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The impact of spatial clustering of occupation on commuting time and employment status

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ABSTRACT
In this study we reveal the impact of spatial clustering of occupations on the probability of employment and commuting time, with particular emphasis on differences between genders and household types. Based on Hungarian 2011 census data our research confirmed previous results of some USA studies according to which women work in less spatially clustered occupations compared to men. Our most important result is that more clustered the occupation, the longer the commuting time, and the lower the probability of employment. The effect of occupational clustering on commuting time is larger for women regardless of household type and for those living in a relationship compared to singles. Our further result is that the greater the occupational diversity of the place of residence, the shorter the commuting time and higher the probability of employment, and the occupational diversity of the place of residence modifies the effect of occupational clustering on commuting time.

JEL codes: R12, J22
Keywords: Commuting time, occupations, employment probabilities

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A foglalkozások térbeli klaszterezdésének hatása az ingázási időre és a foglalkoztatásra

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ÖSSZEFOGLALÓ

Ebben a tanulmányban feltárjuk a foglalkozások térbeli klasztereződésének a hatását foglalkoztatás valószínűségére és az ingázási időre, különös tekintettel a nemek és háztartástípusok között megfigyelhető különbségekre. Kutatásunk a 2011-es Magyar népszámlálási adatok alapján megerősítette néhány korábbi amerikai és brit kutatás eredményeit, amelyek szerint a nők a férfiakhoz képest földrajzilag kevésbé csoportosított foglalkozásokban dolgoznak. Legfontosabb eredményünk, hogy minél klaszterezettebb a foglalkozás térbelileg, annál hosszabb az ingázási idő, és annál kisebb a foglalkoztatásba kerülés valószínűsége. A foglalkozás klaszterezettségének nagyobb a hatása az ingázási időre a nők esetében háztartástípustól függetlenül, valamint a párkapcsolatban élők esetében az egyedülállókhoz képest. További eredményünk, hogy minél nagyobb a lakóhely foglalkozási diverzitása, annál rövidebb az ingázási idő és annál nagyobb a foglalkoztatásba kerülés valószínűsége, valamint a lakóhely foglalkozási diverzitása módosítja a foglalkozás klaszterezettségének ingázási időre gyakorolt hatását.

JEL: R12, J22

Kulcsszavak: ingázási idő, foglalkozások, foglalkoztatás valószínűsége

1. Introduction

Exploring factors influencing commuting time is important not only because it is one of the least enjoyable daily activities undertaken by workers (Kahneman at al., 2004) and has a negative impact on subjective well-being (Stutzer and Frey, 2008; Jacob at al., 2019), but also because there is a gender gap in commuting not perfectly explained. That women typically commute shorter distances has long been established in the literature (Crane 2007; McQuaid and Chen, 2012, Wang and Quin, 2017, Kwon and Akar, 2021). The main explanation of the latter phenomenon offered was the so called Household Responsibilities Hypothesis (HRH) which simply states that married-women have more household and child-care tasks therefore face greater time-constraints and thus choose shorter commutes than men.

Although the HRH has been more-or-less confirmed by several empirical studies earlier (Turner and Niemeier, 1997, Gimenez-Nadal and Molina, 2016), major changes in the socio-economic environment and some new results regarding different spatial distributions of female- and male-dominated occupations warrant further research in this area. In connection with the former several important facts are worth consideration e.g. besides changing gender norms and female labour force participation there is a steady increase in the proportion of single-person households for whom HRH cannot explain the gender gap in commuting time and distance. In connection with the latter it has also been shown by Benson (2014) that women tend to work in geographically more dispersed occupations compared to men. Petrongolo and Ronchi (2020) argued that service jobs that are dominated by women are also the least geographically clustered, therefore these jobs are in average closer from any given place of residence and the resulting shorter commutes - because of their dual roles - are particularly attractive to women. However, there are many other factors – wage, means of transportation, settlement structure – which affect commuting time and the gender gap, that is why the role of geographical clustering of occupations is an open empirical question. For this reason, one of our objectives is to explore the relationship between the spatial distribution of occupations and commuting time by gender and family structures while controlling for a rich set of potential confounders. Specifically, we ask the following questions: (1) Is commuting time longer the more geographically clustered one's occupation is? (2) Does the effect of occupational clustering on commuting time differ by gender and family structure? (3) How does the occupational diversity of residence modify the effect of occupational clustering on commuting time?

Most studies on commuting have ignored the fact that commuting time can only be observed when an individual is employed. However, since it is not random who works and who does not, we also need to estimate the factors affecting employment probability in order to address such a selection bias. Although the literature on estimating the factors affecting selection into employment and job search is vast (Blundell at al., 2011), there are relatively few papers dealing with the geographical barriers of employment. That is why a further important objective of this paper is to explore the impact of geographical clustering of occupations on the probability of employment and how this impact differs by gender and family structure.

In the following section we review some of the related literature, section (3) introduces the data and variables, in section (4) we present the econometric methodology. We report and discuss our results in Section (5). The last section summarizes the results of this paper and suggests policy implications.

2. Literature review

Quite a few empirical studies have shown that women tend to work closer to home (White 1986, Madden 1981, Gordon et al., 1989, Benson 2014, Olivetti and Petrongolo 2017, Petrongolo and Ronchi 2020), while men, especially fathers take longer commutes i.e. commuting is gendered. This fundamental gender difference in commuting time seems persistent across various socio-demographic groups, even after controlling for children and various individual characteristics, household types, over time and across mostly western countries (Turner and Niemeier, 1997) – in OECD countries women commute 33% shorter distances and 11minutes less time than men on average (OECD LMP2.6.A data). Yet empirical evidences are somewhat conflicting and the essential question remains, is the different commuting pattern of women a result of their preferences, and thus a choice or is it due to constraints they face (Rosenthal and Strange, 2012; MacDonald, 1999). Several possible explanations emerged for these observed gender gaps in commuting - linking it to gender roles and different household responsibilities and labor market status, or the gender wage gap (MacDonald 1999, Olivetti and Petrongolo, 2017) allowing for a smaller potential wage gain from commuting for women.

The main explanation for shorter commuting of women is the household responsibilities hypotheses (Turner and Niemeier, 1997, White 1986, Gimenez-Nadal and Molina, 2016.) which states that women usually are more sensitive to longer commutes (both in distance and time) for reasons of them having a dual role, also being household/care providers, therefore face greater time-constraints. Women do travel also for household and childcare reasons, thus try to shorten work-related trips. Not only are their preferences different (and the opportunity cost of commuting for them) resulting in lower reservation wages - i.e. women accepting lower wages in exchange for shorter commuting (Petrongolo and Ronchi, 2020, LeBarbanchon et al., 2019), but also longer commuting causes greater wellbeing losses, a larger disutility for women (Jacob et al, 2019; Roberts et al, 2011; Kahneman at al., 2004; Stutzer and Frey, 2008) especially significant for high-skilled women in leadership positions. According to these authors, such differences in willingness to commute account for 10% of the gender wage gap.

Typically, the birth of children has long-lasting negative consequences on labor market position and wages of women, also known as ’motherhood penalty’ (Bertrand et al., 2010; Angelov et al., 2016; Kleven et al., 2019) and it has been shown to affect mothers’ commuting preferences too (Roberts et al. 2011, Abe, 2013). Interestingly, dispreference of longer commutes is found also among single, childless women– although these commuting preferences also depend on how tight, competitive local labor markets are (Jacob et al., 2019). Another direction of research focuses on how the household structure shapes the gender differences in commuting time and distance. Johnston-Anumonwo (1992) found that the gender difference in commuting distance is larger in households with two breadwinners than the difference between male and female workers in households with a single breadwinner. Lee and McDonald (2003) and Sultana (2005) found that gender differences in commuting time and distance are the same between households with two breadwinners and households with a single breadwinner. Fan (2017) found that there is no gender difference in commuting time among single-breadwinner couples without children and among single households without children. Furthermore, couples with children have significantly larger gender difference in commuting time compared to the single households with children. Fan argued that these results indicate that the magnifying effects of the presence of partner on gender differences in commuting time are conditional on the presence of children.

Although the household responsibilities hypothesis has been confirmed by several empirical studies, the literature is far from being conclusive, questioned by some (Fan, 2017, Hanson and Johnston, 1985). Hanson and Johnston (1985) argue that women's lower incomes, their concentration in female-dominated occupations, and their greater reliance on public transport for mobility are the main factors for shorter commuting times and not so much their dual responsibilities. Moreover, Hanson and Johnston (1985) found some evidence that female-dominated employment opportunities are more uniformly distributed, whereas male-dominated jobs are clustered in certain districts. Benson (2014) main contribution to this literature is the generalization of Duncan’s dissimilarity index in order to measure the spatial clustering of occupations. Based on his generalized Duncan’s dissimilarity index Benson found that never-married men have higher mean clustering scores than women, i.e. women have more geographically dispersed occupations compared to men. Benson argued that this phenomenon may explain why women tend to work closer to home than men. The rise of service sector in the economy has created ’pink collar ’jobs (see e.g., Goldin, 2006, Ngai and Petrongolo, 2017, Rendall, 2018). Such services (kindergarten, nursery, health care, trade) are needed in all settlements, related occupations are mostly female-dominated (Hanson and Johnston 1985) and less segregated in space, than occupations mainly related to manufacturing, mining etc. that are male-dominated and more clustered in certain areas (Petrongolo and Ronchi, 2020).

Hanson and Johnston (1985), Hanson and Pratt (1995) provided the first evidence on gender differences in spatial occupational clustering and its indirect impact on commuting distance in the USA using only descriptive statistics. Hence, our article aims to show the direct effect of spatial clustering of occupations on commuting time and employment probabilities while controlling for a wide set of other confounding factors.

3. Data and descriptive statistics

Most of the data we use comes from the 2011 Hungarian census. For regression analyses the sample was restricted to those of working age between 18-65, singles and/or couples (married/cohabiting) with dependent child(ren) or childless. The full-time students, homeless, and those living in various institutions (e.g prison, retirement home etc.) or members of the armed forces, as well as the self-employed were excluded from the sample. The most important explanatory variable is spatial clustering of occupations, measured by the generalized Duncan dissimilarity index suggested by Benson (2014):

$$C_J^* = \frac{1}{2}\sum_{i=1}^{S}\left|\frac{n_{ij}}{n_j} - \frac{n_i - n_{ij}}{n - n_j}\right|, \qquad (1)$$

where S denotes number of settlements, n is the size of labour force aged 18-65, i stands for municipality, while j for occupation. This index shows what percentage of those working in any given occupation should be re-settled so that being present at exactly the national average ratio in each settlement. Least clustered occupation is that of general office administrators, who represent 2% of the total workforce aged 18-65. The clustering index of this occupation is 0.58% meaning that 0.58% of general office administrators would need to be re-settled in order for them to represent 2% of the workforce in each and every municipality. While the most clustered occupation of vegetable growers represents only 0.11% of the labour force. The Duncan index of this occupation is 35%, meaning that 35% of vegetable growers would need to be re-settled nationally so that they could be present at 0.11% ratio in each settlement. In order to get a roughly normal distribution, we take the log transformation of the clustering index calculated above.

Moreover, among settlements of the same size and population density, there are some, where there are only a few sectors and thus a narrow scale of occupations are available and there are some others, where a wide range of sectors operate and so a more diverse set of occupations can be found. We presume that the more types of occupations demanded by employers in any given settlement, the better employment chances are for the individual and smaller probabilities for having to commute somewhere else - regardless of how clustered one's occupation is. Hence a variable showing occupational diversity of the settlement was included into regressions, that is calculated as such:

$$D_i = \frac{\sum_{j=1}^{485} I_{ij}}{485}, \tag{2}$$

where I_{ij} is an indicator variable taking the value of 1, if there is at least one employee in settlement i in occupation j, and 0 otherwise. 485 in the denominator shows the total number of occupations available in the FEOR-08 (ISCO-08) categorization of occupations for 2011 in Hungary.[1]

The effect of wage on commuting time is statistically significant in the overwhelming majority of the papers (McQuaid and Chen, 2012; Hong at al., 2018), and the predicted wage have an impact on labour supply decisions at the extensive margins. However, data on wage is not available from the Hungarian Population Census, therefore we use the Wage Tariff Survey to estimate a Mincer-type wage equation as follows:

$$logWage_j = \alpha_0 + C_j\zeta + \sum_i \varphi_{i,j} Region_{i,j} + \sum_q \eta_{q,j} Occupation_{q,j} + \upsilon_j \tag{3}$$

, where $logWage_j$ is logarithm of the monthly gross wage for each individual j. C_j is the matrix representing each individual characteristics including age, age squared, education level dummies and gender. Region j and Occupation j indicate the dummy variables reflecting 7 regions and 9 main occupation groups, respectively. The Wage Tariff Survey contains information only about the region of workplace therefore we run separate equation for the employed and unemployed, omitting the regional dummies for the latter. Similar as Hong at al. (2012) we use a predicted wage for each worker and unemployed, as proxy for potential income. Table (1) shows the estimations results for Equation 1.

[1] FEOR-08 follows the international ISCO-08 categorization system in its structure and baselines.

Table 1.
Estimated Results of Wage equations

	(1)		(2)	
Male	0.178***	(0.000632)	0.170***	(0.000617)
Age	0.0269***	(0.000213)	0.0294***	(0.000208)
Age squared	-0.000271***	(2.52e-06)	-0.000296***	(2.46e-06)
Vocational	0.0705***	(0.00102)	0.0787***	(0.000991)
Secondary	0.220***	(0.00111)	0.212***	(0.00108)
Tertiary	0.633***	(0.00152)	0.618***	(0.00148)
Occupations	9		9	
Region of the workplace	-		7	
Constant	10.74***	(0.00439)	10.82**	(0.00429)
Observations	2,353,166		2,353,166	
Adjusted R^2	0.434		0.462	

Notes: Figures in the parentheses are t-values. *, ** and *** represent the statistical significance at the level of 10%, 5%, and 1%, respectively. Base category for region dummies is Central-Hungary and base category for occupation dummies is elementary. Source: 2011 Wage Tariff Survey by National Employment Service

Columns (1) show the results of the estimation without the region of the workplace, these coefficients were used to impute the potential wage of the unemployed, while columns (2) contain the estimated coefficients including the region of workplace, and these results were used to impute the potential wage of employees. According to our estimation results, if the individual is male, the potential wage is higher. The effect of potential wage is positive, the older an individual, the higher the wages they can expect, but the rate of increase is declining. The coefficients of the dummies indicating educational attainment show that the higher the education compared to primary education, the higher the potential wage, keeping all other factors unchanged.

In order to control for settlement size and population, which can be strongly related to settlement diversity of occupations, population density was used in regression models. To calculate population density, the T-Star database of the Hungarian Central Statistical Office was used, which contains data on settlement land area and population for every Hungarian settlement. According to the literature (McQuaid and Chen, 2012; Cook and Ross, 1999) both commuting time and the probability to become employed are affected by basic demographic variables, thus gender, age, age squared, and education level dummies were also included into the regressions.

To be able to sort out the effect of occupational clustering on employment probabilities and commuting time, time spent on home-making and household chores needed to be controlled for too. Such tasks are primarily related to caring for and raising children, and according to the literature they significantly affect gender differences in employment chances and commuting time. The more and younger children in a family, the more household tasks for the parents. Therefore, not only the number of children, but also their age profile is important, hence we included the following two dummies in the models: presence of 0-5 year old child, presence of 6-14 year old child in the household.

Hungary has seven large statistical regions that differ in terms of economic development, settlement structure or industry structure. Such regional differences can have significant effects on employment probabilities and commuting times, hence regions are also controlled for.

In order to handle the mentioned selection bias (sorting into employment) at least one instrument is needed that correlates with the probability of employment but affects commuting time only indirectly. McQuaid and Chen (2012) found health problems not really having an effect on commuting times. We have similar findings, the presence of chronic diseases or disability do not correlate with commuting time, however there is a small, negative correlation between employment probabilities and the presence of chronic diseases or disability. The other candidate for handling selection bias is municipal public nursery provision. Lovász and Szabó-Morvai (2019) using Hungarian data find that improving access to publicly funded childcare increased maternal labour supply by 11.7 percentage points. To measure public nursery coverage, like Lovász and Szabó-Morvai (2019) we used municipal level data on available nursery places and the size of population aged 0-2 years from the T-Star database. The correlation between the micro-regional nursery coverage and commuting time is close to zero, however the correlation between the micro-regional nursery coverage and employment is small and positive. The further potential instrument for correcting selection bias is the micro-regional unemployment rate. Although the micro-regional unemployment rate may have an effect on commuting time, it is much smaller than what it on the likelihood of employment. Summary of descriptive statistics of major variables is provided in Table 2. Based on the data, we can conclude that the employed - making 78 percent of the sample – work in less clustered occupations than the unemployed. Within the employed and the unemployed, there is nearly equal proportion of couples, singles.

Table 2

Descriptive statistics of the sample

	Whole sample				Employed				Unemployed/Inactive			
	Mean	Sd	Min	Max	Mean	Sd	Min	Max	Mean	Sd	Min	Max
Employed	0,78	0,41	0,00	1,00								
Commuting time	52,26	42,74	0,00	240	52,26	42,74	0,00	240				
Log Clustering Index	-1,45	0,45	-2,24	-0,45	-1,46	0,43	-2,24	-0,45	-1,40	0,52	-2,24	-0,45
High occupational diversity	0,21	0,41	0	1	0,19	0,39	0	1	0,28	0,45	0	1
Moderate occupational diversity	0,23	0,42	0	1	0,22	0,42	0	1	0,25	0,44	0	1
Low occupational diversity	0,56	0,50	0	1	0,58	0,49	0	1	0,46	0,50	0	1
Log Potential Wage	12,53	0,48	11,11	14,24	12,60	0,48	11,11	14,24	12,28	0,41	11,22	14,04
Couples	0,75	0,43	0	1	0,75	0,43	0	1	0,76	0,43	0	1
Singles	0,25	0,43	0	1	0,25	0,43	0	1	0,24	0,43	0	1
Man	0,44	0,50	0	1	0,47	0,50	0	1	0,32	0,47	0	1
Age	42,46	10,11	18	65	42,94	9,95	18,00	65,00	40,71	10,47	18	65
Child under 6	0,20	0,40	0	1	0,16	0,37	0	1	0,35	0,48	0	1
Child between 6 and 15	0,19	0,39	0	1	0,19	0,40	0	1	0,17	0,38	0	1
Elementary	0,16	0,36	0	1	0,12	0,32	0	1	0,31	0,46	0	1
Vocational	0,28	0,45	0	1	0,27	0,45	0	1	0,29	0,46	0	1
Secondary	0,31	0,46	0	1	0,33	0,47	0	1	0,25	0,44	0	1
Tertiary	0,25	0,43	0	1	0,28	0,45	0	1	0,14	0,35	0	1
Permanent illness	0,11	0,31	0	1	0,10	0,30	0	1	0,13	0,34	0	1
Nursery coverage	0,14	0,11	0	1	0,15	0,11	0	1	0,12	0,11	0	1
Local unemployment rate	0,13	0,04	0,07	0,28	0,13	0,04	0,07	0,28	0,14	0,04	0,07	0,28
Observations:	3379562				2647976				731586			

Compared to the unemployed and inactive the employed in our sample are on average more educated, male in larger share, live with long term illness or disability in smaller proportions, while there is a higher share of nurseries/childcare provision in their resident municipalities. Consistent with the previous results, we found that men commute longer on average than women, a difference of 2.26 minutes. However, subsamples by household type show that single women commute on average nearly 1 minute longer per day than single men, while married women commute 3.63 minutes less than men living in marriage. Furthermore, it is worth noting that the difference between the average commuting time of single men and men in a relationship is negligible (less than 5.7 seconds). The distribution of commuters by commuting times is shown in Table 3. Slightly more than 40 percent of women living in relationship commute 81 minutes or more a day, compared to just over 30 percent of men in couples. This means that very long commuting time of relatively few men is responsible for the longer average commuting time of men living in couples.

Table 3
Distribution of commuters by commuting time (percent)

Commuting time	Full sample		Couples		Singles	
	Men	Women	Men	Women	Men	Women
0 min	1,97	1,81	1,93	1,90	2,15	1,59
1 to 10 min	7,46	7,38	7,68	7,76	6,58	6,41
11 to 30 min	26,12	23,98	26,87	24,12	23,21	23,60
31 to 50 min	14,96	12,48	15,20	11,96	14,01	13,83
51 to 60 min	11,71	9,64	11,87	8,97	11,11	11,40
61 to 80 min	6,21	5,12	6,22	4,69	6,15	6,24
81 min or more	31,58	39,59	30,23	40,60	36,79	36,95

Similar proportions of single men and single women have long commuting times, 81 or more minutes per day. Method of transportation can significantly affect commuting time, those travelling by car spend on average 48 minutes daily, while those using public transport (local bus, long-distance bus, train) spend 76 minutes daily for their commute. The difference stays when we look at short distance, within municipality commuters or those who commute to longer distances to other cities: travelling by car always offers shorter average commuting time for both gender. Data show (Table 4) that commuting by car is the most frequent in our sample (almost one third of commuters go by car) and only second most frequent is usage of public transport. Within public transport the 57 percent of commuters use local bus, and only 7.3 percent go by train. At the same time there are considerable gender differences, 62 percent of car users are men, and while 16 percent of women use public transport, only 9 percent of men do.

Table 4
Distribution of commuters by commuting mode (percent)

Commuting mode	Share of commuters	Women commuters share	Man commuters share	Occupational Diversity Low	Occupational Diversity Moderate	Occupational Diversity High
Walk, or not commute	15,53	64,61	35,39	13,61	14,423	16,581
Local bus	14,08	68,30	31,70	0,19	0,882	23,734
Long-distance bus	8,72	62,49	37,51	23,39	12,141	2,558
Train	1,82	48,28	51,72	2,07	3,521	1,078
Auto	30,33	37,11	62,89	31,04	31,502	29,643
Bicycle, motorcycle	15,55	54,10	45,90	18,77	23,204	11,549
Several means of transport	12,43	51,93	48,07	8,22	12,228	13,906
Other (truck, ship etc.)	1,54	47,27	52,73	2,69	2,099	0,951

At municipalities with a high occupation diversity (i.e. typically larger cities) commuting by public transport is only 2 percentage point higher than in places with low occupation diversity, however 10 percentage point higher than at places with moderate occupational diversity. In medium and low occupational diversity settlements, the long-distance bus is the most used type by those using public transport, while in places with high occupational diversity, the local bus is the most popular means of public transport.

4. Econometric method

Most studies on commuting so far have ignored the fact that commuting time can only be observed when an individual is employed. If the employment status would be random, we could use ordinary regression to fit our regression model. However, the assumption that becoming unemployed or employed is random is unlikely to be true. Those, who receive job offers only far from their place of residence are less likely to accept them, than those who receive job offers closer to home. Because of this non-random selection into employment, the estimates of the effect of our variables on commuting time may be inconsistent and biased.

In order to correct this sample-selection bias we can choose between two estimators – the Full Information Maximum Likelihood (FIML) and the Heckman two-step estimator. Puhani (2000) argued that both FIML and the Heckman two-step method give acceptable results, but if there is not collinearity, the former is preferable. Nevertheless, in our point of view the main advantage of the Heckman two-step method is that it can always be estimated, while the FIML does not converge in some cases, as we experienced in some of our subsamples too. Therefore, we prefer to use the Heckman two-step method which is composed of two equations. The first, is the regression equation which is the linear model of interest:

$$T_i = \beta_1 + \beta_2 OC_i + \beta_3 OD_i + \beta_4 C_i + \beta_5 Child5_i + \beta_6 Child6\_14_i + \beta_7 Child0\_14_i + \beta_8 Man_i + D_i\gamma + \sum_j \varphi_j Region_{j,i} + e_i \tag{1}$$

, where T_i is the commuting time in seconds for each individual i. OC_i and OD_i denote occupational clustering and occupational diversity[2], respectively. C_i indicate whether individual i is living in a couple or single; Child5, Child6_14 are dummy variables which indicate the presence of child under 6, the presence of child between 6 and 14, respectively. D_i is the matrix representing each individual worker's characteristics including age, age squared, education level, and gender. Region indicates the dummy variables reflecting 7 regions. Due to the selectivity problem, the usual least squares estimators of the coefficients of equation (1) will be biased and inconsistent. That is why, we need to estimate a second equation that determines

[2] In the case of estimates for the whole sample, we measured the occupational diversity of the residence with dummy variables (see table 2).

whether commuting time is observed. This selection equation is expressed in terms of a latent variable E_i^* and which depends on all the explanatory variables of the regression equation plus some additional variables:

$$E_i^* = \gamma_1 + M_i\delta + \gamma_2 ILL_i + \gamma_3 N_i + \gamma_4 UN_i + u_i, \tag{2}$$

where E_i^* is equal to 1, if the person is employed, otherwise is 0, M_i is the matrix representing all the explanatory variables of equation (1); ILL_i is a dummy variable indicating whether individual i is disabled, or not; N_i denotes the nursery coverage of place of residence of individual i; UN_i denotes the unemployment rate of the micro-region of the residence of individual i. After estimating equation (2) by a probit model we can compute the esitmated inverse Mills Ratio as follows:

$$\bar{\lambda}_i = \frac{\varphi(\gamma_1 + M_i\delta + \gamma_2 ILL_i + \gamma_3 N_i + \gamma_4 UN_i)}{\Phi(\gamma_1 + M_i\delta + \gamma_2 ILL_i + \gamma_3 N_i + \gamma_4 UN_i)}$$

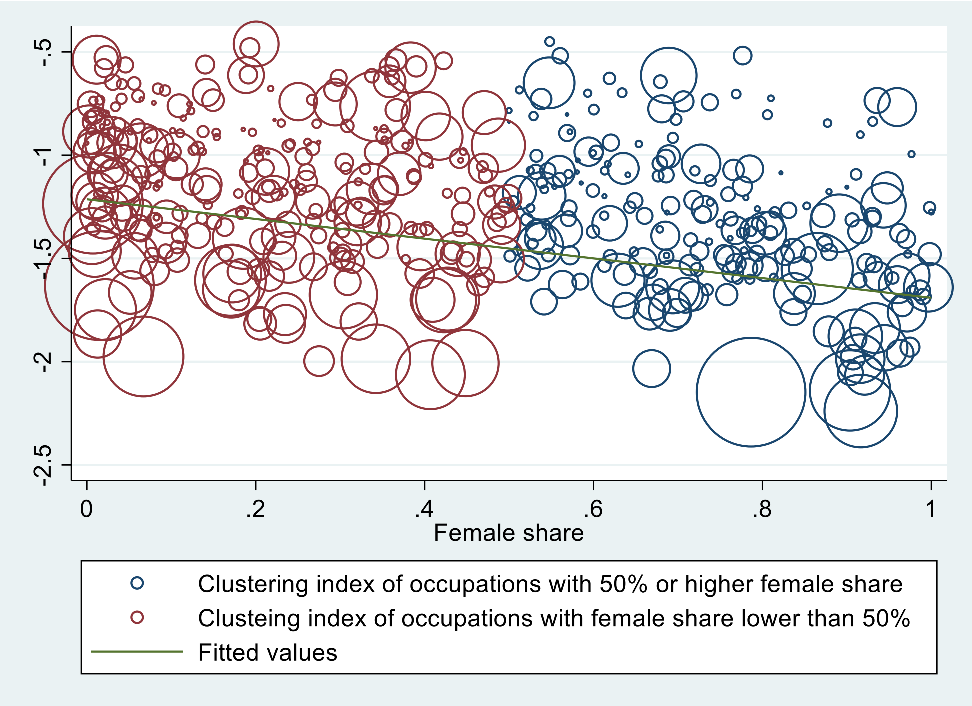
The last step of the Heckman two-step method is to insert $\bar{\lambda}_i$ in the regression equation as an extra explanatory variable and to estimate the augmented equation. This procedure yields consistent estimators of the coefficients of our model of commuting time.

5. Empirical results

5.1 How does the geographical clustering of individuals' occupations differ by gender and family structure?

First, we tested whether women work in occupations which are spatially more dispersed compared to men - based on the data of a small, emerging country. In order to visualize the phenomenon, we computed the female share in each occupation and the log Clustering–index of each occupation, then we plotted these in a common coordinate-system (see Figure 1.). The size of the bubbles aligns with the weight of the occupation within our sample. The fitted line has a slope of -0.4773*** using the number of employees in a given occupation as weights. In the 20 least clustered occupations work the 19 percent of all employees, 71 percent of whom are women. However, in the 20 most clustered occupations, barely 4 percent of the employed work, 61 percent of whom are men.

Figure 1



In the full sample the mean log occupational clustering index of women is -1,54, while that of men is -1,33. The 2 sample t-test rejected the null hypotheses of the estimated means of clustering indices to be equal, with p<0.001. We have similar findings regarding the sub-samples of couples and singles.

Thus it can be concluded that women indeed work in occupations that are more scattered across space, while men's occupations are more spatially clustered. Moreover, we found that the mean of the log occupational clustering index of single men was higher than that of men living in couples. However, the mean of the log occupational clustering index of single women and women living in couples is not different statistically.

5.2 Regression results

Several authors (Petrongolo and Ronchi, 2020; Hanson and Johnston, 1985) have conjectured that the more geographically clustered an occupation or industry is, the longer the commuting time of those with that occupation or working in that industry. We went one step further and tried to find a direct association between commuting time and spatial clustering of occupations by inserting a measure of geographical clustering of occupations into the commuting time equation along with the rich set of control variables. The results of the Heckman-selection model for the full sample are shown in Table 5, while for the sub-samples of singles and couples in Appendix Table 7-8.

Before detailing results for occupational clustering, we shortly discuss the treatment of selection bias. All of our identifying variables are highly significant and affect the probability of employment in the expected way. On all subsamples and on the full sample also nursery coverage is significant and positive, the higher the nursery coverage, the higher is employment probability. If the individual has permanent illness or disability that affects employment probabilities negatively, the effect being slightly larger for women. Similar results are given by regressions run on sub-samples of singles, partnered individuals. These results point to the importance of public policies, e.g., government interventions aiming for widening employment opportunities for the disabled or broadening nursery coverage can in fact increase the probability of employment. Micro-region level unemployment rate has a negative effect, as expected, in areas of higher unemployment the individual employment probabilities are lower. The lambda term is significant and negatively signed – which suggest that the error terms in the selection and the main equation are negatively correlated. So the unobserved factors that make employment more likely tend to be associated with shorter commuting time.

Dummy variables indicating educational attainment and the region of place of residence, as well as population density of residence were included in all regressions. Furthermore, we also inserted the age and the predicted wage as controls in the regressions. Regarding the latter, we found on the total sample, that an increase in the potential wage increases commuting time and the probability of employment. However, in the subsample of single men we found that an increase in the potential wage reduces commuting time.

The most important variable for this paper is the occupational clustering index, which is significant and has a positive impact on commuting time across estimations on all our samples. For the least - and most clustered occupation its value is -2. 2390 and -0.4466048 respectively. With coefficients estimated on the full sample this means, that having the least clustered occupation decreases commuting time with – 5.05 minutes for men and -16.52 minutes for women. While belonging to the most clustered occupation contributes to commuting time with -1.01 minutes for men and -3.3 minutes for women. Thus, our expectation about a more clustered occupation leading to longer commutes ceteris paribus is verified, moreover, the effect is stronger for women than for men. We have similar findings for estimates on subsamples of couples and singles. However, we also found that the estimated coefficient of spatial clustering of occupation is much higher for men and women living in couples compared to single men and single women.

Table 5
Commuting time

	Total sample		Men		Women	
	Commuting time	Employment	Commuting time	Employment	Commuting time	Employment
Log Clustering Index	5.435***	-0.238***	2.262***	-0.260***	7.407***	-0.220***
	(0.0561)	(0.00150)	(0.127)	(0.00307)	(0.0972)	(0.00205)
Low occupational diversity	3.602***	-0.0459***	3.959***	-0.0388***	3.196***	-0.0454***
	(0.107)	(0.00288)	(0.121)	(0.00376)	(0.124)	(0.00335)
High occupational diversity	-4.245***	0.0213***	-6.232***	-0.00556	-2.445***	0.0248***
	(0.0841)	(0.00206)	(0.137)	(0.00400)	(0.0943)	(0.00371)
Log potential wage	3.595***	1.660***	1.792***	1.805***	4.757***	1.611***
	(0.308)	(0.00552)	(0.378)	(0.00853)	(0.388)	(0.00896)
Couples	-2.263***	0.128***	-1.869***	0.362***	-2.095***	-0.0445***
	(0.0646)	(0.00200)	(0.125)	(0.00321)	(0.0725)	(0.00227)
Child under 6	6.410***	-0.788***	0.362**	-0.0985***	11.74***	-1.237***
	(0.143)	(0.00204)	(0.143)	(0.00353)	(0.394)	(0.00335)
Child between 6 and 14	-1.819***	-0.104***	-0.462***	-0.0187***	-3.238***	-0.197***
	(0.0598)	(0.00255)	(0.121)	(0.00413)	(0.0832)	(0.00295)
Man	-3.053***	0.186***				
	(0.0678)	(0.00179)				
Nursery coverage		0.164***		0.135***		0.181***
		(0.0112)		(0.0192)		(0.0121)
Permanent illness, disability		-0.224***		-0.229***		-0.242***
		(0.00271)		(0.00440)		(0.00244)
Local unemployment rate		-2.155***		-2.814***		-1.869***
		(0.0372)		(0.0462)		(0.0441)
Demographic controls	Yes		Yes		Yes	
Regional and settlement controls	Yes		Yes		Yes	
Lambda		-23.13***		-22.03***		-23.37***
		(0.371)		(0.539)		(0.514)
Constant	67.07***	-19.27***	63.22***	-20.21***	65.99***	-18.65***
	(3.704)	(0.0596)	(4.486)	(0.100)	(5.018)	(0.100)
Observations	3,379,562		1,482,340		1,897,222	

Notes: The demographic controls are age, age squared, educational attainment dummies for which the base category is elementary school. The base category of occupational diversity of the place of the residence is medium occupational diversity. The regional and settlement controls are population density of the place of residence as well as the region dummies for which the base category is Central-Hungary. *, ** and *** represent the statistical significance at the level of 10%, 5%, and 1%, respectively.

Geographical clustering of occupations does not only affect commuting time, but also employment status. On the whole sample and on all subsamples, we found that the more clustered the occupation, the lower the chances of employment for the individual and the strength of the effect is approximately the same for men and women. The other important explanatory variable we use is occupational diversity at one's residence municipality. In estimates for the whole sample, we measured occupational diversity of residence with two dummy variables and found that residences with high occupational diversity are associated with shorter commuting time (i.e. easier to find jobs locally) compared to residences with medium occupational diversity, and the effect size is much higher for men. At the same time, residences with low occupational diversity (typically small villages) increase commuting time compared to medium occupational diversity residences and the effect size is slightly larger for men. The occupational diversity of one's residence affects not only commuting time but also the probability of employment. In this regard, we found that places with low occupational diversity reduce the likelihood of employment for both men and women compared to settlements with medium occupational diversity (see Table 5.) High occupational diversity is not significant for men, while it has been found among women to increase the probability of employment compared to residences with medium occupational diversity.

In order to detect how occupation diversity of a settlement might alter the effect of occupational clustering on employment status and commuting time we run the Heckman selection model on two different sub-samples (table 6).

Table 6

Modifying effect of occupational diversity of residence

	Occupation Diversity Low		Occupation Diversity Moderate		Occupation Diversity High	
	Commuting time	Employment	Commuting time	Employment	Commuting time	Employment
			Men			
Log Clustering Index	-2.766***	-0.235***	1.871***	-0.266***	3.540***	-0.279***
	(0.253)	(0.00714)	(0.279)	(0.00577)	(0.171)	(0.00480)
Observations	325,985		345,882		810,473	
			Women			
Log Clustering Index	8.507***	-0.153***	8.738***	-0.215***	4.859***	-0.243***
	(0.206)	(0.00527)	(0.177)	(0.00534)	(0.138)	(0.00471)
Observations	391,684		433,802		1,071,736	

Notes: Demographic, regional and settlement controls were included in all regressions. *, ** and *** represent the statistical significance at the level of 10%, 5%, and 1%, respectively.

The first sample includes those living in settlements with smaller (less than 30%) occupational diversity, the second those from a settlement characterized by 30-70% occupational diversity, while the third includes those living in occupationally very diverse (more than 70%) places. The effect of occupational clustering differs considerably across gender and the occupation diversity of residence. For the women subsample our results show that effect of occupational clustering is smaller at residences with high occupational diversity compared to settlements with moderate or low occupational diversity. The difference regarding the effect size of occupational clustering on commuting time between residences with low and moderate occupational diversity is negligible. The more clustered one's occupation, the lower the probability of employment, and the effect size is somewhat larger in settlements with moderate or high occupational diversity.

We see different pattern for men. Unexpectedly, at places with low occupational diversity the effect of occupational clustering is negative, i.e. the higher the clustering index, the shorter the commuting time, holding all other factors constant. At places with moderate and high occupational diversity the effect of occupational clustering is positive, i.e. the higher the clustering index, the longer the commuting time, and this effect is larger at places with high occupational diversity. For men, the more clustered the occupation, the lower the probability of employment, and the effect size is somewhat larger in settlements with moderate and high occupational diversity.

To better control for household responsibilities – which make leisure time more valuable than time spent with work (including wok-related commuting time) – we included several further variables into our regressions. Regarding family structure (Table 5) we found that compared to single persons couples spend 2.26 minutes shorter time with commuting – controlling for everything else and this effect is somewhat larger for women. There are some evidences that singles have less household duties than couples (Borra at al, 2021). Thus, we can state that more household duties mean shorter time spent with commuting. This results somewhat reinforce earlier results on the household responsibility hypothesis, however HRH is mostly about relating gender differences in child-care to gender differences in commuting time.

According to our results, having a 0-5 year old small child in the household increases commuting time for coupled women with 11.3 minutes, and for single women with 9.7 minutes compared to childless women or ones, who have only 14 year old or older kids in their household - all else being kept constant (see Table 7-8 in Appendix). For coupled men the presence of a 0-5 year old child in the family has a significant negative effect on commuting time compared to childless men or ones with teens, but effect size is rather minuscule (-0.27 min), while for single men it has no significant effect. Thus, it seems, the presence of younger children in the family does not decrease, but on the contrary, increase commuting time of mothers. One possible explanation is that often mothers are the ones taking kids to/picking up from childcare, kindergarten while on the way to or from work, which adds to their commuting times and makes their travels more complex (Madden 1981, Scheiner - Holz-Rau 2017, Hong at al., 2018).

At the same time, it is important, that having at least one child under six significantly decreases employment probability for both coupled and single women and men, compared to the childless or those with 14 year old or older children, but this selection effect is much larger for women. The presence of a 5–14-year-old child in the household is associated with shorter commuting time for both coupled and single women and men, but the effect size is much smaller in the case of men. Presence of a 5–14-year-old child in the household decreases employment probability for both coupled and single women, and increases for single men. Finally, it is worth mentioning that men in a relationship commute 2.8 minutes shorter time while single men 1.5 minutes shorter than women who are similar in all other respects.

6. Conclusion

The aim of this study was to reveal the impact of spatial clustering of occupations on the probability of employment and commuting time, with particular emphasis on differences across gender and family structures. Based on Hungarian census data our research confirmed previous results (Benson, 2010), according to which women work in spatially less clustered occupations compared to men. One of our most important results is that the more clustered one's occupation is geographically, the lower the chance for employment. This result suggests that well-designed retraining programs for the unemployed are worth consideration as the geographical clustering of occupations can have a significant impact on their employment opportunities.

With respect to commuting time we found that the more clustered the occupation the longer the commuting time, and the effect is stronger for women than for men. Furthermore, we found that the effect of occupational clustering on commuting time is greater among couples compared to singles. The other novelty besides occupational clustering we introduce in explaining commuting time and employment is the occupational diversity of one's residence. We found that higher the occupational diversity of residence, the higher the probability of employment, and the shorter the commuting time, as well as that occupational diversity of residence modifies the impact of occupational clustering.

The current study also draws attention to the fact, that family structure indeed has significant effects on commuting time: according to our findings singles commute for longer time than those in a relationship. Moreover, the long-held view, that women typically have shorter commuting times compared to men is not true in our sample for 18-65 years old singles, among them the opposite is true.

Last, but not least we can conclude, that taking selection into employment also into account somewhat decreases the relevance of the household responsibility hypothesis in explaining gender differences of commuting time. Presence of a 0–5-year-old child in the family indeed substantially reduces employment probability for women, however for the ones who do stay employed a young child does not decrease their commuting time (as the HRH would predict), but on the contrary, makes it longer compared to childless women or ones with 14+ children. To sum up, our results confirm that the geographical clustering of occupations affects both employment probabilities and commuting time, a fact worth considering in career choice decisions as well as in retraining and other active labour market policies.

Appendix

Table 7

Commuting time regressions for couples

	Full sample		Men		Women	
	Commuting time	Employment	Commuting time	Employment	Commuting time	Employment
Log Clustering Index	5.571***	-0.230***	2.917***	-0.264***	8.123***	-0.205***
	(0.0826)	(0.00175)	(0.138)	(0.00462)	(0.112)	(0.00266)
Occupational Diversity	-9.365***	0.0714***	-13.56***	0.0159**	-6.022***	0.106***
	(0.134)	(0.00563)	(0.205)	(0.00661)	(0.175)	(0.00784)
Log potential wage	6.471***	1.524***	0.913*	1.743***	6.162***	1.459***
	(0.300)	(0.00884)	(0.543)	(0.00918)	(0.401)	(0.00839)
Child under 6	4.190***	-0.795***	-0.267***	-0.0593***	11.33***	-1.260***
	(0.160)	(0.00244)	(0.0949)	(0.00323)	(0.434)	(0.00279)
Child between 6 and 14	-2.016***	-0.151***	-0.687***	-0.00771*	-3.565***	-0.208***
	(0.0852)	(0.00270)	(0.117)	(0.00407)	(0.139)	(0.00400)
Man	-2.885***	0.376***				
	(0.0940)	(0.00271)				
Nursery coverage		0.150***		0.148***		0.162***
		(0.0116)		(0.0218)		(0.0233)
Permanent illness, disability		-0.217***		-0.220***		-0.231***
		(0.00335)		(0.00454)		(0.00389)
Local unemployment rate		-2.007***		-2.751***		-1.628***
		(0.0416)		(0.0586)		(0.0469)
Demographic controls	Yes		Yes		Yes	
Regional and settlement controls	Yes		Yes		Yes	
Lambda		-19.95***		-26.37***		-23.24***
		(0.436)		(0.858)		(0.668)
Constant	41.21***	-18.20***	84.46***	-19.44***	62.97***	-17.57***
	(3.933)	(0.0991)	(6.669)	(0.105)	(5.099)	(0.0929)
Observations	2,548,862		1,177,122		1,371,740	

Notes: The demographic controls are age, age squared, educational attainment dummies for which the base category is elementary school. The regional and settlement controls are population density of the place of residence as well as the region dummies for which the base category is Central-Hungary. *, ** and *** represent the statistical significance at the level of 10%, 5%, and 1%, respectively.

Table 8

Commuting time regressions for singles

	Full sample		Men		Women	
	Commuting time	Employment	Commuting time	Employment	Commuting time	Employment
Log Clustering Index	4.333***	-0.255***	0.945***	-0.232***	5.604***	-0.258***
	(0.125)	(0.00320)	(0.315)	(0.00693)	(0.184)	(0.00534)
Occupational Diversity	-9.846***	0.120***	-14.41***	0.118***	-6.882***	0.107***
	(0.305)	(0.0108)	(0.597)	(0.0159)	(0.332)	(0.0120)
Log potential wage	0.396	1.997***	-4.564***	1.960***	1.977**	2.026***
	(0.832)	(0.0144)	(1.257)	(0.0204)	(0.847)	(0.0164)
Child under 6	9.909***	-1.106***	-0.796	-0.201***	9.721***	-1.093***
	(0.532)	(0.00811)	(0.996)	(0.0195)	(0.605)	(0.00766)
Child between 6 and 14	-2.428***	-0.195***	-1.625***	0.0594***	-2.718***	-0.186***
	(0.203)	(0.00514)	(0.487)	(0.0164)	(0.226)	(0.00580)
Man	-1.516***	-0.454***				
	(0.189)	(0.00388)				
Nursery coverage		0.150***		0.147***		0.153***
		(0.0304)		(0.0402)		(0.0315)
Permanent illness, disability		-0.253***		-0.256***		-0.262***
		(0.00387)		(0.00857)		(0.00513)
Local unemployment rate		-2.642***		-2.884***		-2.478***
		(0.0756)		(0.132)		(0.105)
Demographic controls	Yes		Yes		Yes	
Regional and settlement controls	Yes		Yes		Yes	
Lambda		-23.25***		-26.15***		-22.74***
		(0.896)		(1.608)		(0.939)
Constant	83.91***	-21.33***	135.2***	-21.22***	69.62***	-21.83***
	(9.971)	(0.166)	(14.73)	(0.243)	(9.968)	(0.189)
Observations	830,700		305,218		525,482	

Notes: The demographic controls are age, age squared, educational attainment dummies for which the base category is elementary school. The regional and settlement controls are population density of the place of residence as well as the region dummies for which the base category is Central-Hungary. *, ** and *** represent the statistical significance at the level of 10%, 5%, and 1%, respectively.

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