THE EFFECT OF UNEMPLOYMENT, AGGREGATE WAGES, AND SPATIAL CONTIGUITY ON LOCAL WAGES – AN INVESTIGATION WITH GERMAN DISTRICT LEVEL DATA

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ABSTRACT

Despite spatial rigidity of collectively negotiated wages the local unemployment rate is found to have a significant negative impact on wages. This impact is shown to be consistent with both the wage-curve hypothesis and modern Phillips-curve modelling. Spatial contiguity effects are found in wages and unemployment and their neglect leads to an underestimation of the effect of local unemployment. Yet, the impact of local unemployment on wages turns out to be quite low as compared to studies for other countries. Some support for the hypothesis that negotiated wages suppress spatial wage flexibility comes from the finding that the impact of local unemployment on local wages decreases with its extent.

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1 INTRODUCTION

Recently economists have paid increasing attention to labor market as well as to regional topics. The wage-curve hypothesis (Blanchflower and Oswald (1990)), stating an inverse relationship between local wages and unemployment, has a natural key position when linking these two fields of interest. A number of studies have already confirmed the existence of wage curves for different countries. Even in Germany, an empirical wage curve has been found, although no consensus on the strength of the influence of the local unemployment has been reached (Blanchflower and Oswald (1994), Wagner (1994), Blien (1995) and Wagner (1996)). The wage curve suggests that wages are formed in local labor markets. But as these are just spatial segments in a national economy, they are more or less integrated by factor mobility, interregional trade, and institutions. This article explores the relationship of two aspects of the integration of local labor markets to the concept and finding of the wage curve: aggregate wage formation and the contiguity of local labor markets.

Related to the Scandinavian countries where wage determination is characterized by the coexistence of local and centralized wage bargaining (Calmfors (1990)), different stages of wage formation can also be found in Germany. In particular, wage negotiations occur at the aggregate level, supraregionally. Yet, wages effectively paid are often higher than those negotiated at the aggregate level, since there is a second stage of wage formation at the firm level. As it is argued in the following, the spatial rigidity of negotiated wages may be substantial for the wage response to local unemployment. Due to the lack of hard data on the level of negotiated wages, their effect cannot be measured directly. However, in the case that negotiated wages matter, we should find a downward rigidity of the actual spatial wage structure.

The second aspect, contiguity, is related to the integration by factor mobility, which questions the arbitrary definition of regions implicit in most datasets used. Any variations in the area and distance of spatial units will cause the level of spatial disaggregation to affect the relationship between local wages and local unemployment. Taking contiguity effects into account might therefore be helpful in the attempt to unravel that relationship, particularly as the employed dataset uses quite small spatial units. The study of contiguity effects might also be of interest, since there is a growing literature applying spatial econometric methods to labor market issues (e.g., Molho (1995), Manning (1994)), but there are very few studies for the German labor market (e.g., Seitz (1995)).

The article starts with a discussion of the scope for wage-curve explanations in Germany, which is concerned specifically with the spatial flexibility in the negotiated wages. Following that, the implications for the wage curve are outlined theoretically. Then, an empirical analysis of wage flexibility in Germany using time-series and cross-section data for 327 districts is presented for the years 1987 to 1994. First, results from basic wage regressions are discussed. Then, spatial effects in wages and unemployment are considered, where robust inference is carried out by means of a spatial block-bootstrap method. Finally, the results are confronted with the Phillips curve in order to test whether the estimated level relation between wages and unemployment holds in a dynamic setting.

2 LOCAL WAGES AND WAGE AGREEMENTS

The peculiarities of the German system of labor relations suggest a distinction between different sources of local wage flexibility:

· the wage agreements could differ between regions

· each wage agreement could allow for local wage differences

· employers might pay more than the negotiated wage

This distinction is important not only for the understanding of the local wage formation and thus for the adaequateness of wage-curve explanations in the German context, but also because of the different objects of analysis. An evaluation of the extent of flexibility due to the first two sources focuses on the negotiated wages, whereas the object of the latter sources of flexibility is the gap between actual earnings and negotiated wages. Although the decomposition of actual earnings into the wage gap and negotiated wages is standard in German labor economics, there is few data dealing with them directly. The mean wage gap for employees paid for working time is estimated to be about 7 % to 12 % depending on skills (Schnabel (1995), see also Meyer (1995)). The lack of data is caused by the difficulties in the measurement of the negotiated wages. Not only is there a vast number of agreements (in 1994 there were nearly 38,000 agreements enforced in Germany's original Laender) for all kinds of occupations, branches and regions. And they do not just determine the wage, but all aspects of working conditions, as for instance working time and overtime payments.

Notwithstanding the difficulties in measuring the wage gap, using a recent investigation into the structure of the German labor agreements by Bispinck et al. (1995) it is possible to evaluate the degree of spatial differentiation by comparison. Bispinck et al. (1995) compared major agreements, which cover about 12 million employees in the old Laender of the Federal Republic of Germany. Table 1 displays specifics of sets of agreements effective at the end of 1992 and covering more than 100,000 employees.

[Table 1 about here.]

Each row shows the characteristics of agreements effective for the employees in a sector, often separated into wage and salary agreements (column (1)). The first type of agreements refers to blue-collar workers, the second to white-collar workers. In some cases joint agreements hold covering both types of labor. Column (2) shows the number of employees subject to the agreements in the considered industry. Column (3) states how many separate agreements can be distinguished in each industry and type. In some cases there is only a single agreement which holds for all regions, for instance in the public service. But in the metal industry, for instance, there are 15 different agreements enforced, each of which holds for a different region. Although the number of regional agreements in a respective industry is not large, they might differ with respect to the wage rate, thereby allowing for some regional differences in negotiated wages. To see if this is relevant, columns (5) to (7) display measures of regional differentiation of the mean monthly basic payment in a medium-skill category for workers with longest tenure as listed in column (4). As the regional agreements are not always comparable there are many dots indicating that no evidence can be given in these cases.

Considering the coefficient of variation (see column (6)) the regional differentiation can be summarized as follows: for nearly a third of the employees the agreements show no differentiation at all (e.g., public service, building ind. and banking). About three tenths are subject to agreements with negligible differentiation (metal industry's blue-collar workers and white collars in retail trade), less than three tenths to agreements which show a mean relative deviation of 2 to 7 %. The agreements for the rest cannot be compared at all or cannot be reasonably compared, since the respective industries are heavily concentrated spatially (iron and steel, coal mining). One might conclude that for the majority of employees there are agreements enforced which are not differentiated in the basic payment with respect to the regions. The first source of local wage flexibility, therefore, seems unimportant in the German context. Yet, as the agreements determine not only wages but also all other aspects of working conditions, the comparison in Table 1 should not be regarded as sufficient to justify that conclusion. However, at least for employees in the metal industry, the chemical industry or the retail trade, there is almost complete conformity between the regional agreements with respect to working time, overtime payments, holidays and holiday payments (Source: statistics on labor relations of the Federal Statistical Office). Since in some of the other cases only a single agreement holds nationwide, a consideration of non-wage aspects will not really make a difference to that conclusion.

The second source of local flexibility deals with individual agreements. The former differentiation of individual agreements with respect to the locality (Ortsklassen) has been dispensed with almost completely (Bispinck et al. (1995)). On the other hand, the flexibility in the working time, agreements allow for using overtime and specialtime bonuses, introduces a variability in mean payments. This variability leads to a flexibility with respect to demand, but only indirectly to the local labor market conditions.

In search of local wage flexibility, one should therefore concentrate on the third source of flexibility, which focuses on firm-specific wage formation. In the German case firm-specific wage formation is generally regarded as restricted by the negotiated wages of the first stage, which more or less act as minimum conditions. Employers, who are members of the employers coalition, are forced to fulfill the agreed terms of employment to union members and other workers equally, and leaving the coalition is seldom favorable (Franz (1995)). Therefore, if one does not want to assume negotiated wages to be negligible for local wages a priori, the application of the wage-curve hypothesis by Blanchflower and Oswald to the German case results in an explanation of spatial variations of the non-negative wage gap. This requires combining elements of firm-specific bargaining or incentive wages with aggregate wage negotiations, where the former provide the link to the local labor markets.

Without giving a complete model of wage formation (see Buettner (1997)), let me show the implication of a combination of firm-specific efficiency wages and sectoral negotiated wages for the local wage flexibility. Suppose each firm i in a given sector (sectoral index is omitted) has the same effort function translating labor from physical to labor in efficiency units, where the firms wage (W_i), the wage in the local neighborhood of the firm (W_{-i}) and the local rate of unemployment (U_i) enter as arguments, formally:

$$E_i \quad = \quad E(\overbrace{W_i}^{+}, \overbrace{W_{-i}}^{-}, \overbrace{U_i}^{+}).$$

By lowering the expected value of opportunities of the firm's employees, the firm's wage and the local rate of unemployment have a positive influence on the effort. And by improving the value of their opportunities, the alternative wage has a negative influence. The optimum wage set by the firm to minimize the cost of labor in efficiency units fulfills the well-known Solow (1979) condition, that the elasticity of the effort with respect to the wage is unity. Provided the effort function has a proper functional form, a firm-specific wage curve can be derived from this condition, stating a relation between the firms optimum wage and the local employment conditions as reflected in the alternative wage and the local rate of unemployment.

$$W_i^* = W(\overbrace{U_i}^{-}, \overbrace{W_{-i}}^{+}),$$

where W_i^* denotes the location specific optimum wage. Local unemployment has a negative, and the alternative wage has a positive effect on the firm's wage. If the labor market is segmented into locations, a spatial wage structure evolves. To see this, assume that there are sectors or sets of firms which share the same technology but are located differently. If the labor market conditions at the locations of the firms differ, we could deduce a set of optimum wages, which are distributed spatially. It should be noted, that the assumption of segmentation into local labor markets does not imply the absence of migration or commuting, but implies the existence of spatial transaction cost.

The use of incentive wages to explain the regional wage differences is, of course, one of the main theoretical explanations of the wage curve. A deviation from that explanation of the spatial wage structure is obtained if one introduces bargaining on a suprafirm level. Suppose there is a sectoral union strong enough to set a minimum wage for all firms in its sector, regardless of their location. In the presence of a sectoral minimum wage, a firm's wage at any location can then be described by the following function:

$$\begin{aligned} W_i &= b_i W^T + (1 - b_i)\, W_i^*, \\ &\text{where} \\ b_i &= \begin{cases} 1 & \text{if} \quad W_i^* \leq W^T \\ 0 & \phantom{\text{if}} \quad W_i^* > W^T \end{cases} . \end{aligned} \tag{1}$$

W^T denotes the negotiated minimum wage. The minimum wage introduces a non-linearity in the effect of local employment conditions on the local wage payment. If, for instance, there is low unemployment in the local area, according to the wage curve the firm will tend to pay wages above the sectoral average. Therefore the minimum condition from the sectoral agreement is not restricting the firm's wage setting ($b_i = 0$) and the wage curve holds. But if there is high unemployment, the firm will tend to pay wages below the sectoral average and the minimum wage condition becomes binding ($b_i = 1$). Hence, there is no wage flexibility in this case. A non-linear relation between the local wage level and the local rate of unemployment is a regular result in the theoretical (and empirical) analysis of the wage curve. It results from the probability of the unemployed getting a job (see Blanchflower and Oswald (1990, 1994)). Here, it stems from the integration of sectoral negotiations and individual wage setting. It is, however, quite difficult to distinguish these explanations empirically.

3 BASIC WAGE REGRESSIONS

Although a number of empirical studies have already been undertaken which are concerned with the estimation of wage curves, there is still no full consensus on the strength of the influence of local labor market conditions on local wages for the German case. Blanchflower and Oswald (1994) and Blien (1995) are supportive, Wagner (1994) gives only weak support and Wagner

(1996) even rejects the wage-curve hypothesis for Germany. Hence, it might be helpful also to use regional average data for the estimation of local wage flexibility, although the empirical wage curve is often related to individual data. Whereas individual data may enable a more precise control for composition effects, aggregation at the regional level is necessary for inference anyway, if the estimation does not explicitly take into account the different levels of data, i.e. the regional and the individual level (Moulton (1990)). Since on the other hand, the omitted-variable bias could be stronger with average wages leading to serial correlation, the empirical investigation does not rely solely on level regression, but also on dynamic wage function estimation.

A special feature of the empirical analysis is the explicit use of national sectoral wages averaged with the local employment shares, measuring the average local wage payment that would be observed if all employees were paid according to the sectors national averages (for the use of a related variable, Blackaby and Manning (1990a),(1990b), and (1992)). This "predicted wage" is used to control for the sectoral wage structure. Since no data on the level of negotiated wages is available, under the strong assumption of a constant average sectoral wage gap it may also serve as a proxy for the negotiated wages.

The results of a set of basic wage-curve regressions are displayed in Table 2. The first column contains results of a regression of the actual manufacturing wage on the predicted wage and the rate of unemployment. Further explanatory variables are the hours per worker, which is important to control for overtime payments, the share of blue-collar workers among all employees, and the total population to capture density effects once fixed regional effects are employed.

[Table 2 about here.]

A logarithmic transformation of all variables is used, as it has been found to reduce the leverage of single observations, and since the White statistic for heteroskedasticity is lowest. However, the specification issue with respect to the unemployment rate is pursued further below. In column (2) regional fixed effects are included into the regression. According to the F-statistic they are strongly significant. After including regional fixed effects, the F-statistic for the pooling falls drastically but is still larger than the critical value. However, as the F-statistic is invalid with heteroskedasticity and is based on the coefficient of determination which always approaches its maximum when the degrees of freedom approach zero, this should not be overemphasized (see Amemiya (1985)). Accepting the pooling restriction, a significant negative coefficient is found for the unemployment rate. Hours per worker has a positive effect and the share of workers among employees has a negative effect on actual pay. Moreover, local pay is positively related to the population level, indicating effects from density.

Whereas some common time effects, such as national price inflation, are already captured by the predicted wage variable, others, such as trends in the explanatory variables and cyclical swings in the national unemployment rate, suggest the use of time dummies as regressors. Note, that this procedure is equivalent to the additional inclusion of the national averages of the explanatory variables in the regression. The corresponding results are displayed in column (3). According to the Wald statistic at the lower part of Table 2, the time effects are jointly significant. The regression results show a slight increase in most coefficients, notably the unemployment-elasticity of pay, defined in absolute terms, increases to a value of 1.9 %.

Throughout the estimations presented so far a dominant effect of the predicted wage was found. Although a large number of regions is used, one might question, whether this result is driven by some endogeneity. Namely, it may be the case that a region is dominated by a single industry, and that the majority of the industry's employment is located in that region. In order to test directly whether the estimated wage curve hinges on the predicted wage as a regressor, column (4) displays results of a regression where the predicted wage is replaced by a set of 33 local employment shares. With the estimated unemployment-elasticity of pay being one standard error lower than in the regression of column (3), the results are hardly affected. Although the adjusted coefficient of determination increases, this specification is not regarded as an improvement. For with many zero values, the local employment shares mix the pure sectoral-composition effect with region-specific characteristics which are captured otherwise by the fixed effects.

The basic regression exercise thus results in an unemployment-elasticity of pay just below 2 %. This number is well below the elasticity of 10 %, which approximately holds for a number of countries (Blanchflower and Oswald (1994)). Moreover, the regressions reveal a remarkably close relation between actual wages and the wages predicted from the local industry composition using the national wage rates. After having included regional fixed effects, almost all regional wage variation is explained by the regression. Yet the previous theoretical discussion suggests that the relation between local pay and local unemployment may vary with the extent of local unemployment. In particular, if the local rate of unemployment is high relative to the national average, further variations in local unemployment rates might have no effects on wages. The basic estimation has relied on a logarithmic specification, which assumes a constant elasticity of pay, and therefore may be too restrictive to show this effect. Therefore, different specifications of the unemployment rate were tested for. From a large number of possible specifications including quadratic and cubic specifications (not shown) best fit was found for the specification with the inverse of the unemployment rate as depicted in column (5). On the basis of the latter specification, the unemployment-elasticity of pay varies according to:

$$\frac{\partial \log W}{\partial \log U} = -\frac{b}{U} = -\frac{0.102}{U},$$

where b is the estimated coefficient of the inverse unemployment rate. With the unemployment rate in the sample varying between 2.5 % and 18 %, the predicted unemployment-elasticity of pay is between 4 % and 0.5 %. With respect to the issue of regional wage flexibility the analysis of the basic wage curve is therefore supportive for a nonlinear relation between unemployment and the level of pay, indicating that the higher the rate of unemployment the lower the responsiveness of wages.

4 SPATIAL CONTIGUITY

Besides the national wage agreements at industry level, there is a second kind of interrelationship, arising from the contiguity of regions, which has been neglected so far. On the one hand, the connection between the regions in a detailed dataset constitutes a possible source of misspecification as observations are not independent (see Anselin (1988a)), but on the other hand it offers an opportunity to explore the (regional) aggregation bias.

For the present purpose, it is useful to distinguish between three types of spatial dependence. First, it may simply occur between fixed regional attributes, arising from the availability of resources or a common history. Although this type of spatial correlation may constitute a severe problem in pure cross-sectional analysis, it is not a problem to the current analysis which exploits also the time-series in the data, as the regional fixed effects capture all time invariant effects. Secondly, correlation may arise from common shocks in contiguous districts, leading to spatial residual autocorrelation (SAR) in the wage equation. And finally, variations in the employment conditions in neighboring districts may directly affect local pay, because they are transmitted by the activity of agents on the labor market, for example by the search behavior of both employers and labor. In some sense, this is the most serious case, as it requires to rethink the model in order to take account of spatial interaction. In the case of wages in contiguous districts affecting local pay, we should expect that the spatially-lagged dependent variable (SLDV) (see Anselin (1988a)) is significant. However, it may also be the case that specific explanatory variables, such as the rate of unemployment in contiguous districts, exert an autonomous influence on local pay.

As the basic model employs fixed effects, and in order to limit the large computational requirements, testing for spatial dependence and estimation of spatial effects are carried out with transformed (within) variables, where the individual and time means have been removed. But the standard errors of parameters and the residual variances are corrected for the degrees of freedom lost by the fixed effects.[1] The choice of the spatial transformation matrix is described in the appendix.

To test for spatial dependence in the basic wage regression, Lagrange multiplier (LM) statistics robust against local misspecification of spatial dependence as suggested by Anselin et al. (1996) are computed. The results are displayed in the last two rows of Table 2. Whereas according to LM(ρ) a spatial lag in the dependent variable is clearly supported, the statistic for spatial residual correlation, LM (λ), shows no significance. Thus, the wage regression should employ a spatial lag of the dependent variable and maximum–likelihood estimation as suggested by Anselin (1988a) is appropriate.

[Table 3 about here.]

The corresponding results are displayed in column (1) of Table 3. According to the likelihood-ratio statistic, the presence of a spatial lag in the wage rate is confirmed. Moreover, a test for additional spatial residual correlation (see Anselin (1988b) and Anselin et al. (1996)), denoted as LM_ρ (λ), shows no significance. Despite the significance of the spatial lag, the differences in the coefficients of the explanatory variables are negligible.

The reported standard errors for the maximum-likelihood (ML) estimates are quite low as compared to the OLS regression (column (5) of Table 2). To obtain heteroscedasticity-consistent standard errors, it is made use of a special block-bootstrap procedure. Application in the context of time series is known as the moving-blocks bootstrap (see Fitzenberger (1997), Kuensch (1989)), application to spatial patterns has been proposed by Hall (1985). Whereas standard bootstrap resampling schemes destroy the dependencies between observations, under the block-bootstrap approach the first observation in a block is drawn randomly and presumably dependent observations are added to form a block. In spatial analysis this implies drawing neighbors of a location into the block. That approach allows circumvention of the residual based bootstrap as suggested by Anselin (1988a,1990). Because of the size of the dataset, there was no room for flexible block design in

[1] In panel data combining time-series and cross-sectional variation the inclusion of fixed effects leads to the incidental parameter problem as the number of parameters rises with the cross-section dimension, and ML estimation is not necessarily consistent. Yet in the case of the linear regression, a conditional likelihood based on the transformed variables exists, which is consistent (Chamberlin (1980)). As is well-known, this consistency is lost when the time lag of the dependent variable is employed, and an asymptotic bias even exists when the true influence of the lagged dependent variable is zero (Hsiao (1986)). In the spatial model matters are less severe, since ML estimation is asymptotically consistent if the coefficient of spatial correlation is zero. This results from the fact, that the difference between the likelihood of the SLDV model and the likelihood of the linear regression model is the value of the determinant $|\mathsf{I} - \rho \mathsf{W}|$, which is unity if $\rho = 0$ (Anselin (1988a)) (I is the identity matrix, W the spatial weight matrix, and ρ the correlation coefficient). In the present estimation the unconditional ML estimator is applied, but the variance covariance matrix is corrected for the degrees of freedom lost in the fixed effects.

the ML estimations, such that for each spatial unit drawn, the observations for all years and neighbors have been added into the block.

The results of block-bootstrap computation of standard errors based on 5,000 replications are reported in column (2) of Table 3. Since it is not known how the maximum-likelihood estimator behaves under residual correlation and heteroscedasticity, it is important to know if the coefficients estimated by (pseudo) ML deviate from the mean bootstrap estimates. Yet a significant bias could not be found for any coefficient. At the bottom of column (2) a statistic for the joint test for all parameters is presented which does not indicate any significant bias. As expected, the standard errors are much higher than those of the maximum-likelihood estimation in column (1). The coefficient of population is no longer significant, but all other coefficients are, including the coefficient of the lagged dependent variable (ρ).

To sum up, the estimations support the presence of some spatial correlation in the basic wage regression such, that a spatially lagged dependent variable model is adaequate. Under that specification, the coefficients of the regressors describe ceteris-paribus effects, holding the neighbors wage rate constant. But the reason behind the effect of the wage rate in the neighborhood is still ambiguous. It might be caused by interaction between the two districts' labor markets in the sense that a rise of a neighboring district's wage raises the opportunity wage of local workers. But it might also be caused by any other correlation in unobserved characteristics. This view is supported by the fact that results for the other regressors are very similar to the above OLS estimates.

The analysis of spatial effects so far was solely concerned with correlation in the error terms and in the wage rate. However, they might also be present in the other central variable of the local labor market, namely the unemployment rate. Since, if the regional classification used is exaggerated in the sense that regional (functional) labor markets extend over contiguous districts, not only wages but also the unemployment rate in the local neighborhood should exert an influence on local pay. To test for this influence, the inverse of the spatially-lagged unemployment rate is added as a regressor into the basic wage estimation. Column (3) reveals that, whereas the influence of the own unemployment turns out to be smaller than in the basic regression, also the unemployment rate in the neighboring districts shows significant effects. However, if both rates of unemployment vary together, or putting it differently, if the unemployment rate in the aggregate region consisting of the district and its neighbors varies, the effect on local wages is somewhat larger.

The reduction in the estimated effect of the own unemployment, once the neighbors' unemployment rate is controlled for, could be explained by spatial correlation in the unemployment rate, which makes the local unemployment a proxy for the regional unemployment rate. Indeed, application of the SLDV model on the districts' unemployment rate reveales strong spatial correlation. Accounting for fixed regional and time effects, a corresponding ML estimation based on the full set of district's unemployment rates, yielded a highly significant coefficient of correlation of about 0.69. Under the hypothesis that the local as well as the neighbors' unemployment rates affect local wages, and since the two are strongly correlated, it seems reasonable to employ some regional average of the unemployment rates, in order to estimate the effects of unemployment on wages. To take the weights given to other regions into account, a window average suggested by Anselin (1992) is computed. For a variable X it is defined as:

$$\overline{X}_r = \frac{X_r + \sum_{j=1}^{m} \tilde{\mathsf{w}}_{r,j} X_j}{1 + \sum_{j=1}^{m} \tilde{\mathsf{w}}_{r,j}},$$

where $\tilde{\mathsf{w}}_{r,j}$ is the unstandardized weight of district j in district r and m is the total number of districts. If the first terms in the numerator and denominator are removed, the transformation using the standardized spatial weight matrix results. Conforming with the previous analysis of spatial effects, the weights for non-contiguous districts are set to zero.

Column (4) of Table 3 displays results of a regression applying the window average to the unemployment rate (symbolized with a bar). As expected, the estimated effect of the inverse unemployment on local wages is larger than in the basic regression, showing coefficients which are higher by one standard error. Since measurement of regional flexibility should be related to the regional labor markets rather than to arbitrary regions, as for instance the districts, one can conclude that the wage regressions using the district's unemployment rate tends to underestimate the unemployment elasticity of pay. However, the effects are rather small, suggesting that only minor errors result from neglecting spatial effects. By using a similar formula as in the previous section, the implied unemployment elasticity of pay is between 5.5 % and 0.8 %, as the window average of the unemployment rate varies between 2.5 % and 17.4 % in the sample.

5 DYNAMIC ASPECTS

Besides spatial effects, a second source of misspecification of the basic wage equation is the neglect of dynamics. As pointed out by Blanchard and Katz (1997) the neglect of dynamics is also a source of misinterpretation, since it is assumed that the observed wage-unemployment combinations are always at their equilibrium level. Therefore, it should be interesting to see whether the estimated relation in the levels holds in a more general setting which does not exclude dynamic relations such as the Phillips curve. Card (1995) suggests to run the following regression:

$$\Delta \log W_{r,t} \quad = \quad c_1 \log U_{r,t} + c_2 X_{r,t} + a_t \tag{2}$$

$$+ \quad d_1 \log U_{r,t-1} + d_2 X_{r,t-1} + e_{r,t},$$

where Δ is the difference operator, r is the index for the region, and t is the time index. $c_j, d_j (j = 1, 2)$ are constants, $X_{r,t}$ stands for the set of other wage determinants, a_t is a time effect, and $e_{r,t}$ denotes the residual. A standard Phillips curve has a coefficient for the lagged unemployment rate not significantly different from zero ($d_1 = 0$), whereas the wage curve requires that the coefficients of the current and the lagged unemployment add to zero ($c_1 = -d_1$).

Table 4 displays results of an application to the district data. All explanatory variables of the basic wage-curve estimate including time dummies have been used, but only the relevant coefficients of the unemployment variables are reported.

[Table 4 about here.]

Two different specifications are shown. Column (1) presents results for the regression with the log rate of unemployment and column (2) reports results for the inverse rate of unemployment. Since lagged unemployment is significant, the Phillips curve is rejected in both cases. Quite to the contrary, the estimations look very much like confirming the wage curve relation in the data. But, according to the Wald statistic, the equality of the unemployment coefficients in absolute value is rejected. Therefore, the result of the test is ambiguous: the standard Phillips curve is rejected, but there are differences in the coefficients. The implication can easily be seen after rearranging equation (2) to obtain:

$$\begin{aligned} \Delta \log W_{r,t} &= c_1 \Delta \log U_{r,t} + c_2 X_{r,t} + a_t \\ &+ (d_1 - c_1) \log U_{r,t-1} + d_2 X_{r,t-1} + e_{r,t}. \end{aligned}$$

As $c_1 \neq 0$ and $d_1 < c_1$, both the change of the unemployment rate and its lagged level exert a negative influence on wages. This is consistent with an augmented Phillips curve, where the lagged level of the unemployment rate determines the current natural rate of unemployment, or often referred to as the non-accelerating-inflation rate of unemployment. In that sense, this constellation indicates partial hysteresis or persistence in unemployment, which is a common finding in the empirical literature (see Blanchard and Summers (1986) and Franz and Gordon (1993).)

Since the Phillips curve is mainly an adjustment hypothesis, "... that the nominal wage rate moves in the direction needed to eliminate the excess demand for labor ..." (Gordon (1987)) it seems to be in contradiction with an equilibrium unemployment concept that is implied by theoretical underpinnings of the wage curve, such as incentive wages. But if the concept of the labor supply curve is replaced by the wage curve, the wage adjustment can be regarded as moving towards a wage equilibrium in the labor market.

Taking this view, a wage curve can be well combined with an adjustment of a Phillips-curve type. This requires the use of an even more general specification than offered by equation (2), namely removing the restriction that the coefficient of the lagged wage rate is unity. This implies combining the wage curve with dynamic wage behavior in an error-correction model. The wage curve then delivers an interpretation for the error-correction term. Formally, a wage equation of the following form should be estimated:

$$\begin{aligned} \Delta \log W_{r,t} &= c_1 \Delta \log U_{r,t} + c_2 \Delta X_{r,t} + c_3 \Delta \log W_{r,t-1} + a_r + a_t \\ &+ d_1 \log U_{r,t-1} + d_2 \log X_{r,t-1} + d_3 \log W_{r,t-1} + e_{r,t}, \end{aligned} \tag{3}$$

where a_r is a regional fixed effect, and the other symbols are as above. Note, that testing for higher order lagged changes of the explanatory variables yielded no significance.

Table 5 displays the results of corresponding dynamic wage regressions, where the time-lag operator L indicates the lagged levels of the respective variables and the hat on the wage denotes the predicted wage.

[Table 5 about here.]

According to column (1), the lagged level of wages is highly significant, showing a coefficient of $-.039$. To get an intuition on the size of the coefficient one might interpret it in the vein of Barro and Sala-i-Martin (1991). They found what they termed the rate of convergence of about 2.3 % for the German case, which was confirmed with district-level data by Seitz (1995). Here the implied rate of convergence is 4 % ($= \log(1 - .039)$), which is much larger. But the regression conditions on other level variables, most notably the interindustrial wage structure captured by the predicted wage. Column (2) reports results for an alternative specification employing fixed effects, which according to the F-statistic are significant. After inclusion of fixed effects the coefficient of the lagged level of wages jumps to a much larger value in absolute terms. This results from conditioning on the permanent regional characteristics. As different regional characteristics are captured by the fixed effects, the long-run values are measured more properly, and the observed speed of adjustment is faster. The implied coefficients of the long-run relation can be obtained by dividing the coefficients of the levels by the absolute value of the coefficient of the lagged wage rate (.507). They are quite similar to the above basic wage curve. The unit elasticity between actual and predicted wage cannot be rejected and the implied unemployment elasticity of pay of about 2.5 % is not far from the above estimates. Also the coefficients of the other explanatory variables (not displayed) are very similar.

However, the inclusion of fixed effects into the dynamic wage regression may lead to biased estimates since the lagged level is correlated with the error term (Hsiao (1986)). Therefore, instrumental-variable estimation (GMM) as suggested by Arrelano and Bond (1991) is carried out after the equation is transformed, such that the current wage rate is the dependent variable. Formally, the estimated equation is:

$$\begin{aligned} \log W_{r,t} &= c_1 \Delta \log U_{r,t} + c_2 \Delta X_{r,t} + a_r + a_t \\ &+ d_1 \log U_{r,t-1} + d_2 \log X_{r,t-1} + (d_3+1) \log W_{r,t-1} + e_{r,t}. \end{aligned} \tag{4}$$

As compared to equation (3), no further lags in the dependent variable are allowed for ($c_3 = 0$). As the lagged change in wages is not significant in the OLS regression with fixed effects, this does not seem to be too restrictive. However, it will be tested for serial autocorrelation.
Column (3) in Table 5 displays results from the basic specification. According to the Sargan statistic at the bottom of column (3), the validity of the set of instruments used cannot be rejected. The second precondition for the appropriability of the GMM estimator is the absence of second-order serial correlation in the residuals, which is also fulfilled. (The corresponding statistics at the bottom of Table 5 are asymptotically distributed as standard normal.) The implied level relation in equation (4) is obtained after setting changes to zero (also $W_{r,t} = W_{r,t-1}$) and solving for the wage rate. In the case of column (3) of Table 5 the implied level relation between wages, predicted wages and unemployment is:

$$\log W_{r,t} = 1.011 \log \widehat{W}_{r,t} - 0.017 \log U_{r,t} + ...,$$

where the dots symbolize the neglect of other determinants. This equation is quite similar to the above results. However, the coefficient of the unemployment is only weakly significant. Column (4) presents results of a regression with the inverse rate of a window average of the rate of unemployment in the local and the contiguous districts, since this specification has been found to have the best fit in the previous analysis. Again, the implied long-run point estimate of the unemployment coefficient (0.117) is very similar to the above result.

However, the case of the predicted wage is different. Its growth seems to have less than proportionate effects on the wage growth. Yet it is important to note that a change in the predicted wage $\Delta\widehat{W}$ reflects two distinct processes: it reflects a change in the industries' wages as well as a change in the local employment weights of the industries. Since the former is a movement at the aggregate level and the latter is resulting from local employment changes, a decomposition of the total change in the predicted wage seems adaequate. The first component shows the effect of changes in sectoral wages at given local employment shares ($\Delta \log \widehat{W} \mid \text{empl.}$). It can be regarded as the true dynamic counterpart of the predicted wage, as it measures the predicted rate of wage growth at a given industrial composition of employment. The second gives the effect of changes in local employment shares at given industry wages ($\Delta \log \widehat{W} \mid \text{wages}$), and a third component is a mixed term determined by the co-movements of the two ($\Delta \log \widehat{W}$mixed). Results from GMM regressions using the decomposition are presented in column (5) of Table 5. Accordingly, local wage growth is proportional to the growth in the industries' wages at fixed employment shares ($\Delta \log \widehat{W} \mid$ empl.). Therefore, the proportionality in the levels carries over to the growth rates. The second component ($\Delta \log \widehat{W} \mid$ wages) has a coefficient below unity. The interpretation is that a redistribution of employment has a less than proportional effect on the local wage level. Given these two results the third mixed term can be expected to show a coefficient in between.

The predicted wage or the predicted rate of wage growth have been found to exert a strong influence empirically. Although it is tempting to interpret this finding as indicating a regionally rigid wage structure, this conclusion is not compelling, as the predicted wage may just successfully describe the mean of the distribution of compositional factors. The interpretation of the proportional relation between the predicted rate of wage growth and the actual wage growth as pressure from national bargaining also fails to explain why the pure redistribution in local employment has less than proportionate effects. Thus, as shown in the theoretical treatment above, the identification of inflexibility due to negotiated wages, in the absence of hard data, must rely solely on the unemployment effects.

Summing up the results, the dynamic regression clearly supports the concept of the wage curve. Despite the short time period the dynamic specification unravels quite the same wage curve as was estimated above. This can be taken as evidence that the wage curve is indeed a long-run or equilibrium relation between the levels. Moreover, the OLS estimator, which is biased and inconsistent in panels with short time series, shows small differences to the instrumental-variable estimator.

6 CONCLUSIONS

The investigation of wages in the manufacturing industry for the large cross-section of regions in the dataset clearly supports the wage-curve hypothesis. However, local unemployment not only affects the level of wages but also the wage growth. Yet this must not be taken as an indication that the wage curve is a misspecified Phillips curve. Rather, wage growth is determined by an error-correction process which contains the wage curve as a long-run equilibrium relation.

The analysis of contiguity effects reveals the presence of spatial correlation in wages. As the coefficients of the local variables are not affected, this might well be caused by omitted variables. Yet a neglect of the spatial correlation in the unemployent rate leads to an underestimation of the effect of local unemployment on the local wages.

The estimated impact of local unemployment on wages is quite small as compared to studies for other countries. It is tempting to relate this finding to the minor spatial flexibility of negotiated wages as revealed by the exploration of wage agreements in Germany. Without being able to directly test whether this is caused by the negotiated wages, theoretical considerations suggest testing for an implied asymmetry of the wage response to unemployment. Namely, if negotiated wages matter directly, local wages should follow the wage-curve hypothesis in regions where unemployment is low, but should not react to changes in the unemployment rate in depressed regions. And indeed, it turned out that the impact of local unemployment on local wages decreases with its extent. However, the significance of this finding fades against the generally low responsiveness of local wages to unemployment.

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APPENDIX: DATA DESCRIPTION

Districts: The data refer to all 327 districts in West Germany. But, because of data protection rules two pairs of contiguous districts in Lower Saxony have been treated as composite regions.
Districts' manufacturing wage rate: Annual sum of payments to employees divided by annual average employment, published by the statistical offices of the German states.
Manufacturing industries' wages: Annual payments to employees and annual average employment for 35 two-digit sectors of the manufacturing industry taken from publications of the Federal Statistical Office.
Manufacturing industries' employment by district: Employment data at two digit level obtained from the Institute for Employment Research at the Federal Employment Service. The data are matched with the data from the Federal Statistical Office by means of a classification with 33 industries (see Buettner (1997)).
Districts' unemployment rate: Taken from the Regaris database of the Institute for Employment Research at the Federal Employment Service. For the two composite regions in Lower Saxony an average unemployment rate is computed using the respective districts' working population supplied by the Regio database of Eurostat.
Hours per worker in districts' manufacturing: Hours worked by blue collar workers during the year divided by the annual average of employed blue collar workers, published by the statistical offices of the German states.
Proportion of workers in districts' manufacturing: Annual average of blue collar workers employed divided by the annual average of total employees, published by the statistical offices of the German states.
Population by district: Annual averages taken from the Eurostat database Regio.
Spatial weight matrix: A digitized map of government locations, obtained from the National Geodetical Institute, has been used to construct a 327×327 weight matrix. Distances are computed without projection as euclidean distances from the latitude and longitude of the location of the

district's public authority. Two pairs of districts (see above) are aggregated by computing average weights. The resulting 325×325 matrix has 1646 non-zero links, where there is one most connected district with 12 neighbors and 28 least connected districts with only 1 neighbor. Because of the hierarchical city-periphery relations exemplified by the number of single connected districts, a row standardized matrix is used for empirical analysis.

Table 1: Spatial Differentiation of Wage Agreements

Sector	Kind of Agree-ment [a] (1)	Emp-loy-ees (1000) (2)	Spa-tial Units (3)	Mean Pay-ment [b] (4)	Stan-dard Dev. [c] (5)	Coef. of Var. [d] (6)	Rela-tive Span (in%) (7)
Metal Industry	wage	2311	15	2614.5	2.2	.001	.3
	salary	1311	15	3099.7	197.4	.064	44.0
Public Service	wage	756	1	3174.0	.0	.0	.0
	salary	1540	1	3091.0	.0	.0	.0
Retail Trade	wage	354	12	3187.6	233.7	.073	9.6
	salary	1440	12	2817.6	9.3	.003	.2
Building Indus. Proper	wage	[e]) 759	1	3439.0	.0	.0	.0
	salary	[f]) 176	1	3462.0	.0	.0	.0
Chemical Industry	joint	723	12	3708.0	66.9	.018	5.8
Hotels & Catering	joint	514	13	.	.	.	.
Private Transport	wage	281	12	.	.	.	.
	salary	140	12	2955.8	169.4	.057	74.4
Banking	joint	380	1	3592.0	0.0	.0	.0
Private Insurance	joint	268	1	3551.0	.0	.0	.0
Repair of Vehicles	wage	213	14	2811.0	129.4	.046	29.2
Textile Industry	wage	[g]) 151	10	2526.5	61.3	.024	7.6
Wood Processing	wage	149	13	2890.6	114.3	.040	15.3
Cleaning (Buildings)	wage	141	11	.	.	.	.
Printing	wage	130	9	3364.0	.0	.0	.0
Clothing	wage	123	12	2260.2	31.6	.014	9.6
Energy	joint	122	8	3917.3	164.1	.042	13.4
Iron & Steel	wage	111	5	.	.	.	.
Coal Mining	wage	100	4	.	.	.	.

Notes: The source is Bispinck et al. (1995). [b]), [c]), and [d]) are own computations.
[a]) "wage" denotes agreements only for blue-collar, "salary" only for white-collar workers, "joint " stands for a joint agreement which covers both type of labor.
[b]) basic payment for a medium skill worker. The numbers of individual agreements are weighted with the employees covered.
[c]) standard deviation of the mean payment.
[d]) standard deviation divided by the mean payment.
[e]) without Hamburg.
[f]) without Bavaria.
[g]) only 85 % of employees listed in column (2) are considered.

Table 2: Basic Wage Regressions

Observations	2,600				
Fixed effects	no	yes	yes	yes	yes
Time effects	no	no	yes	yes	yes
Industry shares	no	no	no	yes	no
	(1)	(2)	(3)	(4)	(5)
Constant	$-.486^{***}$				
	(.053)				
log Predicted	1.001^{***}	$.989^{***}$	1.036^{***}		1.031^{***}
Wage	(.012)	(.012)	(.086)		(.085)
log Rate of	$.009^{***}$	$-.017^{***}$	$-.019^{***}$	$-.015^{***}$	
Unemployment	(.003)	(.002)	(.004)	(.004)	
Inverse Rate of					$.102^{***}$
Unemployment					(.017)
log Hours per	$-.042$	$.236^{***}$	$.255^{***}$	$.271^{***}$	$.259^{***}$
Worker	(.030)	(.023)	(.025)	(.024)	(.025)
log Proportion	$.434^{***}$	$-.299^{***}$	$-.286^{***}$	$-.364^{***}$	$-.282^{***}$
of Workers	(.012)	(.034)	(.033)	(.030)	(.033)
log Population	$.054^{***}$	$.090^{***}$	$.095^{***}$	$.094^{***}$	$.086^{***}$
	(.002)	(.033)	(.033)	(.036)	(.033)
R^2	.8754	.9913	.9914	.9916	.9915
R^2 adj.	.8752	.9900	.9901	.9903	.9902
Pooling (F)	43.7	3.28			
FE (F)		93.4	83.9	57.8	84.4
TE (Wald)			28.8(7)		
LM (λ)					1.534
LM (ρ)					13.27

Notes: OLS estimates. Standard errors in parentheses are heteroskedasticity-consistent following White (1980). Significant coefficients are marked with one, two or three stars for levels of 10%, 5%, and 1%. Pooling (F) is an F-statistic for the equality of the listed coefficients across regions. FE (F) is the F-statistic for joint significance of fixed effects. The critical value for the F-statistics at 5% significance is 1.1. TE (Wald) is a Wald-statistic for joint significance of time dummies based on the heteroscedasticity-consistent covariance matrix. Its critical value at 5 % significance is 14.1. LM (ρ), LM (λ) are statistics for the presence of a spatial lag in the dependent variable and in the residual, respectively, following Anselin et al. (1996) with a critical value of 3.84 at 5% level of significance.

Table 3: Spatial Dependence in the Wage Regression

Observations	2,600			
	(1)	(2)	(3)	(4)
log Predicted Wage	1.000***	1.000***	1.009***	1.017***
	(.048)	(.127)	(.128)	(.129)
$1/U$	.095***	.095***	.064***	
	(.015)	(.019)	(.022)	
$(1/\mathsf{W}U)$			.081 **	
			(.033)	
$1/\overline{U}$				.130***
				(.027)
log Hours per Worker	.259***	.259***	.262***	.258***
	(.016)	(.031)	(.032)	(.031)
log Proportion of Workers	−.276***	−.276***	−.271***	−.275***
	(.022)	(.053)	(.053)	(.052)
log Population	.061 **	.061	.049	.054
	(.029)	(.045)	(.044)	(.044)
ρ	.140***	.140***	.138***	.139***
	(.024)	(.049)	(.050)	(.048)
log Likelihood	7081.4	7081.4	7087.2	7086.4
LR (ρ)	38.4	38.4	37.0	38.1
LM_ρ (λ)	2.43	2.43	1.08	.67
Bias (Wald)		2.22(6)	2.24(7)	2.28(7)

Notes: Maximum-likelihood estimates. ρ is the coefficient of the spatially-lagged dependent variable. W denotes the spatial weight matrix. Standard errors in parentheses. Significant coefficients are marked with one, two or three stars for levels of 10%, 5%, and 1%. All estimations take into account fixed regional and time effects. Column (1) uses standard errors based on analytic second-order derivatives, the degrees of freedom are corrected for the fixed effects. Columns (2) to (4) use standard errors obtained from block-bootstap estimation with 5,000 replications. LR(ρ) tests for the significance of the spatial correlation coefficient. LM_ρ (λ) tests for additional spatial residual correlation in the SLDV model. The LM and LR statistics have a critical value of 3.84 at 5% level of significance. Bias (Wald) is a Wald statistic of the joint significance of the difference between the maximum-likelihood and the bootstrap estimator. The critical value at 5% of significance is 12.6.

Table 4: Differenced Estimations

Observations	2,275	
Fixed Effects	no	
	(1)	(2)
$\log U_t$	$-.024^{\star\star\star}$	
	(.005)	
$\log U_{t-1}$	$.020^{\star\star\star}$	
	(.005)	
$1/U_t$		$.112^{\star\star\star}$
		(.020)
$1/U_{t-1}$		$-.093^{\star\star\star}$
		(.020)
Equality (Wald)	8.75	7.85

Notes: OLS estimates. Standard errors in parentheses are heteroscedasticity-consistent following White (1980). Significant coefficients are marked with one, two or three stars for levels of 10%, 5%, and 1%. Further explanatory variables are current and lagged values of the log predicted wage, the log hours per worker, the log share of blue-collar workers, the log population, and a set of time dummies.

Table 5: Dynamic Wage Regressions

Observations	2275		1950		
Method	OLS		GMM		
Fixed Effects	no	yes	yes	yes	yes
	(1)	(2)	(3)	(4)	(5)
$\Delta \log \widehat{W}$	.873***	.785***	.796***	.792***	
	(.117)	(.097)	(.102)	(.103)	
$\Delta \log \widehat{W} \mid$ empl.					.947***
					(.121)
$\Delta \log \widehat{W} \mid$ wages					.626***
					(.146)
$\Delta \log \widehat{W}$ (mixed)					.819***
					(.187)
$\Delta \log U$	−.022***	−.017***	−.017***		
	(.005)	(.005)	(.006)		
$\Delta\,(1/\overline{U})$				.104***	.111***
				(.028)	(.027)
$\mathsf{L}\Delta \log W$	−.110***	−.007			
	(.030)	.033			
$\mathsf{L} \log W$	−.039***	−.507***	.436***	.438***	.429***
	(.007)	(.032)	(.115)	(.113)	(.114)
$\mathsf{L} \log \widehat{W}$	.060***	.581***	.570***	.566***	.551***
	(.012)	(.086)	(.153)	(.153)	(.156)
$\mathsf{L} \log U$	−.004***	−.013***	−.010*		
	(.001)	(.004)	(.005)		
$\mathsf{L}\,(1/\overline{U})$				.066**	.070***
				(.027)	(.026)
R^2 adj.	.4254	.5244			
FE (F)		2.45			
Sargan			22.6 (26)	23.9 (26)	24.1 (26)
Serial Corr.:					
1st Order			- 4.618	- 4.718	- 4.677
2nd Order			- .969	- .980	- .992

Notes: Standard errors in parentheses in the case of OLS regressions are heteroscedasticity-consistent following White (1980). Column (3) to (5) report estimates obtained from GMM estimation suggested by Arrelano and Bond (1991), the corresponding test statistics are shown at the bottom of the table. Significant coefficients are marked with one, two or three stars for levels of 10%, 5%, and 1%. Further explanatory variables are current and lagged values of the log hours per worker, the log share of blue-collar workers, the log population, and a set of time dummies. FE (F) is the F-statistic for significance of fixed effects (critical value at 5% is 1.1).