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The Italian wage curve revisited: A local and spatial cointegration

This study investigates the effects of spatial interactions on local wages based on a panel data from 20 Italian provinces between 2004 and 2015. Using the Global Moran's I statistic, we have provided empirical evidence for the presence of spatial dependencies in provincial wages. Then, we have estimated the provincial wage equation by using a dynamic spatial panel model as far region and time-period fixed effects are concerned to test the spatial cointegration that controls the spatial heterogeneity and spatial interdependence with other regional characteristics. Parameter estimations are obtained by reformulating the initial model in spatial first differences. The next estimation is done by using the error correction model representation of the dynamics spatial panel model. So, we have examined provincial wages effects and the extent to which a change in unemployment rate and explanatory variables in a particular region affect wages in other regions. The last estimation is obtained by comparing the performance of the spatial weights matrix, and as a result we have proved that the contagion matrix must be replaced by an inverse distance matrix.

Keywords: wage curve; regional labor market; unemployment; dynamic spatial panel model; bias corrected QML; spatial cointegration; wage spillovers.

JEL classification: J30; J60; C21; C23.

1. Introduction

Regional wage inequalities within the most countries have opened a controversial debate in the latest literature. Many studies have examined the determinants of such inequality in different countries, such as Brazil (Fally et al., 2010; Kovak, 2013), China (Liu, Yin, 2008; Huang, Chand, 2015), France (Delteil et al., 2004; Combes et al., 2008), Germany (Blien et al., 2003; Brakman et al., 2004; Longhi et al., 2006; Baltagi, 2012), and Spain (Tirado et al., 2013). In another wage curve studies which are investigated in the same country (Italy) as in our paper, we have referred to some former works like (Blanchflower, Oswald, 1995; Canziani, 1997; Montuenga et al., 2003; Chiarini, Piselli, 1997). But in this recent work we have referred to Ammermüller et al. (2010) based on 19 administrative Italian regions and 16 German Länder.

The novelty of this paper is the application of spatial econometric approach to investigate the Italian wage curve. We have investigated wage spillover impacts between regions drawing on a panel data from 20 Italian regions over the period 2004–2015. Italy is an interesting example due to its rapid growth of regional wage inequality associated with economic growth (Destefanis, Pica, 2011; Lucifora, Moriconi, 2015). Thus, large regional labor market imbalances

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are present. The North–South divide in Italy is particularly noticeable of the European landscape. Hilbert (2008) substantiated the existence of the well-known Italian North–South divide. Italian income inequality was higher in the South than in the North. Koning et al. (2004) state that much greater flexibility of wages, especially between the regions of Europe, is required because much of Europe’s unemployment is concentrated in regions, like Southern Italy, Southern Spain and Eastern Germany, because there is nearly full employment in other parts of the same country: Lombardy, Catalonia or Bavaria. This is a clear sign that relative labor costs are too high in the high unemployment regions. By adopting an opening-up policy since 1970, Italy has experienced a very rapid growth and left more than 2 million Italian children’s lives in poverty, indicated in a UNICEF report (Aslam, Szczuka, 2012). In the South and Islands areas, in the small municipalities the poverty incidence (9.1% for absolute and 22.6% for relative) is almost twice of that in the metropolitan areas (5.9% and 12.1%). In the North of Italy, it is the opposite (3.8% in the small municipalities, 7.2% in the metropolitan areas absolute poverty but 4.8% and 7.5% for relative). When adopting an opening-up policy since 1970, inequalities in Italy income increased. These inequalities are confirmed by the results of the OECD (2011) that emphasize a critical position for Italy and providing an image of an unequal country.

The positive spatial spillovers in terms of economic growth between Italian regions have been noted in some studies, e.g. (Lenzi, Millo, 2005). Nevertheless, little quantitative evidence has been presented on the extent of spatial wage spillovers across regions in Italy. If the regional distribution of wages follows the same pattern as regional economic growth, then there will be a hope that the existing wage disparity in Italy will reduce due to the positive wage spillovers between regions. This work proposes confirmation in support of such a hypothesis by using spatial econometrics have employed Moran’s *I*-statistics to test whether provincial wages are spatially auto correlated. Then, we have used spatial panel models to test the extent of spatial wage spill have deciphered the drivers of spillovers between provinces. This study makes three substantial contributions to the existent literature. First, it is the first to apply the Moran’s *I*-statistics and provide empirical evidence for the presence of spatial dependencies in regional wages in Italy. Second, this study contributes to the existing literature on regional wage disparity by incorporating spatial effects into the determination of regional wages. Third, the findings from this study have policy implications on how spatial interactions may help to reduce regional wage inequality.

We employ the advanced spatial econometric approach for the following reasons: first, it is not clear that the wage should only be influenced by the wage of the nearby regions but also countries located outside the region may matter, e.g. for the reason that these regions are significant trade partners (Bramoulle et al., 2009). Once such feedback effects are accounted for, the regional diffusion effect should be treated like an endogenous rather than an exogenous variable and the estimation’s method should be adjusted therefore. As a result, we employ different spatial weights matrix for comparing the results that will be considered later in the paper. Second and up to now relatively unexplored problem is that the literature doesn’t demonstrate if the wage has a spatial-unit-root and, in consequence, if the wage process is spatially cointegrated. Except for time factors, this may be explained by the fact that economies all over the world are integrated with each other. To illustrate this, Lee and Yu (2010) and Yu et al. (2012) suggest the estimation of a dynamic spatial panel data model and the use of the sum of the coefficient estimates of the dependent variables lagged in space, in time, and in both space and time to verify if the dependent variable is stable. If the dependent variable turns out to be non-stable, that is,

if the sum of these coefficients is equal to or greater than one, Lee and Yu recommend reformulating the model in spatial first-differences. This is why the dynamic spatial panel data model will generate consistent parameter estimates only if the dependent variable is stable or does become stable by taking spatial first-differences. The treatment of dynamic's spatial of panel data models is yet unusual and a few latest works are developed to housing's prices, consumption's (Korniotis, 2010) and commuting (Parent, LeSage, 2011). A third interest is to control for time-period effects. Generally, empirical works lean to find weaker evidence in favor of spatial interaction effects when time-period fixed effects are accounted for Elhorst (2010). The explanation is that most variables tend to increase and decrease together in different spatial units over time (e.g. along the business cycle). If this common effect is not taken into account and thus not separated from the interaction effect among countries, the latter effect might be over estimated. The final interest is measure regional diffusion and the convergence effect.

Our results prove the existence of spatial effects in the Italian wage curve by using Moran test in first step. Then we estimate the parameters of a dynamic spatial panel data model referring to the econometric methodology, developed by Lee and Yu (2010) as well as Yu et al. (2012), to investigate the proprieties of this variable in both space and time. For this purpose, we have used the data on wage and some variables taken from the «Italian National Institute of Statistics» (ISAT) of 20 regions of Italy and covers the period 2004–2015. As the wage variable will turn out to be non-stable, we have reformulated and estimated the parameters of the model in spatial first-differences. Next the variables of the dynamic spatial panel data model in levels are rearranged such the change of the wage of a particular region in a particular year becomes the left hand side variable. Using this model presentation, we find that the degree of wage interaction effects is substantially smaller than that in (Huang, Chand, 2015), 0.970 versus 0.548, provided that time-period fixed effects are taken into consideration. It is shown that the contagion matrix originally used in (Huang, Chand, 2015) must be rejected in favor of an inverse distance matrix with a distance band at 300 km between two different regions² and that the wage is spatially cointegrated. Consequently, the hypothesis that the extent of wage in different regions converged over the period 2004–2015 must be rejected. All explanatory variables appear to have a significant effect on wage in the region itself, when using the inverse distance band matrix. The dynamic spatial panel data model specification is linked to the error correction model representation of the dynamic spatial panel model put forward by Yu et al. (2012). This approach also allows for separating the regional diffusion and convergence effects. Finally, with reference to LeSage and Pace (2009), we have developed the effects of each exogenous variable in our model that has on wage in its home region and wage in other region (direct and indirect effects).

Following these results we make three remarks. First, the presence of significant spatial spillovers indicates that political decisions of local governments affect not only their own regions but also neighboring ones. Second, this work proves that increases in economic growth positively and significantly influence the wage levels in specific regions and those of their neighbors. Third, this a good lesson for eastern France (Bassin Parisien, Centre-Est, and Méditerranée), western Spain, north-western Germany and southern United Kingdom that were charac-

² We use the GEODA software program to build the inverse distance matrix (revised and updated by Luc Anselin in 17.03.2018). One can readily view spatial weights based on a distance cut-off as representing a step function, with the value of 1 for neighbors with $d_{ij} < \delta$, and 0 for others. As before, d_{ij} stands for the distance between observations i and j , and δ is the bandwidth.

terized by a high level of urbanization because overall, regions in the vicinity of any European region seem to have influenced the economic development perspectives of that region (Rodríguez-Pose, Crescenzi, 2008).

The rest of the paper is structured as follows. In Section 2, we present the literature review. In Section 3, we develop our conceptual framework. Then in Section 4, we describe the data series and highlight our data and empirical results. Finally, Section 5 contains the conclusions.

2. Literature review

Since a current literature highlights the meaning of geography affecting regional wages, little notice has been paid to the impact of spatial interactions on regional wages; we quote some previous studies that assume that labor markets are correlated with each other (Longhi et al., 2006; Baltagi et al., 2009; Huang, Chand, 2015). Both impacts are mentioned from the hypothesis of spatial interactions. The first impact is theoretical. In fact, wage in regions are still interconnected given the Walrasian interdependence among labor markets (Katzner, 1989). The second impact is empirical, if regional wages are in reality spatially auto correlated, as revealed in our study, then ignoring spatial impacts in the econometric models will affect the estimation of coefficients and the neglect of spatial correlation in the model specification may either lead to biased coefficient estimates (Franzese, Hays, 2007). To eliminate this gap, our study has employed dynamic spatial panel models to analyze the role of spatial interactions in the determination of provincial wages in Italy.

The lessons on spatial wage spillovers referred to Ross (1947), who demonstrated that «the buyer & seller of labor do meet within some fixed geographic area, but the price at which the exchange takes place is often ultimately determined by other agencies hundreds of miles away without necessary knowledge» (p. 802). While this citation submits to the meaning of wage comparisons in wage negotiation, it also offers plausible details for wage spillovers across regions. As far as wage comparison is concerned, employees may feel unequal if the wage rates in their working's places are lower than others. As a consequence, the local workers stop working and go to places where they can be well-paid (Rees, 1993). In a bilateral monopolistic labor market, the threat to quit can increase the negotiation power of employees in the process of wage determination and therefore let the employers augment the wages (Brechling, 1973). Consequently, there will be a tendency to have a convergence in the distribution of wages between the different regions of a country. Empirical support for this suggestion has been provided by a great number of new studies viewing a statistically significant impact on labor migration by reducing regional wage disparities, e.g. (Niebuhr et al., 2012).

Nevertheless, and in reality, labor migration is not total, which implicates the probability of regional wage convergence inside countries. We propose the work of Drewes (1987) who proved that workers are heterogeneous and therefore may not have the similar preference to migrate to the high wage regions. Additional motivations that may pressure the choice to migrate include family commitments (Mincer, 1978), moving costs (Carrington et al., 1996), and regulatory barriers (Chan, Zhang, 1999). As a result, wages may differ systematically between regions inside a country. Unsatisfactory labor mobility is also caused by the industry's agglomeration that may be in fact an additional reason for regional wage disparity within countries. A lot of studies have added support to the proposition that industry's agglomeration can allow firms

in geographically concentrated regions to pay more for similarly endowed workers than their counterparts located elsewhere (Head, Mayer, 2006). This is because firms in a cluster have more advantages due to low transportation costs (Krugman, 1991), a big market potential (Hanson, 2005) and the availability of a large labor pool (Overman, Puga, 2010). As a result, industry agglomeration can be a force for wage divergence across regions. This assumption is reinforced by the confirmation of intensifying spatial wage inequalities linked through industry agglomeration in Italy (Cerina, Mureddu, 2014).

3. The methodology

Despite the different functional forms of the wage curve that have been dealt with, the log-log form still dominates in the literature, this is the typical 'wage curve' specification, see (Bell et al., 2002). Following Bell et al. (2002), we estimate the wage curve after two steps. a wage equation is estimated for each region j as follows:

$$\log(w_{it}) = \mu_i + \lambda_t + \tau \log(w_{it-1}) + \beta_1 \log(u_{it}) + X'_{it} \beta + \varepsilon_{it}, \quad (1)$$

where w_{it} is the wage rate observed in region i at period t ($i=1, \dots, N$; $t=1, \dots, T$), u_{it} is the unemployment rate in region i at time period t , X_{it} is a set of supplementary exogenous variables of a type conventional in the literature on the wage equations, ε_{it} is the error term, μ_i is the i^{th} individual effect, and λ_t is the time effect.

To take into account spatial heterogeneity and also spatial interdependence, we applied on our theories wage model the spatial panel data model. We introduce in our model the regional characteristics variables to test whether the impact of spatial interactions on local ages, this is referring to (Longhi et al., 2006). The equation to be estimated takes the form³:

$$\begin{aligned} \log(w_{it}) = & \mu_i + \lambda_t + \rho \sum_{j=1}^N W_{ij} \log(w_{it}) + \eta \sum_{j=1}^N W_{ij} \log(w_{it-1}) + \\ & + \tau \log(w_{it-1}) + \beta_1 \log(u_{it}) + X'_{it} \beta + \varepsilon_{it}, \end{aligned} \quad (2)$$

where $j = 1, \dots, N$.

To construct the weight matrix (W_{ij}) we use the Principle of Baltagi et al. (2009) who define inverse distances with cut-off point⁴ at 300 km, fewer than two regions i and j , and compare this result to model estimated with spatial weight matrix constructed by LeSage (1999) who use the principle of Queen Contiguity.

³ For further details see (Elhorst et al., 2013).

⁴ When spatial units would be arranged linearly and the off-diagonal elements of Ware of the form $1/d_{ij}$, where d_{ij} is the distance between two units i and j , each row or column sum is $2 - (1/d + 1/2d + 1/3d + \dots)$, representing a series that is not finite. This is probably one of the reasons why some studies introduce a cut-off point d^* such that $w_{ij} = 0$ if $d_{ij} > d^*$.

Two spatial terms in (2), that is a spatially lagged dependent variable $\sum_{j=1}^N W_{ij} \log(w_{it-1})$ and spatially dependent variable $\sum_{j=1}^N W_{ij} \log(w_{it})$. The former, captured in parameter ρ , represents the direct regional spatial spillover effect of wages.

If the model is non-stable (explosive or spatially cointegrated), Lee, Yu (2012) propose to transform the model in spatial first differences and it will be rewritten as:

$$\begin{aligned} \log(w_{it})^* = & \mu_i + \lambda_t + \rho \sum_{j=1}^N W_{ij}^* \log(w_{it})^* + \eta \sum_{j=1}^N W_{ij}^* \log(w_{it-1})^* + \tau \log(w_{it-1})^* + \\ & + \beta_1 \log(u_{it})^* + X_{it}' \beta + \varepsilon_{it}^*, \end{aligned} \quad (3)$$

with $\log(w_{it})^* = P(I - W) \log(w_{it})$, $W^* = PW(I - W)$, where P is matrix of transformation: $P = \Lambda_{N-1}^{-1/2} F'_{N,N-1}$, Λ_{N-1} denotes the $(N-1) \times (N-1)$ diagonal matrix of non-zero eigenvalues of $\Sigma = (I - W)(I - W)'$ and $F_{N,N-1}$ the corresponding orthonormal $N \times (N-1)$ matrix of eigenvectors.

Lee and Yu (2012) formally demonstrate that the transformed model will be stable, and explain that the dynamic spatial panel data model in equation (2) has a revealing error correction model (ECM) representation:

$$\begin{aligned} \Delta \log(w_{it}) = & \mu_i + \lambda_t + \rho \sum_{j=1}^N W_{ij} \Delta \log(w_{it}) + (\eta + \rho) \sum_{j=1}^N W_{ij} \log(w_{it-1}) + (\tau - 1) \log(w_{it-1}) + \\ & + \beta_1 \log(u_{it}) + X_{it}' \beta + \varepsilon_{it}. \end{aligned} \quad (4)$$

Using this equation, we have obtained the marginal effects of the exogenous variables on endogenous variables ($\log(w)$) below, so we have presented the matrix of partial derivatives of $\Delta \log(w_t)$ concerning the k^{th} exogenous variable of X in region 1 up to region N , both at a certain point in time t , is:

$$\left[\frac{\partial \Delta \log(w)}{\partial x_{1k}} \dots \frac{\partial \Delta \log(w)}{\partial x_{Nk}} \right]_t = \begin{bmatrix} \frac{\partial \Delta \log(w_1)}{\partial x_{1k}} & \dots & \frac{\partial \Delta \log(w_1)}{\partial x_{Nk}} \\ \cdot & \dots & \cdot \\ \cdot & \dots & \cdot \\ \cdot & \dots & \cdot \\ \frac{\partial \Delta \log(w_N)}{\partial x_{1k}} & \dots & \frac{\partial \Delta \log(w_N)}{\partial x_{Nk}} \end{bmatrix}_t = (I - \rho W)^{-1} \beta_k. \quad (5)$$

Exogenous variable in a certain region changes; whenever wages in the original region change, they change in other regions as well. This was respectively described as a direct and an indirect effect. Note that every diagonal element of the matrix on the right-hand side of equation (5) represents a direct effect, and that every non-diagonal element represents an indirect effect.

Then, we have presented the impact estimates of convergence using ECM presentation in equation (4) as:

$$\partial \Delta \log(w_t) / \partial \Delta \log(w_{t-1}) = (I - \rho W)^{-1} [(\tau - 1)I + (\rho + \eta)W]. \quad (6)$$

If $\tau + \rho + \eta = 1$, Yu et al. (2012) label this specific situation as spatial cointegration, after conventional cointegration in the time-series literature. The cointegration's matrix is $(I - W)$ and the cointegration's rank is the number of eigenvalues of W that are smaller than 1, which is $N - 1$. If $\tau + \rho + \eta = 1$, we have

$$\partial \Delta \log(w_t) / \partial \Delta \log(w_{t-1}) = (\tau - 1)(I - \rho W)^{-1}(I - W). \quad (7)$$

4. Data and empirical results

4.1. Data description

The data set used in this study is taken from the Italian National Institute of Statistics, ISTAT (<https://www.istat.it/en/>) and covers the period 2004–2015. The survey has been updated over the years to take into account continual transformations in the labor market on the one hand, and the growing information requirements of users regarding the social and economic reality of our nation, on the other. The most recent change was undertaken at the beginning of in 2004 in line with European Union regulations.

Our variables in the dataset are: the dependent variable is the log of real wage ($\log(w)$), the regional unemployment rates (U) are gathered from ISAT, gross domestic product (GDP) and expenditure components by year-chain linked referenced year 2005 (millions of euro), final consumption expenditure (CON) of general governments by expenditure by purpose and year-chain linked referenced year 2005 (millions of euro) and activity rate (AR).

In Table 2, we test the stationarity of the series by using the Augmented Dickey–Fuller (ADF) (included observations: 10 after adjustments) and Phillips–Perron (PP) unit root tests (included observations: 11 after adjustments). Also, we can check the stationarity by applying the KPSS test (included observations: 12 after adjustments) of Kwiatkowski et al. (1992), in which KPSS considers the series are stationary.

Table 1. Unit root test results

	ADF	PP	KPSS
$\log(w)$	−19.8875***	−19.87875***	0.255
U	−10.87***	8.2356***	0.352
AR	−5.82***	−7.377980***	0.323
GDP	4.24***	3.756***	0.356
$CONS$	9.36***	10.356***	0.289
Critical values:			
1% level	−3.587	−3.58	0.739
5% level	−2.92	−2.92	0.463
10% level	−2.60	−2.60	0.347

Note. *** denotes significance at the 1% level.

Clearly, the ADF and PP tests reject the null hypothesis (have a unit root) for $\log(\cdot)$, U , AR , GDP and $CONS$ at 1% level, because for both tests if the test statistic value is greater than the critical value we will reject the null hypothesis. Thus, the variables $\log(w)$, U , AR , GDP and $CONS$, are regarded as stationary series.

4.2. Empirical results

Previous studies which have used a spatial approach include (Buettner, 1999; Pannenberg, Schwarze, 2000; Longhi et al., 2006; Falk, Leoni, 2011; Kosfeld, Dreger, 2015) and (Huang, Chand, 2015). Buettner (1999) seem to have been the first to estimate a spatial panel model for Germany using maximum likelihood methods. However, for an Italian data there is no work to be considered only some papers using a classical approach like that of Lucifora, Origo (1999), Blanchflower, Oswald (1995, 2000); Montuenga et al. (2003) and Chiarini, Piselli (1997). That is why we have applied in this paper an Italian database, mainly because the inclusion of spatial weighed unemployment is an important device to test the impacts of a spatial effects, for the reason that it reflect the mean indirect (spillover) effect, which is the effect of a unit change in an explanatory variable in the neighboring districts on the dependent variable in a focal district (Elhorst, 2014; LeSage, Pace, 2009; Seldadyo et al., 2010). Based on wage efficiency models as well as wage negotiation approaches, the theory of the wage curve gives no hints for the proper delineation of regional labor markets.

Before setting up a spatial econometric model, it must be verified that there is indeed a spatial phenomenon to be taken into account. In this tutorial we concentrate on two powerful spatial statistical tests: Moran's I and Spatial Regression. Moran's I is a test for spatial autocorrelation, which examines whether a phenomenon is clustered or not. Spatial Regression is regression, or the ability to predict a value of an outcome variable based on values of explanatory variables, but spatial dependency is accounted for in the model. The no significant of variables in the later model do not means absence of autocorrelation. It starts with testing the spatial interdependences of regions wages, so we have implemented the test of Moran (1950). The statistic of this test has been usually used in the literature on spatial studies as it is considered as a useful tool for measuring the degree at which activities in one location are similar to those in neighboring locations, e.g. (Bai et al., 2012; Guillain et al., 2006; Lottmann, 2012).

Table 2 presents the results obtained from the spatial autocorrelation test. It is obvious that the values of the Global Moran's I statistic are positive and significant at reasonable significance levels for the year 2015⁵ which indicates a strong and positive spatial interdependences in provincial wages in Italy. That is to say, provinces with similar wage levels (high or low) tend to be concentrated geographically.

Table 2. Global Moran I statistics for regional real wages

Moran's I value	Standard deviation	p -value
0.174	0.127	0.082

⁵ It is sufficient to calculate the global Moran's test statistics for one year to justify the presence of autocorrelation.

In Table 3 principally column 1 and 2, when estimating the parameters of model (2) referring to Yu et al. (2008), we consider the log likelihood's function of equation (2), having in consideration the Jacobian that reflects the endogeneity of the $W \times \log(w_i)$ variable, i.e. the fact that one region can effect another Italian region, and vice versa. Yu et al. (2012) introduce the BC-QML⁶, which generates consistent parameters, provided that the model is stable $\tau + \rho + \mu < 1$. When this condition is not verified, the model is unstable and the dynamic spatial panel data model will get further complicated. To get rid of possible unstable components in wage, Lee and Yu (2010) and Yu et al. (2012) suggest transforming the initial model in spatial first-differences equation (3) and the estimation is reported in column 3 of Table 3. After that, we estimate the effects that each exogenous variable in the model has on wage in its region and wage in other region (i.e. direct and indirect effects) following the discussion of Lesage and Pace (2009) and Combes et al. (2008) who have derived respectively the mathematical formula of the indirect and direct estimates of spatial econometric models based on cross sectional data and the dynamic panel. The estimations of these marginal effects are reported in columns 4, 5 and 6 using the ECM presentation of equation (5).

The spatial weights matrix (w_{ij}), used in the Table 3 for estimated the dynamic spatial panel data model and test for spatial interdependencies in the Table 2, is constructed according to the principle of Queen Contiguity, i.e., regions are considered neighbors if they share a common border or vertex (LeSage, 1999). This specification is in line with Kelejian et al. (2013) and only takes into account of direct interactions between geographical neighbors. The lone exception to the above is Sardinia region. While it is an isolated island province without land borders, we treat it as sharing a border with cote region.

The second step of the econometrics methodology is to test the existence of time-period fixed effects, column 1 of Table 3 illustrates the results of the BC-QML estimator applied to model (2) without time period fixed effects and the column 2 illustrates the estimations with these effects. The F -test statistic value is 12.79 with (11, 231) degrees of freedom and $p < 0.01$, so it indicates that time-period fixed effects should be included. It should be stressed that we did not use F -test for a standard panel data model here, but for dynamic spatial panel data model including the variables $\log(w_i)$, $W \times \log(w_i)$ and $W \times \log(w_{i-1})$.

To find whether the model including time-period effects is stable, we calculated $\tau + \rho + \mu$ and applied the Wald's test with the null hypothesis is $\tau + \rho + \mu = 1$ ⁷. The results of this test, reported in column 2 of Table 3, show that the dynamic spatial panel data model of the level of wage is explosive, so we adopt the transformation in spatial first-differences that is presented in column 3. The results illustrate that the spatial first-differences is stable, because the condition $\tau + w_{\max-1}(\rho + \eta) < 1$, where $w_{\max-1}$ denotes the second largest eigenvalue of the spatial weights matrix W . We therefore use the parameter estimations of the spatial first-difference model to compute direct and indirect impacts of the different explanatory variables on wage. These direct, indirect and total effects are respectively illustrated in columns 4, 5 and 6 of Table 3, respectively.

⁶ Bias corrected Quasi Maximum Likelihood.

⁷ If $\tau + \rho + \mu$ spatial first-differences turns out to be significantly smaller than 1, the model is stable; if it is superior than 1, the model is explosive; and if the null hypothesis is not rejected, the model may be said to be spatially cointegrated. When the model is not stable (explosive or spatially cointegrated), it must be reformulated and re-estimated in spatial first-differences model (3).

The coefficients of the dependent variable lagged in time $\log(w_{t-1})$ are negative and significant but the dependent variable in space $W \times \log(w_t) \times \lambda$ and the dependent lagged variable in both space and time $W \times \log(w_{t-1})$ are positive and significant in spatial first-differentiated model as shown in column 3. The coefficient of $W \times \log(w_t)$, which may be interpreted as the impact of the regional diffusion effect, amounts to 0.970 and is greater than that found by Huang, Chand (2015). The positive and statistically significant λ signifies that the average wage level in contiguous regions has a positive impact on local wage. This finding is in line with Zhang et al. (2006) which believes the spillover effects between idiosyncratic regional characteristics that influence determinations of wages in neighboring regions (Kelejian et al., 2013).

The coefficient of $\log(w_t)$, which may be interpreted as the impact of the regional diffusion effect, amounts to 0.970 and is smaller than that found by Abiad and Moby (2005). The coefficients of the initial levels of the wage also represent a significant convergence effect. The direct effect based on the coefficient matrix: $(I - \rho W)^{-1} [(\tau - 1)I + (\rho + \eta)W]$ of the variable $\log(w_{t-1})$ is -0.94 (with p -value 0.17), while its indirect effect is -0.65 (with p -value 0.06); the higher the level of wage in the region itself, or the lower the level of wage in other region, the lower the extent of mobility, and vice versa. The total effect is small, but still negative (-1.59 , p -value 0.14).

When we use the effect of some economics variables on local wages we prove an informative conclusion. Indeed, local GDP per capita and Activity rate are found to have significantly positive impacts. While the final consumption expenditure is not statistically significant in the Spatial first-differences model, it is positive as we expect and statistically significant at the 1% level in the Spatial first-differences model. Lastly, unemployment rates are positively associated with local wages as a 1% increase in the local unemployment rate leads to a 0.11% increase in local wages. These results are contrary to conventional result that mentioned the negative effect on regional wages. The reasons that this convergence happens are when introduced the spatial spillovers of wages across contiguous regions and spatial interactions across labor markets can influence the unemployment elasticity of pay (Longhi et al., 2006).

To eliminate the divergence of conclusions of existence of spatial's spillovers; we introduce direct and indirect effect of all exogenous variables. The first authors who introduce this concept are LeSage and Pace (2009). Since the dynamic spatial first-difference panel data with time dummies model is confirmed as the most suitable model in this work, columns 4, 5 and 6 of Table 3 shows the estimated results for the direct, indirect and total (sum of the direct and indirect effects) effects produced by simulating the parameters from dynamic spatial first-difference panel data model using the contagion weights matrix.

The results show that the potential determinant of unemployment is significant in indirect and total effect, but non-significant when using spatial first-differenced model.

The direct effects in the spatial first-differentiated model as shown in column 4 are different from the estimates of the response parameters shown in column 3. This is caused by the feedback effects that arise as a result of shocks passing via to other countries and back to the country itself. These feedback effects, however, turn out to be very small. For example, since the direct effect and the coefficient estimate of unemployment (UN) are, respectively, 0.11 and 0.21, its feedback effect is -0.098^8 . However, the direct effect of a change in one of the explanatory variables in a particular country on other countries appears to be approximately 21% of the in-

⁸ Feedback effect = direct effect coefficient estimate = $0.112 - 0.21 = -0.098$.

Table 3. Estimation results using different model specifications

Determinants	Spatial first-differences estimates					
	No time dummies	Time dummies	Coeff.	Direct	Indirect	Total
	1 ^a	2 ^a	3 ^b	4 ^c	5 ^c	6
$\log(w_{t-1})$	-0.175 (0.00)	-0.151 (0.00)	-0.151 (0.00)			
$W \times \log(w_t)$	0.952 (0.00)	0.966 (0.00)	0.970 (0.00)			
$W \times \log(w_{t-1})$	0.221 (0.01)	0.208 (0.04)	0.210 (0.14)	-0.94 ^d (0.17)	-0.65 ^d (0.06)	-1.59 (0.14)
U	0.082 (0.029)	0.111 (0.031)	0.112 (0.031)	0.21 (0.21)	1.02 (0.05)	1.23 (0.06)
AR	0.671 (0.10)	-0.655 (0.52)	-0.64 (0.54)	-1.56 (0.15)	-12.80 (0.06)	-14.36 (0.06)
GDP	-0.116 (0.81)	-0.735 (0.15)	-0.729 (0.17)	-1.42 (0.16)	-10.98 (0.06)	-12.40 (0.06)
$CONS$	0.165 (0.70)	0.731 (0.16)	0.725 (0.18)	1.44 (0.16)	11.46 (0.06)	12.90 (0.06)
$\tau + \rho + \mu$	0.998	1.023	NR			
Wald test $\tau + \rho + \eta = 1$	0.882	0.279	NR			
p -value Wald test	(0.402)	(0.504)	NR			
$\tau + w_{\max-1}(\rho + \eta)$	NR	NR	-0.439			

Notes. P -values in parentheses, NR = not relevant.

^a BC-QML estimator of equation (2) taken from (Yu et al., 2008).

^b BC-QML estimates of equation (4) taken from (Lee, Yu, 2010, 2012).

^c Direct/indirect effects using equation (5).

^d Direct/indirect effects initial levels the dependent variable using equation (6).

direct effect within that country. Furthermore, based on the t -statistics calculated from a set of 1000 simulated parameter values⁹, all of these indirect effects appear to be significantly different from zero at a significant level of 5%. In other words, if one of these exogenous variables in a particular region changes the wage of other countries will also change.

The indirect effect estimates measure spatial spillovers rather than the coefficient estimate of the spatially lagged endogenous variable (LeSage, Fischer, 2008). This can be explained as how a change in an exogenous variable in all other regions has on a wage in a given region. The positive indirect effect of unemployment suggests that increases in unemployment will not only increase the wage in a particular region but also in its contiguous regions. However, the indirect impact of activity rate is negative and significant at 5% level, which implies that increases in the proportion of activity rate will decrease wages in both the local region and its neighbors. The positive (negative) indirect impacts (or spillovers) arise because changes in those variables

⁹ In order to draw inferences regarding the statistical significance of these effects, we used the variation of 1000 simulated parameter combinations drawn from the multivariate normal distribution implied by the maximum likelihood estimates (see (LeSage, Pace, 2009) for mathematical details).

positively (negatively) influence wages in their own provinces which, in turn, simultaneously influence wages in neighboring provinces due to the existence of positive regional wage spillovers.

Referring to Baltagi et al. (2009) and Elhorst et al. (2013), we have used another spatial weight matrix that best describes the data. In fact, one may compare log-likelihood function values and rely on the model that exhibits the highest value. The best description among the spatial weight matrix considered, is obtained when adopting the inverse distance matrix with a distance band at 300 km between two regions. It has the highest log-likelihood function value and the lowest parameter estimation of the residual variance. Table 4 reports the full estimated results when employing this matrix.

When comparing the estimated results in Table 4 with those in Table 3, we see remarkable changes. First, while $\tau + \rho + \mu$ appeared to be significantly greater than one after using the contagion matrix, $\tau + \rho + \mu$ is smaller than one after using the inverse distance band matrix. Nevertheless, the hypothesis $\tau + \rho + \eta = 1$ and thus the wage which is spatially cointegrated cannot be rejected. For that reason, the coefficient estimation when imposing this restriction, and the corresponding direct, indirect and total effects, are identified in columns 2, 3, 4 and 5 from Table 4.

Table 4. Estimation results using different model specifications

Determinants	Spatial first-differences	Spatial cointegrated $\tau + \rho + \eta = 1$ model and effects estimates			
		Coeff.	Direct	Indirect	Total
	1 ^a	2 ^b	3 ^c	4 ^c	5
$\log(w_{t-1})$	-0.23 (0.00)	-0.245 (0.00)			
$W \times \log(w_t)$	0.79 (0.00)	1.014 (0.00)			
$W \times \log(w_{t-1})$	0.116 (0.14)	0.231 (0.00)	-0.804 ^d (0.97)	0.804 ^d (0.97)	0.00 (0.03)
U	0.111 (0.32)	0.084 (0.503)	1.37 (0.03)	22.87 (0.03)	24.24 (0.03)
AR	-0.72 (0.54)	-0.281 (0.74)	-10.96 (0.02)	-229.80 (0.02)	-240.76 (0.02)
GDP	-0.839 (0.15)	-0.493 (0.32)	8.10 (0.02)	203.12 (0.03)	211.22 (0.03)
$CONS$	0.73 (0.14)	0.485 (0.34)	-7.96 (0.02)	-202.07 (0.03)	-210.03 (0.03)
$\tau + \rho + \mu$	0.629	1			
Wald test $\tau + \rho + \eta = 1$	0.405	NR			
p-value Wald test	(0.512)	NR			
$\tau + w_{\max-1}(\rho + \eta)$	-0.439	NR			

Notes. P-values in parentheses, NR=not relevant.

^a BC-QML estimates of equation (4) taken from (Lee, Yu, 2010, 2012).

^b as ^a, provided that $\tau + \rho + \eta = 1$.

^c Direct/indirect effects using equation (5).

^d Direct/indirect effects initial levels dependent variable using equation (7).

As mentioned, the secondary impact of this so-called spatially cointegrated model is that the convergence effect of the initial levels of the wage is zero. Second, whereas a region's wage is influenced back and forth by all region according to the inverse distance band matrix. Third, unemployment set back wage is related to the contagion matrix and not to the inverse distance matrix. Thus the direct effect of this variable is no longer significant. Production is also important. In fact its impact becomes significant according to the inverse distance band matrix. Finally, whereas the indirect effects as a percentage of the direct effects appeared to be approximately 21% when using the contagion matrix, this ratio increases to approximately 6% when using the inverse distance matrix. Both spatial weights matrices have in common that the indirect effects and direct effect of unemployment, activity, production and consumption are significant at levels fall from 5% after using the inverse distance band matrix.

5. Conclusions

Although the existing literature deals with the factors leading to regional wage disparity, few empirical works believe in the effect of spatial interactions on local wages. In this work, we used spatial panel estimation models to examine spatial wage spillovers as well as their impacts on local wages using data from 20 regions in Italy over the period from 2004 to 2015. This work differs from most preceding works in this field by considering the dynamic spatial panel models to study the role of spatial interactions in the determination of regional wages in Italy. By using standard tests in spatial econometrics, this work proves that regional wages exhibit a significantly spatial interdependence. Consequently, ignoring spatial interdependence when modeling wage equations leads to biased and inefficient parameter estimates.

By examining the spatial patterns of regional wages in 2004 and 2015, this study found that, although high-wage regions are spatially clustered in the southern region of Italy, indeed, the unemployment rate in the South Italy still remained three times higher than in the North Italy (Carter, 2010) and the co-variation (in equilibrium levels) of wages and unemployment is explained by Shapiro and Stiglitz (1984) who reason in terms of efficiency wage models low unemployment requires higher wages to deter workers' shirking. Also, a trend of wage convergence among regions occurred in the 1990s because of the significant labor market reforms in the 1990s. The potential motivation for a decline in regional wage inequality is that high wage regions have a positive transmission effect on their neighboring regions, that is, wage spillovers exist across Italy regions. Indeed, the mobility of employees increase their wage when they move to a region with high remuneration so it is in sort of equilibrium of salary. To test this hypothesis, this work adopted spatial dynamic panel data models and found that wage spillovers play positive and significant roles in determining regional wages in Italy. Moreover, Local GDP per capita and Activity rate are identified as two forces that intensify wage diffusion between regions.

When we estimate a dynamic spatial panel data model, results show that the wage is unstable and these results are in accordance with Huang and Chand (2015). To obtain consistent parameter estimates under these circumstances, Lee and Yu (2010) and Yu et al. (2012) recommend reformulating the dynamic spatial panel data model into spatial first differences. After its parameters have been re-estimated in this way, the transformed model turns out to be stable. By using the error correction model presentation of the dynamic spatial panel data model,

it is then shown that the change in the wage of a particular region, counts on wage in other regions. Using this model presentation, we find that the degree of wage interaction effects is substantially smaller than that in (Huang, Chand, 2015), 0.970 versus 0.548, provided that time-period fixed effects are taken into consideration. Finally, it is shown that the contagion matrix originally used in (Huang, Chand, 2015) must be rejected in favor of an inverse distance matrix with a distance band at 300 km and that the wage is spatially cointegrated. Consequently, the hypothesis that the extent of wage in different regions converged over the period 2004–2015 must be rejected. All explanatory variables appear to have a significant effect on wage in the region itself, when using the inverse distance band matrix.

Three implications derived from these findings. First, the presence of significant spatial spillovers indicates that political decisions of local governments affect not only their own regions but also neighboring ones, thereby requiring the central government to pay special attention to coordination between local administrative units, such as regions. Second, this work proves that increases in economic growth positively and significantly influence the wage levels in specific regions and those of their neighbors. Thus, if the central or local governments invest more in education, the wage spillover effects among regions will be even larger which, in turn, will help to reduce regional wage inequality. Third, this a good lesson for eastern France (Bassin Parisien, Centre-Est, and Mediterranée), western Spain, north-western Germany and southern United Kingdom that were characterized by a high level of urbanization because overall, regions in the vicinity of any European region seem to have influenced the economic development perspectives of that region (Rodríguez-Pose, Crescenzi, 2008). A poor person living in a low wage per capita region surrounded by other poor regions will probably live at that level of wage; whereas a rich person living in a region enclosed by richer regions should live at a high wage level. Therefore local economic externalities effect the economic development in Europe.

Data Appendix. Regions in the dataset

Piemonte	Marche
Valle d'Aosta / Vallée d'Aoste	Lazio
Liguria	Abruzzo
Lombardia	Molise
Trentino Alto Adige / Südtirol	Campania
Veneto	Puglia
Friuli-Venezia Giulia	Basilicata
Emilia-Romagna	Calabria
Toscana	Sicilia
Umbria	Sardegna

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