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ORIGINAL PAPER

The wage curve and local monopsony power

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Abstract
Using longitudinal micro-data from Finland, a country with a geographically dispersed population and relatively long distances between local labor markets, this paper examines the responsiveness of the pay level to local unemployment conditions. In particular, this study tests the hypothesis that the pay level is more responsive to the unemployment level in less agglomerated and more remote regions as might be expected if employers have a higher degree of monopsony power in such regions. The results consistently suggest that the pay level is lower in localities with a higher unemployment level and, hence, provide strong support for the so-called wage curve hypothesis, which predicts that a negative relationship exists between local unemployment and the pay level. Although the results provide some evidence that the magnitude of the regional pay–unemployment relationship varies across different regions of the country, the findings do not provide consistent support for the monopsony power hypothesis. In particular, after controlling for unobserved worker heterogeneity, the responsiveness of the pay level to the local unemployment conditions is similar across regions with different degrees of economic agglomeration.

JEL Classification J31 · J42 · J60 · R23

1 Introduction

Empirical literature has extensively confirmed the wage curve hypothesis proposed by Blanchflower and Oswald (1990, 1994), which suggests that wages are lower in local labor markets with higher unemployment. However, in contrast to the findings of their pioneering empirical work, the magnitude of this inverse relationship seems to vary considerably across countries (see, e.g., Nijkamp and Poot 2005). Based on their empirical findings, Blanchflower and Oswald argued that the responsiveness of wages to local unemployment is not affected by differences in the labor

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market institutions of countries. However, later studies have shown that local wage responsiveness is contingent on labor market institutions. Indirect evidence is based on less elastic wage curves in countries with more centralized wage bargaining systems, such as those in Nordic countries (Albæk et al. 2000; Nijkamp and Poot 2005), and union workers (Card 1995; Barth et al. 2002), while more direct evidence is provided by studies illustrating that the slope of the wage curve changes based on the restructuring of the wage bargaining system and other labor market reforms (Devicienti et al. 2008; Cholezas and Kanellopoulos 2015; Daouli et al. 2017).

Furthermore, prior studies provide evidence that the slope of the wage curve may vary across different regions of the same country. For instance, Turunen (1998) found that the size and significance of the wage curve slope of young workers vary across nine major geographical areas of the USA. Deller (2011) used cross-sectional regional data from the USA to show that wages are negatively related to local unemployment in some parts of the country, but in others, the wage–unemployment relationship is either positive or statistically nonsignificant.

The within-country variation in wage curve estimates is somewhat puzzling: Because the local labor markets of a country typically share the same wage-setting mechanisms and other labor market institutions, the regional variation in the wage curve slopes calls for an explanation that relies on other factors. One potential explanation is provided by Longhi et al. (2006), who argued that within-country variation may arise from local monopsony power. Their reasoning relies on the assumption that the bargaining power of an employee is likely an increasing function of his or her outside job opportunities (i.e., job opportunities in firms other than the current firm). One important determinant of outside job opportunities is the employment conditions in the surrounding labor market. Due to higher mobility costs (job search, commuting and migration costs), job opportunities in distant locations are less relevant for the employee, and hence, the outside options are largely determined by the job opportunities in the local labor market. However, the job opportunities in the locality are partially contingent on the number of unemployed jobseekers as follows: An increase in the local unemployment level increases job competition and, consequently, reduces the outside job opportunities of the employees in the locality. Hence, a higher local unemployment level is likely to reduce the bargaining power of employees and decrease negotiated wages in high-unemployment regions. Outside job opportunities are typically also poorer in regions with a lower degree of economic agglomeration, such as in small cities and urban regions, because of the smaller number of potential employers. When employees have only a few (or, in the extreme case, none) potential alternative employers in the locality, their employers may have monopsony power over them, which they may take advantage of to negotiate lower wages. The monopsony power of employers is presumably particularly strong in remote low-agglomeration regions with high joblessness. Consequently, the wage curve relationship is more pronounced in these regions than in regions with a high concentration of firms and close proximity to neighboring regions.

Using regional data from western Germany, Longhi et al. (2006) provided empirical evidence supporting the monopsony power hypothesis, which posits that the slope of the wage curve is larger in less agglomerated and more isolated regions. Consistent with the monopsony power hypothesis, other studies have illustrated

that the magnitude of the wage curve relationship is contingent on the degree of urbanization, where the pay level is less responsive to local unemployment level in larger cities than in smaller cities and rural regions (Baltagi et al. 2012; Baltagi and Rokicki 2014).

In this paper, we use worker-level panel data from Finland to test the monopsony power explanation of the variation in the regional wage curve. We argue that Finland provides an ideal case for analyzing local monopsony power because long distances between local labor markets create notable job mobility costs. Based on our results and conclusions reported by Solon et al. (1994), we argue that the use of regional aggregate data may partially explain why Longhi et al. (2006) found a more pronounced wage curve in less agglomerated regions. Solon and others argued that using aggregate data to analyze the cyclicality of (real) wages may introduce a composition bias, leading to the underestimation of the true procyclicality of wages. This composition bias arises when aggregate statistics fail to properly account for the changing composition of the workforce over the business cycle. If the size of the composition bias varies across regions with different degrees of economic agglomeration, using regional aggregate data to analyze within-country variation in wage curve slope may lead to incorrect conclusions. As discussed by Solon et al. (1994), a solution to the composition bias problem is to estimate worker-level wage regressions while including worker fixed effects. Thus, to account for composition bias in the analysis of regional variation in the wage curve relationship, we re-estimate the models estimated by Longhi et al. (2006) by using worker fixed effects specifications. Our results suggest that the greater responsiveness of the pay level to local unemployment conditions in less agglomerated regions disappears when we account for unobserved worker heterogeneity.

2 Data and empirical approach

The micro-data analyzed are based on a 7% random sample of the Finnish population drawn in 2001. The data from a sampling year were merged with data from preceding and subsequent years, and the resulting longitudinal data include information on the sampled individuals for the period from 1995 to 2006. For the purposes of the wage curve analysis, these worker-level data were combined with regional data on local unemployment rates measured at the LAU-1 level (79 subregions).[1] Because the micro-data include identifiers for subregions only for the years 1995–2002, the final sample used for the analysis includes observations only for this period. The analysis focuses on non-agricultural private-sector employees who lived in mainland Finland, and consequently, individuals who lived in the Åland Islands (which constitute an autonomous province of Finland) and individuals who were employed in the public sector or by the agriculture, forestry or fishing industries were excluded from

[1] The micro-data were collected by Statistics Finland. The unemployment rates were obtained from the *Employment Service Statistics* compiled by the Ministry of Economic Affairs and Employment and are based on the number of unemployed individuals registered as jobseekers at employment offices.

Table 1 Descriptive statistics (1995–2002)

Variable	Mean	SD	Min	Max
Worker characteristics				
Annual earnings e_{irt} (euros)	24,398	8989	1900	69,000
Age	39.9	10.2	18	68
Work experience	10.2	3.5	1	16
Female dummy	0.422			
Marital dummy	0.540			
Children dummy	0.427			
Education level				
Primary/lower secondary	0.253			
Upper secondary	0.446			
Lowest level tertiary	0.183			
Lower-degree level tertiary	0.063			
Higher-degree level tertiary	0.053			
Doctorate or equivalent	0.002			
Regional variables				
Regional unemployment rate u_{rt}	16.76	4.75	6.38	30.22
Regional agglomeration measure A_{rt}	0.027	0.029	0.008	0.206
Regional agglomeration measure T_{rt}	0.019	0.016	0.006	0.139

The marital dummy equals one if a worker was married and zero otherwise. The children dummy equals one if a worker had children aged under 18 years and zero otherwise

the final sample. Additionally, employees aged under 18 and over 68 were excluded from the sample.

To examine the regional variation in the wage curve relationship, we estimate the following earnings equation:

$$\log\left(e_{irt}\right) = \alpha + \beta \log\left(u_{rt}\right) + \gamma \log\left(u_{rt}\right) \times \mathrm{AM}_{rt} + \lambda \mathrm{AM}_{rt} + \delta X_{irt} + \eta_r + \theta_t + \varepsilon_{irt} \tag{1}$$

where i, r and t represent the individual, subregion and year, respectively; e_{irt} is the annual earnings; u_{rt} is the local unemployment rate of the LAU-1 subregion; $\boldsymbol{X_{irt}}$ is a vector of worker characteristics, including age, age^2, work experience, work experience^2 and a set of dummy variables for gender, native/first language, marital status, children under 18 years old, education level, field of study and industry (and interaction terms of gender with marital status and children dummies); η_r is a region effect; θ_t is a year effect; and ε_{irt} is an error term. Table 1 summarizes the descriptive statistics for the worker characteristics. The regression variables are described in more detail in Table 6 in "Appendix."

Because both the earnings variable and the unemployment variable are in logarithms, coefficient β measures the local unemployment elasticity of pay. According to the wage curve relationship, the unemployment elasticity is negative; hence, we expect to observe a negative coefficient for the estimate of β. As noted by Card (1995), the

relevant dimension for the estimation of the unemployment coefficient β is the product of the number of regions and the number of observation years. Consequently, the estimation of β is effectively based on 632 observations (=79 regions×8 years).

Variable AM_{rt} captures the degree of economic agglomeration of subregion r in year t and is measured in three different ways. The first two measures are adopted from Longhi et al. (2006) and are calculated as follows[2]:

$$A_{rt} = \sum_j 10^{-6} \times \left(E_{jt} \times w_{rj}\right)$$

$$T_{rt} = \sum_j T_{jrt} = \sum_j 10^{-6} \times \left(E_{jt} \times E_{rt}\right)^{0.5} \times w_{rj}$$

where E_{rt} is the total number of employed in subregion r in year t; E_{jt} is the total number of employed in region j neighboring subregion r; and weights w_{rj} are elements of the $R \times R$ spatial weight matrix, where R is the number of subregions (the rows and columns of the matrix have the same ordering of subregions). The elements of the spatial weight matrix are calculated based on the inverses of Euclidean distances between subregion r and its neighboring subregions j, and diagonal elements (w_{rr}) and elements corresponding to non-contiguous subregions (i.e., regions that do not border one another) are set to zero.[3] The weight matrix is "row standardized" by dividing each element of the matrix by the row sum of the elements. Consequently, each row of the final spatial weight matrix sums to zero; that is, for each subregion r, $\sum_j w_{rj} = 1$. Measure A_{rt} is hence a weighted average of the number of employed individuals in subregions surrounding subregion r. Assuming that local monopsony power yields a more elastic wage curve for more remote and less agglomerated regions, we would expect to observe a negative value for parameter γ. Table 1 reports the summary statistics of the agglomeration measures A_{rt} and T_{rt}.

As a third measure of agglomeration variable AM_{rt} in earnings Eq. (1), we use a set of dummy variables that divide subregions into geographical areas with different levels of agglomeration. Based on regional characteristics related to the degree of economic agglomeration reported in Table 2, three dummy variables are generated for the geographical areas of Finland: "South" (high-agglomeration region), "Central" (medium-agglomeration region) and "North" (low-agglomeration region).[4] In this model specification, the southern subregions are used as a

[2] For a more detailed description of these measures, see Longhi et al. (2006), pages 716–720.

[3] Because the subregions comprise two or more municipalities and have more than one local center, the calculation of the elements of the spatial weight matrix is based on the Euclidean distances between the administrative centers of the most populated municipalities within each subregion. The Euclidean distance data were extracted from Google Maps.

[4] "North" comprises the subregions located in the three northernmost NUTS-3 regions (Kainuu, Northern Ostrobothnia and Lapland). "South" comprises the subregions located in the eight contiguous NUTS-3 regions in southwestern Finland (Uusimaa, Itä-Uusimaa, Varsinais-Suomi, Satakunta, Kanta-Häme, Pirkanmaa, Päijät-Häme and Kymenlaakso), constituting the most densely populated area in the country. "Central" comprises the subregions located in the eight NUTS-3 regions of central Finland (South Karelia, Etelä-Savo, Pohjois-Savo, North Karelia, Central Finland, South Ostrobothnia, Ostrobothnia and North Ostrobothnia).

Table 2 Region characteristics in 2002

Variable	Region		
	"South"	"Central"	"North"
Population share (%)	46.3	37.0	16.7
Population/km^2 of land area	32.0	14.6	4.3
Land area (%)	18.4	32.1	49.5
Degree of urbanization (%)[a]	84.7	74.5	67.7
Mean of the Euclidean distance between the subregional centers (km)	57.6	67.2	105.8
Number of municipalities			
< 10 000 inhabitants	141	132	56
10,000–49,999 inhabitants	42	30	15
50,000–99,999 inhabitants	3	5	0
≥ 100,000 inhabitants	5	0	1

[a]Mean of values of included NUTS-3 regions. In 2002, the total population of Finland was 5,180,038, and the total land area was 302,946 km^2 (excluding the population and the land area of Åland Islands). Source: Author's own calculations based on data from Statistics Finland

reference group, and we are particularly interested of the coefficient estimate on the interaction term between the local unemployment variable and the dummy variable for northern subregions. A north–south division provides an ideal setting for a test of the monopsony power hypothesis as an explanation for the within-country variation in wage curve estimates: the population in Finland is heavily concentrated in the southern parts of the country, whereas northern Finland, characterized by a lack of economic agglomerations and long distances between local labor markets, is among the least populated geographical areas in Europe. Hence, based on the monopsony power hypothesis, we would expect to observe a more pronounced wage curve for the northern subregions than for the southern subregions.

The dependent variable of the earnings Eq. (1) is a logarithm of worker's annual earnings. The wage curve relationship essentially describes the relationship between the local unemployment level and the *wage level*, and hence, the preferable dependent variable would be workers' hourly wage. Unfortunately, the micro-data used for the analysis do not include information on hourly wages or working hours. When annual earnings are used as a dependent variable for the regression equation, the coefficient on the unemployment variable, β, may yield inflated estimates of the true wage–unemployment relationship, as β reflects the variation in both hourly wages and annual working hours with respect to local unemployment level. To account for the effects of varying working hours on the wage curve estimates, the final sample used for the analysis excludes (1) employees who worked less than 12 months a year and (2) 5% of the observations from both tails of the annual earnings distribution in each year in each subregion. The final sample employed in the estimation

of different specifications of earnings Eq. (1) consists of 429,414 observations for 92,839 workers.

Earnings Eq. (1) is estimated by using an ordinary least-squares estimator. Additionally, to account for the pay-level effects of unobserved time-invariant worker characteristics, the earnings equation is also estimated by using the fixed effects estimator. In the fixed effects specifications, a worker-specific effect τ_i is included as an additional regressor. Earnings equations that include the worker effects are our preferred specifications, as they account for the potential composition bias that may arise from the compositional changes in the workforce over the business cycle (Solon et al. 1994). To account for the possibility that the different level of aggregation of the dependent and the independent variable, where earnings are measured at the worker level and unemployment is measured at the regional level, may cause error terms ε_{irt} to be correlated across employees working in the same subregion (Moulton 1986, 1990), we cluster standard errors at the regional level (see Cameron and Miller 2011, 2015).

When we estimate the wage curve relationship by using the micro-data, we assume that the logarithm of local unemployment rate is an exogenous variable. While some studies use regional data to show that simultaneity bias, which is caused by the simultaneous determination of local wage and unemployment levels, may have a substantial effect on wage curve estimates (Baltagi and Blien 1998; Baltagi et al. 2000; Longhi et al. 2006), this may be less of a problem when the wage curve is estimated by using micro-data: Local unemployment rates are presumably affected by aggregate wages, not by individual wages (Nijkamp and Poot 2005).

3 Results

3.1 Wage curve estimates based on regionally aggregated data

To ensure the comparability of our results with those reported by Longhi et al. (2006), who employed regional data instead of micro-data, we begin our analysis by estimating regional-level wage curve regressions that closely correspond to their estimates. For this purpose, we first aggregate the micro-data by subregion (i.e., we calculate the mean values of the worker-level variables for each subregion in each year) and then use these data to estimate earnings regressions that include the same explanatory variables of interest that Longhi and others used in their regression models. These earnings regressions also include the following control variables for subregions: the mean age of workers, mean work experience of workers, share of female workers, share of highly educated workers (tertiary or doctorate degree or equivalent), share of workers with a degree in science and share of manufacturing workers. The earnings regressions are first estimated by using the standard OLS estimator, with region fixed effects included.

Next, following Longhi and others, the two-stage least-squares (2SLS) estimator is used to account for the possibility that local pay and unemployment levels may have been simultaneously determined. In the 2SLS estimations, the logarithm of local unemployment rate is instrumented with its 1-year lagged value. The use of lagged unemployment as an instrument raises a question about the validity of the instrument, especially since lagged unemployment can potentially have a direct

impact on earnings. However, because our primary goal is to replicate the results reported by Longhi et al. (2006), we closely follow their empirical approach and use the lagged regional unemployment rate as an instrument.

The results of the earnings regressions estimated using the regionally aggregated data are presented in Table 3. For brevity, only the coefficient estimates of the explanatory variables of interest are reported; the full results are available upon request. The estimates in the first column confirm the existence of the wage curve relationship in Finland, indicating that the pay level is negatively related to the local level of unemployment.[5] The OLS regression results provide a smaller unemployment coefficient (−0.065) than the two-stage least-squares regression results (−0.099). The latter coefficient estimate is identical to the uniform estimate of −0.1 reported by Blanchflower and Oswald (1994) for twelve countries. Furthermore, it closely corresponds to the wage curve estimate found by Maczulskij (2013) for Finnish private-sector workers based on micro-data.

The specifications in the second column incorporate a variable named "neighboring unemployment," which measures the unemployment level in neighboring subregions. The value of this variable for a particular subregion is a logarithm of a weighted sum of the unemployment rates in neighboring subregions, where the weights are the elements of the spatial weight matrix. The coefficient estimate on this variable is negative in both specifications, but it is statistically significant only in the OLS regression (at the 10% level). Hence, the results of the 2SLS regression suggest that unemployment conditions in neighboring subregions play no role in determining the pay level. This finding contradicts the results reported by Longhi et al. (2006), who found that the neighboring unemployment level is a statistically significant determinant of the pay level. The contradiction between our findings and theirs may be attributable to differences in the regional disaggregation of data. While they used 327 regions of Western Germany to define local labor markets, we use a regional classification that disaggregates Finland into 79 subregions.[6] The geographical disaggregation used by Longhi and others may yield regions that are effectively too small to characterize functional local labor markets. In such a case, the pay level of a particular region is likely to be affected by not only the prevailing unemployment level in that region but also the unemployment conditions in neighboring regions (as these regions are within commuting distance for workers and hence effectively constitute a part of their local labor market). The regions used in our analysis, on the other hand, are typically considered reasonable approximations of local labor markets.[7] Unfortunately, our data lack information on identifiers of

[5] Longhi, Nijkamp and Poot also included a squared term of the logarithmic unemployment rate as an explanatory variable and observed a significant positive coefficient estimate of this variable. Our preliminary estimations consistently provided statistically nonsignificant coefficient estimates of the squared term, and hence, this variable was excluded from the final specifications.

[6] The total geographical area of western Germany is approximately 74% of that of Finland.

[7] These LAU-1 regions (also referred to as NUTS-4 regions) consist of two or more neighboring municipalities (LAU-2 regions). A key factor used to delineate the boundaries of these regions is commuting flows between municipalities, and thus, these regions are considered good approximations of the local labor markets (Böckerman 2003; Mukkala 2004).

Table 3 Wage curve estimates (regional data)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Panel A: OLS					
$\log(u_{rt})$	−0.065***	−0.046***	−0.079***	−0.087***	−0.075***
	(0.013)	(0.016)	(0.020)	(0.019)	(0.013)
Neighboring unemployment_{rt}		−0.044*			
		(0.026)			
$\log(u_{rt})*A_{rt}$			0.724**		
			(0.313)		
A_{rt}			0.603**		
			(0.304)		
$\log(u_{rt})*T_{rt}$				3.422***	
				(0.738)	
T_{rt}				5.537***	
				(1.309)	
$\log(u_{rt})$*Central					0.034***
					(0.009)
$\log(u_{rt})$*North					−0.045**
					(0.018)
Region characteristics	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	632	632	632	632	632
R^2_{adjusted}	0.98	0.98	0.98	0.98	0.98
Panel B: 2SLS					
$\log(u_{rt})$	−0.099***	−0.076***	−0.150***	−0.133***	−0.108***
	(0.021)	(0.028)	(0.040)	(0.036)	(0.021)
Neighboring unemployment_{rt}		−0.052			
		(0.033)			
$\log(u_{rt})*A_{rt}$			1.395***		
			(0.525)		
A_{rt}			0.278		
			(0.387)		
$\log(u_{rt})*T_{rt}$				3.872***	
				(0.974)	
T_{rt}				4.835***	
				(1.372)	
$\log(u_{rt})$*Central					0.035***
					(0.009)
$\log(u_{rt})$*North					−0.052***
					(0.018)

Table 3 (continued)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Region characteristics	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	553	553	553	553	553
R^2_{adjusted}	0.98	0.98	0.98	0.98	0.98

Robust standard errors shown in parentheses. All models include the following control variables for the subregions: the mean age of the workers, mean work experience of the workers, share of female workers, share of highly educated workers (tertiary or doctorate degree or equivalent), share of workers with a degree in science and share of manufacturing workers. In the 2SLS specifications, the logarithmic unemployment variable is instrumented by its one-year lagged value. Significant at the *10% level; **5% level; and ***1% level

more disaggregated regions, and we are hence unable to test the effects of different regional disaggregations on our wage curve estimates.

The specifications in columns (3)–(5) assess the regional variation in the wage curve relationship by including interaction terms for the local unemployment variable and different agglomeration measures specified in the previous section.[8] The results shown in columns (3) and (4) confirm the findings reported by Longhi et al. (2006) as follows: The coefficient estimates of the interaction terms of agglomeration variables A_{rt} and T_{rt} are statistically significant and positive, indicating that the wage curve relationship is more pronounced in less agglomerated regions. Furthermore, the estimates in column (5) indicate that the slope of the wage curve is substantially larger in less agglomerated northern subregions than in highly agglomerated southern subregions, and this difference is statistically significant. Overall, the wage curve slopes from the earnings regressions estimated by using the regionally aggregated data provide strong support for the monopsony power hypothesis, according to which the responsiveness of wages to the local unemployment level is stronger in regions with a low degree of economic agglomeration.

3.2 Wage curve estimates based on the micro-data

Next, to make more efficient use of the micro-data, we estimate the alternative specifications of worker-level earnings Eq. (1). The main results of these estimations are

[8] The coefficient estimate of the neighboring unemployment variable is statistically nonsignificant in these specifications, and therefore, the variable was excluded. Furthermore, in contrast to the findings reported by Longhi et al. (2006), our estimations provide a statistically nonsignificant coefficient estimate of the interaction term between the local unemployment variable and neighboring unemployment variable.

reported in Table 4.[9] The specifications reported in the table are parallel to those estimated in Table 3 using regionally aggregated data, and hence, they allow a direct comparison of the regression coefficients of interest. Again, the coefficient estimates on the unemployment variable confirm the existence of the negatively sloping wage curve relationship. However, the estimates demonstrate that the slope of the wage curve is highly sensitive to inclusion of worker effects: When unobserved worker heterogeneity is controlled for, the unemployment coefficient increases from −0.019 to −0.089. Hence, the findings highlight the importance of controlling for worker fixed effects when estimating the local pay–unemployment relationship; otherwise, the true unemployment elasticity of pay may be obscured. The latter estimate suggests that an increase in the local unemployment rate by 100% reduces the pay level by approximately 9%. The results in column (2) once again confirm that the pay level is not related to unemployment conditions in neighboring subregions.

The wage curve estimates shown in columns (3)–(5) challenge the previous findings reported by Longhi et al. (2006) in western Germany as follows: After including worker fixed effects, the coefficient estimates of the interaction terms between the local unemployment variable and alternative agglomeration measures are no longer statistically significant. In other words, the steeper slope of the wage curve of the less agglomerated subregions disappears when unobserved worker heterogeneity is controlled for. Hence, the results do not support the hypothesis that monopsonistic features of more remote and less agglomerated regions generate a more pronounced wage curve relationship for these regions.

The use of regional aggregate data may partially explain why Longhi and others found a larger wage curve slope in regions with a lower degree of economic agglomeration. As noted by Solon et al. (1994), using aggregate data to analyze the responsiveness of wages to unemployment conditions may introduce a composition bias, leading to the underestimation of the true procyclicality of wages. Composition bias arises when aggregate statistics fail to properly control for the changing composition of the workforce over the business cycle. Provided that composition bias is more pronounced in highly agglomerated regions, one may observe a smaller wage curve slope for these regions if the composition bias is not accounted for. As discussed by Solon et al. (1994), a solution to the composition bias problem is to estimate a micro-level wage equation while including worker fixed effects. Our results suggest that once worker fixed effects are included, the wage curve slopes are similar across regions with different degrees of economic agglomeration. Adjusting for the worker composition effects may also explain why Baltagi et al. (2012) found only slightly larger wage curve estimates in Western German regions in rural areas than in regions with large cities.

Although the worker fixed effects specification in column (5) yields a similar slope estimate of the wage curve for the southern and the northern subregions of Finland (approximately −0.09), the estimates suggest that the wage curve slope is smaller for the sub-egions located in the central parts of the country (−0.06).

[9] To save space, only the coefficients of interest are reported. Table 7 in appendix reports the coefficient estimates of the control variables of the specifications estimated in the first column.

Table 4 Wage curve estimates (micro-data)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Panel A: OLS					
$\log(u_{rt})$	−0.019**	−0.048**	−0.019*	−0.053***	−0.025***
	(0.008)	(0.022)	(0.010)	(0.018)	(0.009)
Neighboring unemployment$_{rt}$		0.056			
		(0.040)			
$\log(u_{rt})*A_{rt}$			0.044		
			(0.265)		
A_{rt}			0.132		
			(0.241)		
$\log(u_{rt})*T_{rt}$				0.985**	
				(0.399)	
T_{rt}				1.079**	
				(0.485)	
$\log(u_{rt})$*Central					0.015
					(0.015)
$\log(u_{rt})$*North					−0.075***
					(0.023)
Worker characteristics	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2_{adjusted}	0.44	0.44	0.44	0.44	0.44
Panel B: Worker FE					
$\log(u_{rt})$	−0.089***	−0.088***	−0.101***	−0.035***	−0.085***
	(0.012)	(0.015)	(0.012)	(0.011)	(0.010)
Neighboring unemployment$_{rt}$		−0.003			
		(0.025)			
$\log(u_{rt})*A_{rt}$			0.183		
			(0.200)		
A_{rt}			−0.470***		
			(0.163)		
$\log(u_{rt})*T_{rt}$				0.383	
				(0.244)	
T_{rt}				2.051***	
				(0.265)	
$\log(u_{rt})$*Central					0.025***
					(0.009)
$\log(u_{rt})$*North					−0.007
					(0.023)

Table 4 (continued)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Worker characteristics	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.40	0.40	0.40	0.40	0.40
R^2 (between)	0.31	0.31	0.31	0.30	0.31
R^2 (overall)	0.31	0.31	0.31	0.30	0.31
F-test (worker FE)	14.69	14.68	14.68	14.68	14.68
(p value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Cluster–robust standard errors shown in parentheses (clustered at the regional level). The number of worker–year observations is 429,414 (based on 92,839 individuals), and the number of region–year observations is 632 (=79 regions×8 years). The worker characteristics include the following variables: gender, age, age^2, work experience, work experience^2, marital status (and its interaction with gender), children dummy (and its interaction with gender), native/first language dummies, education level dummies, field of education dummies and industry dummies. (Gender and language dummies are omitted in the worker fixed effects specifications.) Robust Hausman tests reject random effects in favor of fixed effects for all model specifications. The F-statistics test the joint statistical significance of the worker fixed effects. Significant at the *10% level; **5% level; and ***1% level

Regional differences in mobility patterns may partially explain this finding. The wage curve can be expected to be less elastic among workers who are more mobile as employers may find it more difficult to adjust their wages to local unemployment conditions because more mobile workers may relocate if employers attempt to lower their wages as local unemployment increases. When we estimate a regression model that explains the differences in the likelihood of inter-regional mobility, we find that conditional on the worker background characteristics, employees living in the central part of the country were somewhat more likely to move to other subregions than employees living elsewhere.[10] Therefore, a higher probability of relocation may explain why the wage curve is less elastic in central Finland.[11]

In contrast to findings of Deller (2011) for the local labor markets of the USA, our estimates do not provide evidence for a positively sloping wage–unemployment relationship in any of the geographical areas; rather, the coefficient estimates indicate that the pay level is inversely related to the local unemployment level in each geographical area ("North," "Central" and "South"), providing strong evidence in

[10] The probability of relocation was approximately 0.6 percentage points higher in central Finland than elsewhere. The detailed results of the inter-regional mobility regressions are available from the authors upon request.

[11] The authors would like to thank an anonymous reviewer for suggesting this explanation.

favor of the wage curve relationship. Based on the discussion in Card (1995), Deller's cross-sectional results may be partly driven by the lack of region fixed effects: Without controls for regions, the estimated coefficient on the unemployment variable may reflect the potentially positive relationship between the "permanent" regional unemployment level and "permanent" wages, whereas region fixed effects must be included to produce the negative relationship between actual local unemployment and actual wages.

Although the results shown in Table 4 appear to contradict the monopsony power hypothesis, it is still possible that the hypothesis holds among some specific groups of workers because the degree of monopsony power of employers may vary across subgroups of employees. For example, employers may have more monopsony power over less mobile workers as lower mobility reduces the outside job opportunities of workers and, thus, renders them more dependent on their current employer (Michaelides 2010). Employers may also have more monopsony power over their female workers if the labor supply of women is less responsive to wage changes than that of men (e.g., Hirsch et al. 2010).[12] To test these predictions, we re-estimated the models shown in Panel B of Table 4 separately for men, women and "non-movers." The models of "non-movers" were estimated using a sample that excluded individuals who changed region at least once between 1995 and 2002. Furthermore, to assess whether the results differ between immobile men and women, these models were estimated separately by gender. The results are reported in "Appendix" Tables 8 and 9. Consistent with the results reported in Table 4, these subgroup-specific results do not provide evidence supporting the monopsony power hypothesis as follows: The wage curve estimates for the women, men and immobile workers are very similar to those obtained for all employees.

3.3 Additional findings

In the previous analysis, the working hypothesis is that because of the existence of fewer potential employers, employees in the less agglomerated regions have poorer outside job opportunities, which gives local employers monopsony power that they can take advantage of when adjusting wages to local unemployment conditions. However, the degree of regional agglomeration may be a poor measure of local job opportunities, at least for some employees. For example, a low-agglomeration region may have a high concentration of firms operating in a certain industry, improving the local outside job opportunities of the employees working in these firms (or, conversely, high-agglomeration regions may have only few firms operating in certain industries, leaving less outside job opportunities for the employees working in these firms). Hence, to examine the role of local monopsony power as a determinant of the wage curve slope in more detail, a more direct measure of local job opportunities is needed.

[12] Lower job mobility among women provides a potential explanation for why the women's labor supply may be less elastic than the men's (Hirsch et al. 2010).

One such measure is the number of establishments operating in the same industry and region as workers' current employer (hereafter referred to as "local own-industry establishments").[13] In the following analysis, we employ the number of local own-industry establishments to provide a more detailed examination of the effect of local monopsony power on the slope of the wage curve relationship. The number of own-industry establishments is likely to be a more relevant indicator of local monopsony power for some employees than others. In particular, employees in some occupations (e.g., employees in maintenance, clerical and low-level administrative occupations) may more easily change working industries than employees in occupations that require more industry-specific education and training.[14] Furthermore, as job opportunities essentially depend on the amount of open vacancies, employees' outside job opportunities may be limited even in localities with a vast number of own-industry establishments, if only few of the establishments are concurrently offering vacancies (Manning 2003). However, the number of open vacancies is likely to be positively correlated with the number of establishments.

Table 5 presents estimates from the earnings regressions that include the logarithm of the number of own-industry establishments and its interaction term with the unemployment variable as explanatory variables. All estimated specifications include dummy variables for two-digit industries; otherwise, establishment count variables might also capture other industry pay effects. The specifications in columns (1) and (2) are based on the establishment count data for subregions, which contain the number of establishments for 25 manufacturing industries. Compared with the regional classification used in the previous analysis, these data are based on a revised LAU-1 classification that disaggregates Finland into 74 subregions (instead of 79 subregions).[15] The specifications in columns (3) and (4) are estimated by using unemployment statistics and establishment count data for NUTS-3 regions (19 regions). The advantage of using the NUTS-3-level data is that they include the

[13] Previously, Muehlemann et al. (2013) used the number of local own-industry establishments to proxy the degree of local monopsony power of employers. An alternative, widely used measure of local monopsony power is the Herfindahl–Hirschman index. Unfortunately, we lack regional data of firm-level employment shares needed to construct this index; thus, we are unable to use this index in our analysis.

[14] Related studies have analyzed the role of employer monopsony power in the pay determination of occupations that require specific education/qualifications, such as nurses (Hirsch and Schumacher 1995, 2005), teachers (Merrifield 1999) and university faculty (Ransom 1993), whose outside job opportunities are typically limited by the small number of potential local employers (hospitals, schools and universities, respectively).

[15] The reduction in the number of subregions by five is attributable to mergers of the contingent subregions. To estimate the specifications in columns (1) and (2), we had to modify the subregion identifiers of the micro-data to ensure compatibility with the regional classification of the establishment count data. This modification resulted in inaccurate subregion identifiers for some individuals. However, the number of individuals with misspecified identifiers is small, and hence, the measurement error is expected to have a negligible effect on the estimation results. We tested the robustness of the results by re-estimating the models in columns (1) and (2) by using a restricted sample that excluded all observations from the subregions that potentially included individuals with misspecified subregion identifiers. These estimations yielded coefficient estimates that were very similar to those reported in Table 5.

Table 5 Wage curve and local number of establishments

Dependent variable: log(annual earnings)				
Regional level (# of regions)	*LAU-1* (74 regions)		*NUTS-3* (19 regions)	
Estimation period	1995–2002		1995–2006	
Number of two-digit industries	25		52	
OLS				
log(u_{rt})	−0.023	0.004	0.008	0.030**
	(0.014)	(0.058)	(0.016)	(0.014)
log(own-industry establishments$_{rt}$)	0.022***	0.033	0.036***	0.043***
	(0.007)	(0.022)	(0.008)	(0.005)
log(u_{rt})*log(own-industry establishments$_{rt}$)		−0.004		−0.003
		(0.007)		(0.002)
Worker fixed effects				
log (u_{rt})	−0.046***	−0.045**	−0.058***	0.041***
	(0.007)	(0.023)	(0.010)	(0.012)
log(own-industry establishments$_{rt}$)	−0.007**	−0.007	0.012***	0.038***
	(0.004)	(0.009)	(0.003)	(0.004)
log(u_{rt})*log(own-industry establishments$_{rt}$)		−0.0002		−0.012***
		(0.003)		(0.001)
Industry dummies (two-digit)	Yes	Yes	Yes	Yes
Worker characteristics	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Worker–year observations	163,146	163,146	679,268	679,268
OLS				
R^2_{adjusted}	0.48	0.48	0.50	0.50
Worker FE				
R^2 (within)	0.40	0.40	0.48	0.48
R^2 (between)	0.29	0.29	0.36	0.36
R^2 (overall)	0.29	0.29	0.37	0.36
F-test (worker FE)	13.42	13.42	14.28	14.30
(*p*-value)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Cluster–robust standard errors shown in parentheses (clustered at the regional level). The mean value (standard deviation) of the non-logarithmic establishment count variable is 25.2 (57.8) in the LAU-1 level establishment data and 225.2 (671.9) in the NUTS-3 level establishment data. The worker characteristics include the following variables: gender, age, age^2, work experience, work experience^2, marital status (and its interaction with gender), children dummy (and its interaction with gender), native/first language dummies, education level dummies and field of education dummies. (Gender and language dummies are omitted in the worker fixed effects specifications.) Robust Hausman tests reject random effects in favor of fixed effects for all model specifications. The F-statistics test the joint statistical significance of the worker fixed effects. Significant at the *10% level; **5% level; and ***1% level

number of local establishments for a wider range of industries; the data used for the analysis include establishment counts for 52 industries. Furthermore, using NUTS-3 regions instead of LAU-1 subregions allows us to employ the full micro-data, that is, data for the period from 1995 to 2006.

Most of the specifications reported in Table 5 yield a positive and statistically significant coefficient estimate on the establishment count variable, suggesting that the pay level increases with the number of local own-industry establishments. This finding is consistent with the hypothesis that a smaller number of potential employers in the locality reduce the outside job opportunities of workers, giving local employers monopsony power over their employees and consequently allowing employers to pay lower wages. The existence of economies of agglomeration provides another potential explanation for the positive relationship between the pay level and establishment count variable: The regional concentration of firms (industries) may create productivity gains and consequently higher wages (e.g., Ellison et al. 2010; Glaeser 2010).[16] Furthermore, the increase in the number of same-industry firms in the locality may increase competition for workers, resulting in higher wages for the employees working in these firms.

The interaction term for the unemployment variable and the establishment count variable is generally statistically nonsignificant and close to zero, hence contradicting the hypothesis that the magnitude of the wage curve relationship depends on the degree of employer monopsony power. An exception is the worker fixed effects specification in column (4), which provides a significant negative coefficient on the interaction term, suggesting that the slope of the wage curve increases with the number of own-industry establishments.

4 Conclusions

This paper employs longitudinal micro-data on private-sector workers and regional data on 79 local labor markets from Finland to examine the within-country variation in the local unemployment elasticity of pay. The results provide strong support for the existence of the so-called wage curve relationship, which states that the wage level decreases with the regional unemployment rate. Furthermore, the results indicate that conditional on the local unemployment rate, the unemployment conditions in neighboring regions do not play a role in determining the pay level.

The results provide some evidence that the slope of the wage curve varies across different geographical areas of a country. Moreover, the findings indicate that once worker fixed effects are included to control for the composition bias resulting from the changing composition of the workforce (Solon et al. 1994), wage curve slopes are similar across regions with different degrees of economic agglomeration. Hence, the findings contradict the monopsony power hypothesis proposed by Longhi et al.

[16] The concentration-related productivity gains arise from the close geographical proximity of firms, which improves the supply chains of the firms and increases the interaction of firms and flows of workers, technology and information between firms.

(2006), which predicts that the magnitude of the wage curve relationship is stronger in less agglomerated regions because of the higher monopsony power of employers in these regions. Further analysis based on a more direct measure of local monopsony power, namely the number of own-industry establishments in the locality, yields a similar conclusion as follows: The pay responsiveness to local unemployment conditions is not stronger among employees whose employers potentially have more monopsony power over them.

Our findings imply that the failure to control for unobserved worker heterogeneity (composition bias) may explain why Longhi and others found a more pronounced wage curve relationship in low-agglomeration regions than high-agglomeration regions in Western Germany. However, it is possible that the inconsistencies between our conclusions and those reported by Longhi et al. are due to differences in the research methodology, data sets and country characteristics. Further research is needed to confirm whether our findings generalize to other countries.

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Compliance with ethical standards

Conflict of interest The author declares that he has no conflict of interest.

Appendix

See Tables 6, 7, 8, 9.

Table 6 Description of the variables

Variable	Description
Annual earnings	Annual earnings in euros.
Regional unemployment rate	Regional unemployment rate, computed at LAU-1 level (79 subregions). The sources of the unemployment data: Labour Force Survey (LFS), Statistics Finland.
Gender	Female dummy: = 1 if female, = 0 if male
Age	Age in full years
Experience	Work experience in years (since 1987). The values are calculated as follows: (The number of working months since January 1987)/12
Marital status	Marriage dummy: = 1 if married, = 0 otherwise
Native language	Dummy variables for native/first language: 1) Finnish, 2) Swedish or 3) other
Children	Children dummy: = 1 if the worker had children under 18 years, = 0 otherwise
Level of education (based on ISCED 1997)	1) Primary education or lower secondary education (or unknown), 2) upper secondary level education, 3) lowest level tertiary education, 4) lower-degree level tertiary education, 5) higher-degree level tertiary education, 6) doctorate or equivalent level tertiary
Field of study (based on ISCED 1997 classification)	1) General programs (or not known or unspecified), 2) education, 3) humanities and arts, 4) social sciences, business and law, 5) science, 6) engineering, manufacturing and construction, 7) agriculture, 8) health and welfare, 9) services
Industry (based on NACE classification)	1) Agriculture, forestry and fishing (excluded from the analysis), 2) mining and quarrying, 3) manufacturing, 4) electricity, gas and water supply, 5) construction, 6) wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods, 7) hotels and restaurants, 8) transport, storage and communication, 9) financial intermediation, 10) real estate, renting and business activities, 11) public administration and defense; compulsory social security, 12) education, 13) health and social work, 14) other community, social and personal service activities, 15) private households employing domestic staff and undifferentiated production activities of households for own use; extraterritorial organizations and bodies; industry unknown

Source of education and industry classifications: Statistics Finland

Table 7 Earnings equations

Dependent variable: log(annual earnings)				
	OLS		Worker fixed effects	
	Coefficient	Robust SE	Coefficient	Robust SE
$\log(u_{rt})$	−0.019**	(0.008)	−0.089***	(0.012)
Female	−0.168***	(0.010)		
Age	0.016***	(0.004)	0.037***	(0.004)
Age^2	−0.0002***	(0.00005)	−0.0004***	(0.00006)
Work experience	0.036***	(0.001)	0.085***	(0.004)
Work experience^2	−0.0005***	(0.0001)	−0.002***	(0.00008)
Married	0.043***	(0.005)	0.012***	(0.002)
Married*Female	−0.054***	(0.006)	−0.047***	(0.004)
Children dummy	0.0003	(0.003)	−0.010***	(0.002)
Children dummy × Female	−0.039***	(0.008)	−0.079***	(0.012)
Education level				
Primary/lower secondary	(Omitted)		(Omitted)	
Upper secondary	0.084***	(0.013)	−0.009	(0.013)
Lowest level tertiary	0.210***	(0.017)	0.109***	(0.030)
Lower-degree level tertiary	0.336***	(0.025)	0.221***	(0.017)
Higher-degree level tertiary	0.466***	(0.024)	0.350***	(0.024)
Doctorate or equivalent	0.489***	(0.016)	0.452***	(0.028)
Language dummies				
Finnish	(Omitted)			
Swedish	−0.014	(0.019)		
Other/unknown	0.006	(0.008)		
Other controls				
Field of study	Yes		Yes	
Industry	Yes		Yes	
Year	Yes		Yes	
Region	Yes		Yes	
Worker–year observations	429,414		429,414	
Workers	92,839		92,839	
R^2_{adjusted}	0.44			
R^2 (within)			0.40	
R^2 (between)			0.31	
R^2 (overall)			0.31	

These are the same model specifications estimated in column (1) of Table 4. Robust SE = cluster–robust standard errors, clustered at the regional level. Children dummy equals one if a worker had children under 18 years old and zero otherwise. Significant at the *10% level; **5% level; ***1% level

Table 8 Wage curve estimates by gender (micro-data)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Panel A: Women					
$\log(u_{rt})$	−0.085***	−0.077***	−0.095***	−0.033**	−0.077***
	(0.010)	(0.014)	(0.012)	(0.014)	(0.008)
Neighboring unemployment_{rt}		−0.016			
		(0.027)			
$\log(u_{rt})*A_{rt}$			0.213		
			(0.205)		
A_{rt}			−0.189		
			(0.156)		
$\log(u_{rt})*T_{rt}$				0.296	
				(0.254)	
T_{rt}				1.797***	
				(0.276)	
$\log(u_{rt})$*Central					0.036***
					(0.010)
$\log(u_{rt})$*North					0.005
					(0.024)
Observations	181,112	181,112	181,112	181,112	181,112
Number of individuals	39,959	39,959	39,959	39,959	39,959
R^2 (within)	0.34	0.34	0.34	0.34	0.34
R^2 (between)	0.31	0.32	0.32	0.30	0.31
R^2 (overall)	0.31	0.31	0.31	0.29	0.30
Panel B: Men					
$\log(u_{rt})$	−0.098***	−0.101***	−0.112***	−0.034**	−0.095***
	(0.016)	(0.020)	(0.015)	(0.014)	(0.013)
Neighboring unemployment_{rt}		0.007			
		(0.029)			
$\log(u_{rt})*A_{rt}$			0.158		
			(0.259)		
A_{rt}			−0.710***		
			(0.212)		
$\log(u_{rt})*T_{rt}$				0.377	
				(0.284)	
T_{rt}				2.296***	
				(0.339)	
$\log(u_{rt})$*Central					0.020*
					(0.011)
$\log(u_{rt})$*North					−0.015
					(0.024)

Table 8 (continued)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Observations	248,302	248,302	248,302	248,302	248,302
Number of individuals	52,880	52,880	52,880	52,880	52,880
R^2 (within)	0.44	0.44	0.44	0.44	0.44
R^2 (between)	0.28	0.28	0.28	0.28	0.28
R^2 (overall)	0.29	0.29	0.28	0.29	0.29

Cluster–robust standard errors shown in parentheses (clustered at the regional level). All models include year dummies, region dummies and the following control variables: age, age^2, work experience, work experience^2, marital status, children dummy, education level dummies, field of education dummies and industry dummies. Significant at the *10% level; **5% level; and ***1% level

Table 9 Wage curve estimates among non-movers (micro-data)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Panel A: All non-movers					
$\log(u_{rt})$	−0.087***	−0.085***	−0.098***	−0.037***	−0.084***
	(0.011)	(0.016)	(0.012)	(0.012)	(0.009)
Neighboring unemployment$_{rt}$		−0.005			
		(0.027)			
$\log(u_{rt})*A_{rt}$			0.161		
			(0.194)		
A_{rt}			−0.467***		
			(0.156)		
$\log(u_{rt})*T_{rt}$				0.259	
				(0.254)	
T_{rt}				1.713***	
				(0.274)	
$\log(u_{rt})$*Central					0.021**
					(0.009)
$\log(u_{rt})$*North					−0.011
					(0.023)
Observations	381,738	381,738	381,738	381,738	381,738
Number of individuals	79,060	79,060	79,060	79,060	79,060
R^2 (within)	0.39	0.39	0.39	0.39	0.39
R^2 (between)	0.29	0.29	0.29	0.30	0.27
R^2 (overall)	0.29	0.29	0.29	0.30	0.27
Panel B: Female non-movers					
$\log(u_{rt})$	−0.081***	−0.077***	−0.088***	−0.034**	−0.075***
	(0.009)	(0.015)	(0.011)	(0.014)	(0.008)
Neighboring unemployment$_{rt}$		−0.009			
		(0.028)			
$\log(u_{rt})*A_{rt}$			0.095		
			(0.185)		
A_{rt}			−0.358**		
			(0.157)		
$\log(u_{rt})*T_{rt}$				0.155	
				(0.264)	
T_{rt}				1.403***	
				(0.269)	
$\log(u_{rt})$*Central					0.028***
					(0.010)
$\log(u_{rt})$*North					−0.001
					(0.024)

Table 9 (continued)

Dependent variable: log(annual earnings)					
	Baseline model 1	Baseline model 2	Agglomeration measure A_{rt}	Agglomeration measure T_{rt}	Area dummies
Observations	162,331	162,331	162,331	162,331	162,331
Number of individuals	34,128	34,128	34,128	34,128	34,128
R^2 (within)	0.34	0.34	0.34	0.35	0.34
R^2 (between)	0.28	0.28	0.28	0.31	0.25
R^2 (overall)	0.28	0.28	0.28	0.31	0.24
Panel C: Male non-movers					
$\log(u_{rt})$	−0.097***	−0.096***	−0.111***	−0.036***	−0.095***
	(0.015)	(0.019)	(0.015)	(0.014)	(0.012)
Neighboring unemployment_{rt}		−0.002			
		(0.030)			
$\log(u_{rt})*A_{rt}$			0.203		
			(0.257)		
A_{rt}			−0.577***		
			(0.208)		
$\log(u_{rt})*T_{rt}$				0.255	
				(0.286)	
T_{rt}				1.970***	
				(0.347)	
$\log(u_{rt})$*Central					0.018*
					(0.010)
$\log(u_{rt})$*North					−0.018
					(0.025)
Observations	219,407	219,407	219,407	219,407	219,407
Number of individuals	44,932	44,932	44,932	44,932	44,932
R^2 (within)	0.43	0.43	0.43	0.43	0.43
R^2 (between)	0.24	0.24	0.24	0.27	0.23
R^2 (overall)	0.24	0.24	0.24	0.27	0.23

Cluster–robust standard errors shown in parentheses (clustered at the regional level). All models include year dummies and the following control variables: age, age^2, work experience, work experience^2, marital status (and its interaction with gender), children dummy (and its interaction with gender), education level dummies, field of education dummies and industry dummies. (Interaction terms are omitted in the gender-specific specifications.) Significant at the *10% level; **5% level; and ***1% level

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