# The Effect of Tightness on Wages at the Regional Level in Central Europe

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**Abstract**

Estimating the effect of labour market tightness on wages is relevant for at least two reasons. Firstly, from a central bank's perspective it is important to know the effect of tightness on one of the major determinants of cost-push inflation. Secondly, the magnitude of the spillover effect from tightness to wages can help determine the efficiency of a targeted development policy. I examine the effect of tightness on wages in Hungary, Slovakia and Poland using panel IV method on district level data. The direct effects are similar in the three countries, i.e. there is a positive link between tightness and wages. The magnitudes are somewhat different in Poland then in Hungary and Slovakia. There is spatial spillover effect in Hungary but this indirect effect is missing in Poland and Slovakia.

Keywords: local labour markets, labour market tightness, wage equation

JEL codes: J31, J61, J63, J64

## 1 Introduction

In this paper, I examine the effect of tightness (the ratio between vacancies and unemployment) on wages in three Central European countries. This mechanism is relevant from at least two perspectives. Firstly, from the central bank's point of view it is important to know how labour market tightness affects wages, as wages are one of the key components of cost-push inflation. Secondly, from the magnitude of the spatial spillover effects of tightness on wages one can determine whether labour markets are local or not. The degree of locality is important to decide whether a targeted development policy in a disadvantaged area can be effective or not.

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There have been considerable changes in the Hungarian labour market since the financial crisis a decade ago. The number of unemployed has decreased significantly and vacancies have increased. On the other hand, these changes did not take place evenly across regions of the country. The western parts are characterised by a considerable labour shortage, while in the east the number of vacancies has not grown much. In the meantime, there have been other structural changes as well. In 2011 Germany and Austria opened its labour market to the recently joined EU-member states. The local labour market for those, who live close to the Austrian border, expanded a lot. This change exacerbated the labour shortage in the western parts of the country. Although, the overall labour market situation seems to be improving, the spatial pattern has not changed much.

There was a similar pattern in case of Slovakia. The financial crisis hit the Slovakian economy severely, the GDP dropped by more than 5% in 2009. The number of unemployed rose significantly in 2009 and the increasing pace last for 2012. Since 2013 a considerable decline can be observed. The number of vacancies at the Central Office of Labor also decreased in 2009. This was also true for the job advertisements on the largest Slovakian job search portal. After some stagnation the labour demand started increasing around 2013. The regional differences are notable in Slovakia as well. In the East and South-East part of the country the improvement in the labour market conditions was slower than in the Western part of the country. The opening of the Austrian labour market affected the country in the same way as Hungary.

Poland is a more closed economy than the aforementioned two Visegrád countries. There was not any decline in the Polish GDP during the financial crisis. On the other hand, the number of job offers decreased in 2008-2009 and stood still till 2012. Since then a steadily increasing pace characterize the number of job offers. The number of unemployed had grown for 5 years and it has been diminishing since 2013. The spatial pattern of tightness is somewhat more disperse than in the other two countries.

Information about the spatial characteristics of labour markets is important for public policy. If labour markets are local, and the spatial spillover effects are small (people are not willing to commute much), a policy change in a disadvantaged area can be effective. On the other hand, if labour markets are not so local (the spillover effects accross space are strong), a targeted intervention is ineffective since it benefits workers from other, more advantaged areas (Manning et. al. (2017)). The locality of labour markets can be measured by estimating the effect of tightness on wages, including spatial spillover effects.

In this paper, I use annual district level data from Hungary, Slovakia and Poland[1]. Due to data constraints, I define the local labour market as one district. An average district has a bigger town and some villages or smaller towns. The data availability for the three countries is different, therefore I use only the tightness, the proportion of high skilled population, time and region fixed effects. In this way the estimated parameters for the three countries can be compared.

As tightness is endogenous in the wage equation, I use instrumental variables (IVs) to estimate the effect of tightness on wages. My IV is the interaction of a district's geographical distance to the Austrian (in case of Hungary and Slovakia) or German (in case of Poland) border with a dummy variable that indicates the opening of the Austrian and German labor market in 2011 (and after). The commuting cost to Austria or Germany is low in the districts along the western border. After the opening of the Austrian and German labour market to the new member states in 2011, the administrative obstacles were decreased significantly. Due to commuting from these regions, the labour supply is lower, so the tightness is higher. Tightness is correlated with development, which is a potential threat to validity. To overcome this issue I control for development by using regional fixed effects.

Table 1: Panel IV estimation for the effect of log(tightness) on log(wages) between 2009-2015

| | Hungary | Slovakia | Poland |
|---|---|---|---|
| lntight | 0.151** | 0.175** | 0.043 |
| | (0.0428) | (0.0618) | (0.109) |
| Other covariates | Yes | Yes | Yes |

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Other covariates: high skilled, time and regional FE

Estimating panel IV setting, I obtain positive parameter estimates for the tightness effect with a reasonable magnitude. If the tightness grows by 1% then wages increase by 0.16% in Slovakia. Using the annual average wage and tightness growth rate for Hungary and Slovakia during the sample periods the estimated coefficients means that the tighter labour market caused considerable amount of the wage dynamics in these countries. This link is weaker in Poland.

Therefore the tightness has a considerable effect on one of the most important factors of

[1] I also tried to get data on the Czech Republic but I did not managed to get district level wage data.

cost-push inflation; consequently, the central banks should monitor carefully the vacancy to unemployment ratio.

According to the spatial estimations, the tightness has a spatial spillover effects on wages in other neighboring districts in Hungary. The effect of tightness on wages in the same district is almost the same as in the panel IV case. Regarding the spillover effect it is negative but has a smaller magnitude then the direct effect. For Poland and Slovakia I did not find any spatial spillover effects.

The rest of the paper is organized as follows. In Section 2 I summarize a modified version of the Mortensen-Pissarides search and matching model focusing on the wage equation. A short description of spatial econometrics can be found in Section 3. I briefly summarize the related literature in Section 4. I elaborate on the identification method in Section 5. The datasources and the variables which I use for Hungary and the estimated equations can be found in Section 6. The Slovakian results are in Section 7, the Polish can be found in Section 8. I summarize my results in Section 9.

## 2 Model setup

I briefly summarize the Mortensen-Pissarides model or as also known the search and matching theory based on Pissarides (2000), Acemoglu (2001), Wincenciak (2009) and Roshchina (2016).

In this setup, the firms can only produce using capital and labour together. The jobseekers look for an unfilled vacancy. If a vacancy and an unemployed is matched, a productive job is created. It is costly (in time and in other resources) both for the firm and for the unemployed to find a suitable match. This searching time generates frictional unemployment. One of the key concepts of this model is that the probability of matching depends on the ratio of vacancies to the number of unemployed. This ratio is called labour market tightness. In this model, job creation and destruction are independent of market shocks, that is why there are unemployed who are in search for new jobs. The definitions of the labor demand and supply:

$$\begin{aligned} Labour\ demand &= filled\ jobs + vacancies \\ Labour\ supply\ (L) &= unemployed + employed \end{aligned} \tag{1}$$

The unemployment rate is $u = \frac{U}{L}$, the vacancy rate is $v = \frac{V}{L}$ and the total number of matches between jobseekers and vacancies is $mL$. The matching function defines the newly created jobs:

$$m = m(U, V) \tag{2}$$

where

- $m$ number of matches,
- $U$ number of unemployed,
- $V$ number of vacancies.

The $m(u, v)$ function is increasing in both arguments, which can be written in another form:

$$mL = m(uL, vL) \xrightarrow{:\,\mathrm{L}} m = m(u, v). \tag{3}$$

Dividing the matching function with the unemployment rate:

$$\frac{m(u, v)}{u} = m\Big(1, \frac{v}{u}\Big) = p(\theta), \tag{4}$$

gives the job finding probability of the unemployed. This probability is the increasing function of $\theta$. Similarly, dividing by the number of vacancies:

$$\frac{m(u, v)}{v} = m\Big(\frac{u}{v}, 1\Big) = m\Big(1, \frac{v}{u}\Big)\frac{u}{v} = \frac{p(\theta)}{\theta} = q(\theta) \tag{5}$$

gives the rate at which a vacant job is matched to a worker. The $q(\theta)$ function is decreasing in $\theta$, which is intuitive since, if the number of vacancies rise compare to the unemployed, the vacancy filling probability ($q(\theta)$) diminishes.

From now on, I use a modified version of Roshchina (2016) model. In this setup there are $L$ isolated locations. In every location $l$ there is a continuum of firms who can post as many vacancies as they wish. The price $p$ of the final good which they produce is exogenously given. Let the vacancy filling rate be in location $l$:

$$q(\theta_l) = \left(\frac{V_l}{U_l}\right)^{-(1-\sigma)} \tag{6}$$

And the job finding probability is:

$$p(\theta_l) = q(\theta_l)\theta_l = \left(\frac{V_l}{U_l}\right)^{\sigma} \tag{7}$$

## 2.1 Labour supply

For the jobseeker, the return on being unemployed is the unemployment benefit plus the expected value of finding a job with probability $p(\theta_l)$. Consequently, the expected value of unemployment in location $l$:

$$rJ_l^U = z + p(\theta_l)(J_l^E - J_l^U) \tag{8}$$

where

- $z$ is the unemployment benefit, i.e. the outside option of the worker,
- $J_l^U$ the value of unemployment.

For the employee, the flow return on employment is equal to his wage and the expected value of losing the job with probability $s$. So the expected value of employment in location $l$ can be expressed as an asset equation:

$$rJ_l^E = w_l + s(J_l^U - J_l^E) \tag{9}$$

where

- $s$ is the separation rate, the probability that a worker loses his job,
- $J_l^U$ the value of unemployment.

where $\sigma$ is the parameter of the matching function.

## 2.2 Labour demand

Each firm in location $l$ has a flow revenue from the production of $y_l = p + \eta_l$, where $p$ is the price of the good and $\eta_l$ is location specific revenue advantage. For the firms $y_l$ is given and they can only decide on the number of posted vacancies. As in the labour demand case, the flow value of a vacancy and a filled job can be determined as well. For the firm the flow return on a vacancy is the expected gain of finding a suitable worker with probability $q(\theta)$ and the cost of posting the vacancy:

$$rJ_l^V = -\gamma_0 + q(\theta_l)(J_l^F - J_l^V) \tag{10}$$

where

- $J_l^V$ is the value of a vacant job,
- $\gamma_0$ is the cost of an open vacancy, i.e. the cost of the time and resources (e.g. advertising costs) used to find a suitable employee.

Similarly, the value of a filled job is the profit (the difference between revenue and wage) plus the expected value of the job becoming vacant with probability $s$:

$$rJ_l^F = y_l - w_l + s(J_l^V - J_l^F) \tag{11}$$

where

- $J_l^F$ is the value of a filled job,
- $w_l$ is the wage.

### 2.3 Wage determination process

After a match, a surplus is generated because the jobseeker is better off working, and then to be unemployed. The firm is also better off with a filled vacancy then with a vacant one. Using the above equations, we can express the sum of the employer's and employee's surplus. This surplus can be considered as a monopolistic rent and it is divided between the worker and the firm. The split is made during the negotiations. The total surplus, which they can split, is:

$$(J_l^F + J_l^E) - (J_l^V + J_l^U) = \underbrace{J_l^F - J_l^V}_{firm's\ surplus} + \underbrace{J_l^E - J_l^U}_{worker's\ surplus} \tag{12}$$

In this model, the bargaining power of the worker, $\beta$ is exogenously given and the Nash-bargain method is used to determine the distribution of the surplus. In this framework, bargained wage maximizes the geometric average of the two actors' surplus, weighted by their relative bargain power:

$$\max_w \, (J_l^F - J_l^V)^{1-\beta}(J_l^E - J_l^U)^\beta \tag{13}$$

Since the objective function is a Cobb-Douglas type, the first order condition can be expressed as follows:

$$(J_l^E - J_l^U) = \frac{\beta}{1-\beta}(J_l^F - J_l^V) \tag{14}$$

which is

$$(J_l^E - J_l^U) = \beta((J_l^F - J_l^V) - (J_l^E - J_l^U)). \tag{15}$$

Therefore, the worker's surplus is equal to $\beta$ fraction of the total surplus. Subtracting $rJ^U$ (8) from $rJ^E$ (9) the worker's surplus can be calculated in two steps:

$$rJ_l^E - rJ_l^U = w_l + s(J_l^U - J_l^E) - z - p(\theta_l)(J_l^E - J_l^U) \tag{16}$$

After some transformation, the workers surplus is as follows:

$$J_l^E - J_l^U = \frac{w_l - z}{r + s + p(\theta_l)} \tag{17}$$

This means that the worker's surplus depends positively on the difference between wage and unemployment benefit. If the separation rate $s$ increases, the worker's surplus diminishes. This is intuitive since, if the probability of losing the job grows, the surplus (or the expected value of the surplus) shrinks.

In the search and matching models entry is free for the firms to the labour market ($J_l^V = 0$). Plugging this assumption into equation (10): $J_l^F = \frac{\gamma_0}{q(\theta_l)}$. Substituting $J_l^V$ and $J_l^F$ into equation (16) the equilibrium wage is:

$$w_l = \beta(y_l + \gamma_0\theta_l) + (1 - \beta)z \tag{18}$$

This means that the wage is the convex combination of the unemployment benefit and the firm's surplus. The firm's surplus is the sum of the output and the expected cost savings if the firm fills the vacancy. If tightness grows, the probability of filling a vacancy diminishes, and consequently it will be more costly not to fill it. It follows from this mechanism that with the increase in tightness the wage also grows. It is also worth mentioning that labour market conditions only affect the wage through $\theta$. Therefore, unemployment (rate) alone does not have an effect on wages, and it is only the vacancies to unemployment ratio which matters. This is because wages determined in the Nash bargaining process after the firm meets the jobseeker. Tightness determines not only how long a vacancy is open, but also the expected cost to search for an employee.

# 3 Brief summary of spatial econometrics

Both wages and tightness are defined using geographical units (districts); it is worth examining whether neighbouring districts have an effect on each other. For this purpose, spatial econometrics is an ideal choice. In this section, I briefly summarize those parts of spatial econometrics which are essentially needed (this section is based on Elhorst (2014). For further information, see e.g. Elhorst (2014), LeSage (1999) or LeSage et. al. (2009).

The main difference between a conventional OLS estimation and a spatial econometric estimation is the usage of the spatial weight matrix ($W$). This matrix contains information about the spatial connections between geographical units. The simplest case is when $W$ indicates whether two spatial units are neighboured or not. There is one in the given position if the units are neighboured and there is zero if not. The main diagonal of the matrix is zero by definition. To get the $W$ matrix, the rows should be normalised by the row sums. This method is called spatial contiguity weighting. Other types of matrices can contain distances in space, in time or travelling costs as well. In these cases, the inverse distances are included and the rows are normalized. Each element is calculated in the following way:

$$w_{ij} = \frac{d_{ij}^{-1}}{\sum d_{ij}^{-1}}. \tag{19}$$

where $d_{ij}$ is a distance measure between location $i$ and $j$.

By definition, the main diagonal elements are 0 in every spatial weighting matrix. Multiplying with this matrix creates the weighted average of the spatial units based on the inverse of their distance. The different types of spatial weight matrices can be used for robustness checks. The general specification of the Spatial Durbin model, which I use is the following:

$$Y = \delta WY + \alpha\iota + X\beta + WX\phi + \epsilon \tag{20}$$

In equation (20) the dependent variable regressed on its spatial lagged variable, which means that $Y$ depend on its neighbours $Y$ value as well (similar to the time lagged values in time series analysis). In this specification, $Y$ also depend on the spatial lagged values of $X$. It can be tested whether parameter $\delta$ or $\phi$ is zero. If both are zero, the specification become an OLS.

On the other hand, if $\delta$ or $\phi$ are both insignificant it does not mean that spatial spillover effects do not exist. Equation (20) can be rewritten in the following form:

$$Y = (I - \delta W)^{-1}(X\beta + WX\phi) + R \tag{21}$$

where $R$ contains the intercept and the error terms. If we differentiate Equation (21) with respect to $X$, we get:

$$\frac{\partial E(\mathbf{Y})}{\partial x_k} = (\mathbf{I} - \delta\mathbf{W})^{-1} \begin{bmatrix} \beta_k & w_{12}\phi_k & \cdots & w_{1N}\phi_k \\ w_{12}\phi_k & \beta_k & \cdots & w_{2N}\phi_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\phi_k & w_{N2}\phi_k & \cdots & \beta_k \end{bmatrix} \tag{22}$$

From this derivative, we can distinguish the direct and indirect effects. The direct effects are measured by the main diagonal elements of this matrix product. It measures the effect of an explanatory variable in a given spatial unit on a dependent variable in the same spatial unit. There are two main factors, which determine the direct effect. Firstly, the explanatory variable in a focal spatial unit has an effect on the dependent variable in that spatial unit. Secondly, there exists a feedback effect, where the focal explanatory variable has got an effect on the dependent variable in the neighboruing spatial units, and these have got an effect on the dependent variable in the focal spatial unit. The direct effect is different for every spatial unit if $\delta \neq 0$.

The off-diagonal elements are the indirect effects. The indirect effect is the effect of a unit change in the explanatory variable in the focal spatial unit on the dependent variable in the neighbouring spatial units. For instance, the first row of the product matrix measures the effect of explanatory variable $x_k$ in spatial unit 1, on all dependent variables in spatial unit $1, 2, \ldots, n$ (so the first element is the direct effect). It can be seen that direct and indirect effects are different for every spatial unit. Depending on the number of spatial units, the number of these effects can be very large. To compress this information, LeSage - Pace (2009) suggested to report the average of the diagonal elements of the matrix in Equation (22) for the direct and the average of the row sums or column sums for the indirect effect. In the OLS model, the direct effect is simply the estimated coefficient ($\beta_k$), while the indirect effect is 0 by construction.

The first factor of the multiplication in Equation (22) can be written in an extended form:

$$(\mathbf{I} - \delta\mathbf{W})^{-1} = \mathbf{I} + \delta\mathbf{W} + \delta^2\mathbf{W}^2 + \delta^3\mathbf{W}^3 + \ldots \tag{23}$$

Equation (23) is called the Neumann-series expansion of the Leontiev-inverse (the Leontiev-inverse is widely used in input-output models as well). It can be shown that, if the Neumann-series is convergent, it equals the Leontiev-inverse. The conditions for existence of non-negative inverse of a Leontiev matrix are summarized in the Perron-Frobenius theorem.

In the Neumann-series, the identity matrix shows a direct effect of a change in $X$. By construction (see above), the diagonal elements of $\delta\mathbf{W}$ are 0, and therefore this term represents an indirect effect in change of $X$. Because $W$ is in the first power, it represents the indirect effect only on the first-order neighbours. In the case of a spatial contiguity weighting, the off-diagonal elements of $\delta\mathbf{W}$ are the indirect effects on the bordering spatial units. The higher order terms represent higher-order direct and indirect effects. For instance, the diagonal elements of $\delta^2\mathbf{W}^2$ represent the second order direct effect, which is a feedback effect, meaning that the impact passes through neighbouring spatial units and get back to the original unit ($1 \to 2 \to 3 \to 2 \to 1$). Due to these feedback effects, the overall direct effect is different from the parameter estimation of $\beta_k$ (of course when $\delta \neq 0$). The off-diagonal elements of $\delta^2\mathbf{W}^2$ represent second order indirect effects. In the case of spatial contiguity weighting this is the effects on a given spatial unit's neighbours' neighbours.

# 4 Literature review

There have been several research projects on spatial labour market analysis in recent years. On the other hand, according to my current understanding the effect of tightness on wages has not yet been examined. There are articles about matching quality and labour demand elasticities, where tightness is another covariate but not the parameter of interest.

Harmon (2013) examined the effect of labour market size on match quality. He found that in a larger labour market unemployed people find jobs which are better fit to their qualification and skills. Labour market tightness is also included in the wage equations. But he got ambiguous results about the sign and the magnitude of the parameter and concluded that according to theory it should have been positive, so further research is needed.

Manning et. al. (2017) argue that to determine the size of the local labour market is important from a policy perspective, since it helps to develop targeted policies. If labour markets are local than a targeted policy can help to improve the given region, since the effect of the policy stays in that region. On the other hand, if labour markets are not so local the targeted intervention is ineffective, since it benefits workers from other, more advantaged areas as well. On an English-Welsh database they found that average commuting time is short or, in other words, the cost of commuting is very high in England and Wales and labour markets can be considered as local. Despite this fact, simulations show that a targeted policy to reduce unemployment is ineffective because ripple effects dilute the shock across space.

Antczak et. al. (2016) estimated matching functions for Poland using spatial econometric techniques. They found that spatial dependency positively affected the matching process. Labour market tightness had a positive significant effect on job creation.

Roshchina (2016) used the modified version Mortensen-Pissarides model to identify the elasticity of employment with respect to tightness and wages. She found that in Brasil the employment is more sensitive to wage changes then to changes in tightness.

## 5 Identification method

I would like to estimate the effect of labour tightness on wages. The main issue here is that not only tightness has an effect on wages, but wages also affect tightness. If tightness grows, it indicates more competitive labour demand, which results in higher wages. On the other hand, growing wages mean that the outside option (unemployment benefit) is less desirable. Higher wages attract inactive people to the labour market. Firstly, these people become unemployed and later can find a job. This process results in an expanding number of unemployed, which means that tightness decreases.

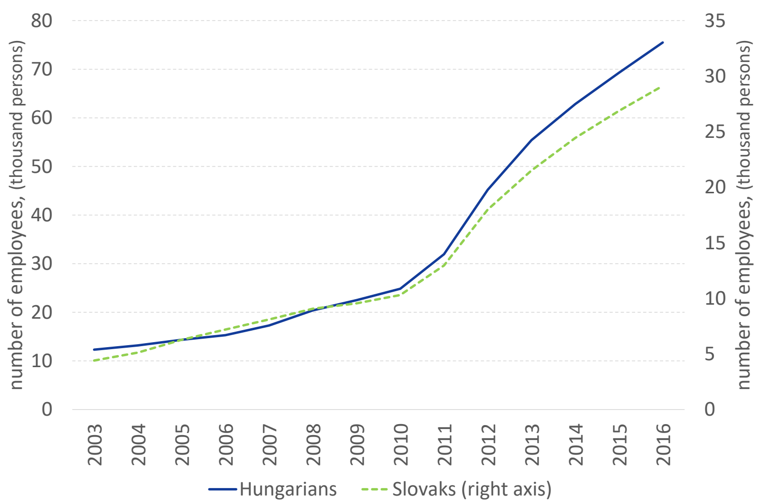


Figure 1: Number of Hungarians and Slovaks, who work in Austria, source: Austrian Social Security Database

The above mentioned endogenity problem means that the causal effect can be estimated using an instrumental variable. My instrumental variable is the distance from the Austrian border (in case of Poland from the German border). Living closer to Austria (or Germany) means that the cost of commuting is smaller. The external shock is the opening of the Austrian and German labour market in 2011 for the newly joined members of the European Union. After 2011 every administrative obstacle was removed from the newly joined member states to work in Austria and Germany. The exact IV is the cross-product of the distance and the after 2011 dummy.

In 2011 the dynamics of the number of Hungarians who work in Austria rose considerably (see Figure 1). Based on the Austrian Social Security Database the highest percent of Hungarian employees is along the border (Figure 2). Although, the place of residence is not know in this Database, one can suppose that closer to the border Hungarians commute since it is more worth to spend their Austrian wage in Hungary then in Austria.

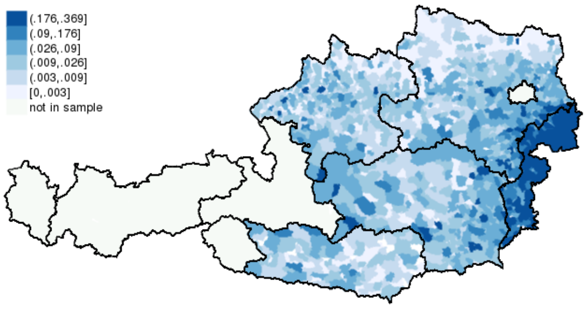


Figure 2: Proportion of Hungarian workers in Austria by municipality 2011-2015, (source: Austrian Social Security Database)

The decreasing number of the Hungarian labour force resulted in rising labour market tightness. The difference in the yearly changes of the district level and country level tightness is the largest in districts close to the Austrian border in 2011 (see Figure 3). Therefore, tightness grows faster than the country average in these districts (see Figure 4) and this phenomenon is also true in every year between 2011-2015 (except for 2013).

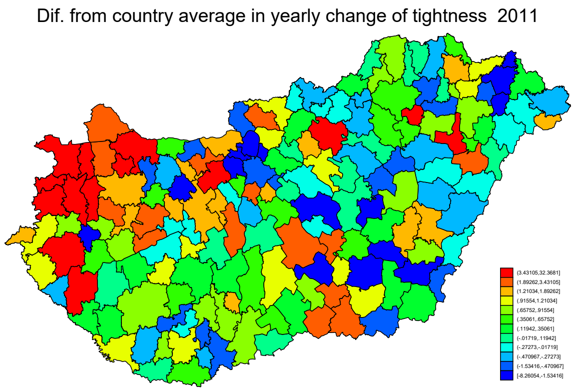


Figure 3: Deviation from the country average yearly change in tightness, 2011 (source: NES)

The number of Slovak citizens has been also growing rapidly since the labour market opening in 2011. According to the Austrian Social Security database the number of Slovak citizens, who worked in Austria was around 10 thousand at the beginning of 2011 and it tripled by the end of 2016 like in the Hungarian case.

There can be potential threats to the IV's validity. The distance from Austria is correlated with development, since the more developed districts are in the western part of the country both in Hungary and Slovakia. In the developed districts wages are also higher. Therefore, I have to control for development for which I use regional fixed effects.

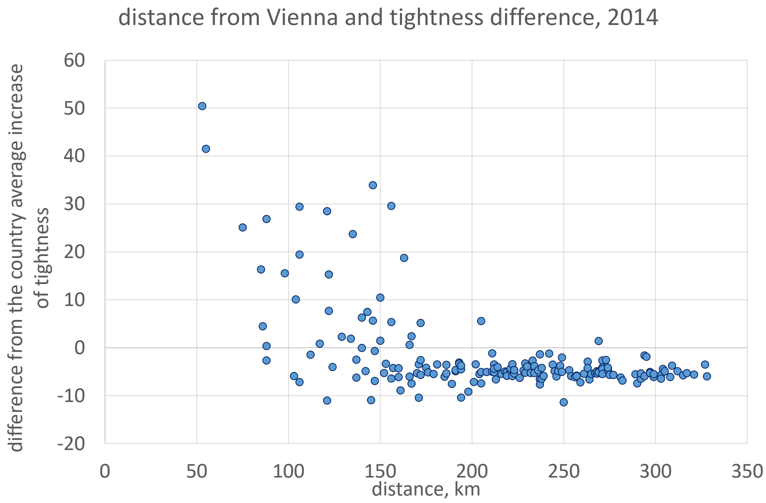


Figure 4: Deviation from the country average yearly change in tightness, 2014 (source: NES)

I estimate equation (18). I introduced several types of estimation: simple OLS, IV and panel estimation with IV. I concluded that the panel IV estimation is the most reliable one in my context. Panel IV is followed by spatial panel estimation for every three countries. I also make some robustness checks.

To have comparable results across countries I use the same controls in the OLS and panel IV cases. This narrows the scope of covariates due to data availability reasons in the different countries.

# 6 Estimation results for Hungary

## 6.1 Description of the Hungarian data

I use annual frequency data. I state if it is otherwise.

Calculating the tightness, I use data from the National Employment Service (NES). Both unemployment and vacancy statistics are available on a settlement level, so I could aggregate them to district (*járás*) level (Figure 5). There are 176 districts in Hungary, with the capital city considered as one district. It is monthly data, which I average across years. It is compulsory for firms to report their vacancies to the Employment Service, although there is no sanction if they do not do so. I use only non-subsidized vacancy data, as I would like to measure the effects of market forces (therefore, the vacancies of

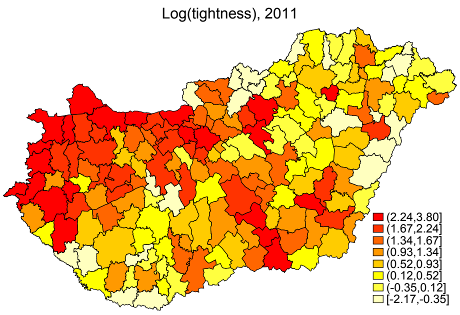


Figure 5: The logarithm of tightness (2011), source: NES

the public employment programme are excluded).

The unemployment data is the number of those who have registered at the local job centre. The number of registered unemployed is not the same as those in the Central Statistical Office (CSO) reports using the ILO definition (LFS unemployment). On the other hand, the dynamics of the two time series are rather similar (see Figure 6). LFS unemployment is not available neither on a settlement nor on a district level. Therefore, for district level tightness I can use only the NES's data.

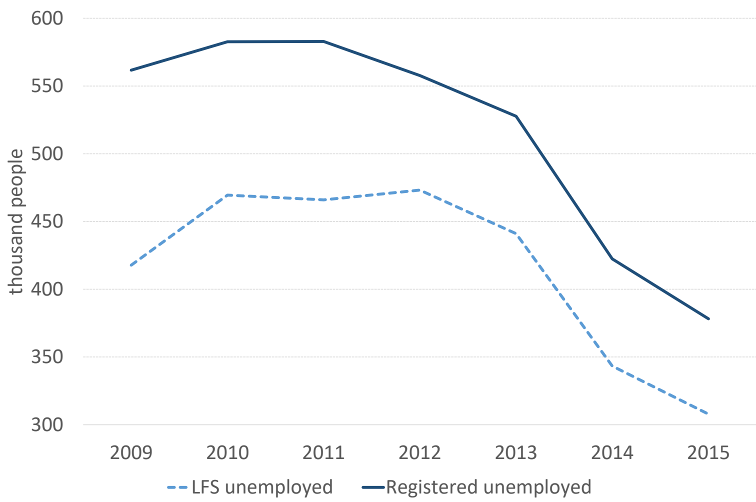


Figure 6: The LFS and registered jobseekers (source: CSO and NES)

The wage data comes from the yearly Wage Survey (*Bértarifa*). The Wage Survey includes all firms which have more than 50 employees and a random sample of firms with 5-50 employees. For firms with more than 50 employees a random sample of employees are included, for the smaller firms the data of every employee can be found. The dependent variable in my research is the log of private sector gross wage.

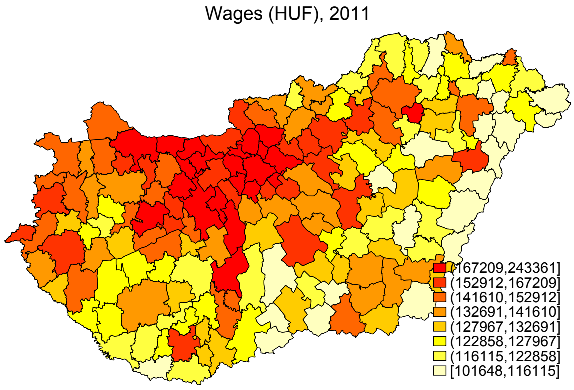


Figure 7: Private sector gross wages

I include some socio-economic variables of a given district. These variables are the proportion of children, elderly, those who receive social allowances, and those who receive medicine free of charge. The latter two are a measure of deprivation in a given district.

The distance between the district capitals and Vienna and Graz are from the page rome2rio.com. It contains not only the distance in km but also in travelling time using different means of transport (car, train and bus). These measures are highly correlated.

Calculating the distance $W$ matrix, I use the database of the Hungarian Academy of Sciences. In this database the distance between two settlements is available if they are in the same county or in neighbouring counties. I calculated the average distance between two districts in the following way. I averaged the distances from all settlements in one district to the settlements in the other district. This measure can be better constructed if one uses the population as a weight for each settlement.

Table 2: Summary statistics for districts in Hungary (2009-2015)

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|
| Tightness | 7.25 | 12.76 | 0.07 | 185.44 |
| Vienna, Graz average time by car (min) | 236.5 | 71.9 | 82 | 367.5 |
| At least college degree (%) | 9.6 | 4.15 | 3.97 | 27.05 |
| Population (thousand persons) | 56.4 | 133.7 | 8.5 | 1759.4 |

## 6.2 OLS and panel estimations for Hungary

In the pooled OLS case the sign of tightness is positive and the magnitude is rather small. For instance, in the first case a 1% increase in tightness raises wages by 0.024% (see Tabel 3). At first glance, this measure seems to be a very small effect. It is worth noting that country level tightness increased by 18% on a yearly average between 2009 and 2015. If this growth rate is used, the yearly average wage change is 0.4%.

Table 3: Estimation results for Hungary (2009-2015)

| | OLS | IV | Panel IV | Panel IV† | Panel IV‡ |
|---|---|---|---|---|---|
| VARIABLES | lnw | lnw | lnw | lnw | lnw |
| lntight | 0.0241** | 0.152*** | 0.151** | 0.198** | 0.0987 |
| | (0.00946) | (0.0352) | (0.0604) | (0.0841) | (0.0930) |
| high skilled | 0.0187*** | 0.00999*** | 0.0107** | 0.00492 | 0.0149** |
| | (0.00120) | (0.00257) | (0.00470) | (0.00694) | (0.00593) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,232 | 1,232 | 1,232 | 553 | 679 |
| $R^2$ | 0.420 | 0.319 | | | |
| Overall $R^2$ | | | 0.345 | 0.368 | 0.331 |

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
† below 200 minutes from Austria, ‡ above 200 minutes from Austria

In the panel IV case, I need the distance from the Austrian border. This can be measured in several ways. I downloaded the distance of the district capitals from Vienna and from Graz in minutes by car. These are the two main cities not far from the Hungarian border. I defined the distance from the Austrian border as the minimum distance from these two cities. It can be defined as the average of these distances or simply using only one city distance but these are highly correlated measures therefore it do not change the estimations significantly.

In the literature the wage equation almost always contains the level of education. I have this data from the 2011 Census, so it does not change over my sample period. The composition of the highest educational level changes slowly in a given district. There can be other types of important factors, which do not or only slowly change over time, e.g. the average experience level of workers. For these factors, one can include fixed effects as well.

I also include time fixed effects, as wages grow steadily over time. Since the regulations on the unemployment benefit are the same across the country and they usually change yearly, time fixed effects also capture the unemployment benefit, which is in Equation (18).

In the first stage equations, the coefficient of the $distance \times after2011$ variable is negative (see Table 10 in Appendix). This is intuitive, since it means that the farther a district from Austria, the smaller the tightness after the opening of the Austrian labour market. After the opening of the Austrian labour market in 2011 the tightness declines by 0.1 percent for every additional 1 minute travelling time to Austria. This means that if a district is 30 minutes from Austria and another is 90 minutes, tightness is 6% smaller in the easternmost district.

In the second stage the coefficient of the tightness is positive and around 0.15 (see Table 3). The coefficient of the tightness means that if the tightness increase by 1% the wages grow by 0.15%. Therefore, if the tightness rises by 18% (average annual tightness growth rate on the country level) the wages expand by 2.7%. This measure is considerable since the yearly average change in wages was 5.2% between 2009-2015. It is important to mark that the district level tightness and wage changes can be considerably different from the country average.

As a robustness check I restricted the sample to those districts, which are at most 200 minutes from the Austrian border. This is roughly 40% of the total sample. Using these closer districts the parameter estimate of tightness is higher. This result is intuitive since from these districts it is more worth commuting to Austria then from farther districts. This means that to closer to the western border the higher the effect of commuting on tightness. Moreover, using the rest of the sample the tightness parameter is smaller and has higher robust standard errors. This is also in-line with the intuition, namely that commuting is more appealing to the people living closer to the Austrian border.

### 6.3 Spatial estimation

The first step in spatial econometric analysis is to test for the existence of spatial clustering. The Moran's I test (and Geary's c test) statistics null hypothesis is that there is no spatial autocorrelation. As a robustness check, I use the adjacency matrix and the distance matrix as well. For every year for both weighting matrices $H_0$ can be rejected, so there is a spatial autocorrelation in the OLS residuals (except for 2014, see Table 11 and 12 in Appendix). From the previous maps, one can conclude that there is spatial autocorrelation as well.

I estimated the following spatial panel IV model:

$$\begin{aligned}\ln w_{it} = \beta_0 + \beta_1 \ln \theta_{it} + \beta_2 W\theta_{it} + \\ \beta_3 highskill_i + \rho W \ln w_{it} + \epsilon_{it} \\ \epsilon_{it} = \lambda W \epsilon_{it} + \eta_{it}\end{aligned} \tag{24}$$

Table 4: Spatial panel IV estimation for Hungary

| VARIABLES | lnw |
|---|---|
| lntight | 0.0151 |
| | (0.0170) |
| high skilled | 0.0183*** |
| | (0.00158) |
| $W_{km}lnw$ | -1.348*** |
| | (0.315) |
| $W_{km}e$ | 0.378** |
| | (0.161) |
| $W_{km}lnt$ | 0.153* |
| | (0.0850) |
| Constant | 26.95*** |
| | (3.689) |
| Pseudo $R^2$ | 0.419 |
| Observations | 1,232 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In this equation, both the dependent and independent variables are spatially lagged. The results are in Table 4.

Table 5: Direct and indirect effect of tightness

| | direct | | indirect | | total | |
|---|---|---|---|---|---|---|
| | dy/dx | P>z | dy/dx | P>z | dy/dx | P>z |
| lntight | 0.02 | 0.371 | -0.01 | 0.363 | 0.01 | 0.388 |
| wkm_lnt | 0.16* | 0.073 | -0.09* | 0.087 | 0.07* | 0.071 |

The parameter of tightness of neighbouring districts has got a positive and significant effect on wages. As I mentioned in Section 3, the estimated coefficients are not measuring the total effect of tightness on wages. I also computed the direct and indirect effects based on Equation 22. This shows that the indirect effect is negative and significant (see Table 5). This means that the spatial spillover effect reduces the tightness' direct effect. To understand this phenomenon let's have a simple example. If there is a district, which is an island and there are no other neighbouring districts from which people can come to work then the estimated tightness parameter captures the true effect. This is the $\beta_1$ parameter in Equation 24. On the other hand, if there are neighbouring districts then people can commute to here and in this way reduce the wage-increasing effect of tightness. This is the intuitive explanation for the negative indirect effect. Summarizing the total effect of tightness on wage at the sample average is 0.08. This means that during the sample time horizon the average 18% tightness increase caused a 1.44% wage increase. This is one third of the yearly average wage growth. This affect contains not only the direct but also the indirect effects, which can be considered as spillover effects from the neighbouring districts.

# 7 Estimations for Slovakia

It seems reasonable to check this IV setup on other countries. Slovakia joined the EU at the same time as Hungary, so the labour market opening affected the two countries at the same time. Moreover, it has got also a common border with Austria and the distance magnitudes between Vienna and Slovakian towns is similar to the Hungarian counterparts.

## 7.1 Data

As in the Hungarian case I use annual data, the time span is between 2009 and 2017. For the unemployment I use the registered unemployment data.

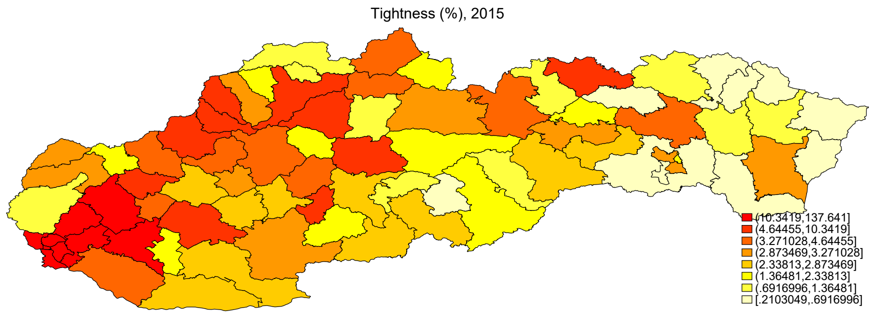


Figure 8: Tightness in Slovakia, 2015 (source: own calculations based on ÚPSVaR and SOSR data)

I created the district (*okres*) level vacancy data using two data sources. The district level vacancy data comes from the Central Office of Labour, Social Affairs and Family (*ÚPSVaR*). Unfortunately during the examined period there were frequent undocumented changes to the vacancy data methodology so for time series purposes this data alone is not suitable. On the other hand, there is another vacancy data from the Statistical Office of the Slovak Republic but this data is only on regional level. I divided the regional vacancy data to districts using the weights coming from the first mentioned data source. In this way I got district level vacancy numbers, which show the level, the dynamics and the spatial distribution as correctly as possible.

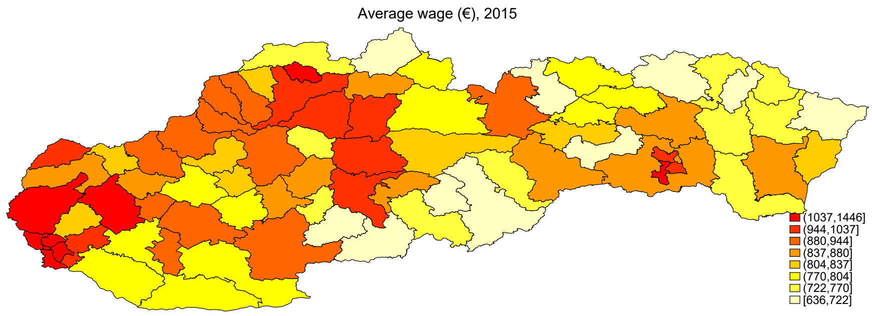


Figure 9: Wages in Slovakia, 2015 (source: SOSR)

The proportion of those who have higher education comes from the 2011 Census. The distances of the district capitals and Vienna are from the page rome2rio.com as in case of Hungary. For the spatial weight matrices I used the distance between the centroids of each district.

Table 6: Summary statistics for Slovakia, 2009-2017

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** |
|---|---|---|---|---|
| Wage (€) | 818.9 | 177.2 | 465.6 | 1517 |
| Distance from Vienna by car (min) | 198.2 | 96.7 | 52 | 390 |
| Tightness (%) | 9.2 | 22.2 | 0 | 164.1 |
| At least college degree (%) | 14.7 | 5.8 | 8.1 | 37.7 |
| Population (thousand persons) | 68.3 | 36.4 | 12.5 | 169.4 |

Figure 10 illustrates the validity of the IV in case of Slovakia. In Austria the highest percent of Slovak employees work along the border. This suggests that these workers commute from Slovakia to Austria (although there is no data on place of residence in the Austrian Social Security Databse).

### 7.2 Estimation results for Slovakia

The estimated coefficients are similar in magnitude as in the Hungarian case (see Table 7). The simple OLS estimation for the tightness parameter is approx. 10% of the IV parameter similar to the Hungarian estimation. Using the $distance \times after2011$ IV the tightness parameter is 0.16. This means that in case of a 1% increase in tightness the wage increases by 0.16%. The yearly average wage growth between 2009-2017 was 4%, the

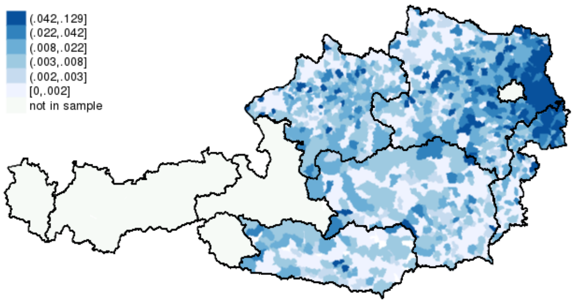


Figure 10: Proportion of Slovak workers in Austria by municipality 2011-2015, (source: Austrian Social Security Database

yearly average tightness growth was 7.1% during the same period. This means that the tightness caused one fourth of the yearly wage growth, which is a considerable amount.

I also made some robustness checks in case of Slovakia as well. Firstly, I restricted the sample to the same time interval as in the Hungarian case. This helps to have comparable parameters to the Hungarian estimation. Furthermore, it also shows that the estimated tightness parameter is robust to the time interval changes.

Secondly, I restricted to those districts, which are less then 200 minutes from Vienna. This restricted sample contains 57% of all districts. I expect that the tightness effect is higher, since the distance from the Austrian border is lower. Since the commuting is less costly, therefore it worth for more people. I also make a restricted sample with the remaining eastern districts. In this case the tightness parameter is lower and not significant, which is intuitive. The farther the Austrian border is, the lower the labour shortage is, which reflects in smaller impact of tightness on wages (see the last two columns of Table 7).

The spatial estimation gives different results than in the Hungarian case. Almost in every year the Moran's I and Geary's c statistics cannot refuse the $H_0$ hypothesis, which means that there is no spatial autocorrelation in the residuals of the IV estimation (see Table 13 in Appendix). On the other hand, I also tried to include the spatial errorlag and the spatial lag into the regression but non of them was significant (see Table 14). The spatial spillover effect from tightness to wages on district level cannot be detected using these methods (Table 15).

The results of the estimation exercise on Slovak data show that the effect of tightness on wages is similar to the Hungarian case. This suggests that tightness has got a similar impact on one of the most important components of cost-push inflation in both countries. On the other hand, there is no spatial spillover effects from tightness to wages on district

Table 7: Estimation results for Slovakia (2009-2017)

| | OLS | IV | Panel IV | Panel IV¶ | Panel IV† | Panel IV‡ |
|---|---|---|---|---|---|---|
| lnt | 0.0195*** | 0.161*** | 0.161*** | 0.175** | 0.327** | 0.0253 |
| | (0.00703) | (0.0606) | (0.0618) | (0.0757) | (0.166) | (0.0398) |
| high skilled | 0.0168*** | 0.00453 | 0.00453 | 0.00405 | -0.0053 | 0.0175*** |
| | (0.00307) | (0.00658) | (0.00670) | (0.00779) | (0.0149) | (0.00565) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 691 | 691 | 691 | 533 | 402 | 289 |
| R-squared | 0.771 | 0.360 | | | | |
| Overall $R^2$ | | | 0.528 | 0.436 | 0.286 | 0.751 |

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
† below 200 minutes from Austria, ‡ above 200 minutes from Austria
¶ on the same sample as for Hungary (2009-2015)

level in Slovakia. The spatial analysis shows that the districts can be considered as local labour markets in Slovakia, where targeted development policies can be effective.

# 8 Estimation for Poland

Poland is a closed economy compared to Hungary and Slovakia. It has a bigger internal market and the proportion of export to GDP is lower. These structural difference contributed to that Poland managed to avoid the financial crisis without recession. Comparing to Hungary and Slovakia there are more Polish people, who work abroad relative to the population. This can affect the estimation results.

## 8.1 Data

For Poland I used annual data between 2005-2017. As in the previous cases I use registered unemployment data. The source of the data is Statistics Poland (Główny Urząd Statystyczny GUS). The proportion of those who have higher educations comes from the 2011 Census. The distances of district capitals from Berlin and Dresden are from the rome2rio.com page.

Table 8: Summary statistics for districts in Poland (2005-2017)

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Berlin, Dresden minimum distance (min) | 295.2 | 106.4 | 70.0 | 527.0 |
| Tightness (%) | 2.2 | 4.6 | 0.0 | 84.4 |
| High skill proportion (%) | 13.7 | 5.0 | 7.8 | 37.8 |
| Population (thousand persons) | 101.2 | 117 | 20.3 | 1764.6 |

## 8.2 Estimation results

If tightness grows by 1% then wages grow by 0.033%. On the sample period the annual average wage growth was 5% the tightness growth was 27%. This means that tightness caused almost one eighth of the wage dynamics.

Table 9: Estimation results for Poland (2005-2017)

| | OLS | IV | IV | Panel IV | Panel IV | Panel IV† |
|---|---|---|---|---|---|---|
| VARIABLES | lnwage | lnwage | lnwage | lnwage | lnwage | lnwage |
| lntight | 0.00456 | 0.0337*** | 0.121* | 0.0311** | 0.0330 | 0.0432 |
| | (0.00343) | (0.0126) | (0.0714) | (0.0154) | (0.0357) | (0.109) |
| higher | 0.0134*** | 0.0122*** | 0.00402 | 0.0123*** | 0.0111*** | 0.0102 |
| | (0.00102) | (0.00142) | (0.00588) | (0.00154) | (0.00306) | (0.00809) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Voivodeship FE | Yes | No | Yes | No | Yes | Yes |
| Constant | 7.511*** | 7.526*** | 7.737*** | 7.522*** | 7.564*** | 7.818*** |
| | (0.0295) | (0.0358) | (0.146) | (0.0418) | (0.0733) | (0.0917) |
| Observations | 4,516 | 4,516 | 4,516 | 4,516 | 4,516 | 2,510 |
| R-squared | 0.802 | 0.757 | 0.472 | | | |
| Overall R-squared | | | | 0.76 | 0.782 | 0.517 |

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
† on the same sample as in the case of Hungary (2009-2015)

The magnitudes of the tightness parameter (0.033) is somewhat smaller then in the Hungarian (0.15) or in the Slovakian case (0.16) and it has high robust standard errors on both the full sample and between 2009-2015. In case of Poland this IV captures only that variation, on which distance from Germany has an impact. In this setup I measure only that potential variation, which comes from cross border commuting or that emigration which aims neighbouring regions. From the examined countries Poland has the highest level and rate of citizens who live in other EU countries by which Poland is not bordered on (Figure 11). This phenomenon means that the strength of the IV for Poland is smaller than in the case of Hungary or Slovakia. This could be the potential explanation for the smaller magnitude and higher robust standard errors of the tightness parameter.

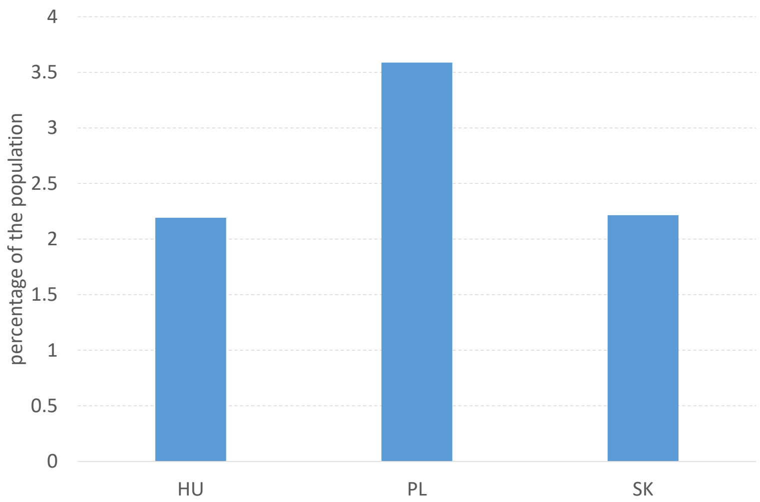


Figure 11: Proportion of those who live in another EU country except for the neighbouring countries, 2009-2017 average (source: Eurostat)

The spatial estimations give similar result as in the case of Slovakia. The Moran and Geary test (Table 16 in Appendix) cannot refuse the no spatial autocorrelation $H_0$. The neighbour districts' tightness parameter is not significant in the panel specification (column (1) in Table 17 in Appendix). Neither the indirect effect (Table 18 in Appendix) nor the spatial lag of wages is significant (column (2) in Table 17 in Appendix). From these exercises one can conclude that there is no spatial connection between tightness and wages in Poland.

# 9 Summary

In this paper I analysed the effect of tightness on wages in three Central European countries. I used annual district level data to have variation across space and time. For the identification, I applied an instrumental variable method, since tightness is endogenous in the wage equation. My IV variable was the interaction of the distance between a district and the Austrian or German border and a time dummy. I concluded that tightness has a significant positive effect on one of the main part of cost-push inflation. The magnitude of this effect is smaller in Poland then in Hungary and Slovakia. Based on my estimation there are spatial spillover effects in the Hungarian labour market. On the other hand there are not any of these effects in case of Slovakia and Poland.

For further research, it is worth examining whether my results are robust to a larger sample period. Using a spatial weight matrix measured in a more sophisticated way could also improve the validity of my results.

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# Appendix

Table 10: First stage of panel IV estimation for Hungray (2009-2015)

| VARIABLES | lntight |
|---|---|
| min(Vienna,Graz)$\times$after2011 | -0.00092 |
| | (0.000637) |
| Observations | 1,232 |
| Overall R-squared | 0.617 |
| Wald $\chi^2$ | 3726 |
| P-value of Wald $\chi^2$ | 0.000 |

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Other covariates: county and time FE,
high skilled and minimum distance from Vienna, Graz

Table 11: Moran's I test for Hungary

| | Weights: km | | | Weights: adjacency | | |
|---|---|---|---|---|---|---|
| Residuals in year | I | z | p-value* | I | z | p-value |
| 2009 | 0.036 | 3.05 | 0.001 | 0.110 | 2.525 | 0.006 |
| 2010 | 0.036 | 3.043 | 0.001 | 0.232 | 5.145 | 0.000 |
| 2011 | 0.108 | 8.433 | 0 | 0.264 | 5.859 | 0.000 |
| 2012 | 0.069 | 5.546 | 0 | 0.250 | 5.544 | 0.000 |
| 2013 | 0.05 | 4.127 | 0 | 0.186 | 4.147 | 0.000 |
| 2014 | 0.013 | 1.362 | 0.087 | 0.133 | 3.016 | 0.001 |
| 2015 | 0.011 | 1.221 | 0.111 | 0.140 | 3.163 | 0.001 |

$H_0$: there is no spatial autocorrelation

Table 12: Geary's c test for Hungary

| | Weights: km | | | Weights: adjacency | | |
|---|---|---|---|---|---|---|
| Residuals in year | I | z | p-value | I | z | p-value |
| 2009 | 0.925 | -2.572 | 0.005 | 0.885 | -2.187 | 0.014 |
| 2010 | 0.922 | -3.054 | 0.001 | 0.772 | -4.492 | 0 |
| 2011 | 0.837 | -5.757 | 0 | 0.727 | -5.254 | 0 |
| 2012 | 0.852 | -5.68 | 0 | 0.749 | -4.939 | 0 |
| 2013 | 0.892 | -4.507 | 0 | 0.812 | -3.756 | 0 |
| 2014 | 0.965 | -1.149 | 0.125 | 0.87 | -2.458 | 0.007 |
| 2015 | 0.958 | -1.654 | 0.049 | 0.884 | -2.29 | 0.011 |

$H_0$: there is no spatial autocorrelation

Table 13: Moran's I and Geary's c statistics for spatial autocorrelation for Slovakia

| Residuals | Moran's I | | | Geary's c | | |
|---|---|---|---|---|---|---|
| in year | I | z | p-value | c | z | p-value |
| 2009 | -0.015 | -0.021 | 0.492 | 0.960 | -1.253 | 0.105 |
| 2010 | 0.003 | 0.846 | 0.199 | 0.974 | -0.775 | 0.219 |
| 2011 | -0.032 | -0.789 | 0.215 | 0.961 | -1.187 | 0.118 |
| 2012 | -0.044 | -1.313 | 0.095 | 1.018 | 0.607 | 0.272 |
| 2013 | 0.024 | 1.761 | 0.039 | 0.950 | -1.814 | 0.035 |
| 2014 | -0.021 | -0.267 | 0.395 | 0.997 | -0.112 | 0.455 |
| 2015 | -0.033 | -0.849 | 0.198 | 1.011 | 0.349 | 0.364 |
| 2016 | -0.025 | -0.478 | 0.316 | 0.976 | -0.803 | 0.211 |
| 2017 | -0.032 | -0.794 | 0.214 | 1.006 | 0.194 | 0.423 |

$H_0$: there is no spatial autocorrelation

Table 14: Spatial IV estiamtion for Slovakia

| | (1) | (3) |
|---|---|---|
| VARIABLES | lnw | lnw |
| | | |
| lnt | 0.0450*** | 0.0252*** |
| | (0.0122) | (0.00914) |
| higher skilled | 0.0150*** | 0.0163*** |
| | (0.00145) | (0.00126) |
| $\mathrm{W}_{km}e$ | -0.417 | |
| | (0.260) | |
| $\mathrm{W}_{km}lnw$ | | -0.0131 |
| | | (0.0225) |
| Constant | 6.267*** | 6.385*** |
| | (0.0344) | (0.154) |
| Pseudo $\mathrm{R}^2$ | 0.759 | 0.77 |
| Observations | 691 | 691 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Direct, indirect and total effect of tightness on wages in specification (2) in Table 14

| | dy/dx | p-value |
|---|---|---|
| direct | 0.0252*** | 0.006 |
| indirect | -0.00032 | 0.56 |
| total | 0.025*** | 0.006 |

Table 16: Moran's I and Geary's c statistics for spatial autocorrelation for Poland

| Residuals | Moran's I | | | Geary's c | | |
|---|---|---|---|---|---|---|
| in year | I | z | p-value | c | z | p-value |
| 2010 | -0.016 | -0.396 | 0.346 | 0.993 | -0.117 | 0.453 |
| 2011 | -0.009 | -0.197 | 0.422 | 0.956 | -0.696 | 0.243 |
| 2012 | -0.021 | -0.523 | 0.300 | 0.979 | -0.347 | 0.364 |
| 2013 | -0.011 | -0.243 | 0.404 | 0.957 | -0.692 | 0.245 |
| 2014 | -0.015 | -0.350 | 0.363 | 0.965 | -0.584 | 0.280 |
| 2015 | -0.015 | -0.352 | 0.362 | 0.982 | -0.314 | 0.377 |
| 2016 | -0.038 | -1.007 | 0.157 | 1.012 | 0.213 | 0.416 |
| 2017 | -0.043 | -1.155 | 0.124 | 1.009 | 0.154 | 0.439 |

$H_0$: there is no spatial autocorrelation

Table 17: Spatial estiamtes for Poland (2009-2013)

| | (1) | (2) |
|---|---|---|
| VARIABLES | lnwage | lnwage |
| lntight | 0.0166* | 0.0394*** |
| | (0.00920) | (0.00662) |
| W*lntight | 0.0114 | |
| | (0.0190) | |
| higher | 0.0120*** | 0.0115*** |
| | (0.00113) | (0.0007) |
| W*lnw | | 0.00529 |
| | | (0.00455) |
| W*e | | 0.159*** |
| | | (0.031) |
| Time FE | Yes | Yes |
| Constant | 7.841*** | 7.738*** |
| | (0.0279) | (0.0386) |
| Observations | 2,893 | 1778 |

Robust standard errors in parentheses in column (1)
Standard errors in parentheses in column (2)
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Direct, indirect and total effect of tightness on wages in specification (2) in Table 17

| | dy/dx | p-value |
|---|---|---|
| direct | 0.0394*** | 0 |
| indirect | 0.000208 | 0.255 |
| total | 0.0396*** | 0 |