first-stage wage statistics and u_{it} is the natural logarithm of the unemployment rate. The unemployment rates are the region unemployment rates for the whole population and the male unemployment rates. Sampling weights are used to compute these unemployment rates.

Our empirical model may present some problems of inference. First, there is the possible problem of measurement errors in the dependent variables. For example, Bell (1997a) shows how important measurement errors in the dependent variable could be in a dynamic specification like the one we estimate. He suggests that a good instrument would be the dependent variable lagged twice. Measurement errors in individual earnings seems to be aggravated when independent measures of earnings and hours are used to compute an hourly statistic, much more when the time unit of measurement of both variables differs (see Bound et al., 1994).

Second, unemployment may also need to be instrumented. Although it is plausible that the unemployment rate at the regional level is essentially a predetermined variable in the context of the wage equations we estimate, it may be the case that the unemployment rate is not exogenous for the parameters of interest. This may be even due to a problem of measurement error. In regions with small sample size and in time periods of low unemployment, the size of the confidence intervals of the estimates of the unemployment rates is not ignorable.

Unfortunately, as it is often the case, there is some uncertainty associated with the selection of instruments. Two issues are involved. First, the instruments must not change the conditional expectation of the dependent variable. They must also be reasonably correlated with the instrumented variable, otherwise, the instrumental variables standard errors are too large. Second, given the specification adopted, the model is only identified if the instrumental variables present variation both across regions and time.

Finally, even if the errors of the wage equation are i.i.d, this model cannot be consistently estimated by the method of dummy variables least squares as long as the number of periods is small (see Nickell, 1981). This semi-inconsistency is due to the asymptotic correlation that exists between the transformed lagged dependent variable and the transformed error term. Nickell (1981) proves that in an autorregresive model with no other exogenous regressors the bias is of order in probability one over the panel time dimension length (T), $O_p(T^{-1})$. He also shows that the bias is aggravated if the model also includes exogenous regressors. However, we do have a panel of sixteen cross-sections and hence this bias may not be a serious problem. Indeed, in our case T tends to N, the cross-section dimension of the panel, which exhausts the population studied.

Arellano and Bond (1991) propose an efficient (among its class) linear estimator that is consistent even for short time dimension panels. To estimate the parameters in dynamic panel data models, they suggest to take first differences of the regression function to eliminate the individual specific effects, and estimate the differenced model by a Generalized Method of Momemts (GMM) estimator using appropriately lagged endogenous and predetermined variables as instruments in the transformed equations.

Note, nonetheless, that after differencing, y_{it-1} is correlated with the differenced equation error, $\Delta\varepsilon_{it}$. Additionally, both u_{it} and u_{it-1} may also be correlated with $\Delta\varepsilon_{it}$ if u_t is not exogenous for the parameters of interests. However, as long as ε_{it} is serially uncorrelated, all lags on y and u beyond t-1 are valid instrument for the differenced equation at period t. Hence, using appropriately lagged variables as instruments, we get consistent estimators of the parameters of interest.

Thus, in addition to within group estimates, we present linear GMM estimates of the parameters of interest by implementing the estimator suggested by Arellano and Bond (1991). Note that this estimator will not only deal with the semi-inconsistency bias, presumably small, but also with the possible measurement errors in the dependent variable and the possible correlation between the current dated unemployment rate and the error in the equation in levels.

The consistency of the GMM estimator we use depends crucially on the absence of serial correlation in ε_{it}. If the disturbance ε_{it} is not serially correlated, there should be evidence of significant negative first order serial correlation in the differenced residuals, and there should not be any evidence of second order serial correlation in the differenced residuals. Arellano and Bond (1991) develop tests for first order and second order correlation in the differenced residuals. These tests are asymptotically standard normal distributed under the null hypothesis of no serial correlation. More generally, we present Sargan test of overidentifying restrictions to evaluate the specification of the model. The null hypothesis of the Sargan test is that the instruments are not correlated with the residuals in the first-difference equation. Under the null hypothesis, the asymptotic distribution of this statistic is Chi-squared with as many degrees of freedom as overidentifying restrictions are imposed in the estimation of the model.

Tables 1 and 2 present the estimated dynamic wage equations using monthly and hourly wages respectively. We do have an unbalanced panel. Columns (1) and (2) present the within group coefficient estimates. Naturally, whether the dependent variable is the average regional wage or it is the new entrants' regional wage, the estimated coefficients of interest are similar. Hence, in tables 1 and 2 we only report the estimates of the modelization of the average regional wages. In the models, we alternatively include the current value of the regional unemployment rate or its value lagged once.[7] Some other authors only consider the current unemployment rate but they estimate their models using yearly frequency data instead of sixth monthly frequency data. Thus, by working at a higher frequency, lower frequency dynamics cannot be accounted for in the model and if present, they will tend to be mixed in the model's estimated coefficients. In any case, it is plausible that the regional unemployment affect the wage setting with some lag.

First, we do not find a statistically significant effect of the regional unemployment on the monthly regional earnings under this specification. We find some statistically significant effect of the lag unemployment on hourly wages only. The lag unemployment elasticity of hourly pay is –0.024 for males and –0.015 for the whole population. The coefficient on the lagged dependent variable shows an important positive correlation of regional earnings. The coefficient of the lagged dependent variable is 0.6 when the dependent variable is the monthly earnings and around 0.5 when it is the hourly earnings. This finding does not depend on whether or not unemployment enters with a lag in the model.

We next instrument the lagged dependent variable. Columns (3) and (5) report the results. There are no differences at all in the autocorrelation coefficient in any of the specifications. However, the estimated unemployment elasticity of pay increases in all cases. The estimated lag unemployment elasticity of hourly pay is –0.046 for males and

[7] We also enter both unemployment rates in the same equation but they were never statistically significant. The lag unemployment has always a higher impact on wages on every model's specification.

–0.034 for the whole population. Also, for males, the lag unemployment elasticity of monthly pay is statistically different from zero at the 10 percent level of significance. It is –0.023.

Table 1: Dynamic regional wage equations

Dependent Variable: Log of monthly wages (Log Y2)

Independent variable	OLS (Within-Group) (1)	OLS (Within-Group) (2)	GMM (First-Differences) (3)	GMM (First-Differences) (4)	GMM (First-Differences) (5)	GMM (First-Differences) (6)
	Males					
Log $Y2_{it-1}$	0.61	0.60	0.57	0.53	0.57	0.54
	(0.053)	(0.05)	(0.08)	(0.07)	(0.09)	(0.08)
Log U_{it}	-0.007	-----	-0.01	-0.015	-----	-----
	(0.01)		(0.01)	(0.017)		
Log U_{it-1}	-----	-.0.012	-----	-----	-0.023 *	-0.027
		(0.01)			(0.013)	(0.019)
Equation standard error	0.038	0.038	0.035	0.034	0.034	0.33
Sargan Test	-----	-----	0.93	0.78	0.94	0.87
m_1	0.94	0.90	0.001	0.001	0.001	0.001
m_2	0.99	0.91	0.79	0.97	0.70	0.85
	Whole Population					
Log $Y2_{it-1}$	0.57	0.57	0.58	0.57	0.58	0.58
	(0.057)	(0.058)	(0.089)	(0.088)	(0.09)	(0.09)
Log U_{it}	-0.005	-----	-0.01	-0.004	-----	-----
	(0.01)		(0.01)	(0.017)		
Log U_{it-1}	-----	-0.006	-----	-----	-0.008	-0.018
		(0.01)			(0.01)	(0.017)
Equation standard error	0.038	0.038	0.035	0.034	0.034	0.35
Sargan Test	-----	-----	0.89	0.87	0.91	0.95
m_1	0.53	0.53	0.001	0.001	0.001	0.001
m_2	0.35	0.69	0.88	0.86	0.82	0.83
No. of observations	350	350	325	325	325	325

Notes: (i) Log U is the logarithm of the respective unemployment rate. (ii) Time dummies are included in all equations. (iii) Asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses. (iv) * Statistically different from zero at the 0.10 level of significance. ** Statistically different from zero at the 0.05 level of significance. The autorregresive coefficient is always significant at the 0.01 level of significance. (v) For the Sargan, m_1 and m_2 tests, the statistics reported are the p-values (i.e. the probability of generating the calculated test statistic under the null hypothesis). (vi) The equation standard error refers to the equation in levels. (vi) Columns (3) and (5): the basic instrument set is of the form Zi = diag[$y_{i1},\ldots,y_{is}$: $\Delta x_{is+2(1)}$], (s = 1,…,14), where $x_{it(-1)}$ is the vector of predetermined variables included in the regression. Column (4): the instrument set is of the form Zi = diag[$y_{i1},\ldots,y_{is}$, Δu_{is}, $\Delta lfpr_{is+2}$], (s = 1,…,14). Column (6): the instrument set is of the form Zi = diag[$y_{i1},\ldots,y_{is}$, Δu_{is}, $\Delta lfpr_{is+1}$] (s = 1,…,14). $lfpr_{it}$ is the labor force participation rate in region i in period t.

Table 2: Dynamic regional wage equations

Dependent Variable: Log of hourly wages (Log W2)

Independent variable	OLS (Within-Group) (1)	OLS (Within-Group) (2)	GMM (First-Differences) (3)	GMM (First-Differences) (4)	GMM (First-Differences) (5)	GMM (First-Differences) (6)
	Males					
Log $W2_{it-1}$	0.48	0.48	0.55	0.49	0.53	0.48
	(0.06)	(0.06)	(0.09)	(0.10)	(0.09)	(0.09)
Log U_{it}	-0.007	-----	-0.02	-0.045 *	-----	-----
	(0.01)		(0.016)	(0.028)		
Log U_{it-1}	-----	-.0.024 **	-----	-----	-0.046 **	-0.057 *
		(0.011)			(0.021)	(0.035)
Equation standard error	0.043	0.042	0.042	0.039	0.040	0.038
Sargan Test	-----	-----	0.80	0.28	0.79	0.26
m_1	0.45	0.63	0.001	0.003	0.002	0.001
m_2	0.44	0.41	0.14	0.21	0.18	0.34
	Whole Population					
Log $W2_{it-1}$	0.48	0.48	0.51	0.50	0.50	0.49
	(0.058)	(0.057)	(0.1)	(0.10)	(0.09)	(0.09)
Log U_{it}	-0.003	-----	-0.019	-0.031	-----	-----
	(0.01)		(0.015)	(0.026)		
Log U_{it-1}	-----	-0.015 *	-----	-----	-0.034 **	-0.04 **
		(0.009)			(0.014)	(0.02)
Equation standard error	0.044	0.044	0.042	0.042	0.042	0.042
Sargan Test	-----	-----	0.64	0.63	0.65	0.62
M_1	0.29	0.34	0.001	0.001	0.001	0.001
M_2	0.46	0.50	0.07	0.06	0.16	0.19
No. of observations	350	350	325	325	325	325

Notes: see table 1.

In columns (3) and (5), u_t is at least (implicitly) assumed to be a predetermined variable although, given our sample size, the over-identifying restrictions arising from this assumption are not exploited in the estimation. We do not reject the null hypothesis of the validity of the over-identifying restrictions nor the lack of autocorrelation in the ε_{it} at the conventional levels of statistical confidence, that is, we do not reject the hypothesis of first-order autocorrelation in $\Delta\varepsilon_{it}$ nor the lack of second-order autocorrelation in $\Delta\varepsilon_{it}$.

These results suggest that the “Nickell” bias is not a problem in this case but also suggest that there is no reason to be concerned about measurement error in the dependent variable in this data.[8]

Finally, in columns (4) and (6) we deal with the possible correlation of u_t and ε_{it}. We first use lagged unemployment as an instrument since this is the standard response. Again, given our sample size, we do not exploit all the over-identifying restrictions arising from the predetermination of the lagged values of u_t. In almost every case, the estimated unemployment elasticity of pay is increased. We then add the first difference of the regional labor force participation rates as an instrument in the differenced equations we estimate. The results do not change at all. Again, in these specifications we do not reject the null hypothesis of the validity of the over-identifying restrictions nor the lack of autocorrelation in the ε_{it}. Finally, we alternatively instrument regional unemployment with a regional GDP growth measure calculated by weighting quarterly industry GDP figures by the employment share of the industry in the region in the previous wave of the survey (see Blanchard and Katz, 1992). The estimates are almost identically and are not statistically different from the estimates reported in columns (4) and (6) although in some cases the estimates are less precise.

The GMM estimates presented in tables 1 and 2 are all one-step estimates. Although there exists two-step estimators that are asymptotically more efficient, it is well know (see Arellano and Bond, 1991) that the two-step estimated standard errors in dynamic models can be seriously biased downward, and for that reason, one-step estimates with robust standard errors are often preferred.

[8] We check the robustness of this result by recursively eliminating the instruments in the later cross-sections without obtaining any significant change in the estimates.

The coefficient estimates for our preferred specification in column (6) suggest that regional wages are autocorrelated. Hence, we reject the wage curve specification in favor of a dynamic regional wage equation. We find that the degree of autocorrelation is higher for monthly earnings than for hourly earnings while the opposite is true for the unemployment elasticity of pay. We believe that it is plausible that the regional unemployment affects regional wages with a lag. The short run unemployment elasticity of hourly pay is statistically significant for both males and the whole population. It is -0.057 and –0.04 respectively while the short run unemployment elasticity of monthly pay is only marginally significant (at the 0.15 level of significance) for males. It is –0.027, half the value of the hourly elasticity of pay. Thus, the local labor market conditions seem to affect more the pay of males than that of the females and it affects more the hourly earnings than the monthly earnings. Finally, we do not reject a long run unemployment elasticity of local pay of –0.1 for hourly wages although we find it is significantly lower than –0.1 for monthly wages.

The finding that the unemployment elasticity of hourly pay is higher than the unemployment elasticity of monthly pay is quite interesting. It only can be the outcome of a positive correlation between local hours worked and local unemployment.[9] Hence, we rule-out any non-interesting negative relationship between pay and unemployment because of a reduction of hours worked of any type. Additionally, it is interesting because the period during which unemployment increased was one of absolutely stability in the

[9] To quantify this relationship, we estimate the following regression function:

$$\mathrm{h}_{\mathrm{it}} = \underset{(2.12)}{0.014}\, u_{it-1} + \boldsymbol{m}_i + \boldsymbol{l}_t + \boldsymbol{n}_{it}$$

where h_{it} is the logarithm of the average number of hours over the same observations we use to estimate our statistics on regional earnings in region i in period t. The parenthetical figure is the t-statistic.

price level. Thus, the increase in hours worked seems to have provided an additional source of wage flexibility.

Turning to the international comparison of results, it is interesting to compare our findings with the results reported in Bell (1997a, 1997b). For empirical models similar to the one presented in table 2, although estimated by the method of LSDV, Bell (1997a) finds, for US for the period 1980-1991, an autoregresive coefficient equal to 0.82 and an unemployment elasticity of pay coefficient equal to –0.047. The dependent variable is the hourly wage obtained from the CPS March files. Our estimates show a similar elasticity of pay but much less persistence in wages. Hence, the long-run regional unemployment elasticity of regional pay is higher in US than in Argentina. Bell (1997b) finds, for UK for the period 1975-1995, using weekly wages, an autoregressive coefficient equal to 0.71 and an unemployment elasticity of pay coefficient equal to –0.014. Thus, both the short and long run regional unemployment elasticity of regional pay in UK are lower than the respective elasticities in Argentina. The same results hold in term of the regional unemployment semi-elasticities of local pay although the differences with UK are smaller while the differences with US are bigger.

To conclude this sub-section, we shall discuss two other results of our empirical model. First, between the first wave of the survey in 1994 and the end of the period studied, for example, the unweighted monthly wage of the average male worker decreased eight percent while the unweighted male unemployment rate increased approximately forty percent (indeed, this figure is the change in unemployment between the last wave of survey of 1993 and the end of the period studied). Hence, given the regional unemployment elasticity of regional pay we have estimated, some other factors have to account for the decrease in wages. This other factors are captured in the common year effects and consequently, they are aggregate factors. Thus, aggregate factors have to account for more than half of the decrease in average wages. Second, and precisely, there is no point in discussing whether or not the autoregressive coefficient in the regional wage equation suggests that wages are non-stationary. There is ample evidence suggesting that wages are non-stationary. Naturally, there is nothing that precludes the time effects being non-stationary. Thus, a priori, there is no necessity to reconcile the unit-root normally found in aggregate wage equations with the autoregressive coefficient that is usually found in dynamic regional wage two-way fixed effects error component equations.

3.3. Long-term unemployment and wages

The empirical models of section 3.2 impose the unemployment elasticity of pay to be unaffected by the duration composition of the stock of unemployed individuals. However, it is often argued that the long-term unemployment represents a less effective component of the pool of unemployed workers than do their short-term counterparts (see Layard et al, 1991). For example, Layard and Nickell (1985, 1986 and 1987) present time series evidence for UK that shows that disinflationary pressure is weakened as unemployment duration increases. Bell (1997b) also shows the empirical relevance of this hypothesis for UK using regional data. Interestingly, during the 80s, long-term unemployed were nearly half the unemployed pool in UK, where an individual is considered as a long-term unemployed if he has experienced a current spell longer than a year. The hypothesis that long-run unemployment reduces the unemployment elasticity of pay is not tested for US, where most unemployment experiences are of short-term duration. For example, neither Bell (1997a) nor Blanchard and Katz (1997) explore the role of long-term unemployment in wage determination in US.

In Argentina, most unemployment episodes conclude after short periods of time. For example, roughly, in every region, for every wave of the survey during the sample period, around thirty percent of the unemployed has been in this state at most a month. Naturally, after the huge increase in the unemployment rate in 1994 and 1995, unemployment duration has increased although the mean duration of all unemployment episodes is still quite low while the mean duration of the current spells has not increased that much neither.

We explore the hypothesis that unemployment duration weakens wage pressures, *ceteris paribus*, using the following model

$$y_{it} = \varphi y_{it-1} - \beta u_{it} + \delta \frac{\mathrm{U}^{\mathrm{L}}_{\mathrm{it}}}{\mathrm{U}_{\mathrm{it}}} + \lambda_t + \mu_i + \varepsilon_{it} \qquad (3)$$

where $\mathrm{U}^{\mathrm{L}}_{\mathrm{it}} / \mathrm{U}_{\mathrm{it}}$ is the proportion of long-term unemployment, where someone is considered long-term unemployed if he has experienced a current spell longer than six months. Layard and Nickell (1985) show that the results are not substantially altered if this definition is adopted. We adopt this definition based on data restrictions. This model specification is close to the one often adopted in the literature.

As we expected, the results obtained do not alter at all those we present in columns (4) and (6) of both tables 1 and 2. In every specification, the coefficient δ is positive but not statistically different from zero and it is always numerically close to zero.

3.4. Aggregate unemployment and wages: towards a wage equation

We now evaluate whether or not aggregate unemployment affects regional wages, and more generally, we study the general form of a wage equation that does not condition on the time period studied.

Jimeno and Bentolila (1998) estimate a regional wage equation for Spain and enter both regional and national unemployment rates as regressors. They found that the national unemployment rate is more significant in explaining regional wages than the regional unemployment rate. They suggest that this outcome is the result of an explicit effort by Spanish unions to reduce wage dispersion across regions.

Turning to Argentina, its union density is estimated to be forty-five percent while union coverage is approximately fifty percent. Most workers whose pay is covered by a collective agreement have their wages determined, at least initially, by industry-wide bargains struck between a national industry union and one or more employers federations. Further wage agreements may be struck at lower levels right down to the firm level using the industry-wide agreement as a basis. Additionally, in some sectors, collective agreements include regional wage clauses or there may exist regional agreements.

Jimeno and Bentolila (1998) also find that the regional unemployment coefficient is unstable in the models they estimate. It decreases substantially when they enter both unemployment rates compared to the coefficient they obtain when they only enter the regional unemployment rate in the model. We think, this is a consequence of their model specification.

To illustrate this point, we estimate some dynamic regional regression functions in which we also include aggregate variables. In columns (1) and (3) of table 3 we estimate the same model we report in column (6) of table 2 but we drop the time-dummies and include in their replacement the following set of aggregate variables: the logarithm of the aggregate total unemployment rate and its lag (Log U_s), the logarithm of and index of aggregate labor productivity and its lag (Log $prod_s$) and the change in the average inflation rates between the periods May-October and November-April. prod is given by real GDP (at prices of 1986) in the quarter the household survey is conducted divided by total employment in the respective wave of the survey and it is equal to 100 in May 1990. We also add a constant to the differenced equation.

Columns (2) and (4) of table 3 reproduce column (6) of table 2. Note that here, the set of aggregate variables, the trend and the set of dummies included in these specifications span the same subspace that is spanned by the set of time-dummies included in the regression functions of column (6) in table 2 and hence they are the same model.

The models in columns (1) and (3) are restricted versions of the models in columns (2) and (4) respectively. What turns out is that they are not valid reductions of the unrestricted models. The set of aggregate regressors (together with the time trend) included does not span the same subspace that is spanned by the full set of time dummies. There are other aggregate variables that affect wages and/or the functional form of the model is not valid. In any case, the result is that we get biased estimates of both local and

Table 3: Dynamic regional wage equations

Dependent Variable: Log of hourly wages (Log W2)

Independent variable	GMM (First-Differences) (1)	GMM (First-Differences) (2)	GMM (First-Differences) (3)	GMM (First-Differences) (4)
	Whole population		Males	
Log $W2_{it-1}$	0.83	0.49	0.70	0.48
	(0.06)	(0.09)	(0.07)	(0.09)
Log U_{it-1}	-0.03 *	-0.04 **	-0.04 **	-0.057 *
	(0.016)	(0.02)	(0.02)	(0.035)
Log U_t	-0.09 **	0.02	-0.04 **	-0.45 **
	(0.02)	(0.16)	(0.01)	(0.17)
Log U_{t-1}	-0.01	-0.04	-0.02	0.21 **
	(0.02)	(0.09)	(0.02)	(0.09)
Log $prod_t$	-0.12 *	-0.04	0.15 **	1.77 **
	(0.07)	(0.68)	(0.07)	(0.70)
Log $prod_{t-1}$	0.30 **	0.01	0.07	0.13
	(0.11)	(0.16)	(0.10)	(0.18)
$\Delta\Pi_t$	-0.003 **	0.001	-0.002 **	0.02 **
	(0.001)	(0.008)	(0.001)	(0.007)
Trend	yes	Yes	yes	yes
Set of identifiable time- dummies	no	Yes	no	yes
Equation standard error	0.042	0.042	0.04	0.038
Sargan Test	0.50	0.62	0.08	0.26
m_1	0.001	0.001	0.001	0.001
m_2	0.85	0.19	0.57	0.34
Wald test	-----	141.22	-----	117.36
(df = 8)		(0.000)		(0.000)
No. of observations	325	325	325	325

Notes: (i) Asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses. (ii) * Statistically different from zero at the 0.10 level of significance. ** Statistically different from zero at the 0.05 level of significance. The autorregresive coefficient is always significant at the 0.01 level of significance. (iii) For the Sargan, m_1 and m_2 tests, the statistics reported are the p-values (i.e. the probability of generating the calculated the test statistic under the null hypothesis). (iv) The equation standard error refers to the equation in levels. (v) The basic instrument set is of the form Zi = diag[$y_{i1}, \ldots, y_{is}$, Δu_{is}, $\Delta lfpr_{is+1}$: $\Delta x_{is+2(1)}$], (s = 1,…,14), where $x_{it(-1)}$ is the vector of predetermined variables included in the regression. All the aggregate variables are taken as predetermined.

aggregate coefficients.

Additionally, the estimated coefficients of the aggregate variables in the models of columns (2) and (4) do not provide us with the estimates of the impact of these aggregate variables on wages. These coefficients have no meaning. Their values depend on which time-dummies are included in the model. We test that this is the case, that is, we test that the coefficients of the set of identifiable dummies included in both models are jointly not different from zero. For both models, the Wald statistic obtained lead us to reject the null hypothesis (the statistics and the p-values are reported in table 3).

Furthermore, there is much time series evidence that shows that aggregate wages are highly autocorrelated. For this reason we propose a three-step estimator to identify the whole set of parameters of interest. Otherwise, we are not able to condition the common aggregate component of wages on its lagged value.

As we discussed above, the two-step estimator we adopted in sections 3.2 and 3.3 provides us with consistent estimates of the local coefficients. Moreover, it also provides us with consistent estimates of the common-aggregate effects on wages. On that account, we can estimate a time-series regression function to explain the common aggregate effects on wages. If this regression function is well specified and, now crucially, T is large, we also obtain consistent estimates of the impact of aggregate variables on wages. Even if T is not large, if there is not omitted aggregated variables that are correlated with aggregate unemployment, the exercise is worth to be pursued.

Unfortunately, in our case, T is not large at all. Indeed, it is quite short. Hence, the results of the following estimates are only exploratory. Nevertheless, for other countries, it is possible to apply this three-step procedure to successfully study wage determination.

Turning to the specification of the aggregate equation, Blanchard and Katz (1997) suggest that, although for the US the Phillips curve seems to fit the data reasonably, it may be a misspecified model and a better representation may be an equilibrium correction specification. Equilibrium correction mechanism models (ECM) were initially adopted as a method for implementing economic theory in econometric models, which is a reasonable thing to do (see Sargan, 1964 and Davidson et al., 1978). Indeed, ECMs are a general class of models isomorphic to cointegration. Interestingly, the Phillips curve specification is nested in the ECM specification. Hence, we estimate regression functions of the following general form:

$$\Delta \hat{\lambda}_t = a_w + \alpha \Delta x_t - \gamma \left(\hat{\lambda}_{t-1} - (1-\hat{\varphi})\, x_{t-1} \right) + \theta(L) \Delta \pi_t - \beta_w u_t + d_s + \omega_t \qquad (4)$$

where λ_t is the common aggregate component of wages at period t, that is, the year effects in equation (2), u_t is log U_t and x_t is the logarithm of productivity. d_s is a dummy variable in period s. We have reasons to add a dummy variable taking the value one in the second wave of the survey in 1991. A major stabilization program was launched in May 1991 and the change in inflation is not an adequate measure of inflation surprises at that point in time. Thus, the inclusion of this dummy variable tries to capture a regime-shift in the economy. Notwithstanding, we also conduct the analysis without adding the dummy variable to our empirical models.

Note that we also impose a theoretical restriction in equation (4). We define the error correction mechanism as $\mathrm{ECM} = \lambda_{t-1} - (1-\hat{\varphi})\, x_{t-1}$. The reason is that without imposing this restriction, the wage equation we obtain is not consistent with unemployment being untrended over the very long term (see Layard et al., 1991). After all, as Blanchard and Katz (1997) emphasize, any (empirical) model has to satisfy this condition. Thus, in steady state, our wage equation is given by (for $\gamma > 0$):

$$w_i = \vartheta_i + x - \frac{\beta}{1-\varphi}\, u_i - \frac{\beta_w}{\gamma(1-\varphi)}\, u \tag{5}$$

Note that this specification is more appealing that the one provided in Jimeno and Bentolila (1998) because regional wages depend on productivity instead of aggregate wages.

In a concurrent contribution, Blanchard and Katz (1999) address a very important related issue. They try to reconcile time-series evidence with theoretical wage relations. They argue that aggregate wages are well represented by an equation nested in equation (4), where λ_t is replaced by the aggregate wage while theory suggest that the level of aggregate wages are determined as a function of the reservation wages, the level of productivity and the tightness of the labor market measured, for example, by aggregate unemployment. They suggest that the route to reconcile theory and empirical evidence is to assume that the reservation wage depends, among other variables, on the lagged wage.

Thus, Blanchard and Katz (1999) suggest that the Phillips curve is a valid reduction of a version of equation (4) if productivity neither affects the reservation wage nor affects wages given the reservation wage. Additionally, and independently of whether or not this reduction is valid, their theoretical derivation of an aggregate wage equation comparable to equation (4) is testable because it implies that α and γ should have the same value in their equation. Blanchard and Katz (1999) do not provide evidence on this. Instead, they claim that the evidence, presented for example in OECD (1997), suggest that for US γ is zero and hence the Phillips curve is a valid representation of the data while for most European countries it is on average 0.25, so the Phillips curve is not supported by the data. However, the model specification adopted in OECD (1997) imposes α to be zero for most countries although for US, where they find γ to be statistically not different from zero, they estimate a positive α that is statistically significant. Of course, this evidence does not suggest that the reservation wage is not a function of the lagged wage but suggest that the issue is not settled at all and further research is required. Indeed, lagged wages may enter the wage equation through the reservation wage although in a more complex form than that suggested by Blanchard and Katz (1999). However, it also suggest that it is not possible, based on the available evidence, to claim that productivity neither affects the reservation wage nor affects wages given the reservation wage in US. It is not enough to find that γ is zero to support this hypothesis.[10]

Furthermore, we think that the best specification of the empirical model is not necessarily the aggregate level. Working at that level of aggregation, local heterogeneity is neglected. For example, in US, wage growth in the 80s shows impressive differences across states. Additionally, regional shocks may have persistent effects in wage setting at the regional level as Card's (1990) findings suggest. Thus, we believe it is better to work

[10] Grubb (1986) also estimates wage curves for OECD countries. However, his model specification does not include the change in productivity (his models include both trend productivity in levels and an error correction mechanism that is a function of a quadratic trend productivity). Thus, his estimated coefficients

at the regional level and try to identify the effect of both regional and national variables on wage setting. A strong argument in favor of this modeling strategy is that the study of the local determinants of wages is as interesting as the aggregate determinants of wages. That is, the parameters of equation (6) are the parameters of interest. As we suggest here, a three-step procedure may provide consistent estimates of the whole set of parameters of interest.

Before reporting the results of estimating equation (4), it is worth noting the following issue. The dependent variable is the change in the year effects not its level. Indeed, the coefficients of the set of time dummies in both models of column (6) in both tables 1 and 2 provide us exactly with the change in the year effect between May 1991 and October 1997. Thus, we use these sets of coefficients as our dependent variables. However, to estimate the error correction mechanism we need the time year effects in equation (2). Thus, to overcome this difficulty, we estimate the level common wage effect in October 1990 by applying the LSDV estimator of the year effect, using our coefficient estimates given in column 6 of tables (1) and (2) and the necessary respective means of the variables. This estimator is also consistent. Finally, we compute the ECM in a straightforward way. Hence, our time series cover the period October 1990 – October 1997.

It is worth to be repeated that, given our time-series sample size, all the results reported here are only exploratory. Table 4 reports the results for males. The models in columns (1) and (3) uses the whole sample and include the dummy variable for the stabilization program lunch period while the models in columns (2) and (4) are estimated

---

are not exactly the one desired. If anything, the evidence he gathers for US is not conclusive about this hypothesis.

since the beginning of 1992 and hence do not include the dummy variable. The first important thing to note is that the estimated models in columns (1) and (2) are statistically identical. The same is true for the models in columns (3) and (4). Thus, these models are stable to this change in the period of estimation.

Table 4: Aggregate wage equations

Independent variable	OLS (ECM) (1)	OLS (ECM) (2)	OLS (ECM) (3)	OLS (ECM) (4)
	Dependent variable:			
	Common effect on Log W_2	Common effect on Log W_2	Common effect on Log Y_2	Common effect on Log Y_2
Δ Log $Prod_t$	0.24 **	0.24 **	0.30 **	0.30 **
	(0.09)	(0.09)	(0.11)	(0.09)
ECM	-0.19	-0.2	-0.47 **	-0.52 **
	(0.11)	(0.12)	(0.14)	(0.12)
Log U_t	-0.037 **	-0.04 **	-0.06 **	-0.07 **
	(0.01)	(0.014)	(0.014)	(0.014)
$\Delta\Pi_t$	-0.046 **	-0.045 **	-0.05 **	-0.04 **
	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta\Pi_{t-1}$	0.008 **	0.008 **	0.009 **	0.011 **
	(0.0014)	(0.002)	(0.0016)	(0.002)
D_4	yes	no	yes	no
Constant	yes	yes	yes	yes
Equation standard error	0.009	0.009	0.01	0.009
R^2	0.87	0.85	0.92	0.91
Mis-specification tests:				
First-order autocorrelation	F(1,6) = 1.58	F(1,5) = 0.76	F(1,6) = 0.99	F(1,5) = 0.12
	(0.26)	(0.42)	(0.36)	(0.74)
ARCH	F(1,5) = 0.96	F(1,4) = 0.43	F(1,5) = 0.31	F(1,4) = 0.61
	(0.37)	(0.55)	(0.60)	(0.48)
Normality $\chi^2(2)$	0.18	0.44	0.65	0.41
	(0.92)	(0.80)	(0.72)	(0.82)
RESET	F(1,6) = 0.25	F(1,5) = 0.53	F(1,6) = 1.18	F(1,5) = 0.23
	(0.64)	(0.50)	(0.32)	(0.65)
No. of observations	14	12	14	12

Notes: (i) * Statistically different from zero at the 0.10 level of significance. ** Statistically different from zero at the 0.05 level of significance. (ii) The definition of variables are in tables 1 and 3.

All the coefficients have the expected sign and are statistically significant different from zero at the five percent confidence level with the exception of the error correction coefficient in columns (1) and (2) that is only marginally significant (we do not reject the null of zero only slightly above the ten percent confidence level). Additionally, with the exception of the coefficients of both the error correction and the unemployment elasticity of pay, the remaining coefficients are statistically the same in all specifications. For the monthly pay, both the error correction and the unemployment elasticity of pay are higher in absolute value.

To check the specifications reported we provide a set of mis-specification tests. We test the null hypothesis of no first-order residual autocorrelation, the null of no first-order autocorrelated squared errors (in both cases we report the preferred F-statistic), the null hypothesis of normality of the distribution of the residuals and the null hypothesis of correct specification of the original model against the alternative that powers of the predicted value of the dependent variable have been omitted in the specification of the model (the RESET test). For the four specifications reported in table 4, we do not reject the null hypotheses of these tests at the conventional level of statistical significance (the statistics and the p-values are reported in table 4). Additionally, a graphical analysis, based on recursive estimation of the models, of the null hypothesis of constant parameters reveal no problems.

Thus, without ignoring the caveats of the analysis, we shall tentatively conclude the following: wage determination at the regional level is influenced by both regional and aggregate factors. The common aggregate component of regional wages is well represented by a dynamic model where the equilibrium correction operates as a servomechanism in the adjustment process. Hence, tentatively, we reject the Phillips curve representation in favor of the equilibrium correction representation for the common aggregate component of regional wages. Therefore, we conclude that regional wages and productivity are cointegrated. Although we imposed homogeneity in the cointegration relationship, the restricted version performed better than an unrestricted version of our models. Therefore, we find some support for wages to be determined, in equilibrium, by equation (5), an equation that is supported for most economic theories of wage determination. We also conclude that wages are negatively affected by local and aggregate conditions. Both the local and the aggregate unemployment rates significatively affects wages. Indeed, the estimated long run unemployment elasticity of local pay is quite high. Finally, we shall say that the estimated equations are a plausible representation of the data set studied.

5. Conclusions

In this paper we studied wage determination in Argentina. We believe that both regional and national factors affect wage setting. Thus, we favor the modelization at the regional level of aggregation. However, we show that a regional wage two-way fixed effects error component model does not identify the effect of aggregate variables on wages though it controls for them. Thus, the claim that the estimated unemployment elasticity of pay in this model provides a measure of wage flexibility may be misleading. Therefore, we propose a three-step estimator to consistently identify the whole set of parameters of interest in a wage equation. That is, we propose a statistical approach that may consistently estimate the coefficients of both local and aggregate variables that affect wage setting. The estimator proposed requires the availability of a reasonable large time series but this requirement is always present if one desire consistent estimates of aggregate relationships. We also show that attempts to estimate both aggregate and local variables in wage determination in a one-way fixed effects error component model may produce severe pitfalls. Our model strategy may not be entirely successful but at least it provides us with a good opportunity. Additionally, several test of model mis-specification can easily be implemented to gain confidence in the third-stage model specification. Hence, it has much to be recommended.

Turning to the results, they suggest that regional wages are autocorrelated and that the short-run local unemployment elasticity of local pay is substantially below –0.1. Only for hourly wages, the long-run unemployment elasticity of local pay is close to –0.1. Indeed, it is –0.1. Hence, on this data, we reject the wage curve specification in favor of a dynamic regional wage equation or a dynamic wage curve.

We model the common aggregate effects on wages. We favor an error correction mechanism instead of a Phillips curve type regression function for them. However, we shall recall that these results are only exploratory. Additionally, our discussion makes clear that the wage curve relies not only on the cross-section variation but also on the time-series variation of wages and unemployment.

Without ignoring the caveats of the analysis, we conclude that wages are influenced by both regional and aggregate factors. We also conclude that wages are negatively affected by both local and aggregate unemployment. Indeed, the estimated long run unemployment elasticity of local pay is high. The same is true of the respective semi-elasticity.

Thus, interestingly enough, we find that during the period studied, Argentina showed a reasonable response of wages to unemployment. What is more, aggregate factors seem to be important in reducing wages. Indeed, the regional average unweighted wages have at the end of the period studied the same values they had at the end of 1991 in spite of the huge increase in labor productivity during the same period.

References

Abowd, J. and Card, D. (1989): “On the covariance structure of earnings and hours changes”, Econometrica, vol. 57, pp. 411-45.

Alogoskoufis, G. and Manning, A. (1988): “Unemployment persistence”, Economic Policy, vol. 7, pp. 428-69.

Bean, C. (1994): “European Unemployment: A Survey”, Journal of Economic Literature, vol. XXXII, pp. 573-619.

Bean, C., Layard, R. and Nickell, S. (1986): “The rise in unemployment: A multi-country study”, Economica, vol. 53, pp. S1-S22.

Beaudry, P. and DiNardo, J. (1991): “The effect of implicit contracts on the movement of wages over the business cycle: evidence from micro data”, Journal of Political Economy, vol. 99, pp. 665-88.

Bell, B. (1997a): “Wage curve or Phillips curve?”, Institute of Economics and Statistics, University of Oxford, mimeo.

Bell, B. (1997b): “Notes on the wage curve”, Institute of Economics and Statistics, University of Oxford, mimeo.

Bils, M. (1985): “Real wages over the business cycle: evidence from panel data”, Journal of Political Economy, vol. 93, pp. 666-89.

Blanchard, O. and Katz, L. (1992): “Regional Evolutions”, Brookings Paper on Economic Activity, vol. 1, pp. 1-75.

Blanchard, O. and Katz, L. (1997): “What we know and do not know about the natural rate of unemployment”, Journal of Economic Perspectives, vol. 11, pp. 51-72.

Blanchard, O. and Katz, L. (1999): “Wage dynamics: reconciling theory and evidence”, NBER working paper series No. 6924.

Blanchflower, D. and Oswald, A. (1990): “The wage curve”, Scandinavian Journal of Economics, vol. 92, pp. 215-35.

Blanchflower, D. and Oswald, A. (1994): The Wage Curve, MIT Press.

Blanchflower, D. and Oswald, A. (1995): “An introduction to the wage curve”, Journal of Economic Perspectives, vol. 9, pp. 153-167.

Bound J., Brown C., Duncan G. and Rodgers W. (1994): “Evidence on the Validity of Cross-sectional and Longitudinal Labor Market Data”, Journal of Labor Economics, vol. 12, pp. 345-68.

Canziani, P. (1997): “The wage curve in Italy and Spain. Are European wages flexible?”, Centre for Economic Performance Discussion paper No. 375.

Card, D. (1990): “Unexpected inflation, real wages, and employment determination in union contracts”, American Economic Review, vol. 80, pp. 669-88.

Card, D. (1995): “The wage curve: A review”, Journal of Economic Literature, vol. XXXIII, pp. 785-99.

Card, D. and Hyslop, D. (1997): “Does inflation grease the wheels of the labor market?” in Reducing Inflation: Motivation and Strategy, Romer, C. and Romer, D. (eds.), NBER and University of Chicago Press.

Davidson, J.; Hendry, D.; Srba, F. and Yeo, J. (1978): “Econometric modelling of the aggregate time-series relationship between consumers’ expenditure and income in the United Kingdom”, Economic Journal, vol. 88, pp. 661-92.

Dickens, W. and Katz, L. (1986): “Inter-industry wage differences and industry characteristics”, in Unemployment and the Structure of Labor Markets, Lang, K. and Leonard, J. (eds.), Basil Blackwell.

Dickens, R. (1996): “The evolution of individual male earnings in Great Britain: 1975-94”, Centre for Economic Performance, LSE, Discussion paper N0. 365.

DuMouchel, W. and Duncan, G. (1983): "Using sample survey weights in multiple regression analysis of stratified samples", Journal of the American Statistical Association, vol. 78, pp. 535-43.
Grubb, D. (1986): "Topics in the OECD Phillips curve", Economic Journal, vol. 96, pp. 55-79.
Harris, J. and Todaro, M. (1970): "Migration, unemployment and development: A two-sector analysis", American Economic Review, vol. 60, pp. 126-142.
Hoddinot, J. (1993): "Wages and unemployment in urban Cote d'Ivore", Centre for the Study of African Economics, University of Oxford, mimeo.
Huber, P. (1967): "The behavior of maximum likelihood estimates under non-standard conditions", in Proceedings of the Fifth Berkeley Symposium in Mathematical Statistics and Probability, University of California Press.
Janssens, S. and Konings, J. (1998): "One more wage curve: the case of Belgium", Economic Letters, vol. 60, pp. 223-27.
Jimeno, J. and Bentolila, S. (1998): "Regional unemployment persistence (Spain, 1976-1994)", Labour Economics, vol. 5, pp. 25-51.
Kish L. and Frankel M. (1974): "Inference from Complex Samples", Journal of the Royal Statistical Society, Series B, 1-22.
Layard, R. and Nickell, S. (1985): "The causes of British unemployment", National Institute Economic Review, pp. 62-85.
Layard, R. and Nickell, S. (1986): "Unemployment in Britain", Economica, pp.289-316.
Layard, R. and Nickell, S. (1987): "The labour market", in The Performance of the British Economy, Dornbush, R. and Layard, R. (eds.), Oxford University Press.
Layard, R., Nickell, S. and Jackman, R. (1991): Unemployment: Macroeconomic Performance and the Labour Market, Oxford University Press.
Lillard, L., Smith, P. and Welch, F. (1986): "What do we really know about wages? The importance of nonreporting and census imputation", Journal of Political Economy, vol. 94, pp. 489-506.
Moffit, R. and Gottschalk, P. (1993): "Trends in the covariance structure of earnings in the US: 1969-87", Brown University, working paper No. 93-9.
Moulton, B. (1986): "Random group effects and the precision of regression estimates", Journal of Econometrics, vol. 32, pp. 385-97.
Newell, A. and Symons, J. (1985): "Wages and unemployment in OECD countries", London School of Economics Centre for Labour Economics, Discussion paper No. 1038.
Nickell S. (1981): "Biases in Dynamic Models with Fixed Effects", Econometrica, vol. 49, pp.1417-26.
OECD (1997): Employment Outlook, OECD.
Pissarides, C. (1990): Equilibrium unemployment theory, Basil Blackwell.
Sargan, D. (1964): "Wages and prices in the United Kingdom: A study in econometric methodology", in Econometric Analysis for National Economic Planning, Hart, P.; Mills, G. and Whitaker, J. (eds.), Butterworth Co.
Solon, G.; Barsky, R. and Parker, J. (1994): "Measuring the cyclicality of real wages: how important is composition biases?", Quarterly Journal of Economics, vol. 109, pp.1-26.
Suits D. (1984): "Dummy Variables: Mechanics vs. Interpretation", Review of Economics and Statistics, vol. LXVI, pp. 177-80.
Teulings, C. and Hartog, J. (1988): Corporatism or competition? Labour contracts, Institutions and wage structures in international comparison, Cambridge University Press.