

Regional Unemployment in Argentina

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Abstract:

In this paper we study the regional evolution of unemployment in Argentina for the period 1980-1997. We show that its regional unemployment structure is not very persistent. We then apply panel data unit root tests to show that unemployment itself is not highly persistent. Indeed, we reject the null of a unit root in the unemployment series. Finally, we model the conditional means of regional unemployment. We adopt a dynamic two way fixed effects error component model specification. We measure the persistence of unemployment to shocks based on our conditional model. We believe this provides us with a better measure of persistence than the commonly used in the literature. We find a low degree of unemployment persistence to shocks. Finally, we also find regional factors that explain regional unemployment differences and whose changes may account for the low persistence of the regional unemployment structure.

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1. Introduction

Unemployment has become the main economic problem in the 90s in Argentina. Unfortunately, the country has moved from high inflation in the 80s to high unemployment in the 90s. Unlike high inflation rates, unemployment rates are not homogeneous across the country. Consequently, it is natural to study the regional evolution of the unemployment rates. The main objective of this paper is to accomplish this task. Thus, in this paper, we study unemployment from a regional perspective.

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 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 quite relevant to study whether or not the regional evolution of unemployment has been the same, and hence, the unemployment regional structure has remained invariant. If this is the case, then the aggregate unemployment rates would be a sufficient statistic of the process and the paragraph above would be a good summary of the same. But if it is not the case, the aggregate unemployment rates are not a sufficient statistic of the process and a study of the regional evolution of unemployment becomes very pertinent.

Of course, a study of regional unemployment will not shed light on some important determinants of unemployment. Indeed, several determinants of equilibrium unemployment are national ones and hence it is unlikely to identify them in a cross-regional study. However, the study of the regional structure of unemployment is as interesting and relevant as the study of aggregate unemployment itself. Additionally, if the time-variant common effects affecting unemployment across regions are not significant, then the changes in the

aggregate unemployment rate is the result of changes in the regional unemployment structure and hence, a study of the determinants of the latter is also very informative about the determinants of the former.

In any case, the study of regional unemployment arises two very important issues. First, it is entirely relevant to establish the degree of persistence of both the regional structure of unemployment itself and the persistence of shocks at the regional level. The second interesting issue is the determinants of equilibrium regional unemployment. What makes a region to have a higher equilibrium unemployment rate than other regions? In this paper, we address these issues.

The outline of the paper is as follows. In section 2 we study the degree of persistence of the regional structure of unemployment. In section 3 we address the issue of whether or not unemployment is a stationary process. This is important because the dominant approach in the literature assumes that the unemployment series (and/or a function of it in the case of regional series) follow an autoregressive process and measure the degree of persistence by the sum of the autoregressive coefficients. If the sum is one, innovations of the process have permanent effects on the level of the series and the same is considered to have the higher degree of persistence. However, we understand that there are sound reasons to believe unemployment is a stationary process. We discuss them and we also apply to our unemployment series a test of the hypothesis of unit root for panel data proposed by Levin and Lin (1993). In section 4, we model the conditional means of the regional unemployment rates and explain the determinants of equilibrium unemployment. Based on this conditional model we propose an alternative measure of persistence. We have no doubt our alternative (conditional) measure is more appropriated than the one based on unconditional representations of the unemployment series. The reason lies in that our measure of persistence takes account of both the changes in the (unconditional) mean of the series and the likely persistence of the common shocks. Thus, our measure of persistence is not biased by changes in the mean level of unemployment nor, in short samples, by the persistence of the common shocks. Consequently, we believe that this is an important contribution to the literature of regional unemployment persistence. Section 5 concludes.

2. The changing pattern of regional unemployment

Countries show different patterns of regional unemployment. For example, European countries show a high degree of persistence in their regional unemployment structure. The persistence of the relative regional unemployment rates in the United Kingdom has been remarkably stable. Its ranking of regional unemployment rates was little changed between the First World War and the 1990s. However, this ranking has been altered since the recession of 1990-93 (see Evans and McCormick, 1994).

Decressin and Fattás (1995) show that the differences in the relative unemployment rates between regions seem to be more persistent in Europe than in the United States. They fit a line using the relative regional unemployment rates of 1968 and 1987 both for Europe and the United States and take the slope of the fitted line as a measurement of persistence. Jimeno and Bentolila (1998) show, similarly, a high degree of persistence for Spain. In figure 1, we illustrate, using the same methodology, that the differences in the relative unemployment rates in Argentina do not show any persistence at all. The contrast with both the United Kingdom and Spain is evident.

A comparison of rank-order correlation between the United States and Europe also shows less persistence in the regional unemployment structure in the former country than across the EU (see Baddeley, Martin and Tyler, 1997 and Bertola and Ichino, 1996). Table 2.1 presents the rank-order correlations for some countries in selected years. We also include Argentina in the table. This shows that Argentina presents even less persistence in its regional unemployment structure than the US.

Turning back to figure 1, this evidence suggests that the relative positions in the Argentine regional unemployment ranking are completely unrelated between 1980 and 1997. To test this hypothesis, we compute simple correlation coefficients between both rankings (Spearman correlation). The Spearman coefficient is -0.05 and it is not statistically significantly different from zero. Hence, this result establishes that the structure of the unemployment rates has changed dramatically in Argentina between 1980 and 1997.

Nevertheless, the conclusions of this type of analysis are always conditioned on the periods selected for comparison. Even though, in the Argentine case, it is clear that the unemployment structure has changed during the period studied. Hence, given the changes

occurred in the Argentine economy during the period studied, the following question arise naturally. Was this change smooth or was it sharpened in any particular time period as, for example, the 90s?

Figure 1: Regional rankings correlations

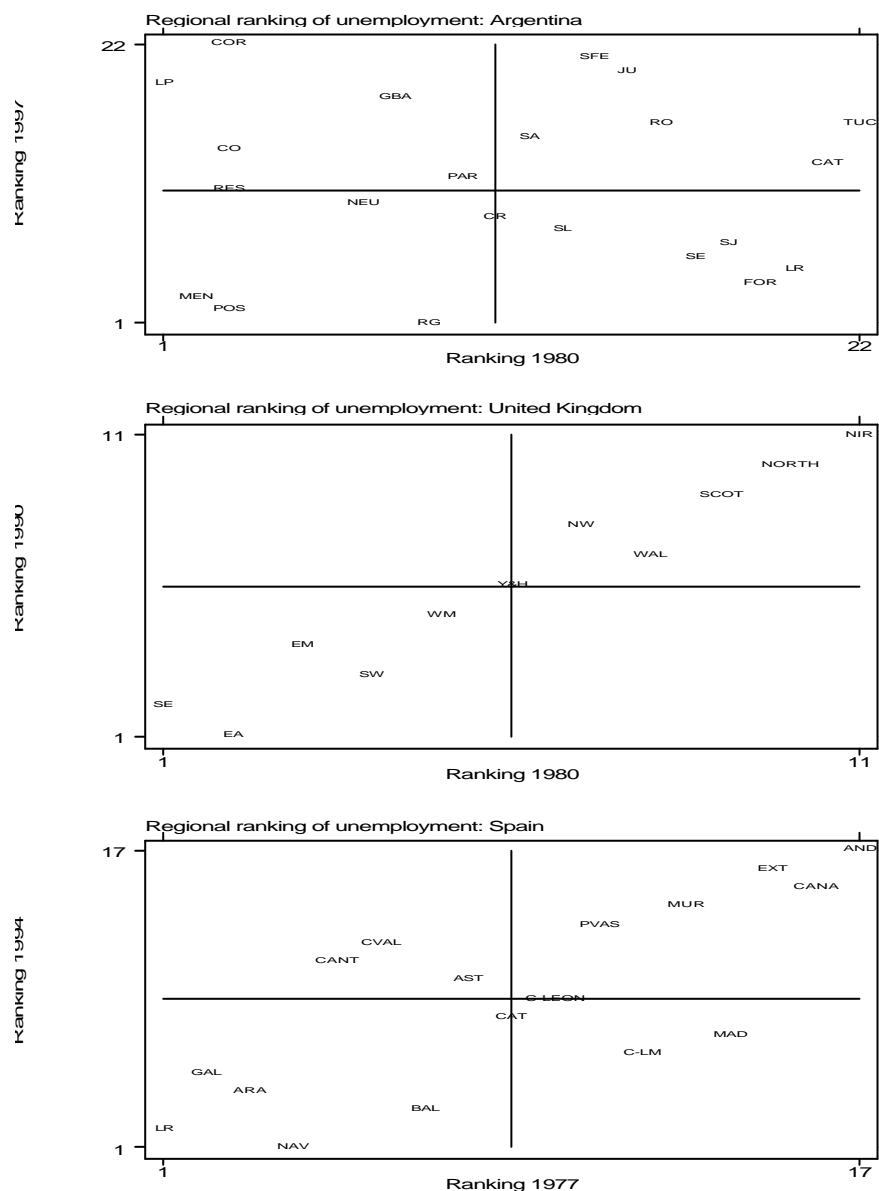


Table 2.1: Persistence of regional unemployment in selected EU member countries, United States and Argentina: Rank-order correlations, 1980-94.

	1981	1982	1985	1988	1990	1992	1994
United Kingdom	0.97	0.96	0.88	0.84	0.82	0.75	0.77

Germany	1.00	0.99	0.88	0.83	0.89	0.73	0.85
France	0.89	0.82	0.78	0.71	0.68	0.70	0.66
Denmark	0.90	0.88	0.87	0.85	0.84	0.80	0.83
Italy	0.97	0.94	0.96	0.94	0.91	0.90	0.88
Spain	0.98	0.93	0.95	0.76	0.71	0.70	0.74
United States	0.91	0.86	0.67	0.40	0.52	0.39	0.39
Argentina	0.62	0.69	0.26	0.33	0.37	0.56	0.03

Notes: Rank-order correlation coefficients of the 1980 regional unemployment rates with those in subsequent years. For EU countries, NUTS1-level unemployment regions. For USA and Argentina, state-level unemployment rates.

Source: Martin, R. (1998), table 1.3 and authors elaboration.

Both to evaluate the dynamic of the changes in the regional unemployment structure and to establish the robustness of the conclusion reached, we compute the Spearman correlation between two-year unemployment rankings among all possible pair of years for the period studied. The results are presented in table 2.2.

First, we confirm the dramatic change in the Argentine regional unemployment structure. There is no association between the relative unemployment situation at the beginning of the 80s with the situation at the mid-90s. Second, it is clearly observed that these changes never occurred abruptly. Looking at the Spearman coefficients, we can say that the unemployment structure never changed in a period shorter than five years. Third, the unemployment ranking changed relatively more in the early 90s than in the 80s. The coefficients of Spearman between the beginning of the 80s and the beginning of the 90s ranges between 0.25 and 0.45 while the same coefficient for the period 91-97 is 0.12.

It is worth mentioning here that the analysis we made in terms of rankings is not only appropriate but also relevant because, for any year, the differences in the unemployment rates across regions are quite large. Hence, a change in the ranking is a good statistic to capture meaningful changes in the regional unemployment structure.

Table 2.2: Spearman correlation coefficients (1980-1997)

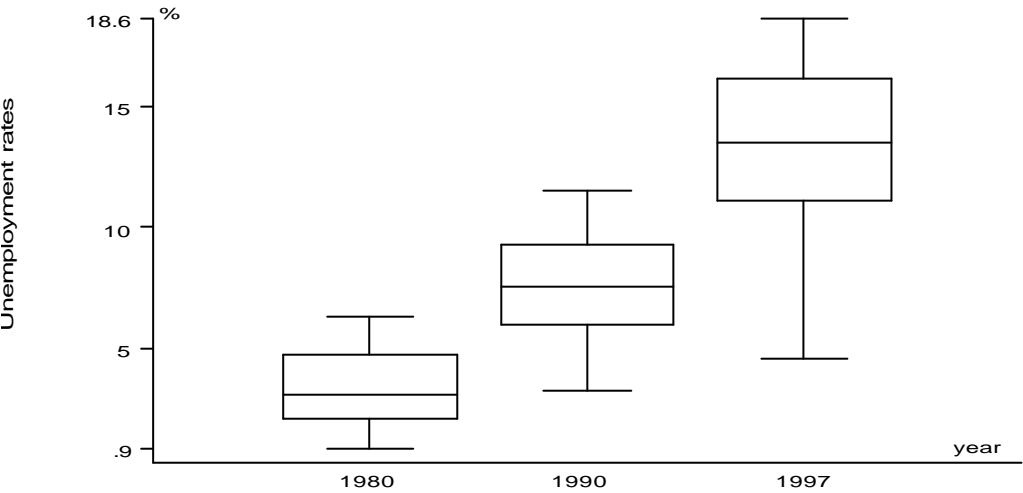
	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97
80	1																	
81	0.62	1																
82	0.69	0.56	1															
83	0.50	0.58	0.84	1														
84	0.36	0.34	0.60	0.52	1													
85	0.26	0.46	0.65	0.56	0.78	1												
86	0.36	0.51	0.55	0.52	0.64	0.71	1											
87	0.21	0.38	0.48	0.42	0.52	0.62	0.84	1										
88	0.33	0.37	0.58	0.49	0.40	0.50	0.67	0.93	1									
89	0.50	0.32	0.41	0.22	0.42	0.31	0.60	0.68	0.65	1								
90	0.37	0.25	0.45	0.23	0.53	0.56	0.64	0.67	0.61	0.72	1							
91	0.43	0.21	0.42	0.24	0.35	0.40	0.59	0.70	0.76	0.68	0.76	1						
92	0.56	0.35	0.54	0.31	0.50	0.53	0.53	0.51	0.56	0.55	0.83	0.80	1					
93	0.33	0.13	0.32	0.11	0.29	0.31	0.35	0.42	0.51	0.58	0.70	0.73	0.77	1				
94	0.03	0.06	0.31	0.12	0.45	0.65	0.46	0.63	0.60	0.50	0.78	0.66	0.61	0.68	1			
95	0.05	0.15	0.20	0.04	0.57	0.55	0.32	0.47	0.40	0.55	0.63	0.45	0.45	0.61	0.79	1		
96	0.14	0.20	0.20	0.05	0.53	0.51	0.38	0.37	0.28	0.58	0.62	0.44	0.52	0.63	0.67	0.89	1	
97	-0.05	0.02	0.18	0.11	0.54	0.46	0.25	0.22	0.11	0.40	0.46	0.12	0.33	0.44	0.49	0.74	0.81	1

Figure 2 illustrates the regional unemployment variability. Each box diagram presents a particular year. In each diagram, the bottom line measures the minimum unemployment rate while the upper line measures the maximum unemployment rate for that year. The central box shows the range within which we find seventy five percent of the regional unemployment rates. As it is observed, the unemployment rates are now much less uniformly distributed than they were at the beginning of the 80s. The range of variability in the regional unemployment rates has increased over time.

Finally, we focus the analysis in relative terms. We evaluate, for the entire period studied, both the ratio of the range of variability in unemployment at period s to the sum of the two extreme values of the variable at the same period and the ratio of the interquartile range of regional unemployment at period s to the sum of the two extreme values of the variable at the same period. The advantage of these measures is that both of them are robust to the influence of extreme observations (see Machado and Mata, 1997). Looking at this statistics, we find that the regions have become more homogenous with respect to the global unemployment, specially, during the 80s.

Thus, regarding the persistence in the regional unemployment structure, we find that, during the period studied, it shows very low persistence. We find evidence suggesting that it is even less persistent than the US regional unemployment structure. The regional unemployment structure has changed during this period but the changes were never abrupt. Also, these changes have been stronger during the beginning of the 90s, coinciding with a period of structural reform in the country. Finally, we find that unemployment has trended up during the period studied and the range of variability in the regional unemployment rates increased *pari passu*.

Figure 2: Unemployment dispersion diagrams



3. The stationarity of the unemployment process

Layard et al. (1991) establishes several empirical facts about unemployment. Two of them are relevant for the point we want to address here. First, unemployment fluctuates over time. Some of these fluctuations are short-term changes that get reversed quite quickly. But there are also big secular changes. Second, unemployment is untrended over the very long term. That is, unemployment seems to be a stationary process.

Certainly, one could argue that unemployment is $I(0)$ as follows: Suppose it is not, that is, let unemployment be $I(1)$. Then, it cannot have a drift. Otherwise, it would be trended even in the long run, which we know it is not. Incongruous, it will tend to infinity (with a positive drift). But if it does not have a drift, then unemployment would be a process having zero unconditional expectation. Thus, it would tend to cross zero most often than never, which we also know it is not the case. Hence, by contradiction we suggest that unemployment is $I(0)$. We believe that it is likely that unemployment is an autoregressive stationary process with positive mean, which is significantly shifted from time to time.

The relevance of determining whether or not unemployment is $I(0)$ for our case is evident. If it were $I(1)$, as we mentioned, unemployment would have the higher degree of persistence. Thus, in addition to the simple argument in favor of the stationarity of unemployment we state above, we pursue a test of the hypothesis of unit root in the unemployment series.

It is often the case that the unconditional representation of the unemployment stochastic process both at the national level and at the regional level presents a high degree of autocorrelation. Dickey-Fuller tests of the hypothesis of unit root applied to univariate unemployment series most often do not reject the null hypothesis of non-stationarity. Unfortunately, even if the null hypothesis is false, this result may arise as a result of two facts. First, it is well known that unit root tests tend to lack power. Thus, they do not tend to reject the null hypothesis at all when it is false, even though they may reject it when it is true. Additionally, if a break in the data generating process occurs during the period analyzed, such as a change in the mean of the process, the test is also biased to the non-rejection of the null hypothesis when it is false (see Perron, 1989).

Both Blanchard and Katz (1992) and Decressin and Fattás (1995) test the null hypothesis of a unit root in the regional relative (to the aggregate) unemployment rate series for US and Europe respectively. They apply Dickey-Fuller type tests to each series. For the majority of regions, none of them rejects the null hypothesis of a unit root in the regional relative unemployment rates. Because the null hypothesis was implausible in the first place, both papers ignore these results and pursue their analysis assuming stationarity in the relative regional unemployment rates. However, we want to establish not only that the regional relative unemployment rates are stationary but also that the regional

unemployment rates are stationary. Note that the latter is sufficient for the former although it is not necessary.

Thus, in this section we present a test of unit roots for panel data. However, we face several limitations in order to implement a test for the unit root hypothesis in the Argentine unemployment series. We want to test the unit root hypothesis for the same period we estimate our conditional models of regional unemployment. Thus, the largest sample period for each region is at most 14 years, which makes large sample based inference using standard unit root tests unreliable.¹ For this reason we make explicit use of the panel structure of the data, and test the null hypothesis of unit root imposing cross-equation restrictions on the first order partial autocorrelation coefficients, from which we should expect a corresponding gain in power in testing for the null hypothesis. This is the logic behind the Levin-Lin (1993) test for unit root in panel data, which has been extensively used in practice. The test procedure (described in the appendix) allows for heterogeneity in every respect other than the autoregressive coefficient leading (eventually) to the presence of a unit root. The test statistic is a modified version of the original augmented Dickey-Fuller procedure, which is based on the t-statistic of the lagged level of a variable of interest in a regression of the first difference of that variable on itself, and lagged differences to account for serial correlation. In general terms, the Levin-Lin test is an augmented Dickey-Fuller statistic with a mean and variance correction to give account for heterogeneity and the bias present in ordinary least squares estimates of dynamic panels (see section 4). Unlike the Dickey-Fuller statistic, the Levin-Lin statistic is shown to have a limiting standard normal distribution under the null hypothesis of a unit root (see Levin and Lin, 1993).

The limited information available led us to rely on several simplifying assumptions in order to implement the test using the most parsimonious specification. We use the unemployment series for the period 1985-1998 (14 periods), that is, a year larger than the one used for the estimation of the conditional model in section 4. Also, we use only one lag to control for serial correlation. Under the null hypothesis the unemployment rate follows a unit root process. Regarding the alternative hypothesis, due to the considerations made above, we discard the possibility of a trend in the unemployment process, but we allowed

¹ The same would be true even if we use the unbalanced data available for the period 1980-98.

for a non-zero mean in the unemployment rate under the alternative hypothesis (unemployment is non-zero mean stationary process).

The corresponding Levin-Lin modified t-statistic for the test of the null hypothesis of the presence of a unit root gives a value of 2.069, which suggest that the null should be clearly rejected in favor of the alternative hypothesis of a stationary process in unemployment. Thus, armed with this result, in the next section we proceed to model the conditional means of the regional unemployment series.

4. A model of regional unemployment

In this section we search for a dynamic model of regional unemployment. The objective is twofold. On the one hand, we would like the model to help us explain the changes in the regional structure of unemployment. On the other hand, we believe that a dynamic model that also conditions unemployment on a set of additional covariates may provide us with a better measure of the regional unemployment persistence to the regional shocks than the one provided by the sum of the coefficients in a univariate autoregressive model.

Recently, the empirical literature on regional unemployment has emphasized the role of persistence in fixed effects autoregressive models (see Blanchard and Katz, 1992 and Decressin and Fattás, 1995). This literature studies the regional labor markets adjustment to exogenous perturbations. Behind the regional fixed effects formulation adopted in this literature there is the idea that it exists equilibrium unemployment differences among regions.

Martson (1985) present some evidence on the existence of unemployment equilibrium differences for US regions. He claims that these differences are generated by different amenities provided by regions, that is, the unemployment differences should be viewed as equalizing amenity differences. Additionally, he agrees that they may also be generated by the existence of wage differences among regions, a result that is consistent with the theory of compensating wage differentials. Topel (1986) emphasizes the compensating wage differential theory to explain the existence of regional unemployment differences. This

latter hypothesis is similar to the Harris-Todaro (1970) explanation of the rural-urban unemployment differences.

Two points deserve our attention here. Although the fixed effects vector autoregressive representation of regional unemployment differences may not be rejected a priori for countries that seems to have an stable regional unemployment structure, it does not seem to be an appropriate representation of the regional unemployment structure for US and Argentina. The reason is that these countries do not show a stable regional unemployment structure. In these cases, a better representation of the data would be a dynamic model in which the changes in the unemployment structure are accounted by a set of additional covariates. Note that the inclusion of regional fixed effects in this model may still be appropriate. It captures, for example, equalizing amenity differences that may exist even though the regional unemployment structure is not stable. Of course, these amenities may be measured and added to the set of covariates in the empirical model but, most often, they are elusive to an econometrician and hence it may be preferable to capture them by including regional fixed effects in an empirical model.

Turning on to the set of covariates which should be included in an empirical model of regional unemployment, Summers (1986) points-out that regional unemployment differences seem to be associated to the different industry evolutions located heterogeneously across a country. For example, in Europe, many of the regions specializing in mining, steel, textiles and heavy manufacturing industry have experienced steep falls in employment since the 1970s. Although the process of de-industrialization in these regions has promoted out-migration of labor to other areas or the workers have tended to be reallocated in the same region, the regions most affected by the contraction in traditional industry and manufacturing have tended to experience more persistent unemployment. However, one should be cautious before adjudicating the process of industrial restructuring as an important source of the increase in unemployment during the 70s and 80s in Europe. First, Layard et al. (1991) presents evidence that shows that this process has not accelerated during that period of time. Second, it also occurred in US where unemployment increased almost exclusively during the recessions of 1975 and 1982. Other factors, perhaps in combination with the de-industrialization process, have to have played a main role in the

raise in unemployment in Europe. Certainly, the one most often cited is the generous unemployment benefit system developed in most European countries.

In any case, in the short run, a process of de-industrialization certainly affects the regional distribution of unemployment. Additionally, and most relevant, there is some other evidence which shows that the industry composition of regions have a main role in explaining the regional variability of unemployment. Both Baussola and Fioritto (1994) and Forrest and Naisbitt (1988) report this result for Italy and United Kingdom respectively.

Finally, Taylor and Bradley (1997) reports that a substantial proportion of the variation in regional unemployment rates in Germany, Italy and the UK is explained by three regional variables: (i) unit labor costs, (ii) the industry mix, and (iii) employment density.

Thus, previous theoretical and empirical work suggest that the regional differences in unemployment are explained by equilibrium equalizing amenity differences, compensating wage differentials, the industry mix and, perhaps, by differences in the matching process among regions that are not accounted by the industry mix. Therefore, the equilibrium regional unemployment structure is not necessarily time-invariant. Certainly, at any time, we will observe out-of-equilibrium regional unemployment differences due to shocks both to regional labor demand and regional labor supply. Finally, regional unemployment levels are surely much affected by national factors. Accordingly, this inherited knowledge about regional unemployment rates guides our empirical analysis.

4.1. Some methodological considerations

Decressin and Fattás (1995) estimate a dynamic one-way error component model for both Europe and the US of the form:

$$u_{it} = \mathbf{a}_{1i} + \mathbf{a}_2(L) u_{it-1} + v_{it} \quad (1)$$

where u_{it} is alternatively the difference in region i unemployment to a function of the national unemployment rate in period t or just the region i unemployment rate in period t .² They estimate a polynomial of order two. They find, in the former case, that US shows more persistence than Europe while, in the latter case, they find exactly the opposite. The authors suggest that this result is only due to the lack of inclusion of common year-effects in the former specification. Hence, they suggest that it is the common shocks that have permanent effects in Europe.

In this paper, we propose to model the regional unemployment using a dynamic two-way error component model of the form:

$$u_{it} = \mathbf{r}(L) u_{it-1} + \mathbf{b}(L) X_{it} + \boldsymbol{\mu} + \mathbf{I}_t + \mathbf{e}_{it} \quad (2)$$

where X_{it} is a matrix of covariates that varies both across regions and time. We model the error components of the model, μ and λ , as fixed effects. Thus, comparing models (1) and (2), the latter allows the regional mean level of unemployment to be time-variant without imposing any common structure in its changes. This specification seems to be the one suggested by the analysis in section 2. We allow the regional mean to change smoothly due to smooth changes in the regional covariates and we also allow the level of the series to be affected by common year effects.

Thus, the empirical model (2) may help us to explain the changes in the regional unemployment structure if we find some covariates that explain some of the variance of the regional unemployment and have also changed accordingly. Additionally, if the covariates are strongly exogenous variables for $\beta(L)$ and $\rho(L)$ (see Engle et al., 1983), then $\rho(L)$ provides us with a better measure of persistence than $\alpha_2(L)$. To see this, let us assume that (2) is the data generating process. Assume X is persistent to shocks but u is not, say $\rho(L)$ is a zero vector. Thus, if we estimate model (1), the estimate of α_2 will pick-up the persistence on the X s. Consequently, to obtain unbiased estimates of the persistence of regional unemployment to pure regional shocks, we should estimate model (2) instead.

² Blanchard and Katz (1992) also estimate a regression function like (1) using relative unemployment rates for the US.

Unfortunately, it is likely that the typical shocks to regional unemployment also affect some of the regional covariates. However, all is fine if the affected covariates lack persistence with respect to unemployment regional innovations. We do not evaluate this here because it would require us to model the marginal process of the X s. Consequently, we keep it as a maintained hypothesis when we measure persistence by our estimates of $\rho(L)$.

In terms of the estimation of model (2), first note that whenever the parameters of interest are $\rho(L)$ and $\beta(L)$, once year fixed effects are included in the model it is the same whether or not model (2) is estimated using regional variables that are measured in relation to national ones.

However, in terms of the interpretation of our empirical model, it matters whether or not we believe a covariate enters the data generating process in levels or instead as a difference to its aggregate value. Minimally, we want our model to be data coherent and data admissible. Note that we establish in section 3 that u_t is stationary. This imposes X_{it} to be, if not stationary, cointegrated.³

Finally, we shall discuss the method we use to estimate our empirical model. We eliminate the regional fixed effects, μ_i , by differencing the regional unemployment equation (2). Thus, we obtain,

$$\Delta u_{it} = \mathbf{r}(L) \Delta u_{it-1} + \mathbf{b}(L) \Delta X_{it} + \mathbf{f}_t + \Delta \mathbf{e}_{it} \quad (3)$$

The reason to apply this transformation to the model instead of the within-group transformation is that the ordinary least squares estimator applied to the latter is semi-inconsistent in dynamic panels. The bias of the parameter of interest is caused by having to eliminate the unknown regional effect from each observation, which creates a correlation of order $(1/T)$, where T is the time series dimension of the panel, between the explanatory variables and the residuals in the transformed model (see Nickell, 1979).

Note, however, that after differencing, u_{it-1} is correlated with the equation error, $\Delta \mathbf{e}_{it}$. Additionally, X_{it} and \mathbf{e}_{it} may also be correlated. Consider, for example, the industry mix variables. A regional demand shocks that affect regional employment and unemployment

³ Certainly, it is unlikely that a good representation of the data generating process would imply that X_{it} and λ_t are cointegrated while X_{it} is not.

would likely affect the industry mix. As long as ε_{it} is serially uncorrelated, that is, $E(\varepsilon_{it} \varepsilon_{is}) = 0$ for $t \neq s$, all lags on u and X beyond $t-1$ are valid instruments in the differenced equation for period t . Therefore, for $T \geq 3$, and assuming, for example, that L is zero in equation (2), the model implies the following linear moment restrictions:

$$E(\Delta \mathbf{e}_{it} \mathbf{u}_{it-j}) = 0 \quad \text{and} \quad E(\Delta \mathbf{e}_{it} \mathbf{z}_{it-j}) = 0 \quad (j = 2, \dots, t-1; t = 3, \dots, T) \quad (4)$$

where z is any vector of X . In addition, it is necessary to make an standard assumption concerning the initial condition u_{i1} (see Ahn and Schmidt, 1995). If any variable z is predetermined or a strictly exogenous, then there exists additional linear moment restrictions available. Additionally, if any variable z is not correlated to with μ_i , additional moment restrictions exploiting this lack of correlation in the equations in levels become available. Arellano and Bond (1991) proposes a generalized method of moments (GMM) estimator which exploits these linear moment restrictions generated by the serially uncorrelated error. We apply this linear estimator to estimate equation (3).⁴

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 statistical significant negative first order serial correlation in the differenced residuals while there should not be any evidence of second order serial correlation in the differenced residuals. Arellano and Bond (1991) develops 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.

⁴ Unfortunately, there is always a caveat when using instrumental variables. Even though every valid set of instruments will yield consistent estimates, different choices will yield different estimates in finite samples.

4.2. Econometric results

We present here two alternative specifications of the regional unemployment model for Argentina. Our data set, explained in detail in the data appendix, covers the period 1985-1997. Unfortunately, there are some limitations in the availability of data. The main source of data used in this paper is the permanent household survey (EPH) conducted by the Argentine National Institute of Statistics and Census (INDEC). The household survey is conducted twice per year in the main urban agglomerates. For the period covered, there is data available for twenty-three urban agglomerates. Although, the household survey is conducted twice per year, we specify our empirical models using yearly data, mainly, because some other relevant variables are only measured with a yearly frequency.

Both empirical specifications include as covariates the following set of variables, all of which varies both across regions and time periods. (1) The industries mix. We have two measures to capture this effect. The ratio of tradable goods to non-tradable goods (tnt) and the share of employment in four main aggregate sectors: manufacturing, trade, services and construction. We have reasons to enter them dynamically. There is evidence that shows that the cyclical response of unemployment differs among regions depending on their industry mix. Additionally, the impact of a demand shock or a sectorial shock on unemployment depends on the employment composition before the shock occurs. Thus, we also enter these variables with lags in our models.

(2) Gross geographical product per employee (RGDPpE). This is a measure of partial labor regional productivity. Unemployment rates viewed over the long run is untrended, indeed, as we argued in section 3, it is a stationary process, despite the tremendous increases in productivity occurred in the last century. As Blanchard and Katz (1997) states it, any model should satisfy the condition that there is no long run effect of the level of productivity on the natural rate of unemployment. In the short run, however, technological change, which is associated with structural change, may affect the unemployment rate positively (see Mortensen and Pissarides, 1994). Additionally, productivity determines pay levels. Hence, the compensating wage differential theory also suggests that this variable affects unemployment positively. However, both explanations

requires that the variable that affects the unemployment level would not be the productivity level but the regional differences in productivity, that is, the difference in region i productivity level to the aggregate productivity level.

(3) Labor costs. Taxation on labor typically operates via the wedge between the real cost of a worker to an employer and the real consumption wage of the worker. Nickell (1997) suggest measuring this wedge by the sum of payroll taxes, income taxes and consumption taxes. Among regions, there are no substantial differences in these taxes in Argentina. Nonetheless, during the period studied there were some changes in the payroll tax, which were differentiated by regions. We expect the identified impact on unemployment, if any, to be positive. However, the variability on payroll taxes, t , may not be enough to identify any statistically significant effect. The changes in the payroll tax were related to the macroeconomic policy and hence, we treat them as exogenous at the regional level. Of course, this policy was introduced to stimulate employment creation but the point here is that the differentiated changes in the payroll taxes were not related to the regional innovations in equation (2) at the time they were introduced. Taylor and Bradley (1997) suggest that labor costs affect unemployment with a lag.

(4) Shocks to labor supply. A common argument relates unemployment increases to higher labor force participation rates. That is, if more people search for a job, unemployment would increase. While it is possible that there may be short run dynamic effects, in the long term there tends to be no relationship between labor force growth and unemployment (see Nickell, 1995). We measure labor supply shocks by the change in the regional labor force participation rate, $\Delta lfpr$. We also enter this variable with lags in our models.

Notwithstanding, and alternatively to the model specification that includes $\Delta lfpr$, we include the labor force participation density scaled by a thousand, $lfprsup$. We arrived to this model specification following Taylor and Bradley (1997) reports that the employment density (employment per square kilometer) affects positively regional unemployment. However, the reason for this finding is not clear at all. First, employment density is clearly trended in every region if the period studied is not too short. Thus, it is unlikely that it enters in the model in levels. Nevertheless, if this variable were to pick-up a matching phenomenon, it is not clear why it would enter in the model in terms of its regional relative

value instead of in levels. Second, if instead it were to capture, as Taylor and Bradley (1997) suggests, the urban-rural mix on a region's unemployment rate, we believe this effect to be unimportant in this study and in any case, it would be controlled by the region fixed effects.

It is plausible that during the period studied we find the specification of the model including $lfprsup$ valid. Even if in the long run labor force participation is not correlated with unemployment, conditioned in our sample, we may identify medium term effects. Additionally, in our sample, labor force participation presents a peculiar characteristic. It is volatile and sudden increases tend to get partially reversed quickly. Thus, this variable may also capture the short run impacts of labor force participation rates changes on the regional unemployment.

(4) Finally, we include a measure of regional differences in skill levels. We measure it by the school achievement of the labor force. We use the following categories. Unskilled: the proportion of members in the labor force with less than secondary school. Semi-skilled: the proportion of members in the labor force with secondary school. The left-out category is the skilled proportion of workers. However, these variables were never statistically significant.

The panel we have is balanced. Three cross-sections are lost in constructing lags and taking first differences, so that the estimation period is 1988-1997. We begin by estimating unrestricted models. Unemployment lagged twice was never statistically significant. Additionally, neither the current nor the lagged value of tnt were found to have a statistically significant impact on unemployment in any specification of the models we estimate.

In table 4.1 we present the results of some restricted specifications for the regional unemployment models. In columns (1) and (2), we only instrument the lagged dependent variable. Here, all variables other than the lagged dependent variables are at least (implicitly) assumed to be predetermined although, given our sample size, none of the over-identifying restrictions that follow from this assumption are exploited.⁵

⁵ There is always a trade-off when applying an instrumental variable estimator. We want to obtain estimates that are as efficient as possible asymptotically while avoiding small finite-sample bias.

We find a low autocorrelation coefficient in both models.⁶ Assuming the X's are strictly exogenous, after a year, only forty percent of a regional shock to unemployment will be affecting regional unemployment. Consider a specific shock to region j equal to the equation standard error. Hence, during the year of the shock, unemployment in region j increases 1.56 percentage points. A year later, unemployment is, ceteris paribus, only 0.61 percentage points higher than its level before the shock while two years later it is only 0.24 percentage points above its pre-shock level. Certainly, unemployment, at the regional level, presents a very low persistence to idiosyncratic shocks, or more generally, to aggregate shocks. This result is very important. In section 2 we establish that the regional unemployment structure in Argentina is not very persistent. Of course, it is not altered by aggregate shocks. Nevertheless, the regional shocks may also be large. If they themselves or their effect on unemployment were persistent, they may explain by themselves the low persistence of the regional unemployment structure. However, the regional shocks are found to be uncorrelated and their effect on unemployment does not persist much either. Therefore, the low persistence of the regional unemployment structure has to be explained by the changes in the (time-variant) regional equilibrium unemployment.

Table 4.1: Dynamic regional unemployment equations: 1988-1997
Dependent variable: U_{it} (unemployment rate (%) in region i in period t)

Independent variables	GMM (First-Differences) (1)	GMM (First-Differences) (2)	GMM (First-Differences) (3)	GMM (First-Differences) (4)
U_{it-1}	0.37 (0.11) **	0.39 (0.12) **	0.21 (0.11) **	0.26 (0.10) **
$RGDPpE_{it}$	5.47 (1.44) **	4.73 (1.58) **	5.47 (1.83) **	5.13 (1.84) **
$Manufacturing_{it-1}$	-0.10 (0.1)	-0.10 (0.09)	-0.10 (0.10)	-0.09 (0.11)
$Manufacturing_{it-2}$	0.02 (0.09)	-0.03 (0.11)	0.05 (0.09)	0.02 (0.10)
$Trade_{it-1}$	-0.12 (0.09)	-0.09 (0.08)	-0.04 (0.10)	-0.06 (0.09)
$Trade_{it-2}$	0.32 (0.09) **	0.34 (0.09) **	0.29 (0.09) **	0.32 (0.08) **
$Services_{it-1}$	-0.12 (0.065) *	-0.09 (0.06)	-0.09 (0.05) *	-0.09 (0.05) *
$Services_{it-2}$	-0.01 (0.06)	-0.03 (0.06)	0.03 (0.07)	0.01 (0.06)
$Construction_{it-1}$	-0.02 (0.13)	0.005 (0.13)	-0.06 (0.14)	0.02 (0.14)
$Construction_{it-2}$	0.25 (0.15) *	0.14 (0.14)	0.25 (0.12) **	0.19 (0.11) *
T_{it-1}	13.9 (11.9)	16.5 (11.2)	14.1 (12.9)	18.8 (10.6) *

⁶ Blundell and Bond (1998) shows that if the true ρ were close to one and (especially if) T is short, the linear GMM estimator may be also biased downward. This would occur as a consequence of the instruments becoming weak ones (see Staiger and Stock, 1997). They show that a system GMM estimator exploiting both equations in differences and in levels performs better. We estimate versions of both models by the system GMM estimator and we never find estimates of ρ higher than the ones obtained by the GMM estimator exploiting only the restrictions gathered by the equations in first differenced. To reinforce this result, it is also worth to report here that the system GMM estimate of an univariate autoregressive model is only 0.3.

Δlfpr_{it}	----	0.35 (0.10) **	----	0.28 (0.12) **
$\Delta \text{lfpr}_{it-1}$	----	0.13 (0.07) *	----	0.14 (0.07) **
Lfprsup_{it}	3.12 (1.49) **	----	1.56 (0.71) **	----
Lfprsup_{it-1}	0.80 (1.17)	----	0.64 (0.90)	----
Equation standard error	1.58	1.56	1.48	1.47
Sargan Test	0.12	0.15	0.16	0.07
m_1	0.001	0.001	0.001	0.001
m_2	0.07	0.13	0.11	0.13
Number of Observations	230	230	230	230

Notes: (1) Time dummies are included in all equations. (2) Asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses. (3) * Statistically different from zero at the 0.10 level of significance. ** Statistically different from zero at the 0.05 level of significance. (4) 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). (5) The equation standard error refers to the equation in levels. (6) Columns (1) and (2): the basic instrument set is of the form $Z_i = \text{diag}[U_{i1}, \dots, U_{is} : \Delta X_{is+2}]$, ($s = 1, \dots, 11$), where X_{it} is the matrix of covariates of individual i in period t . Column (3): the basic instrument set is of the form $Z_i = \text{diag}[U_{i1}, \dots, U_{is}, m_{is}, tr_{is}, s_{is}, c_{is}, \text{lfprsup}_{is-1}, \text{lfprsup}_{is} : \Delta m_{is}, \Delta tr_{is}, \Delta s_{is}, \Delta c_{is}, \Delta \text{RGDPpE}_{is}, \Delta t_{is+1}]$, ($s = 1, \dots, 11$), where m : manufacturing, tr : trade, s : services and c : construction. Column (4): the basic instrument set is of the form $Z_i = \text{diag}[U_{i1}, \dots, U_{is}, m_{is}, tr_{is}, s_{is}, c_{is}, \text{lfpr}_{is-1}, \text{lfpr}_{is} : \Delta m_{is}, \Delta tr_{is}, \Delta s_{is}, \Delta c_{is}, \Delta \text{RGDPpE}_{is}, \Delta t_{is+1}]$, ($s = 1, \dots, 11$).

Hence, turning to the determinants of equilibrium unemployment differences, we find that the regional gross domestic product per capita affects unemployment positively as expected. This may give support to the theory of compensating wage differentials as a determinant of equilibrium unemployment differences among regions. However, as we point-out above, it may also reflect an out-of-equilibrium phenomenon in that it may also capture some short run effect of the technological change on unemployment. It also appears that regions with higher employment shares in trade and construction have higher equilibrium unemployment rates while regions with higher employment shares in services have lower equilibrium unemployment rates.

Additionally, given the changes that occurred in the productive structure during the period studied, the industry-mix effect on unemployment is not minor. To evaluate its impact, let us divide it in its immediate impact (after two years) and its long run equilibrium impact. Consider, for example, taking the magnitude of the change in the employment mix between 1985 and 1997 as a once and for all change for the higher urban agglomerate (an agglomerate that move substantially up in the ranking of unemployment

during this period). Its immediate impact on unemployment is to increase it by approximately 1.2 percentage points, a magnitude slightly below the equation standard error. However, given the low persistence of an idiosyncratic shock, the permanent effect of a once and for all change in the industry mix appears to be quite relevant. What is more, the long run increase on unemployment is approximately 2.4 percentage points. This figure would represent an increase in the main urban agglomerate unemployment of approximately 45 percent with respect to its 1985 unemployment rate.

Finally, the payroll tax appears to be positively related to the unemployment rate however its effect is not statistically significant. Thus, a reduction in the payroll taxes would presumably reduce unemployment. Again, for example, the higher urban agglomerate is among the less benefited by the reduction in taxes. This also has contributed to move this region up in the ranking of unemployment.

Additionally, we find a positive statistically significant impact of the current and lagged changes in labor supply on unemployment. In the alternative specification, we find that the current level of labor supply affects unemployment positively.

Again, the higher urban agglomerate is the one that experienced the higher increase in labor force participation during the period studied. Finally, it is also among the ones that experienced the highest increases in the gross domestic product per employee. Therefore, we find several reasons to explain why this agglomerate has moved up in the unemployment ranking.

For both models in columns (1) and (2), we do not reject the null hypothesis of the validity of the over-identification restrictions nor the lack of autocorrelation in ε_{it} at the conventional levels of statistical confidence.

The GMM estimates presented in table 1 are all one-step estimates. Although there exists two-step estimators that are asymptotically more efficient, it is well known (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.

In column (3) and (4) we deal with the possible correlation of X_{it} and ε_{it} . Again, given our sample size, we do not exploit all the over-identifying restrictions arising from the predetermination of the lagged values of X_{it} . In both specifications of the empirical

model there is a main change: the degree of unemployment persistence to shocks is even lower than the one estimated in the models in columns (1) and (2). There are not any substantial changes in the other estimated coefficients. This suggests that the endogeneity problems we suspected were not very serious, if it is at all present. The coefficient of t is also statistically unchanged but it is more precisely estimated and becomes significant at the ten-percent significant level. Again, for both models, we do not reject the null hypothesis of the validity of the over-identification restrictions nor the lack of autocorrelation in ε_{it} at the conventional levels of statistical confidence.

Given these findings, we prefer the estimates of column (1) and (2). Both finite sample theory and Monte Carlo results suggest that the instrumental variable estimator tends to become biased as the number of instruments increases, eventually approaching the ordinary least squares estimates. Note that the ordinary least square estimator of ρ in equation 3 is biased downward if ε_{it} is not serially correlated.

5. Conclusions

Argentina is an interesting case to study regional unemployment. Contrary to the European countries like Spain and UK, which exhibit a high degree of persistence in their relative regional unemployment rates, our findings reveal that Argentina has experienced significant changes in its unemployment ranking during the period studied. Surprisingly, the Argentine unemployment ranking appears to show even less persistence than the US ranking.

Thus, in this paper we show that the regional unemployment structure in Argentina during the period studied did not show much persistence. Thus, although during that period the economy suffered huge aggregate shocks that moved all regional unemployment rates together substantially (for example, in 1995 the estimated year effect is over 5 percentage points), the mere fact that the regional unemployment structure has changed dramatically proves that the regional determinants of unemployment have played a significant role in

the determination of regional unemployment. However, it is also worth to mention here that all our results are only valid for the period studied.

We also show that unemployment is a stationary process. This is a very important result. What is more, in a conditional model of the mean regional unemployment rates we find that the degree of persistence of unemployment to shocks is low, around 0.4. Thus, the changes in the regional unemployment structure occurred during the period studied have to be explained by changes in the regional determinants of unemployment. Additionally, we believe the measure of regional unemployment persistence we propose in this paper is better than the one commonly used in the literature and it is also justified by our analysis in section 2.

Finally, we find that the important variables in explaining the regional changes in unemployment are the industry mix, the labor force participation rate and the differences in the regional domestic gross product per employee. Additionally, we can also say that it is somewhat likely that the payroll tax affects positively unemployment.

Thus, we find some support for the compensating wage differential explanation of unemployment differences. However, as we pointed-out, it is also possible that this variable captures a short run effect of productivity on unemployment. Unfortunately, we cannot disentangle these two effects.

Indeed, it is always possible that also the industry mix impact on unemployment is also capturing medium term effects on unemployment and not necessarily equilibrium changes. Thus, it is worth remembering that during the period studied occurred severe changes in the industry mix.

In any case, the evidence we present in this paper permit us to conclude that the identified regional factors play an important role in the explaining the regional evolution of unemployment.

Appendix

The Levin-Lin test for a unit root in panel data

The test is a modification of the original augmented Dickey-Fuller test. Here, we provide an outline of the procedure. A detailed description of the test may be found in Levin and Lin (1993). Let Y_{it} $i = 1, \dots, N; t = 1, \dots, T$ be the unemployment rate for a panel of N regions observed over T periods. We assume that Y_{it} is generated by:

$$\Delta Y_{it} = \alpha_{0i} + \delta_i Y_{it-1}$$

that is, we allow for region specific intercepts but, according to the discussion in the paper, no time trend. We are interested in evaluating the null hypothesis that $\delta_i = 0$ for all regions. The Levin-Lin test proceeds in five steps, as follows:

Step 1: Subtract cross-section averages from data. From this step on, the analysis refers to these modified variables.

Step 2: Regress ΔY_{it} and Y_{it-1} on lags of ΔY_{it} and other deterministic variables that may affect the process (individual specific intercepts, in our case). Calculate the residuals of these regressions (called e_{it} and v_{it} , respectively). Note that by the Frisch-Waugh-Lovell Theorem (see Davidson and MacKinnon, 1993), the ADF unit root test would be based on the slope t-statistic of a regression of e_{it} on v_{it-1} . In order to control for heterogeneity across regions, e_{it} and v_{it} are normalized by the standard error of the regression of e_{it} on v_{it-1} . The normalized errors are denoted e_{it}^* and v_{it}^* .

Step 3: Estimate the ratio of long run to short-run standard deviations for each region, and calculate the average ratio for the panel. The formulae are given in Levin-Lin. We denote this quantity S^* .

Step 4: Compute the panel test statistic: regress e_{it}^* on v_{it-1}^* . Let t^* be the slope t-statistic, δ^* the estimated slope coefficient, σ^* the estimated standard error of the regression and RSE^* the estimated standard error of δ^* . The adjusted statistic is:

$$t_A = (t^* - NT^* S^* \sigma^{*-2} RSE^* \mu_A) / \sigma_A$$

which has a standard normal distribution (asymptotically) under the null hypothesis. T^* is the number of periods corrected for the number of observations dropped when computing lags and differences while μ_A and σ_A are mean and variance adjustments tabulated in Levin and Lin (1993) for a given specification.

Data Appendix

For the entire period 1980-1998, there is no homogeneous data available. In section 2, we use data for 22 regions for which it is available for the entire period. In section 3, we use data for 23 regions for which we have the entire data set used in section 4.

Description of Regions in figure 1:

Argentina: PO: Posadas; RG: Río Gallegos; MEN: Gran Mendoza; FO: Fomosa; SJ: Gran San Juan; SL: San Luis; LR: La Rioja; SE: Santiago del Estero; RE: Resistencia; CR: Comodoro Rivadavia; PA: Paraná; LP: Gran La Plata; COR: Gran Córdoba; CO: Corrientes; NE: Neuquén; RO: Gran Rosario; GBA: Gran Buenos Aires; SA: Salta; TUC: Gran San Miguel del Tucumán; SFE: Santa Fe; JU: S.S. de Jujuy.

United Kingdom: EA: East Anglia; SE: South East; SW: South West; EM: East Midlands; WM: West Midlands; Y&H: Yorkshire and Humberside; WAL: Wales; NW: North West; SCOT: Scotland; NOR: North; NIR: Northern Ireland.

Spain: LR: La Rioja; NAV: Navarra; BAL: Baleares; ARA: Aragón; GAL: Galicia; C-LM: Castilla-La Mancha; MAD: Madrid; CAT: Cataluña; C-LEON: Castilla-León; AST: Asturias; CANT: Cantabria; CVAL: Comunidad Valenciana; PVAS: País Vasco; MUR: Murcia; CANA: Canarias; EXT: Extremadura; AND: Andalucía.

Description of Variables

RGDPpC: gross geographical product per employee (source: SAREP and EPH); *Manufacturing*: employees as a percent of total employment in the manufacturing sector (EPH); *Trade*: employees as a percent of total employment in the trade sector (EPH); *Services*: employees as a percent of total employment in the service sector (EPH); *Construction*: employees as a percent of total employment in construction (EPH); *t*: payroll tax (Argentina's law); *Dfpr*: change in the regional labor force participation rate (EPH); *lfprsup*: labor force participation density (EPH).

Description of Data

The source for the regional data on labor force participation, employment and unemployment is:

EPH, Instituto Nacional de Estadísticas y Censos -INDEC-, 1980-1997.

The source for the regional data on gross geographical product is:

SAREP, Secretaría de Asistencia para la Reforma Provincial, 1980-1997.

The source for the regional data on payroll tax is Argentine law.

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