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Abstract ampliado

RESUMEN AMPLIADO

Title: Spatial heterogeneity in the Spanish labour market after the Great Recession

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Economic downturns have a deep impact on regional labour markets, with varying effects and responses. The depth and diversity of such reactions have been evident since the 2008 Great Recession, as job losses and unemployment skyrocketed and local labour markets became sluggish for several years. The concept of resilience entered economic discourse as key tool to describe responses to shocks to local economies. Martin and Sunley (2015) describe three main interpretations of the concept: engineering resilience (the ability to recuperate from a shock), ecological resilience (changes in growth patterns after a shock), and adaptive resilience (course changes in economic activity after a shock).

As highlighted by Ubago Martínez et al. (2019), there are no standards for measuring resilience, although measures of employment outcomes are commonly used, as employment takes longer to recuperate than output, it is not dependent on deflation, and it is statistically stable (Martin, 2012, Di Caro, 2015 and Sensier et al., 2016). Moreover, considering employment allows for an accounting of the determinants of resilience (Fratesi and Perucca, 2018) and contributes to the study of labour market conditions (Eriksson and Hane-Weijman, 2017). Other works use alternative indicators to capture resilience: Lewin et al. (2018) use



personal income data, Pontarollo and Serpieri (2020a, 2020b) use GDP per capita, and several other use composite indicators of economic and employment outcomes (Rizzi et al., 2018, Ubago Martínez et al., 2019).

Interestingly, most analysis of the impact of the Great Recession has concentrated on the analysis of output or employment measures and not on unemployment, with the exception of those estimating the so-called Okun's law (see, for instance, Groot et al. 2011). Our paper departs from this literature,¹ as we investigate how the global shock affected the stability of the wage curve, i.e., the negative relationship between regional unemployment and the real wage level, for the Spanish labour market. Following the seminal works of Blanchflower and Oswald (1990, 1994, 2005) and the meta-analysis of Nijkamp and Poot (2005), a consensus has emerged (an empirical law of economics, according to Card, 1995) on a stable long-term elasticity of wages with respect to regional unemployment, which has been averaged between -0.07 and -0.1, although there are substantial disparities over population and employment groups.

The wage curve parameter can be analysed as a measurement of wage flexibility, as strong and fast wage responses to growth in unemployment can lead to lower rates of unemployment, and consequently, to a faster recovery from economic shocks (Johansen et al., 2019). Consequently, our work allows for a novel inspection of resilience. We do not analyse employment or economic outcomes, but the underlying mechanism of efficiency in labour markets, which is behind regional recoverability. We try to better understand previous results in the literature, such as that more developed economies are expected to be more resilient (Deller and Watson, 2016).

¹ Monastiriotis and Martelli (2021) also adopt a different approach to examine adjustments to shocks in Greek regions during the Great Recession. Using micro-data from the Greek Labour Force Survey (LFS) they first estimate the contribution of various individual and household characteristics to individual unemployment risk during and after the crisis. Next they apply a decomposition analysis to identify the relative contribution of the shock, compositional effects, and price adjustments.

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Our work is innovative in several ways. First, it is the first to implement a flexible approach to the wage curve, both in terms of all spatial and time units, using Geographical and Temporal Weighted Regression (GTWR) techniques. Second, we implement the analysis over a full economic cycle of the Spanish economy, starting in 2002 and ending in 2018, once the economic recovery after the Great Recession was fully stabilised. Third, we link the study of labour market flexibility with the literature on resilience, as we study the association between wages and unemployment within the framework of the wage curve in a very interesting period from a policy perspective, as the strategy of the Spanish government was precisely to increase wage flexibility as a way to restore international competitiveness during the crisis.

For carrying this job, we focus on the analysis of wage curve elasticities as a measure of the efficiency and adaptation resilience of Spanish local labour markets by estimating local responses to the changing labour market conditions. As a consequence, our empirical approach involves estimating local wage curves, assuming spatial heterogeneity in local labour markets. In this sense, Blanchflower and Oswald's (1990, 1994) specification of the wage curve consisted of a regression of the logarithm of individual wages on a number of control variables related to individual and job characteristics and the regional unemployment rate. However, as Moulton (1986) demonstrates, the OLS estimation of this equation, which includes a variable of interest (unemployment rate) that is defined at a higher level of aggregation than the dependent variable (individual), will bias the values of the test of individual significance for this variable upward. Moreover, the inclusion of additional variables in order to correct for the possible omission of relevant variables at the regional level usually induces collinearity problems.

For these reasons, the standard approach in more recent literature consists of applying a two-step procedure, as in Bell et al. (2002) and more recently in Ramos et al. (2015) for the Spanish case. The first step consists of a Mincer equation estimated at the individual level, including controls at the individual and the firm level and time-varying regional dummies. These dummies can be interpreted as



adjusted wages in the local labour market, corrected for composition effects. In particular, the first step of the procedure involves estimating the following equation:

$$\ln(w_{irt}) = \alpha Z_{irt} + \delta_{rt} + \pi_t + \theta_r + \varepsilon_{irt} \quad (1)$$

where $\ln(w_{irt})$ is the natural logarithm of the wage of individual i who lives in region r at time t ; Z_{irt} is a set of individual factors that can affect the individual's wages, such as the level of schooling, his/her experience, or other characteristics such as occupation; π_t and θ_r are monadic period and region fixed effects; while δ_{rt} are region-period dyadic specific effects that can be interpreted as average wages in region r at time t corrected for composition effects and free of global business cycle and region fixed effects. Finally, ε_{irt} is a random error term that follows a normal distribution with zero mean and constant variance.

In the second step, the wage curve is estimated using the composition corrected wages δ_{rt} obtained in the first step, as the endogenous variable and the natural logarithm of the regional unemployment $\ln(u_{rt})$ is introduced as an explanatory variable together with time fixed effects γ_t , that control for all common shocks to the considered regions; regional fixed effects δ_r , capturing unobservable regional heterogeneity; and additional time varying regional characteristics Z_{rt} that can also affect regional wages, such as aggregate regional productivity:

$$\widehat{\delta}_{rt} = \beta \ln(u_{rt}) + \theta Z_{rt} + \gamma_t + \delta_r + v_{rt} \quad (2)$$

Usually, this second equation is estimated by OLS or instrumental variables procedures, depending on the assumption of the endogeneity of the level of unemployment on wage formation. There is a vast body of literature developing spatial analysis in order to capture the spatial nature of the association. Nevertheless, we are not interested in the estimation of the elasticity of the wage



curve alone. We want to describe the local response of every administrative region, which we see as a strong enough approximation to every local labour market, during the Great Recession. Consequently, we are interested in the local heterogeneity of such elasticity.

Several works have been focused on the study of the spatial heterogeneity of the wage curve. Longhi et al. (2006) hypothesise that the cause of spatial non-stationarity is differentiated labour market accessibility, and that this parameter can be stronger in rural than in urban areas. Both Longhi et al. (2006) and Deller (2011) estimate cross section Geographic Weighted Regressions (GWR) to show local heterogeneity in the wage curve, finding important differences over the space. Other works consider heterogeneity from different points of view, including rural-urban (Baltagi and Rokicki, 2014; Jokinen, 2020), level of development (Bande et al., 2012), and time (Devicienti et al., 2008, Daouli et al., 2017).

In our work, we simultaneously consider a double source of heterogeneity. Specifically, we use a GTWR approach to simultaneously account for spatial and time heterogeneity in the estimation of equation (2). GTWR (Huang et al., 2010, Wu et al., 2014, Fotheringham et al., 2015) is an extension of GWR accounting for local effects in both space and time. The main advantage of the chosen approach is that time effects are not constrained to being constant over space. This technique extends the traditional regression framework and assumes the existence of non-stationarity. In addition to GWR, time is also a variable considered in the weighting scheme of the estimation. The GTWR can be expressed as:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad (3)$$

The parameters will vary in space and time, and the estimation is based on a weighting scheme in which the weighting matrix depends on the spatial and time distance between observations. In the traditional GWR framework, weights are defined as spatial kernels based on the physical distance, d_{ij} , and are usually transformed following Gaussian or bi-square functions, which can be fixed or



adaptative. In GTWR models, distances are also complex, as they include time distance. Wu et al. (2014) propose a spatio-temporal distance between observations i and j observed in different locations and times, labelled as t_i and t_j :

$$\begin{cases} d_{ij}^{ST} = d_{ij}^S \otimes d_{ij}^T = \lambda d_{ij}^S + \mu d_{ij}^T + 2\sqrt{\lambda d_{ij}^S \mu d_{ij}^T} \cos(\xi), & t_j < t_i \\ d_{ij}^{ST} = \infty & t_j > t_i \end{cases} \quad (4)$$

where d_{ij}^{ST} is the spatio-temporal distance, d_{ij}^S and d_{ij}^T are the physical and time distance respectively, and λ , μ and $\xi \in [0, \pi]$ are adjustment parameters that can be optimised with cross validation procedures in terms of R^2 or AIC values. The interaction between space and time is governed by parameter ξ : when $\xi = 0$, space and time have the maximal effects, while if $\xi = \pi/2$, if there is no interaction between both dimensions. In practical terms, the weight assigned to the spatial (λ) versus the time distance (μ) can be normalised assuming $\mu = 1$, which leaves parameter λ with the relative weighting role. Consequently, in addition to the usual spatial kernels parameters, two additional parameters, λ and ξ , need to be chosen.

Our findings show weak elasticity of wages to the unemployment rate. Still, we observe an increasing pattern in the absolute value of the parameter during the Great Recession, which continues over time despite the start of the economic recovery in 2014, which we link with the reforms of the labour market implemented by two consecutive governments (2010 and 2012). We also find a strong spatial heterogeneity of the parameter, which is negative and significant in a subset in the northeast of the country. On the opposite side, we find southwestern provinces, particularly the less dynamic region of Extremadura and other western Andalusian provinces. When we estimate together spatial and time varying parameters, we find a time-varying response that is more intense in those provinces with already high elasticity values.



Our results suggest that the labour market reforms of 2010 and 2012 had important effects, which are observed nationally and at the local level. Nevertheless, the effect is heterogeneous over local labour markets. In policy terms, we find that global labour market reforms are important mechanisms to improve the efficiency of the labour market. Nevertheless, they should be also be defined in local terms, as suggested by López Mourelo and Malo (2015).

We understand that our work can be improved a several areas. First, we assume that we could have worked with a more sophisticated empirical model, for instance assuming lagged wages as an explanatory variable or including spatial dependence in the analysis, as other papers in the literature have done. In any case, as our focus is the analysis of spatio-temporal heterogeneity, we believe that our results are not invalidated for alternative specifications. We also agree that we do not perform a causal evaluation of the labour market reforms, which is not our main aim. Finally, we understand that the inspection of the causes of the observed heterogeneity in the spatial labour markets can be of substantial interest for further research.

Palabras Clave: *Regional Labour Market, Resilience, Wage Curve, Geographical and Temporal Weighted Regression*

Clasificación JEL: J64, J31, R23, C23