LAJOS TAMÁS SZABÓ

THE EFFECT OF TIGHTNESS ON WAGES AT THE REGIONAL LEVEL IN THREE CENTRAL EUROPEAN COUNTRIES

MNB WORKING PAPERS | 4

2019
DECEMBER

THE EFFECT OF TIGHTNESS ON WAGES AT THE REGIONAL LEVEL IN THREE CENTRAL EUROPEAN COUNTRIES

MNB WORKING PAPERS | 4

2019

DECEMBER

The views expressed are those of the authors' and do not necessarily reflect the official view of the central bank of Hungary (Magyar Nemzeti Bank).

MNB Working Papers 2019/4

The Effect of Tightness on Wages at the Regional Level in Three Central European Countries *

(A feszesség hatása a bérekre három közép-európai ország régióiban)

Written by Lajos Tamás Szabó

Budapest, December 2019

Published by the Magyar Nemzeti Bank

Publisher in charge: Eszter Hergár

Szabadság tér 9., H-1054 Budapest

www.mnb.hu

ISSN 1585-5600 (online)

*I would like to thank Andrea Weber, Róbert Lieli and Sergey Lychagin for their useful comments and suggestions. I am also grateful to Olivér Rácz for our discussions about the topic. Any remaining errors are my own.

"for the labourer is worthy of his hire"

Luke 10:7

Contents

Abstract

In this paper, I examine the effect of tightness on wages in three Central European countries. The estimation is relevant for at least three reasons. Firstly, it is a novel exercise to check the implication of the Mortansen–Pissarides model on Central European data. Secondly, from the central bank's perspective it is important to know the effect of tightness on wages, since these are the major determinants of cost-push inflation. Thirdly, the magnitude of the spillover effect from tightness to wages can help determine the efficiency of a targeted development policy. My contribution is directly identifying the effect of tightness on wages from regional heterogeneity. 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.

JEL: J31, J61, J63, J64.

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

Összefoglaló

Ebben a tanulmányban a munkapiaci feszesség bérekre gyakorolt hatását vizsgálom három közép-európai országban. Ez a becslés legalább három szempontból fontos. Egyrészt, egy újszerű megközelítés a Mortansen–Pissarides model következtetéseink ellenőrzésére közép-európai adatokon. Másrészt a jegybank szempontjából fontos tudni a feszesség bérekre gyakorolt hatását, mivel a keresetek a fő összetevői a költségoldali inflációnak. Harmadrészt a feszesség bérekre gyakorolt tovagyűrűző hatásaiból következtetni lehet a célzott fejlesztési programok hatékonyságára. A tanulmány újszerűsége abban áll, hogy regionális különbségekből közvetlenül azonosítom a feszesség bérekre gyakorolt hatását. A feszesség bérekre gyakorolt hatását magyar, szlovák és lengyel járási szintű adatokon vizsgálom panel IV módszerrel. A közvetlen hatások hasonlóak a három országban, azaz pozitív a kapcsolat a feszesség és a keresetek között. Térbeli tovagyűrűző hatásokat azonban csak Magyarországon sikerült azonosítani, ezek az indirekt hatások nincsenek jelen Szlovákiában és Lengyelországban.

1 Introduction

In this paper, I examine the effect of tightness (the ratio between vacancies and unemployment) on wages in three Central European countries. My contribution is directly identifying the effect of tightness on wages from regional heterogeneity using data from three Central European countries.

This mechanism is relevant from at least three perspectives. Firstly, it is worth examining in practice the implication of the Mortansen–Pissarides model for effects of tightness on wages. Secondly, 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. Thirdly, 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.

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.

Since commuting cost is higher the further away from the western border the IV is not strong enough in the eastern parts of these countries. That is why my main specification contains roughly the western half of these countries.

Table 1
Panel IV estimation for the effect of log(tightness) on log(wages) between 2009-2015 in the western parts of the countries

	Hungary	Slovakia	Poland
lntight	0.198**	0.312*	0.0171
	(0.0841)	(0.0168)	(0.0137)
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 0.2% in Hungary. Using the annual average wage and tightness growth rate

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

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. Due to the different commuting and emigration patterns this link is much weaker in Poland.

The tightness has a considerable effect on one of the most important factors of 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 neighboring districts in Hungary. 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. As a robustness check I use Slovakian and Polish data to find out whether the Hungarian results are similar to two other Visegrád countries. This exercise can be found in Section 7. I summarize my results in Section 8.

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:

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

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:

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

Dividing the matching function with the unemployment rate:

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

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

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

gives the rate at which a vacant job is matched to a worker. The $q(\theta)$ function is decreasing in θ, 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 σ 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 η_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,
- γ_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, β 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 β 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 θ. 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:

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

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 δ or ϕ is zero. If both are zero, the specification become an OLS.

On the other hand, if δ or ϕ 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, ... , 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 (β_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:

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

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 ($1 \rightarrow 2 \rightarrow 3 \rightarrow 2 \rightarrow 1$). Due to these feedback effects, the overall direct effect is different from the parameter estimation of β_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) argued 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.

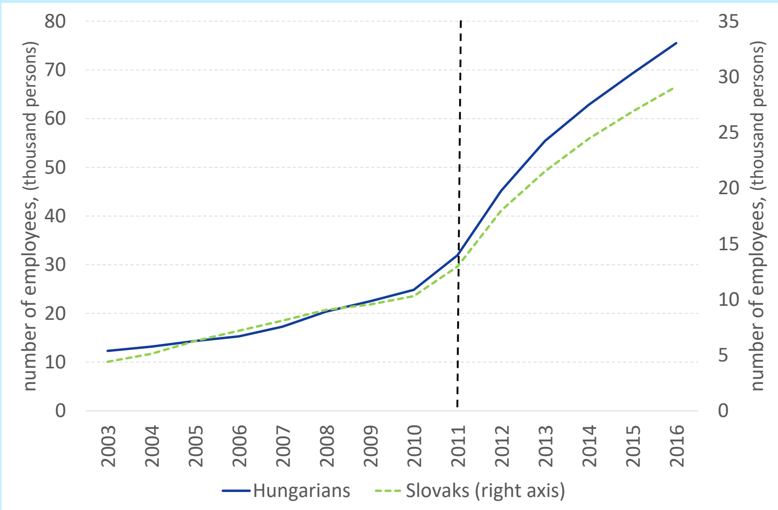
Roshchina (2016) used the modified version Mortensen-Pissarides model to identify the elasticity of employment with respect to tightness and wages. She found that in Brasil the employment is more sensitive to wage changes then to changes in tightness.

Dustman et. al. (2015) used Polish LFS data between 1998-2007 to identify the effect of emigration on Polish wages. They found that mostly intermediate-level skilled workers left the country and the wages of this skilled group increased the most. They found zero effect in the low-skilled group and a slightly positive in the high skilled group. The authors also emphasis that form 1998 to 2007 the emigrant share increased from 0.5 to 2.3% and in some regions to 5.6%, which was a considerable change in the emigration process.

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

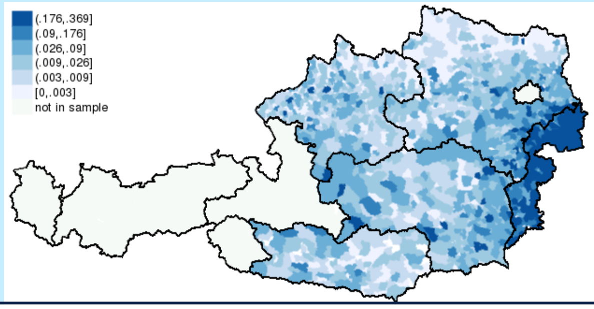


The above mentioned endogenity problem means that the causal effect can be estimated using an instrumental variable. To construct the instrumental variable I use the distance from the Austrian border (in case of Poland from the German border). Living closer to Austria (or Germany) means that the cost 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.

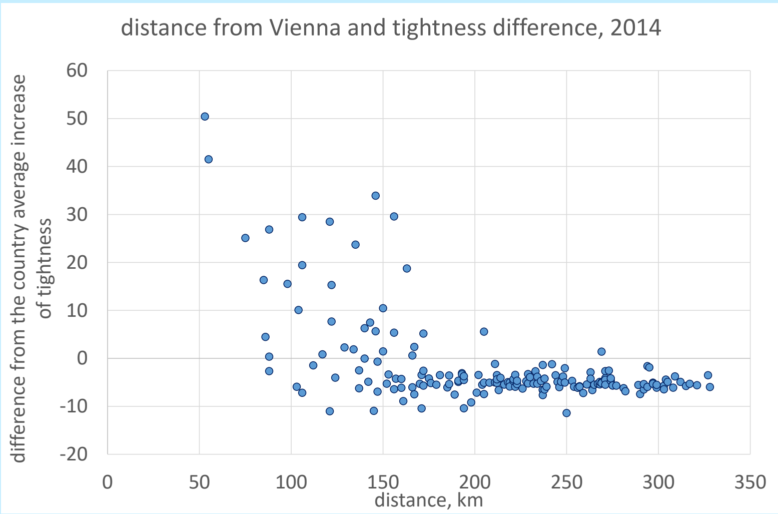
The Hungarian Labour Force Survey contains some of the commuters to other countries. This commuting pattern could be daily, weekly, monthly but this cannot be detected from the survey. On the other hand, since these commuters has someone, who is resident in Hungary they can answer the questionnaire instead of the commuter. Based on the LFS in 2011 there were 20.8 thousand Hungarians, who worked in Austria, which was 32% of the commuters. In 2015 the number of commuters to Austria increased to 58 thousand, which was 43% of the covered commuters in the LFS. 75% of those, who were commuters to Austria lived in Western-Danubia and Central-Danubia regions, which are the closest to Austria. This fact point towards that my IV is strong in the Western part of Hungary, which is also confirmed by the estimation results.

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. Therefore, tightness grows faster than the country average in these districts (see Figure 3) 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, 2014 (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.

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. I also make some robustness checks.

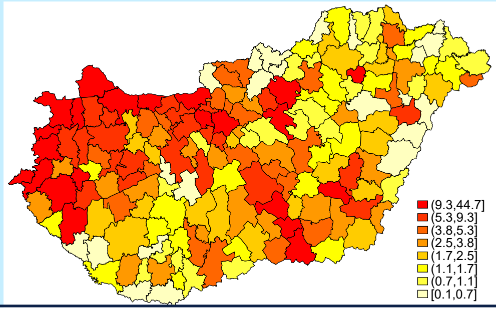
To have comparable results across countries I use the same controls in the OLS and panel IV cases. This narrows the scope of covariates due to data availability reasons in the different countries.

6 Estimation results for Hungary

6.1 DESCRIPTION OF THE HUNGARIAN DATA

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

Figure 4
The logarithm of tightness (2011), source: NES



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.

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 4). 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 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 5). 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.

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.

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.

Figure 5
The LFS and registered jobseekers (source: CSO and NES)

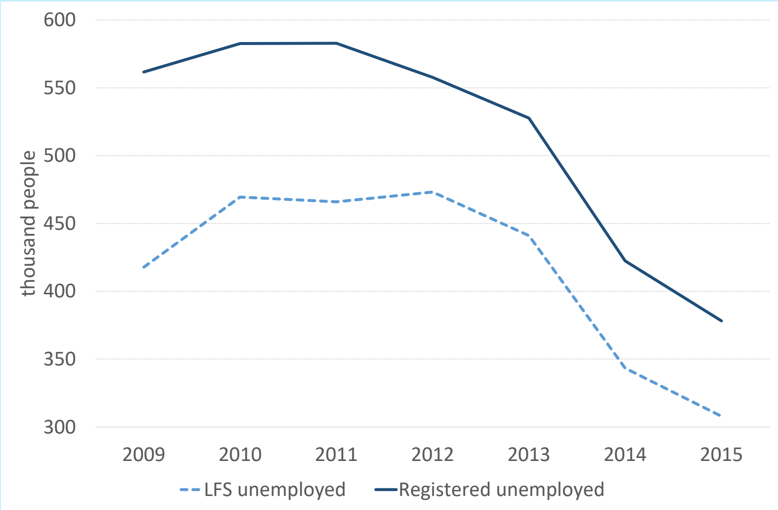
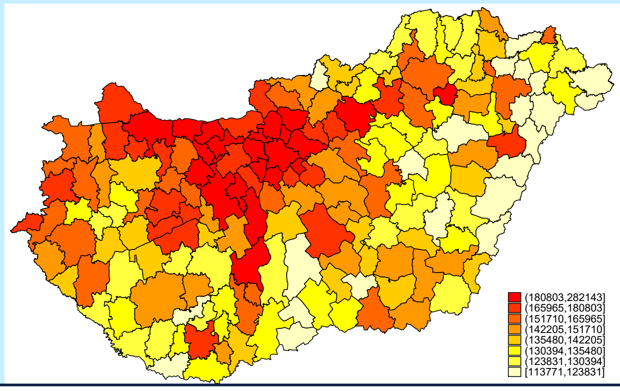


Figure 6
Private sector gross wages (2011)



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 0.056% (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 1%.

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.

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

Variable	Mean	Std. Dev.	Min.	Max.
Tightness (%)	7.2	12.8	0.1	185.4
High skilled (%)	30.2	7.3	15.3	55.3
Vienna time by car (min)	210.1	64.4	53	328
Graz time by car (min)	262.9	85	59	407
Vienna and Graz average time by car (min)	236.5	71.9	82	367.5
min(Vienna, Graz) time by car (min)	203.9	67.3	53	328
Population (thousand persons)	56.4	133.7	8.5	1759.4

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

	OLS	Simple IV	Panel IV
VARIABLES	lnw	lnw	lnw
lntight	0.0564***	0.211***	0.198**
	(0.0150)	(0.0491)	(0.0841)
Other covariates	Yes	Yes	Yes
Observations	553	553	553
R-squared	0.440	0.311	
R-overall			0.368

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
‡ in those districts, which are closer to Austria then 200 minutes
Other covariates: time and county FE, proportion of high skilled

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 9 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 0.7 percent for every additional 1 minute travelling time to Austria. This means that if a district is 20 minutes closer to Austria then an another, tightness is 14% smaller in the easternmost district.

In the reduced form, where I directly estimate the effect of $distance \times after2011$ on wages I got similar results. Namely the distance after 2011 negatively affects the wages (see Table 9 in Appendix).

I estimate the following equation system in the panel IV case:

Second stage:

$$\ln wage_{it} = \beta_0 + \beta_1 \ln tight_{it} + \beta X_{it} + u_{it} \tag{24}$$

First stage:

$$\ln tight_{it} = \alpha_0 + \alpha_1 dist_i + \alpha_2 post2011_t + \ + \alpha_3 post2011_t \times dist_i + \delta X_{it} + u_{it} \tag{25}$$

where the variables are the following:

- X_{it} - other covariates (FE's, high skilled)
- $dist_i$ - distance from the Western border (in minutes by car)
- $post2011_t = 1$ if $year > 2010$, 0 otherwise

In the second stage the coefficient of the tightness is positive and around 0.2 (see Table 3). The coefficient of the tightness means that if the tightness increase by 1% the wages grow by 0.2%. Therefore, if the tightness rises by 18% (average annual tightness growth rate for the western districts) the wages expand by 3.6%. 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 used different thresholds for commuting time restriction. If I increase the time the coefficient start decreasing (see Table 10), which is intuitive since the farther someone lives from the border it is less worth of commuting. Therefore the effect of tightness on wages is smaller. If I use the data of all districts the coefficient is 0.15, which is slightly lower then in the main specification. For another type of robustness check I used different measures of distance and I get similar results as in the main specification[2] (see Table 11).

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. For every year for both tests H_0 can be rejected, so

[2] I also tried the specification in which I included tightness rather then log(tightness). The qualitative inference did not change. The parameter estimate of tightness on lnwages was 0.0072 (with clustered st. errors 0.00372), which is a semi-elasticity measure. This means that if the tightness grows by 1 percentage point the wages grow by 0.7%. For instance, in 2014 the tighness growth was 3 percentage point on the country average, while the wages increased by 4.3%. This means that the tighter labour market caused 2.1% wage increase.

there is a spatial autocorrelation in the OLS residuals (except for one year, see Table 12 and **??** in Appendix). From the previous maps, one can conclude that there is spatial autocorrelation as well.

I estimated the following spatial panel IV model:

$$\ln w_{it} = \beta_0 + \beta_1 \ln \theta_{it} + \beta_2 highskill_i + \rho W \ln w_{it} + \epsilon_{it} \tag{26}$$

Table 4
Spatial panel IV estimation for Hungary (2009-2015)

VARIABLES	lnw
lntight	0.0415**
	(0.0187)
Wlnw	0.371***
	(0.0869)
Constant	6.872***
	(1.057)
Observations	1232
Pseudo R-squared	0.411

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

In this equation, the dependent variable are spatially lagged, which enables us to calculate the direct and indirect effect (see Section 3). The results are in Table 4.

I use the adjacency matrix, which contains 1 if two districts are bordered on each other, otherwise it is 0.The matrix is row-normalised. The parameter of wages of neighbouring districts has got a positive sign and it is significant. This means that if the wages increase in a district then it has a positive effect on its neighbours' wages as well. The parameter of tightness is also positive as in the panel IV case. Furthermore, the sign of the direct and indirect effect of tightness is also positive. This means that the tightness in a given district also has an effect on its' neighbours wages (see Table 13 in Appendix), although with a smaller magnitude.

7 Robustness checks using other CEE countries

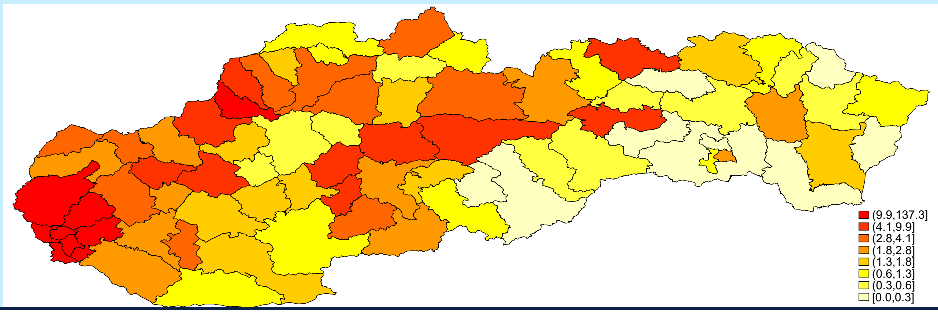
It seems reasonable to check this IV setup on other countries. Slovakia joined the EU at the same time as Hungary, so the labour market opening affected the two countries at the same time. Moreover, it has got also a common border with Austria and the distance magnitudes between Vienna and Slovakian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

7.1 SLOVAKIAN DATA

There were similar economic patterns in case of Slovakia as in Hungary. 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.

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

Figure 7
Tightness in Slovakia, 2011 (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.

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.

Figure 9 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).

Figure 8
Wages in Slovakia, 2011 (source: SOSR)

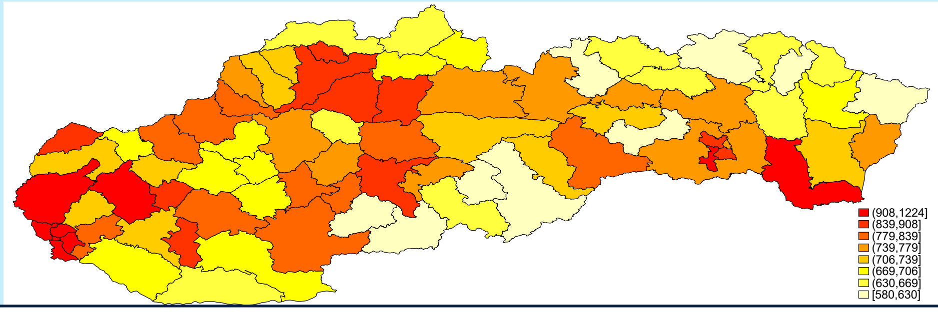
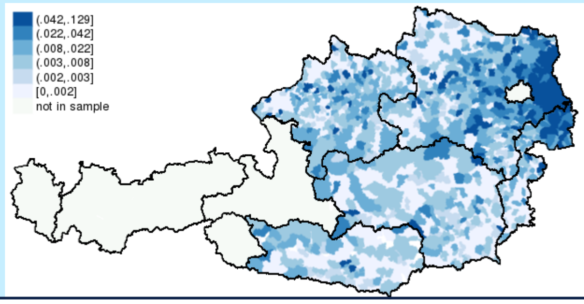


Table 5
Summary statistics for Slovakia, 2009-2017

Variable	Mean	Std. Dev.	Min.	Max.
Wage (€)	818.9	177.2	465.6	1517
Tightness (%)	9.2	22.2	0	164.1
At least college degree (%)	14.7	5.8	8.1	37.7
Distance from Vienna (min)	308.5	146.4	65	649
Population (thousand persons)	68.3	36.4	12.5	169.4

Figure 9
Proportion of Slovak workers in Austria by municipality 2011-2015, (source: Austrian Social Security Database



7.2 ESTIMATION RESULTS FOR SLOVAKIA

The estimated coefficients are similar in magnitude as in the Hungarian case (see Table 6). The simple OLS estimation for the tightness parameter is approx. 10% of the IV parameter, which is similar to the Hungarian estimation. Using the *distance* × *after*2011 IV the tightness parameter is 0.31. This means that in case of a 1% increase in tightness the wage increases by 0.31%. The yearly average wage growth between 2009-2017 was 4%, the yearly average tightness growth was 7.1% during the same period. This means that the tightness caused half of the yearly wage growth, which is a considerable amount. If I use the whole country, not just those districts which are less then 200 minutes from Vienna, the parameter of interest somewhat declines as in the case of Hungary.

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 14 in Appendix). On the other hand, I also tried the same specification as in the Hungarian case but non of the spatial coefficients was significant (see Table 15). The spatial spillover effect from tightness to wages on district level cannot be detected using these methods (Table 16).

Table 6
Estimation results for Slovakia (2009-2015)

	OLS‡	Simple IV‡	Panel IV‡	Full sample
VARIABLES	lnw	lnw	lnw	lnw
lntight	0.0350***	0.306***	0.312*	0.173***
	(0.0128)	(0.115)	(0.168)	(0.0568)
Observations	154	154	154	691
R-squared	0.717			
R-overall			0.340	0.503

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
‡in those districts, which are closer to Austria then 200 minutes

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 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.

7.3 POLISH DATA

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. 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. Comparing to Hungary and Slovakia there are more Polish people, who work abroad relative to the population. This can affect the estimation results.

For Poland I have 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 7
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

7.4 POLISH ESTIMATION RESULTS

If tightness grows by 1% then wages grow by 0.017%. On the sample period the annual average wage growth was 5% the tightness growth was 27%. This means that tightness caused almost one 10% of the wage dynamics, which is quite

The magnitudes of the tightness parameter (0.017) is smaller then in the Hungarian (0.2) or in the Slovakian case (0.3) and it has high robust standard errors on both the full sample and for the western districts. 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 after 2011.

Table 8
Estimation results for Poland (2005-2015)

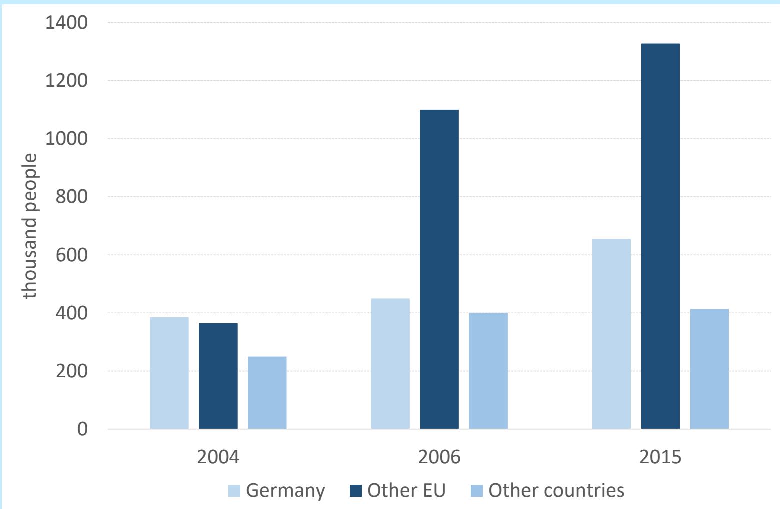
	OLS	IV	Panel IV	Full sample
VARIABLES	lnwage	lnwage	lnwage	lnwage
lntight	0.00623	0.0659	0.0171	0.0432
	(0.00530)	(0.0427)	(0.0137)	(0.109)
Observations	1,735	1,735	1,735	2,510
R-squared	0.577	0.415		
R-overall			0.572	0.517

District level clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Poland has a different emigration pattern than Hungary and Slovakia. There were around 770 thousand Poles, who worked in the EU at the year of the EU enlargement (half of them in Germany). From the same data source (Hungarian LFS) this was around 13 thousand in Hungary. The Polish data corresponds to 5% of the number of employees, while the Hungarian is 0.3%. This shows that the Poles were more mobile even before the EU enlargement.

After the new member states joined to the EU in 2004, three old member states opened its labour market immediately to the newcomers (Ireland, Sweden and the United Kingdom). This has a significant effect on the Polish labour market, since two years after the EU-enlargement the number of Poles, who worked in the old member states almost tripled (Figure 10). The main target country was Ireland and the UK. There was only a slight increase to Germany. After 2011 the number of Poles, who work in Germany also increase but not in that magnitude as for the UK and Ireland after 2004. This means that the same IV is not strong enough to capture the effect of tightness on wages in case of Poland.[3] Furthermore, in Poland the number of Ukrainian immigrants is high. There are several estimates estimates of their exact number (between 1-2 million, see e.g. Jaroszewicz (2018)). The inflow of Ukrainians can decrease the wages through labour market tightness. On the other hand, this would be a separate study.

Figure 10
Polish workers abroad (source: Polish LFS)



[3] The yearly district level emigration rates probably would give a stronger IV.

The spatial estimations give similar result as in the case of Slovakia. The Moran and Geary test (Table 17 in Appendix) cannot refuse the no spatial autocorrelation H_0. Although the parameter of Wlnw is significant the magnitude is quite low (0.0087). Neither the direct not the indirect effect (Table 19 in Appendix) of tightness is significant. From these exercises one can conclude that there is no spatial connection between tightness and wages in Poland.

8 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. Since the commuting is only a viable option for those who live close to the western border, my main specification is includes those districts, which are close to the border. I concluded that tightness has a positive effect on one of the main part of cost-push inflation in three Central European countries. In Hungary and Slovakia this effect is significant and the coefficients has similar magnitude. On the other hand, the magnitude of this effect is smaller in Poland then in Hungary and Slovakia. My IV setup is not strong enough in Poland because of the different emigration pattern of Poles. Based on my estimation there are spatial spillover effects in the Hungarian labour market. On the contrary, 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 different countries as well. Using a spatial weight matrix measured in a more sophisticated way could also improve the validity of my results. In case of Poland an other type of instrumental setup would probably lead to similar results as in other two Visegrád countries. This IV could be the annual emigration rate from districts.

References

[1] Antczak, Elzbieta - Galecka-Burdziak, Ewa - Pater, Robert (2016): Spatial Labour Market Matching, CERGE EI Working Paper Series 578

[2] Acemoglu, Daron (2001): Labour Economics, Lecture 12: Equilibrium search and matching, MIT

Dustmann, Christian - Frattini, Tommaso - Rosso, Anna (2015): The Effect of Emigration from Poland on Polish Wages, The Scandinavian Journal of Economics, Vol. 117, Issue 2, pp. 522-564

[3] Elhorst, Paul J. (2014): Spatial Econometrics From Cross-Sectional Data to Spatial Panels, Springer

[4] Jaroszewicz, Marta (2018): Migration from Ukraine to Poland the trend stabilises, Centre for Eastern Studies, Warsaw

[5] Harmon, Nikolaj A. (2013): Are Workers Better Matched in Large Labor Markets?, Princeton University

[6] LeSage, James (1999): The Theory and Practise of Spatial Econometrics, CRC Press

[7] LeSage, James - Pace, Kelly R. (2009): Introduction to spatial econometrics, CRC Press

[8] Manning, Alan - Petrongolo, Barbara (2017): How Local Are Labor Markets? Evidence from a Spatial Job Search Model, American Economic Review, Vol. 107, pp. 2877-2907.

[9] Pissarides, Christopher (2000): Equilibrium unemployment theory, MIT Press

[10] Roshchina, Ekaterina (2016): Essays on Job Search and Labor Market Dynamics, Department of Economics Duke University, PhD Dissertaion

[11] Wincenciak, Leszek (2009): Lecture 5: Search and matching theory, Warsaw University

Appendix

Table 9
First stage of panel IV estimation and the reduced form for Hungray (2009-2015)‡

	1st stage	Reduced form
VARIABLES	lntight	lnw
min(Vienna, Graz) × after2011	-0.00715***	-0.00135**
	(0.00154)	(0.000668)
Observations	553	553
R-overall	0.632	0.444
H_0 : min(Vienna, Graz) × after2011 = 0		
χ^2	21.69	4.08
Prob.	0.00	0.04

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Other covariates: county and time FE, high skilled, distance from Austria
‡ for those districts, which are closer to Austria then 200 minutes

Table 10
Robustness check for Hungray (2009-2015) with different thresholds of distance

	Distance from Austira less then				Full
	200 min	225 min	250 min	275 min	sample
lntight	0.198**	0.192***	0.145***	0.113***	0.151**
	(0.0841)	(0.0722)	(0.0535)	(0.0433)	(0.0604)
Observations	553	721	896	1,036	1,232
R-overall	0.368	0.369	0.385	0.378	0.346

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

Table 11
Robustness check for Hungray (2009-2015) with different means of transport

	Distance from		
	Vienna	avg(Vienna, Graz)	Graz
lntight	0.150**	0.142**	0.200*
	(0.0609)	(0.0633)	(0.107)
Observations	511	553	553
R-overall	0.391	0.401	0.364

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

Table 12
Moran's I and Geary's c test for Hungary

	Moran			Geary's c		
Residuals in year	I	z	p-value	I	z	p-value
2009	0.110	2.525	0.006	0.885	-2.187	0.014
2010	0.232	5.145	0.000	0.772	-4.492	0
2011	0.264	5.859	0.000	0.727	-5.254	0
2012	0.250	5.544	0.000	0.749	-4.939	0
2013	0.186	4.147	0.000	0.812	-3.756	0
2014	0.133	3.016	0.001	0.87	-2.458	0.007
2015	0.140	3.163	0.001	0.884	-2.29	0.011

H_0: there is no spatial autocorrelation

Table 13
Direct and indirect effect of tightness for Hungary

	dy/dx	Std. Err.	z	P>z
direct	0.043**	0.019	2.230	0.026
indirect	0.023*	0.012	1.880	0.060
total	0.066**	0.030	2.220	0.026

Table 14
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 15
Spatial IV estiamtion for Slovakia

VARIABLES	lnw
lntight	0.0252***
	(0.00914)
Wlnw	-0.0131
	(0.0225)
Constant	6.385***
	(0.154)
Pseudo R^2	0.77
Observations	691

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Other covariates: region and time FE, high skilled

Table 16
Direct, indirect and total effect of tightness on wages in specification (2) in Table 15

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

Table 17
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 18
Spatial estiamtes for Poland (2009-2013)

	Spatial IV
VARIABLES	lnwage
lntight	0.00614
	(0.00757)
Wlnwage	0.00875**
	(0.00410)
Constant	7.721***
	(0.0350)
Pseudo R2	0.533
Observations	1778

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

Table 19
Direct, indirect and total effect of tightness on wages in specification (2) in Table 18

	dy/dx	P>z
direct	0.0061	0.417
indirect	0.0001	0.441
total	0.0062	0.417

MNB Working Papers 2019/4

The Effect of Tightness on Wages at the Regional Level in Three Central European Countries

Budapest, December 2019

mnb.hu

1054 BUDAPEST, SZABADSÁG TÉR 9.