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Persistence and regional disparities in unemployment (Argentina 1980–1997)

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Abstract

We study the regional evolution of unemployment in Argentina for the period 1980–1997. First, we show that the Argentine regional unemployment structure is not very persistent. We find less persistence in Argentina than in the US. Second, we model the conditional means of regional unemployment and measure the persistence of unemployment to shocks based on our conditional model. We find a low degree of unemployment persistence to shocks. Finally, we identify regional factors that explain regional unemployment differences and whose changes account for the low persistence of the regional unemployment structure.

JEL classification: R23; J64; C23
Keywords: Regional unemployment; Structural dynamic models; Persistence; Panel data unit root tests and Argentina

1. Introduction

Unemployment rates differ among regions, and in many countries these differences persist over time. What determines these differences in regional unemployment rates? At a point in time, the observed differences in regional unemployment

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rates are the result of both differences in the equilibrium levels of unemployment and transitory factors. Two questions arise naturally. First, what determines equilibrium unemployment at the local level? Second, how persistent are regional unemployment shocks? We argue that these two questions have to be addressed simultaneously.

In this paper we study these questions using regional data from Argentina for the period 1980–1997. During this period, regional unemployment series present wide variability across both regions and time. Unlike European countries that exhibit a high degree of persistence in their regional unemployment structures, Argentina presents significant changes in its unemployment ranking; and unlike the US, these changes occurred in a period in which, on average, unemployment trended upward significantly. This wide variability in both the temporal and cross-section dimensions of regional unemployment provides a unique opportunity to study the determinants of equilibrium local unemployment and its dynamic structure. However, because of the properties of the series studied, it is inappropriate to study unemployment dynamics without specifying a model that also incorporates the other determinants of the unemployment series. Both questions have to be answered by the same structural model.

A highly related question has received much attention recently: what are the adjustment mechanisms of unemployment at the regional level? The degree of persistence of regional unemployment is found to be an important parameter in answering this question (see, among others, Blanchard and Katz, 1992; Decressin and Fatás, 1995). However, as we argue in this paper, at least in cases where the means of the regional unemployment series change over time, the identification of this parameter requires the specification of a dynamic model that explains the equilibrium unemployment differences across regions and time.

In addition, Argentina is a very interesting case study in itself since unemployment has become one of the main economic problems of the country. The country has moved from very high inflation with relatively low unemployment in the 1980s to low inflation and high unemployment in the 1990s. Unlike high inflation rates, unemployment rates are not homogeneous across regions. Aggregate unemployment rates are averages of their regional unemployment rates. Hence, temporal variations in the overall unemployment rate arise as a consequence of both country-wide effects on unemployment that affect all regions, and of changes in the regional structure of unemployment. Thus, our study also sheds light over some of the factors that increased unemployment. However, it is also worth noting at the onset that a study of regional unemployment does not identify other important factors, those common to all regions, affecting aggregate unemployment.

The rest of the paper is organized as follows. In Section 2, we study the degree of persistence of the regional structure of unemployment. Section 3 addresses the issue of whether or not unemployment is a stationary process. We apply to our unemployment series a test of the hypothesis of a unit root for panel data proposed by Levin et al. (2002). Then, in Section 4, we model the conditional means of the regional unemployment rates and explain the determinants of equilibrium unemployment by estimating a structural dynamic model, and based on our empirical model we propose an alternative measure of persistence. Our *conditional* measure is more appropriate than the one based on unconditional representations of the unemployment series because our measure of persistence takes account of both the changes in the conditional mean of the series and the likely persistence of the common shocks. Thus, our measure of persistence is not contaminated by changes in the mean level of unemployment. Therefore, our model answers the two questions of interest: what explains the equilibrium of the regional unemployment series and what is its dynamics? Section 5 analyzes wage flexibility at the regional level since it is likely to be the main factor behind the degree of persistence of shocks on local unemployment. Section 6 concludes.

2. The evolution of the regional unemployment structure

Countries show different patterns of regional unemployment. For example, in Fig. 1 we show that, in contrast to the cases of both the UK and Spain but similar to the case of the US, the structure of regional unemployment in Argentina does not present any persistence. To test this hypothesis we compute the rank correlation coefficient between the unemployment rankings. The Spearman coefficient is not statistically

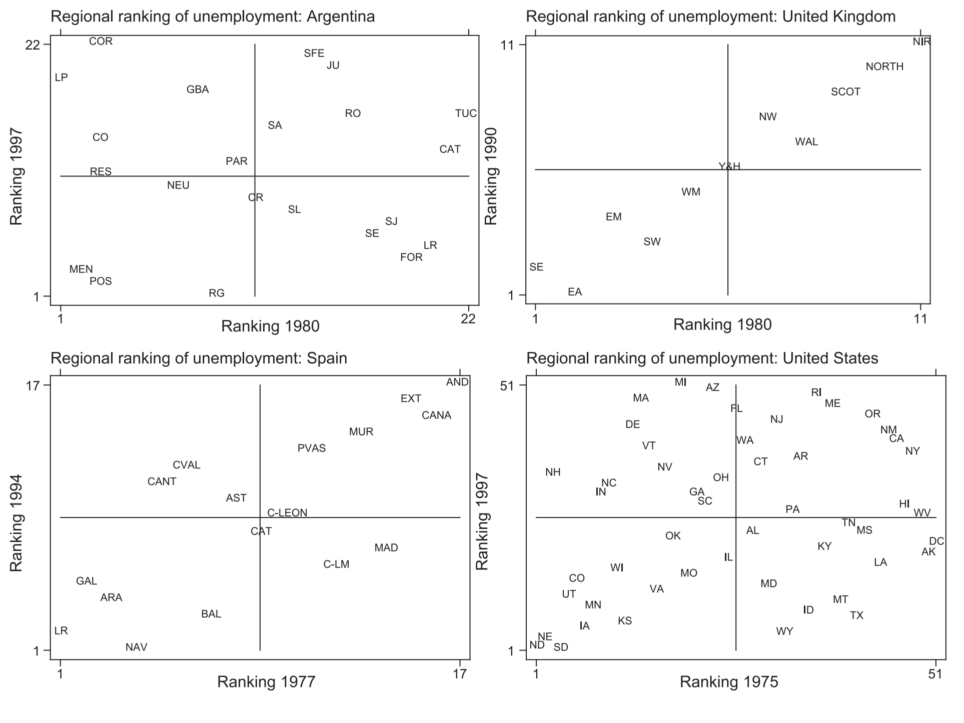


Fig. 1. Regional rankings correlations.

Table 1
Persistence of regional unemployment rankings in selected EU member countries, the US and Argentina: rank-order correlations, 1980–1994

	1981	1982	1985	1988	1990	1992	1994
UK	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
US	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

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: Table 1.3 in Martin (1997), and authors' elaboration.

significantly different from zero, indicating that the structure of the unemployment rates has changed significantly in Argentina between 1980 and 1997.

The regional structure of unemployment in the US has been extensively studied and found to be much less persistent than that of European countries (see Baddeley et al., 1998; Bertola and Ichino, 1995).[1] Table 1 presents rank-order correlations for several European countries, the US, and Argentina for selected years, clearly showing that Argentina presents even less persistence in its regional unemployment structure than the US.

In order to evaluate the dynamics of the changes in the regional unemployment structure, in Table 2 we compute Spearman correlations for unemployment rankings between all possible pairs of years in the period studied. First, we confirm the dramatic change in the regional unemployment structure of Argentina. There is no association between the relative unemployment situation at the beginning of the 1980s with that at the mid-1990s. Second, these changes never occurred abruptly; the unemployment structure never changed drastically in a period shorter than 5 years. Finally, the unemployment ranking changed relatively more in the early 1990s than in the 1980s. The Spearman coefficients between the beginning of the 1980s and the beginning of the 1990s range between 0.25 and 0.45 while the same statistic for the period 1991–1997 is 0.12.

To summarize, during the period studied the regional structure of unemployment in Argentina shows very low persistence; in fact, it is even less persistent than in the US. Moreover, this structure has changed during this period and these changes were

[1] Baddeley et al. (1998) explicitly test the presence of structural breaks in the regional structure of unemployment in the UK.

Table 2
Spearman correlation coefficients (1980–1997)

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
1980	1																	
1981	0.62	1																
1982	0.69	0.56	1															
1983	0.50	0.58	0.84	1														
1984	0.36	0.34	0.60	0.52	1													
1985	0.26	0.46	0.65	0.56	0.78	1												
1986	0.36	0.51	0.55	0.52	0.64	0.71	1											
1987	0.21	0.38	0.48	0.42	0.52	0.62	0.84	1										
1988	0.33	0.37	0.58	0.49	0.40	0.50	0.67	0.93	1									
1989	0.50	0.32	0.41	0.22	0.42	0.31	0.60	0.68	0.65	1								
1990	0.37	0.25	0.45	0.23	0.53	0.56	0.64	0.67	0.61	0.72	1							
1991	0.43	0.21	0.42	0.24	0.35	0.40	0.59	0.70	0.76	0.68	0.76	1						
1992	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					
1993	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				
1994	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			
1995	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		
1996	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	
1997	−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

stronger during the early 1990s, coinciding with a period of structural reform in the country. Additionally, it is worth noting that unemployment trended up dramatically during the period studied and the range of variability in the regional unemployment rates increased, pari passu.

3. Testing for unit roots in regional unemployment

A standard fact about unemployment is that over the very long term it is untrended, that is, unemployment is not adequately represented by an $I(1)$ random walk with drift process. However, the question remains as to whether unemployment may be a non-trended $I(1)$ process like a standard random walk. In such case, the unemployment series would have a non-stationary degree of persistence. 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 do not, in most cases, 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, unit root tests tend to lack power in very small samples; thus, they tend not to reject the null hypothesis at all when it is false, even though they may reject it when it is true. Second, 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 towards the non-rejection of the null hypothesis when it is false (see Perron, 1989).

This section tests whether the regional absolute unemployment rates are $I(1)$.[2] Our sample size makes large sample based inference using standard unit root tests unreliable. 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 et al. (2002) test for unit roots in panel data, which has been extensively used in practice. The test procedure 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 et al., 2002).

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. 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 outlined above, we discard the possibility of a trend in the unemployment process, but we allow for a non-zero mean in the unemployment rate under the alternative hypothesis.

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 suggests that the null should be rejected. It is worth mentioning that the possible low power of the Levin–Lin test for the small sample available should have biased the result toward accepting the null, contrary to our result. Thus, armed with this result, in the next section we proceed to model the conditional means of the regional unemployment series.

4. A dynamic model of regional unemployment

In this section, we search for a dynamic model of regional unemployment. The goal is twofold. On the one hand, we require the model to help us explain the changes in the regional structure of unemployment. On the other hand, we believe that a structural

[2] Blanchard and Katz (1992) and Decressin and Fatás (1995) test the null hypothesis of a unit root in regional relative (to the aggregate) unemployment rate series for Europe and the US, respectively, using Dickey–Fuller type tests for each series. For most regions, they do not reject the null hypothesis of a unit root in the regional relative unemployment rates. Because the null hypothesis was unlikely in the first place, both papers ignore these results and pursue their analysis assuming stationarity in the relative regional unemployment rates.

dynamic model provides a better measure of the regional unemployment persistence to regional shocks than the one provided by the sum of the coefficients in a univariate autoregressive model.

Summers (1986) points out that differences in regional unemployment seem to be associated with different industry evolutions located heterogeneously across a country. For example, in Europe, many of the regions specializing in mining, steel, textiles and heavy manufacturing industries 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 reallocation of workers in the same region, the regions most affected by the contraction in traditional industries 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 1970s and 1980s in Europe (see Layard et al., 1991). 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 evidence showing that the industry composition of regions played a major role in explaining the regional variability of unemployment. Baussola and Fiorito (1994) report this result for Italy.

Marston (1985) presents 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. Nevertheless, 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.

Thus, previous theoretical and empirical work suggests that regional differences in unemployment are explained by equilibrium equalizing amenity differences, compensating wage differentials and 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 to both 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. Methodological considerations

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

$$u_{it} = \alpha_{1i} + \alpha_2(L)u_{it-1} + v_{it} \tag{1}$$

where u_{it} is alternatively the difference between the unemployment rate in region i and the national unemployment rate in period t, or just the unemployment rate in region i and period t,[3] using a lag polynomial of order 2. In the former case, they find that the US shows more persistence than Europe while, in the latter case, they find exactly the opposite. The authors suggest that this result is 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 model regional unemployment by means of a dynamic fixed effect two-way error component model of the form:

$$u_{it} = \rho(L)u_{it-1} + \beta(L)X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

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

Thus, this empirical model may explain the changes in the regional unemployment structure. Additionally, assuming that the covariates included in the model are strongly exogenous for $\beta(L)$ and $\rho(L)$ (Engle et al., 1983), $\rho(L)$ identifies the true persistence of the shocks into the unemployment series and, hence, it is a better measure of this persistence than $\alpha_2(L)$. To see why, let us assume that Eq. (2) generates the data (i.e., it is the data generating process) but $\rho(L)$ is a zero vector. Assume further that the X's are persistent series. The estimate of α_2 in model (1) picks up the persistence of the X's and confounds it with the persistence of the shocks of the unemployment series. As a result, to obtain consistent estimates of the persistence of regional unemployment to pure regional shocks, one should estimate model (2) instead.

In terms of the estimation of model (2), 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.

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 (Eq. (2)). We apply this transformation instead of the within-group transformation because the ordinary least squares estimator is semi-inconsistent in the latter case (see Nickell, 1981). Thus, we obtain:

$$\Delta u_{it} = \rho(L)\Delta u_{it-1} + \beta(L)\Delta X_{it} + \phi_t + \Delta\varepsilon_{it} \tag{3}$$

Note, however, that in Eq. (3), Δu_{it-1} is correlated with the equation error, $\Delta\varepsilon_{it}$. Additionally, X_{it} and ε_{it} may also be correlated. Consider, for example, the industry mix variables. A regional demand shock that affects regional employment and unemployment

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

would likely affect the industry mix. As long as ε_{it} is serially uncorrelated, 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 Eq. (2), the model implies the following linear moment restrictions:

$$E(\Delta\varepsilon_{it}u_{it-j}) = 0 \text{ and } E(\Delta\varepsilon_{it}z_{it-j}) = 0 \qquad (j = 2, \ldots, t-1;\ t = 3, \ldots, T) \tag{4}$$

where z is a vector of the X's variables, and the expectations are conditional on the covariates and the fixed effects. In addition, it is necessary to make a standard assumption concerning the initial condition, u_{i1} (see Ahn and Schmidt, 1995). Arellano and Bond (1991) propose a generalized method of moments (GMM) estimator that exploits these linear moment restrictions generated by the serially uncorrelated error. We apply this linear estimator to estimate Eq. (3).

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 statistically 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) develop tests for first- and second-order correlations in the differenced residuals. These tests are asymptotically standard normal distributed under the null hypothesis of no serial correlation. More generally, we compute Sargan tests of over-identifying restrictions to evaluate the specification of the model. Under the null hypothesis, the instruments are not correlated with the residuals in the first-difference equation and the test statistic is asymptotically distributed chi-squared with as many degrees of freedom as over-identifying restrictions are imposed in the estimation of the model.

4.2. Econometric results

Our dataset covers the period 1985–1997 (see Appendix A). The main source of data used in this paper is the Permanent Household Survey conducted by the Argentine National Institute of Statistics and Census (INDEC). This survey, which is similar to the CPS in the US, is a large national survey comprised of interviews of 30,000 households in each wave. It is stratified at the regional level and all the sample statistics derived from this survey are precisely estimated at that level, which is the one used in this paper.

Our empirical specifications include as covariates the following set of variables, all of which vary across both regions and time. (1) *The industry mix.* There is evidence that shows that the cyclical response of unemployment differs among regions depending on their industry mix. We have two alternative proxies for this variable; the ratio of tradable goods to non-tradable goods (tnt), and the share of employment in five main aggregate sectors: manufacturing, trade, services, construction and other sectors. There are good reasons to enter them in the empirical models dynamically. First, most applied work that only analyzes the static impact of industry mix on local unemployment finds no effect at all (see Elhorst, 2003). Additionally, and more importantly, it is likely that the impact of a shock on unemployment will depend on the employment composition before the shock occurs while the shock itself will affect both unemployment and the employment composition.

(2) *Real Gross geographical product per capita (RGDPpC).* This is a measure of partial labor regional productivity. Unemployment rates viewed over the long-run are untrended despite the tremendous increases in productivity which occurred in the last century. As Blanchard and Katz (1997) state, 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 associated with structural change may impact unemployment positively (see Mortensen and Pissarides, 1994). Thus, a process of economic restructuring that induces an increase in productivity is prone to be associated with an increase in unemployment for a while (see also Aghion and Howitt, 1994). This is likely to be the case in our study since during the period studied, the economy went trough a large process of structural change associated to trade liberalization, privatization of state-owned enterprises, wide deregulation of markets and openness to foreign investment. This process surely had a differential impact among regions. This is the main reason to include this variable among the set of regressors.

(3) *Labor taxes.* 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) suggests 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 (Ptax), which were differentiated by regions. We expect the identified impact on unemployment to be positive. A very important feature of the changes in the payroll tax is that they are not a response to the regional unemployment structure and, hence, we treat them as exogenous at the regional level.[4] Finally, Taylor and Bradley (1997) suggest that labor costs also 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 will 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, Δlfpr. We also enter this variable with lags in our models.

(5) *Regional differences in skills levels.* We measure this factor by the school achievement level of the labor force. We use the following categories. Unskilled: the proportion of members in the labor force with less than secondary school diplomas. Semi-skilled: the proportion of members in the labor force who have completed secondary school. The left-out category is the proportion of skilled workers.

[4] Of course, this policy was introduced to stimulate employment creation. However, the payroll tax is established by the Federal Government, not by regional governments, and the changes in payroll taxes were established using the distance of each region to the Federal Capital. For example, payroll taxes decreased less in regions closer to the Federal Capital than those located farther away. Thus, they were unrelated to the shocks to unemployment at the local level, i.e., ε_{it} in Eq. (2), even though, they might have been related to the fixed effect in that equation.

Table 3
Dynamic regional unemployment equations: 1988–1997

Independent variables	GMM (first-differences) (1)	GMM (first-differences) (2)	GMM (first-differences) (3)
U_{it-1}	0.39 (0.12)***	0.43 (0.11)***	0.26 (0.10)***
RGDPpC_{it}	4.73 (1.58) ***	–	5.13 (1.84)***
$\text{Manufacturing}_{it-1}$	− 0.10 (0.09)	− 0.07 (0.09)	− 0.09 (0.11)
$\text{Manufacturing}_{it-2}$	− 0.03 (0.11)	− 0.05 (0.10)	0.02 (0.10)
Trade_{it-1}	− 0.09 (0.08)	− 0.08 (0.08)	− 0.06 (0.09)
Trade_{it-2}	0.34 (0.09)***	0.34 (0.09)***	0.32 (0.08)***
Services_{it-1}	− 0.09 (0.07)	− 0.07 (0.06)	− 0.09 (0.05)*
Services_{it-2}	− 0.03 (0.06)	− 0.04 (0.05)	0.01 (0.06)
$\text{Construction}_{it-1}$	0.005 (0.13)	0.04 (0.13)	0.02 (0.14)
$\text{Construction}_{it-2}$	0.14 (0.14)	0.13 (0.14)	0.19 (0.11)*
Ptax_{it--1}	16.5 (11.2)	17.1 (10.8)	18.8 (10.6)*
Δlfpr_{it}	0.35 (0.10)***	0.38 (0.09)***	0.28 (0.12)**
Δlfpr_{it-1}	0.13 (0.07)*	0.14 (0.07)**	0.14 (0.07)**
Equation standard error	1.56	1.57	1.47
Sargan test	0.15	0.08	0.07
m_1	0.001	0.001	0.001
m_2	0.13	0.16	0.13
Number of observations	230	230	230

Dependent variable: U_{it} (unemployment rate (%) in region i in period t).
Time dummies are included in all equations. Asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses. For the Sargan, m_1 and m_2 tests, the statistics reported are the p-values. The equation standard error refers to the equation in levels.
Columns (1) and (2): the basic instrument set is of the form $Zi = \text{diag}[U_{i1},\ldots,U_{is}: \Delta X_{is+j}]$ $(s=1,\ldots,11)$, where X_{it} is the matrix of covariates of individual i in period t, and where $j=0,1,2$.
Column (3): the basic instrument set is of the form $Zi = \text{diag}[U_{i1},\ldots,U_{is}, m_{is}, \text{tr}_{is}, s_{is}, c_{is}, \text{lfpr}_{is-1}, \text{lfpr}_{is}: \Delta m_{is}, \Delta\text{tr}_{is}, \Delta s_{is}, \Delta c_{is}, \Delta\text{RGDPpE}_{is}, \Delta t_{is+1}]$ $(s=1,\ldots,11)$.
* Statistically different from zero at the 0.10 level of significance.
** Statistically different from zero at the 0.05 level of significance.
*** Statistically different from zero at the 0.01 level of significance.

For the period studied in this section, we have a balanced panel of 23 regions. Three cross-sections are lost in constructing lags and taking first differences, so the estimation period is 1988–1997. We begin by estimating unrestricted models. Unemployment lagged twice was never statistically significant and, 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. The same result holds for the schooling variables and for the current values of the industry mix and labor taxes.

In Table 3, we present the results of our preferred restricted specification for the regional unemployment models. In column (1), we only instrument the lagged dependent variable. Here, all variables other than the lagged dependent variables are assumed to be predetermined although, given our sample size, none of the over-identifying restrictions that follow from this assumption are exploited.[5] For the model

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

in column (1), 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 3 are one-step estimates. Although there exist two-steps 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.

In column (2), we exclude from the model GDPpC. The coefficient of lagged unemployment slightly increases, as we argued it is the case when a persistent non-ignorable variable is omitted from the model. Nevertheless, the other coefficients do not change significantly. In column (3), we deal with the possible correlation between 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}. The degree of unemployment persistence to shocks is even lower than the one estimated in the model in column (1). There are not any substantial changes in the other estimated coefficients. This suggests that the endogeneity of the X's is not a concern in this case. The coefficient of Ptax is also unchanged but it is more precisely estimated and becomes statistically significant at the 10% level of significance. Again, we do not reject the null hypothesis of the validity of the over-identification restrictions nor the lack of autocorrelation in ε_{it} at conventional levels of statistical significance.

In summary, we find a low autocorrelation coefficient in the regional unemployment series after conditioning on the set of X's that also determines the series, year and region fixed effects. After a year, only 40% of a regional shock to unemployment will be affecting regional unemployment. Consider a specific shock to region j equal to the equation standard error. During the year of the shock, unemployment in region j would increase 1.56 percentage points. A year later, unemployment would be, ceteris paribus, only 0.61 percentage points higher than its level before the shock while 2 years later it would be only 0.24 percentage points above its pre-shock level. Consequently, unemployment, at the regional level, presents a very low persistence to idiosyncratic shocks.[6] In Section 2, we established that the regional unemployment structure in Argentina is not very persistent. Of course, it is not altered by aggregate common shocks but, nevertheless, regional shocks may also be large. If these regional shocks or their effect on unemployment were persistent, they might explain by themselves the low persistence of the regional unemployment structure. However, 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 determinants of equilibrium unemployment.

Turning to the determinants of equilibrium unemployment differences, we find that the regional gross domestic product per capita, once we control by regional fixed effects and regional differences in skill levels, affects unemployment positively. This likely

[6] Nevertheless, it is worth noting that other studies that attempt to identify this parameter do not use the same identification strategy implemented in this paper and hence, we do not have a clear cut reference for comparison.

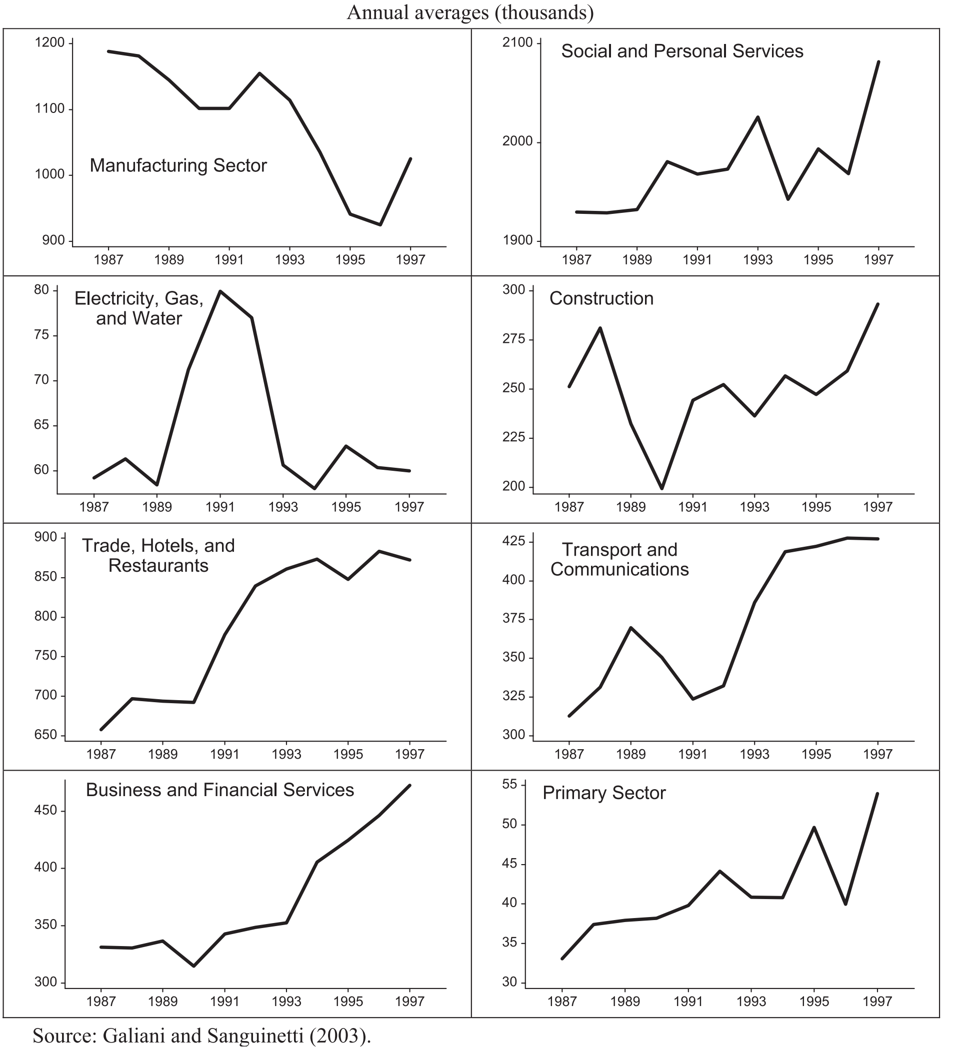
reflects an out-of-equilibrium phenomenon. We argue that this effect captures the process of creative destruction induced by the intense reforms adopted during the period studied (see Aghion and Howitt, 1994). Additionally, we find that regions with higher employment shares in trade and construction have higher equilibrium unemployment. The payroll tax appears to be positively related to the unemployment rate. Thus, a reduction in the payroll taxes would presumably reduce unemployment. Finally, we find a positive statistically significant impact of the current and lagged changes in labor supply on unemployment. This latter effect is transitory in nature, since female labor force participation rates cannot increase forever. However, during the period studied, on average, and with appreciable differences across regions, female participation rates increased.

As it was already mentioned, during the 1990s, Argentina made considerable progress in implementing market-oriented structural reforms. The reform package was based on three pillars: (a) a large opening of the economy; (b) an ambitious privatization and deregulation program; and (c) the stabilization of prices based on a predetermined nominal exchange rate anchor, instrumented by implementing a monetary currency board in 1991. A natural question arises: how did these reforms affect regional unemployment?

The answer to this question is not directly estimated in our structural model but, to some extent, it may be inferred from it by relying on auxiliary information.[7] Certainly, reforms (a) and (b) caused a change in the industry mix (see Fig. 2). Galiani and Sanguinetti (2003) show a link between trade liberalization and employment in the manufacturing sector while Galiani et al. (in press) demonstrate that privatization caused a reduction of 50% in the employment of the privatized firms (mainly clustered in the manufacturing and electricity, gas and water sectors). Nevertheless, it is worth noting that total employment in the privatized firms was only a small share in total employment. Interestingly enough, the sector that grew the most during the 1990s is the trade sector. Thus, the changes in the industry-mix induced by the reforms adopted during the 1990s affected regional unemployment. What is more, this effect was not minor.

To evaluate the impact of the changes in the industry-mix on regional unemployment, we divide it in a short-run impact (first 2 years) and a long-run impact. Consider the main urban agglomerate, GBA, which moved substantially up in the ranking of unemployment during this period, and that by itself explains approximately 50% of the aggregate labor market outcomes. We take the magnitude of the change in the employment mix between 1985 and 1997 as a once-and-for-all change. Its immediate impact on unemployment was 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 permanent change in the industry mix appears to be substantial. Moreover, the long-run increase in unemployment is approximately 2.4 percentage points. This change represents an increase in the main urban agglomerate unemployment rate of approximately 45% with respect to its 1985 figure, and suggests that the impact of the reforms adopted on the 1990s on regional unemployment might have been substantial.

[7] Clearly, to answer this question directly, a reduced form equation needs to be estimated instead. However, it is not clear how to do this exercise since these reforms were implemented nationally, not regionally.

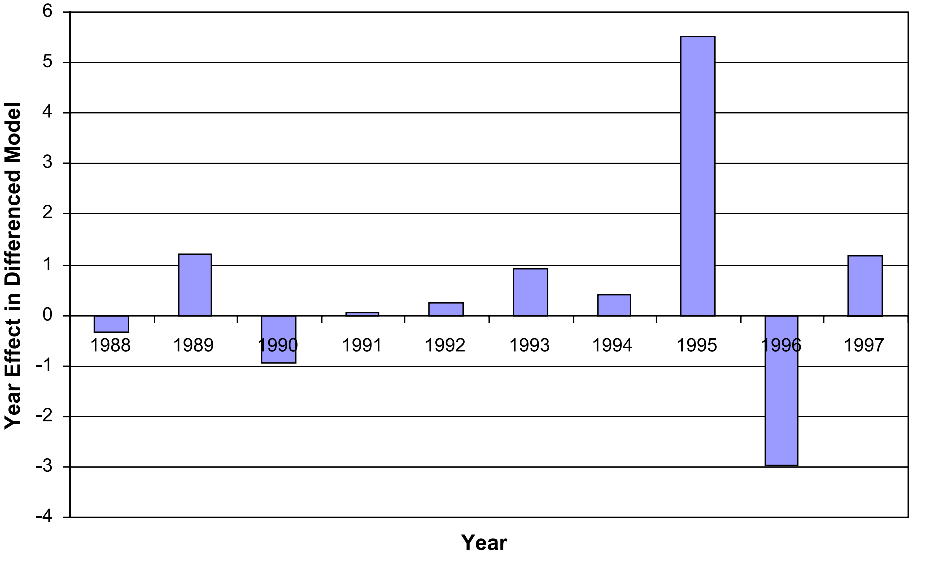


Source: Galiani and Sanguinetti (2003).

Fig. 2. Employment by sector: employees.

In addition, GBA is among the regions least benefited by the tax reductions; it is the region that experienced the highest increase in labor force participation, and it is also among the regions that experienced the highest increases in the gross domestic product per capita, which was also partially affected by the reforms adopted during the period. Therefore, our model is able to explain why this agglomerate has moved up in the unemployment ranking.

Finally, during the 1990s unemployment went through the roof in Argentina. To a large extent, this was caused by the deep recession induced by the financial crisis of 1995. The



Note: Year effects from the model in Table 3, Column 1.

Fig. 3. Aggregate shocks to unemployment.

year effects from our model show this result (see Fig. 3).[8] Nevertheless, before 1995, unemployment increased by approximately 5 percentage points. This is the period in which the regional unemployment structure changed the most and, hence, it would be possible to attribute this increase in unemployment to the structural changes that took place in the economy during this period. Indeed, the large jump in unemployment before 1995 is not captured by the year effects in the model, proving this point (see Fig. 3).

5. Regional wages

It is well known that the degree of persistence of the shocks to unemployment is decreasing in the responsiveness of unemployment to wages (see Layard et al., 1991). In this section, we investigate the responsiveness of local wages to local unemployment.

Consider the following dynamic specification for regional wages:

$$w_{it} = \varphi w_{it-1} - \beta u_{it-1} + \lambda_t + \mu_t + \varepsilon_{it} \tag{5}$$

where w_{it} is the logarithm of regional wages and u_{it} is the logarithm of the regional unemployment rate. Model (5) is known in the literature as a dynamic wage curve after the work of Blanchflower and Oswald (1994).

[8] It is worth noting that the estimated year effects in our model are the differenced year effects and, hence, they capture the common change in unemployment between two subsequent years.

Table 4
Dynamic wage equations

Independent variable	GMM (first-differences) (1)	GMM (first-differences) (2)
Log W_{it-1}	0.53 (0.09)***	0.48 (0.09)***
Log U_{it-1}	− 0.046 (0.021)**	− 0.057 (0.035)*
Equation standard error	0.041	0.039
Sargan test	0.79	0.26
m_1 (first-order serial correlation test)	0.001	0.001
m_2 (second-order serial correlation test)	0.18	0.34
Number of observations	325	325

Dependent variable: Log of hourly wages (Log W).
Log U_i is the logarithm of the regional unemployment rate for males. Time dummies are included in all equations. Asymptotic standard errors robust to general cross-section and time series heteroskedasticity are reported in parentheses. The GMM estimates are all one-step estimates. For the Sargan, m_1 and m_2 tests, the statistic reported is the p-value. The equation standard error refers to the equation in levels.
Column (1): the basic instrument set is of the form $\mathrm{Zi} = \mathrm{diag}[w_{i1},\ldots,w_{is}: \Delta u_{is+1}]$ ($s = 1,\ldots,14$), where x_{it} is the vector of predetermined variables included in the regression, where $s = 1,\ldots,16$.
Column (2): the instrument set is of the form $\mathrm{Zi} = \mathrm{diag}[w_{i1},\ldots,w_{is}, \Delta u_{is}, \Delta \mathrm{lfpr}_{is+2}]$ ($s = 1,\ldots,14$), where lfpr_{it} is the labor force participation rate in region i in period t, and where in the information set there is unemployment data for $s = 0$.
* Statistically different from zero at the 0.1 level of significance.
** Statistically different from zero at the 0.05 level of significance.
*** Statistically different from zero at the 0.01 level of significance.

Table 4 presents our estimates of Eq. (5) for the period 1990–1997. The dataset used is obtained from the microdata tapes of the Argentine household survey.[9] Since the survey is conducted twice per year, we have 16 cross-sections available. We estimate our model using the data for employees who report monthly earnings and have only one job. The dependent variable is the hourly wage.[10]

Following Blanchard and Katz (1997), we estimate Eq. (5) in two steps. In the first step, we estimate a conditional expectation function for hourly wages. We assume, as 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. While these are by no means an exhaustive set of controls, we know that they are the most important explanatory variables in standard cross-section wage equations. In the second step, we estimate model (5), using the first step expected regional wages as the dependent variable. Model (5) is also estimated using the estimator proposed in Arellano and Bond (1991) (see Section 4.1).

The coefficient on the lagged dependent variable shows a positive correlation of regional earnings. It is approximately 0.5. In column (1), u_{it-1} is at least (implicitly)

[9] Unfortunately, microdata tapes are only available since 1990.
[10] Additionally, we exclude, in every wave of the survey, some observations of individuals who report an extremely high number of hours worked per week.

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 residuals of the model at the conventional levels of statistical confidence. The estimated unemployment elasticity of pay is -0.046 and it is statistically different from zero at the 5% level of significance.

In column (2), we deal with the possible correlation of u_{it-1} and ε_{it}. We first use the first difference of the lagged unemployment as an instrument in the differenced equations we estimate since this is the standard response. The unemployment elasticity of pay increases. We then add as a second instrument, the first difference of the regional labor force participation rates. 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 residuals of the model. Considering our preferred specification in column (2), we find that the short-run unemployment elasticity of hourly pay is -0.057 and it is statistically significant.

It is interesting to compare our findings with the results reported in Bell (1997a,b). For US, for the period 1980–1991, he finds an autoregressive 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. Thus, the short-run regional unemployment elasticity of regional pay in Argentina is similar to the one estimated by the US. However, the long-run regional unemployment elasticity of regional pay is higher in US than in Argentina. For UK, for the period 1975–1995, he finds an autoregressive coefficient equal to 0.71 and an unemployment elasticity of pay coefficient equal to -0.014. The dependent variable is the monthly wage. Thus, both the short- and long-run regional unemployment elasticities of regional pay in UK are lower than the respective elasticities in Argentina.

6. Conclusions

In this paper we study what determines equilibrium unemployment at a local level and how persistent regional unemployment shocks are using regional data from Argentina. The wide variability in both the temporal and cross-section dimensions provides a unique opportunity to study the determinants and dynamics of regional unemployment. However, because of the properties of the series studied, it is inappropriate to study unemployment dynamics without specifying a model that also incorporates the other determinants of the unemployment series. Both issues have to be answered by a conditional model. We believe that the proposed specification is preferred to the one commonly used in the literature, based on unconditional models, since it does not confound persistence of unemployment shocks with persistence of the regional determinants of unemployment.

In contrast to UK and Spain, but similar to US, the structure of regional unemployment in Argentina does not present much persistence. Though the economy suffered huge aggregate shocks that moved local unemployment rates together substantially, the fact that the regional unemployment structure has changed dramatically proves that regional determinants of unemployment have played a significant role. We find that the industry mix, the labor force participation rate and the differences in the regional domestic gross product per capita are quite important in explaining the changes in regional unemployment. Although the effect of reforms is not directly estimated in our model, we indicate that trade liberalization and privatization might have changed the industry mix and output per capita, and consequently affected regional unemployment structure. We also state that it is likely that the payroll tax affects unemployment positively. Indeed, the evidence presented in this paper allows us to conclude that the identified regional factors play an important role in explaining the regional evolution of unemployment.

We also show that unemployment is not a unit root process, which is an important result since previous evidence is non-conclusive on this fact. Then, 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 that took place during the period studied is explained by changes in the regional determinants of unemployment.

Finally, we also identified that one of the reasons why regional unemployment shocks display low persistence on local unemployment is that the regional unemployment elasticity of regional pay in Argentina is high and comparable to the one estimated in the literature for the US and UK.

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Appendix A. Data appendix

A.1. Description of regions in Fig. 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.

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.

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

US: AL: Alabama; AK: Alaska; AZ: Arizona; AR: Arkansas; CA: California; CO: Colorado; CT: Connecticut; DE: Delaware; DC: District of Columbia; FL: Florida; GA: Georgia; HI: Hawaii; ID: Idaho; IL: Illinois; IN: Indiana; IA: Iowa; KS: Kansas; KY: Kentucky; LA: Louisiana; ME: Maine; MD: Maryland; MA: Massachusetts; MI: Michigan; MN: Minnesota; MS: Mississippi; MO: Missouri; MT: Montana; NE: Nebraska; NV: Nevada; NH: New Hampshire; NJ: New Jersey; NM: New Mexico; NY: New York; NC: North Carolina; ND: North Dakota; OH: Ohio; OK: Oklahoma; OR: Oregon; PA: Pennsylvania; RI: Rhode Island; SC: South Carolina; SD: South Dakota; TN: Tennessee; TX: Texas; UT: Utah; VT: Vermont; VA: Virginia; WA: Washington; WV: West Virginia; WI: Wisconsin; WY: Wyoming.

A.2. 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 the Argentine law.

A.3. Description of variables

RGDPpC: gross geographical product per capita (SAREP); 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); Ptax*:* payroll tax (Argentina's law); Δlfpr*:* change in the regional labor force participation rate (EPH).

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