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Are urban labour markets more dynamic? Vacancies and urban scaling

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Abstract

This paper shows that there is superlinear scaling of vacancies with employment size. That is, there are disproportionally more vacancies relative to employment in urban areas, not just for overall employment, but also for occupational and educational classes. Hence vacancies are more strongly concentrated than the jobs to which they refer. Moreover, we find that, compared to all employment, the concentration of labour demand increases with required skill levels. We show that the stronger growth of jobs in cities is unable to explain this finding and propose an alternative explanation based on vacancy chains in spatially related labour markets. The results suggest that on-the-job searchers have better possibilities in cities to improve their position. This helps explain the higher mobility of especially younger workers in cities and the superior quality of job-worker matches in large labour markets.

Keywords

agglomeration, employment, jobs, matching, scaling, vacancies

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摘要
本文表明，职位空缺与就业人数之间呈现超线性标度关系。也就是说，相对就业人数而言，城市地区的职位空缺更多且不成比例，不仅总体就业情况如此，不同职业和教育阶层的情况也如此。因此，职位空缺比其对应的职位更集中。此外，我们发现，就总的就业情况来看，劳动力需求的集中度随着所需技能水平的提高而增加。我们表明，城市职位增长更强劲无法解释这一发现，并提出了基于空间相关的劳动力市场的空缺链的另一种解释。结果表明，在职求职者在城市更可能提升自己的职位。这有助于解释城市工人尤其是年轻的城市工人的流动性更高，以及大型劳动力市场中人岗匹配的质量更高。

关键词
集聚、就业、职位、匹配、标度、职位空缺

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Introduction

This paper analyses an important aspect of spatial labour markets that has hitherto gone unnoticed: there is superlinear scaling between vacancies and jobs. That is, the number of vacancies *per 1000 jobs* is higher where the density of jobs is higher. This means that there are not just more jobs on offer in large cities – a well-known fact – but that the number of vacancies increases disproportionally with the number of jobs per square kilometre. With all else equal, on-the-job searchers in cities thus have more possibilities for finding another job, which suggests an explanation for the higher job mobility of (especially young) workers and of the better worker-to-job matches in urban areas that have been repeatedly observed in the literature.

Cities make people more productive. This is reflected in their wages as the urban wage premium (Baum-Snow and Pavan, 2012; De la Roca and Puga, 2017; Glaeser and Maré, 2001). An important reason why people are more productive in cities is that they may be able to find a better match for their skills and capabilities in a large and diversified labour market (Andersson et al., 2007; Kok, 2014; Matsuo, 2014). Dauth et al. (2022) report that high productivity workers tend to be associated with high productivity jobs, but much more so in large urban labour markets than in small ones. Large cities offer higher employment probabilities and higher wages for new graduates (Ahlin et al., 2014). But even in large labour markets realising the optimal worker–job match may not be easy because requirements of vacant positions and characteristics of applicants are incompletely observed. This suggests that labour market search accessibility and mobility play a significant role in realising the superior allocation of workers to jobs in cities (Jin and Paulsen, 2018). Indeed, Topel and Ward (1992) show that job-to-job mobility is important in the first stage of labour market participation. Later research has shown that workers in urban areas tend to switch between industries more often in their early careers then elsewhere, whereas later in their careers they tend to switch less (Bleakley and Lin, 2012; Wheeler, 2008). Moreover, Wheeler (2006) finds that job changes play an important role in the wage growth of younger workers. Yankow (2006), who tests competing theories of the urban wage premium, argues that a significant part of the urban wage premium results from the cumulative effect of job changes on wages of urban workers. Andersson and Thulin (2013) find that a higher employment density increases the probability of job switches, especially for high skilled workers.

Helsley and Strange (1990) provide a simple model in which the size of the local labour

market facilitates a better match because the average distance between job requirements and workers skills is smaller when more firms and workers are present in a given city. In their setup workers know their skills and the requirements of all the jobs in their city of residence. However, the literature just discussed suggests that in fact costly and time-consuming search in the local labour market is needed to find a good match. Only after having tried a number of jobs, often in different industries, do workers find a match that is difficult to improve upon.

This suggests that cities offer returns to scale in labour market matching through lower search costs. If larger cities allow firms and workers to conduct searches with greater ease this could explain why after an initial phase of high job mobility and wage growth matches are reached that are difficult to further improve upon. It seems indeed plausible that spatial concentration permits workers to search more extensively and generate more productive matches. While in small towns, workers with a suboptimal match may remain underproductive because alternatives are lacking, diversified cities will offer more opportunities to increase one's wage by improving the quality of the match.

However, the idea that matching workers to jobs will be easier in denser local labour markets has received little endorsement in the literature.[1] It has generally been found that the matching function has constant returns to scale (see Petrongolo and Pissarides, 2006, for a survey and, among others, Gautier and Teulings, 2009). This suggests that large local labour markets not only provide more vacancies but also more competitors for the vacant positions, thereby making job search on average not more attractive.

The implied paradox can at least be partly resolved if cities offer more vacancies *per searcher*. Searchers need not be unemployed workers, on-the-job search is also important and the ratio of vacancies to jobs may be interpreted as an indicator of the labour market tightness of this type of search. This is exactly the point of the present paper: we show that the number of vacancies per employed worker increases with city size.[2] Employed workers in urban areas thus have more opportunities for applying to open positions than workers elsewhere. A constant returns to scale matching function would then imply – with all else equal – a higher job finding rate for on-the-job searchers in cities, which helps to explain many of the benefits of urban labour markets that have been discussed above. Moreover, we show that this is not just the case for the total number of vacancies, but also if we disaggregate with respect to education and job type and that it is true in particular for jobs requiring higher educated workers, for which there are few unemployed searchers.

The labour market literature has paid much less attention to vacancies than to unemployment.[3] Until recently, a good part of the papers studying vacancies looked at the matching function or duration of vacancies (van Ours and Ridder, 1992). Vacancies emerge when firms want to create new jobs, or continue older ones after the employee quit (Davis et al., 2013). Bagger et al. (2022) show that separations indeed lead to vacancy postings and that this effect is larger for separations leading to employment. This is in line with the idea that companies continue jobs after a worker quits and the occurrence of vacancy chains. Moreover, they find that employment growth at the firm level is linked to a higher number of vacancy postings. Since employment is increasingly concentrated in urban labour markets (Desmet and Fafchamps, 2006), especially for high skilled workers (Autor, 2020; Davis and Dingel, 2019; Larsson, 2017; Simon, 1998), this suggests that the vacancy-to-employment ratio will be higher in cities. Apart from total employment, the

composition and the growth rates in the various parts are also relevant. The fastest growing sectors may be overrepresented in cities. However, we find that employment growth does not provide a good explanation for the higher vacancy-to-employment rate in cities. In the second section we therefore provide a model that is able to explain this regularity on the basis of vacancy chain.

This paper is also related to recent work in economic geography that combines insights from economic complexity literature with work on urban scaling to study the evolution of employment in cities (Balland et al., 2020). In the first stream of literature, the complexity of economic activities is pointed out as the driver of economic growth (Hidalgo and Hausmann, 2009). In the latter, superlinear relationships between population size and economic output have been revealed, which mean that output per capita is higher in larger cities. If a city doubles its population size, its output becomes more than twice as large (Bettencourt, 2013; van Raan et al., 2016; Youn et al., 2016).

Our contribution to the literature is twofold. First, we show that there is superlinear scaling between vacancies and jobs and that this is not due to employment growth. This is an important insight which helps explain the superior quality of job-worker matches in large labour markets and the higher mobility of (younger) workers in cities. Secondly, in our model of two interactive labour markets, we provide a theoretical explanation for the higher vacancy rates in urban labour markets as a result of vacancy chains.

The paper unfolds as follows. In the next section we present our theoretical model. In the third section we introduce the dataset. In the fourth section we explore the link between the number of vacancies and the size of the local labour market. The fifth section concludes.

A vacancy chain model with two regions

In this section we develop a simple two-region model with connected spatial labour markets that provides an alternative explanation for a higher vacancy rate in urban areas. We show that the interaction between a large and a small labour market can under specific conditions result in a higher vacancy-to-employment rate in the larger market. The reason is that vacancies in one market can be filled by on-the-job searchers from the other. If this happens, often a vacancy emerges for the quitted job. We identify plausible conditions that imply that vacancy chains tend to move to the larger labour market and proceed there. The concept of vacancy chains has received some attention in the recent labour market literature, see for instance Gianelle and Tattara (2014), Elsby et al. (2022) and Mercan and Schoefer (2020).

We consider two contiguous local labour markets, distinguished by a suffix u for the urban market and r for the rural market. The two markets are distinguished only by the number of jobs and workers living there and they are connected in the sense that workers from one market can apply to vacancies in the other. The familiar Diamond-Mortensen-Pissarides two-sided search and matching structure applies. For concreteness we take in mind the model with on-the-job search in chapter 4 of Pissarides (2000). In this model employers always choose to create a new job after a worker quits an existing job.

In Pissarides' setup there is only one market, and matching on this market is random. The matching function is $M(E + U, V)$ where E is the number of employed workers, U the number of unemployed workers and V the number of vacancies. All variables without a suffix refer to totals in both markets. For instance, $E = E_u + E_r$ the sum of

the number of workers in the urban and in the rural market. An important assumption is that on-the-job searchers and unemployed searchers are matched in the same way to vacancies. In this situation the probability that a vacant position will be filled by an on-the-job searcher of any of the two locations is independent of the location of the vacancy.

Let the numbers of newly created (i.e. not in response to workers quitting existing jobs) positions be μE_u and μE_r. If these new positions are filled by on-the-job searchers, new vacancies will emerge. To see what happens, let $\pi_{i,j}, i,j = u,r$ denote the probability that a vacant position in i is filled by an on-the-job searcher until then employed in j, which is equal to the probability that a filled vacancy in i generates a new vacancy in j. The new vacancies generated by filling the newly created positions V_u^1 and V_r^1 are then equal to:

$$V_u^1 = \pi_{uu}\mu E_u + \pi_{ru}\mu E_r \tag{1a}$$

$$V_r^1 = \pi_{ur}\mu E_u + \pi_{rr}\mu E_r \tag{1b}$$

These additional vacancies will be filled by job seekers in the same way as the newly created positions, et cetera. Elementary linear algebra leads to the conclusion that the total number of vacancies V_u and V_r will in equilibrium be equal to:

$$\begin{bmatrix} V_u \\ V_r \end{bmatrix} = \frac{1}{det}\begin{bmatrix} 1-\pi_{rr} & \pi_{ru} \\ \pi_{ur} & 1-\pi_{uu} \end{bmatrix}\begin{bmatrix} \mu E_u \\ \mu E_r \end{bmatrix} \tag{2}$$

where $det = (1-\pi_{rr})(1-\pi_{uu}) - \pi_{ru}\pi_{ur}$, which is positive.[4] Carrying out the multiplication and dividing the first line by E_u and the second by E_r gives:

$$V_u/E_u = (1-\pi_{rr})\mu + \pi_{ru}\mu(E_r/E_u) \tag{3a}$$

$$V_r/E_r = (1-\pi_{uu})\mu + \pi_{ur}\mu(E_u/E_r) \tag{3b}$$

Following Pisssarides, and hence assuming away any impact of space (commuting) on the matching process, we have:

$$\begin{aligned} \pi_{uu} &= \pi_{ru} = E_u/(E+U) \text{ and} \\ \pi_{rr} &= \pi_{ur} = E_r/(E+U) \end{aligned} \tag{4}$$

Substitution in (3) then shows that vacancy to employment ratios are equal in both regions, as should be expected. It is therefore clear that the proportionality embodied in equation (4) is incompatible with a higher vacancy-to-employment ratio in the urban area. This proportionality is an implication of random matching of searchers to vacancies that may be regarded as unrealistic in the spatial setting of this paper. In what follows we discuss several deviations from random matching that lead to higher vacancy-to-employment ratios in the urban market.[5]

A natural way to break it down is to assume that job seekers that are employed in the area where the vacancy is present have an advantage. For instance, one could assume that:

$$\begin{aligned} \pi_{uu} &= kE_u/(E+U) \text{ and} \\ \pi_{rr} &= kE_r/(E+U) \end{aligned} \tag{5}$$

for some $k>1$ that reflects the 'bias' for candidates from the same labour market. The higher than proportional job filling probabilities could be the result of information advantages associated with being employed in positions that are geographically close to the vacancy.[6] Alternatively, they may be associated with the desire of applicants to avoid longer commutes.[7]

The higher-than-proportional probabilities for job seekers employed in the vicinity may be accompanied by lower -than-proportional probabilities for those from the alternative area. If we assume that π_{ur} and π_{ru} become a fraction $k' < 1$ of the proportional values in (4), it follows that the difference in vacancy-to-employment rates is:

$$\frac{V_u}{E_u} - \frac{V_r}{E_r} = (k - k') \frac{E_u - E_r}{E + U} \quad (6)$$

Note that the difference between the two vacancy-to-employment ratios will still be positive if either k or k' is replaced by 1 (but not both). In Appendix A we empirically test this first explanation for the higher vacancy-to-employment ratios in urban areas. We test if workers who recently accepted a job in the urban (rural) part of the labour market should have been disproportionally working in that same area before ($k>1$). An analysis using the Dutch Labour Force Survey shows support for the existence of this mechanism.

An alternative possibility is that job seekers employed in the urban area have an advantage over those employed in the rural area. This may result in vacancy filling probabilities:

$$\pi_{uu} = mE_u/(E + U) \text{ and } \pi_{ru} = mE_u/(E + U), \quad (7)$$

For some $m>1$, while the other two probabilities could be multiplied by a factor $m' < 1$. A preference for job seekers currently employed in the urban area could result from inhabitants of the urban area being more productive. This may be related to a higher average education of urban workers (see, e.g. Glaeser and Saiz, 2003) or urban work experience that made them more productive (De la Roca and Puga, 2017; Glaeser and Maré, 2001).[8] Moreover, better job-to-worker matches in the urban area makes those with work experience there more productive in subsequent jobs.[9] This results in a difference in the vacancy-to-employment rates:

$$\frac{V_u}{E_u} - \frac{V_r}{E_r} = (m - m') \frac{E_u + E_r}{E + U} \quad (8)$$

Thirdly, it could be the case that job seekers currently employed in the urban area have a more than proportional probability of filling jobs in the rural area and/or that job seekers currently employed in the rural area have a less than proportional probability of filling jobs in the urban area. This could be related to traffic conditions. The concentration of jobs in cities implies that it is usually much more problematic to commute from a rural area into a city than in the opposite direction. The desire to avoid congested traffic could induce job seekers currently employed in the rural area to apply less than proportionally to vacancies in the urban area, especially as they imply a commute crossing the CBD, while for job seekers currently employed in the urban area the possibility to avoid traffic congestion could make applying to jobs in rural areas more attractive than would otherwise be expected. This could result in the following changes to (5):

$$\pi_{ru} = nE_u/(E + U), \; \pi_{ur} = n'E_r/(E + U), \quad (9)$$

with $n>1$ and $n' < 1$. This results in the following difference in vacancy-to-employment rates:

$$\frac{V_u}{E_u} - \frac{V_r}{E_r} = (1 - n') \frac{E_u}{E + U} + (n - 1) \frac{E_r}{E + U} \quad (10)$$

Finally, we note that introducing differences in employment growth with $\mu_u > \mu_r$, where suffixes indicate the area, results in a difference in vacancy-to-employment rates that equals the difference in growth rates as can as can be easily checked by substituting the proportional vacancy filling probabilities (4) into (3a) and (3b).

Of course, the various mechanisms could be simultaneously present. There may also be different mechanisms, not considered here, that lead to the same result. The analysis here suffices to show that there are plausible reasons for expecting the vacancy-to-employment rate to be higher in urban

areas in settings that are close to Pissarides (2000) chapter 4.[10]

We have thus found two possible mechanisms that may lead to a higher vacancy to employment ratio in urban areas. The first most obvious mechanism is a faster growth rate of jobs in cities, the second and more subtle but also potentially empirically relevant mechanism is an asymmetry in the spatial connection between adjacent large (urban) and small (rural) markets, which makes it more burdensome to move into urban centres than *vice versa*.

Data

The data we use to analyse the spatial concentration of demand for labour is provided by Textkernel, an Amsterdam-based HR Software company that collects vacancies from webpages using scraping algorithms. The scraping technique is advanced to a level in which virtually all online vacancies are captured. The data covers the years 2017 and 2018. Vacancies are often posted multiple times and on several online platforms. Textkernel has developed a de-duplication algorithm and classifies the information from the job description in variables like job type, location and required education level.

Statistics Netherlands (CBS) and the public employment service (UWV) have both used the data from Textkernel already for several years for their publications in addition to a vacancy questionnaire in which employers are asked to provide information about their open vacancies. They weight the data as they have found that some sectors are overrepresented (ITC) and some underrepresented in the data (education and agriculture). Furthermore, they show that the number of vacancies directly posted by firms reflects the number of vacancies that are found in the official national vacancy survey best (Mooij et al., 2020). Therefore, we filter out the vacancies that are posted by intermediaries and use the ones that are directly posted by the firms. Intermediaries might also often search in a broader area which makes the location in these observations less reliable. We also removed vacancies with missing information regarding job location, job type (ISCO) and required education. Original vacancy data observations included 14 education levels, we combined the six different high-school diplomas into one education level, resulting in a total of eight ascending education levels. In total, we analyse about 2 million vacancies, which is about 70% of the original sample.

Although online vacancy data provides detailed information on the demand side of the labour market, like any data source, it has limitations (Kureková et al., 2015) and cannot be expected to be perfectly representative of all vacancies in the economy. However, for this study, it is not so much the occupational but the geographical representativeness that is of importance. It can be argued that there is a difference in job posting behaviour between urban and rural regions. Firms in rural regions might for example depend more on personal networks. However, also the opposite can be said, namely that in a tight rural labour market companies have to seek harder to find the right worker because of the lower number of potential applicants and therefore post more vacancies online. Official information about the spatial distribution of vacancies from Statistics Netherlands is available on the level of the 12 provinces.[11] We find an adjusted R^2 of 0.998 for both 2017 and 2018 when correlating the official data with the Textkernel data. Because of the relatively large difference in job density between the provinces this result indicates a good geographical representation. All in all, we do not find persuasive arguments to assume spatial biases in vacancies postings in the dataset.

Unfortunately, detailed data on the supply side is not available and it is unknown if

vacancies are filled at the time they are taken off the website. However, to the extent that unfilled vacancies disappear because the firm finds other ways to realise its desired production level, the analysis of demand for labour is not affected. Another consideration is the growing number of people (over a million workers) in the Netherlands that are (solo) self-employed. For these types of jobs, no or considerably less vacancies are put online. However, the fact that there is other demand for labour in the form of specific tasks does not necessarily influence the relationship between vacancy rates and the size of the labour market that is the focus of this paper.

We combine the vacancy data with employment data from the Dutch national information system for jobs (LISA), which provides the number of workers per municipality per year and aggregate this data to COROP regions, the Dutch NUTS3 regions which are constructed as urban cores with a hinterland. So, every region can be considered to be an urban labour market and we compare small labour markets with large ones. By controlling for the geographical size of the labour market areas we make sure that we measure an effect of density, which is presumably the most important characteristic of urban areas.

For employment in specific occupations, we use data from the Research Centre for Education and the Labour Market (ROA) in Maastricht. This data consists of the average number of workers per occupation group for the years 2017 and 2018 for the 35 Labour market areas. We use the International Standard Classification of Occupations (ISCO) information to link the demand and the existing number of workers in different occupations classes. Because data on employment in labour market areas in the Netherlands is only available in the 12 occupations classes that are used by ROA, we follow these instead of ISCO groups. The terms cities and urban areas are used interchangeably but refer to the 40 COROP or 35 labour market areas of the Netherlands which are used in the analysis.

As a starting point for our analysis we test the relationship between the number of vacancies per job and GDP per capita while controlling for the number of jobs and a number of other control variables. The results show a significant positive association on the NUTS3 level ($\beta = 0.266$, SE = 0.106, $p < 0.10$). This result supports the idea that a disproportionately larger number of vacancies in urban labour markets is relevant for productivity differences between urban and rural areas.

Method and results

All jobs

We are interested in the relationship between the number of vacancies V in a particular area a and the total number of employed persons E in the same area:

$$\ln V_a = \alpha + \beta \ln E_a + \gamma X_a + \varepsilon_a \qquad (1)$$

where X is a vector of control variables and ε an error term. The vacancy-to-employment rate VER equals V/E, which means that we can rewrite (10) as:

$$\ln VER_a = \alpha + (\beta - 1) \ln E_a + \gamma X_a + \varepsilon_a \qquad (1')$$

This shows that this ratio is increasing in employment for $\beta > 1$. By controlling for the area of the region, we make sure that it refers to more employment in an area of given size, that is of a higher density.

Table 1 presents estimation results for NUTS3 (COROP) regions.[12] Column 1 shows a simple version of the model in which no controls are used. It suggests that a 1% increase in workers in a region results in 1.23% more vacancies. This shows that

Table 1. Vacancies and total employment for NUTS3 areas in the Netherlands.

Variable	(1) OLS	(2) OLS	(3) 2SLS
Jobs (log)	1.234***	1.260***	1.264***
	(0.043)	(0.058)	(0.058)
Job growth %		−0.005	−0.005
		(0.035)	(0.035)
Large firms (>200) %		−0.001	−0.001
		(0.005)	(0.005)
Young people (<35) %		−0.001	−0.002
		(0.005)	(0.010)
Duration (log)		−0.322	−0.326
		(0.364)	(0.365)
Area (log)		−0.054	−0.055
		(0.042)	(0.041)
Observations	40	40	40
Adjusted *R*-squared	0.956	0.952	0.952
Wald test (Jobs(log)= 1) Chisq	29.663***	19.924***	20.781***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$, Robust standard errors in models 1 and 2.

vacancies concentrate disproportionally in cities. Equation (10) can be interpreted as a scaling law[13] showing that the number of vacancies per 1000 jobs in urban areas is higher than in rural areas, regardless of the type of job. In concrete terms: in 2018 there are 371 vacancies per 1000 jobs in urban COROP area Amsterdam compared to 103 vacancies per 1000 jobs for the rural COROP area Delfzijl. A Wald test is used to investigate if the coefficient of logged employment is significantly differing from 1. A coefficient of 1 would imply proportional growth of the number of vacancies with the number of jobs per area.

Column 2 addresses five possible concerns with this result. The first is that a disproportionally larger number of vacancies in urban areas is simply a reflection of the faster employment growth in cities. To control for this, the percentage job growth compared to the previous year is included.[14] Secondly, we control for the percentage of vacancies posted by large firms (over 200 employees) since it can be the case that urban areas have more large firms in for example sectors for which employment is growing or in which typical jobs are shorter; this would imply that there are more vacancies in urban areas. Thirdly, a control for the percentage of young people (below the age of 35) in a specific area is added since young people change jobs more often and thus may create more vacancies. Fourthly, a higher stock of vacancies could be the result of greater tightness in urban labour markets. When it is harder to find the right workers through, for example, personal networks or internships, it makes sense to post more vacancies online. If urban areas have more vacancies that are hard to fill a longer average duration of vacancies can be expected. This suggests controlling for the duration of vacancies. A fifth concern is that large employment is not necessarily associated with agglomeration, but could simply be due to a larger geographical area. This suggests controlling for geographical area. In this setup the coefficient for employment size measures the impact of more employment while keeping the size of the area constant, and hence the impact of an increase in employment density. The

estimation results show that the coefficient for employment hardly changes after adding these five variables.[15]

Another possible concern is that the number of vacancies could have an impact on employment. If, in a particular period, there are many vacancies in a region, this may signal that many jobs are not filled, which depresses employment. Alternatively, it may be the case that strong growth in employment leads to a high number of vacancies, which may cause an upward bias in our estimated coefficient. To address the implied endogeneity, we have instrumented regional employment with that in 2010. The validity of this instrument is based on the assumption that employment in 2010 is unrelated to unobserved factors that influence the vacancy rates in 2018 but strongly correlated to employment in 2018.[16] The estimation results (column 3) remain virtually unchanged.

Although COROP regions have been constructed as urban cores with a surrounding hinterland, the selection of the cores and the determination of the boundaries was inevitably somewhat arbitrary.[17] The Netherlands is a relatively small country while workers are highly mobile and can commute from one NUTS3 region to another. We have therefore estimated the same equations using labour market areas and municipalities. Labour market areas are, like Core Base Statistical Areas (CBSAs) in the United States, statistical unities without an administrative function. They consist of several municipalities and relate to urban areas that include in a central city and the surrounding area that is linked to this city. The results are qualitatively the same. The coefficient for logged employment in the equations including control variables is the same if we use labour market areas (1.24) and somewhat larger if we use municipalities (1.31). See Tables C1 and C2 in Appendix C for the results.

Decomposition by occupation

In this section we look at the relationship between vacancy rates and employment at the level of specific occupations. For a precise analysis we use existing number of jobs per occupation as a scaling measure instead of the total number of jobs. We have good information about the total number of workers per occupation. This means that our results now refer to vacancy rates in a specific segment of the labour market. Figures of existing employment are available for 12 general occupation groups which cover all jobs in the Netherlands. The occupation classification information (ISCO) that is available in the vacancy data is used to link vacancies to employment groups.

We estimate the same regression as in the previous section but now with the vacancies referring to the 12 occupation groups while the existing employment in those 12 groups is used as the explanatory variable. Figure 1 shows the scaling relationships without control variables. Nine out of twelve occupation groups show significant superlinear scaling. Vacancies in sectors which can be intuitively expected to require high education levels like pedagogical occupations ($\hat{\beta} = 1.36$), Business and administration ($\hat{\beta} = 1.34$) and service ($\hat{\beta} = 1.27$) concentrate most. Vacancies in Public administration ($\hat{\beta} = 1.07$), Creative and linguistics ($\hat{\beta} = 0.94$) and Agriculture ($\hat{\beta} = 0.89$) seem to concentrate least. A striking result is that of the Transport and Logistic sector; this one of the few sectors which has been rapidly growing. When adding control variables (see Tables D1 and D2 in Appendix D) we find only small differences in the estimated coefficients for logged employment. Only the coefficients for employment in the occupation groups Creative and linguistics, Public administration, ICT and Agriculture do not significantly differ from 1.

The results presented in this sub-section show that the number of vacancies per 1000 workers in a specific occupation is higher in

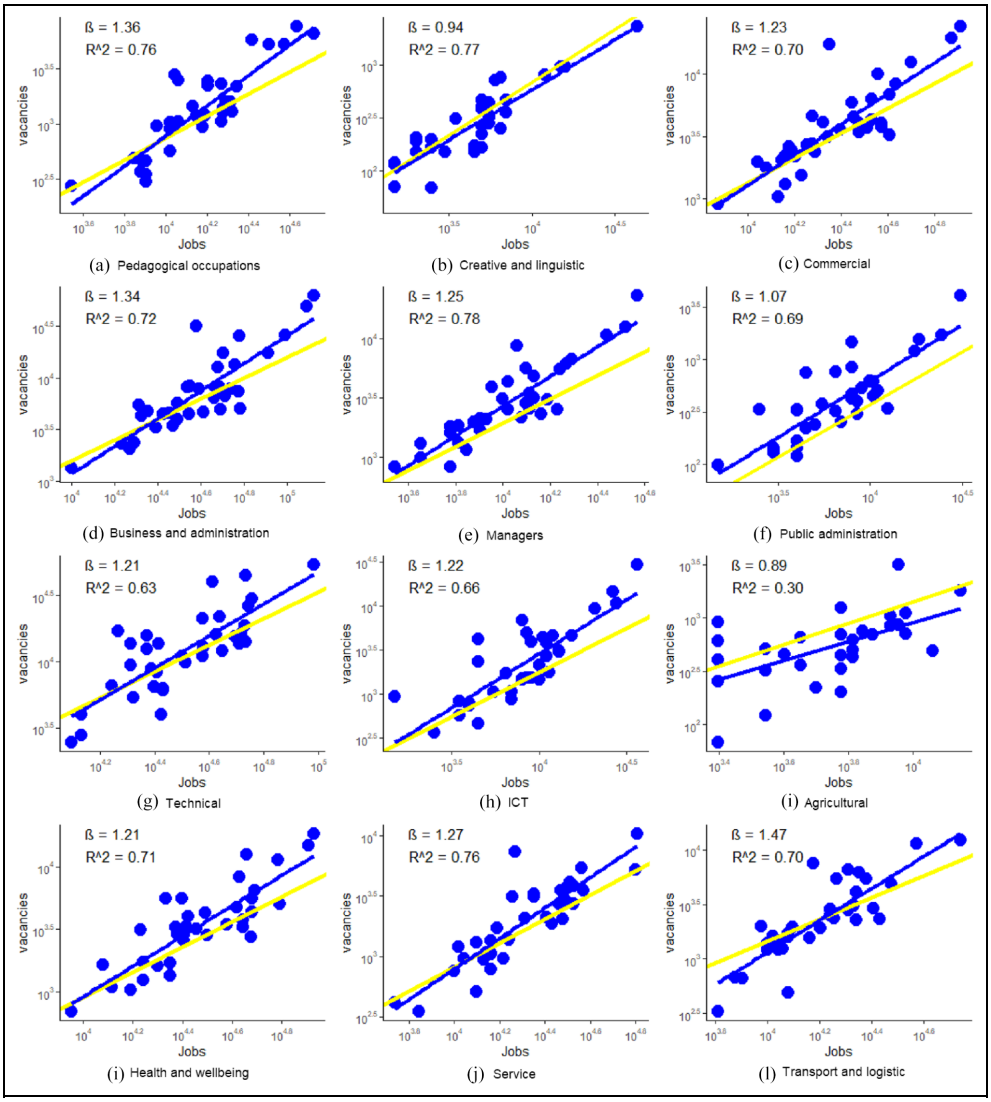

Figure 1. Spatial concentration of demand for specific sectors. (a–l) Scaling relationships between the number of vacancies in a sector and the number (*y*-axis) of existing jobs in that sector (*x*-axis) per labour market area in the Netherlands (average for 2017–2018). The yellow lines show the situation in which the scaling relationship is linear.
Source: Authors' own calculations.

locations where the number of jobs in this sector is already relatively large compared to locations where the number of jobs in this sector is relatively small. The results for the aggregated data reported above are therefore not due to differences in the occupational structure of employment between urban and rural areas, but are present in

almost all segments of the labour market we considered, Agriculture and Creative and linguistics being the only exceptions.

Decomposition by education

The next step is to consider if the relationship between vacancy rates and employment also holds for education levels. However, we should note immediately that we don't have information about employment for all the educational classes we distinguish. We therefore have to use overall employment in all educational classes as our main explanatory variable. This is likely to have an impact on our results, as it is well known that jobs requiring higher education are overrepresented in urban areas. It should therefore be expected a priori that our results are biased: they reflect the combined effect of over- or underrepresentation of employment and that of vacancies. The bias will be downwards for the lower educated, which are underrepresented in cities, and upwards for the higher educated which are overrepresented in these areas.

The abundant evidence that jobs for the higher educated concentrate more in urban areas than those of the lower educated (Autor, 2020; Davis and Dingel, 2019; Larsson, 2017; Simon, 1998) may suggest that the higher vacancy rates in urban areas refer especially or exclusively to the higher educated. This will especially be true if the employment growth is also concentrated in cities. Figure 2 shows the results of estimating the same regression as in the previous sections (with overall employment as an explanatory variable and without controls) but now with the vacancies referring to a specific education level as the dependent variable.[18] Vacancies are divided into eight ascending levels of required education and the total number of jobs in 35 labour market areas in the Netherlands. Scaling levels of vacancies increase with the required level of education. For the three lowest education levels we estimate an elasticity close to 1, which indicates linear scaling. The five remaining education levels show increasing concentration effects as the level of education increases. For the highest educational levels (6, 7 and 8) we find strong superlinear scaling, suggesting that – at least for the higher educated – there may be substantially higher vacancy rates on top of the unknown geographical overrepresentation of employment.[19]

To create a better understanding of the education scaling relationships, Figure 2(i)–(l) depicts the spatial concentration of demand for four ascending levels of required education in vacancies in 35 labour market areas in Netherlands. Dots are proportional to the number of vacancies requiring a certain education level per labour market area. The maps show increasing concentration in the larger cities in the Netherlands as education levels increase. Tables D1 and D2 in Appendix D presents the results when the same control variables that have been used before are added. We find comparable results and for most education levels the scaling exponents are even larger than without controls.

The results presented in this section confirm the specialisation of cities in jobs for which higher educated and presumably high skilled workers are required. They are also consistent with faster growth of such jobs in cities. Even with bias of high-skilled employment in cities we find a considerable higher vacancy rate in urban labour markets.

Overall, we observe that the spatial concentration of demand for labour increases with required skill levels and existing sector size.

Conclusion

High skilled workers and jobs are overrepresented in cities. Moreover, the quality of job–worker matches is better in cities in the sense that high productivity workers are more often employed in high productivity

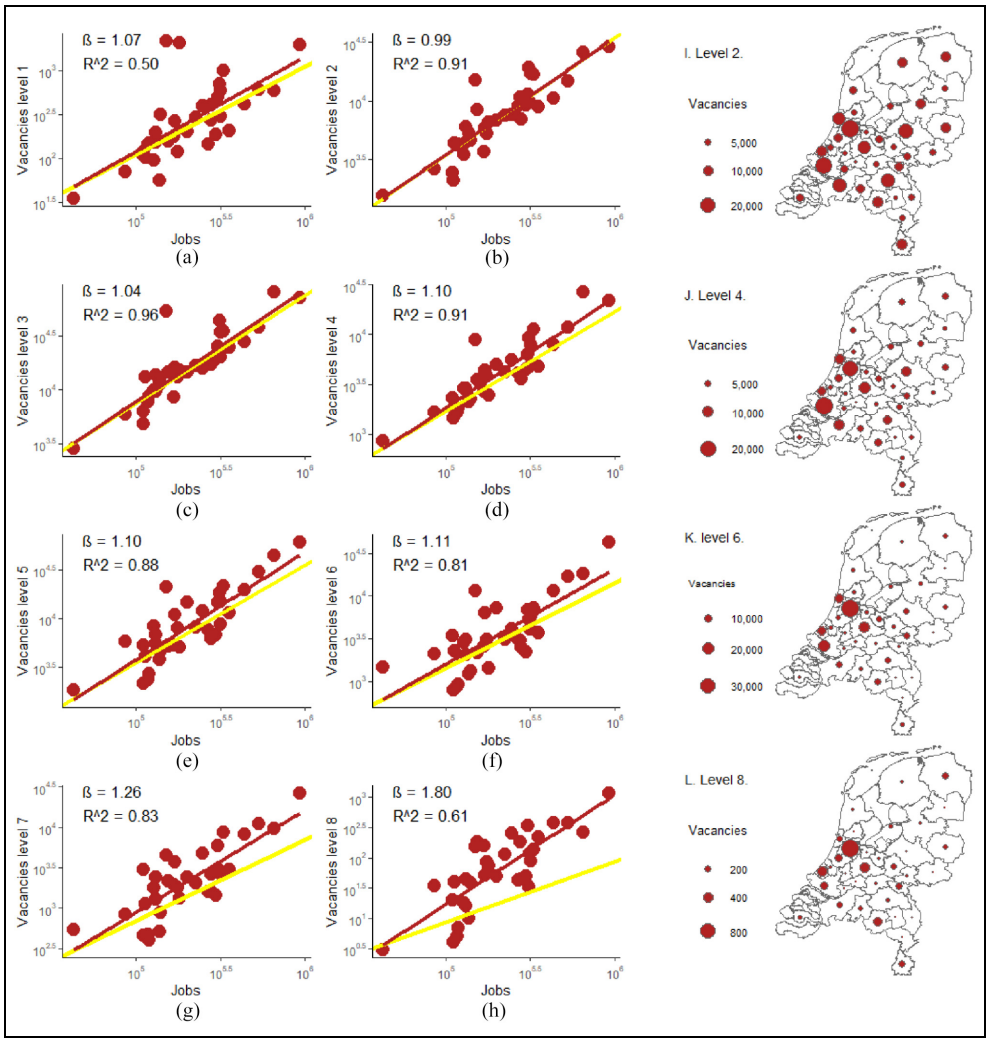

Figure 2. Spatial concentration of demand. (a–h) Scaling relationships between eight ascending levels of required education in vacancies per labour market areas (*y*-axis) and the total number of jobs in 2018 in the Netherlands (*x*-axis): level 1: elementary (a), level 2: high school (b), level 3: intermediate vocational education (c), level 4: intermediate vocational education / higher vocational education (d), level 5: higher vocational education (e), level 6: higher vocational education/university degree (f), level 7: university degree (g), level 8: PhD degree (h). In (a–h) the yellow lines show the situation in which the scaling relationship is linear. (i–l) Maps showing the absolute number of vacancies per labour market area for education levels 2 (i), 4 (j), 6 (k) and 8 (l).
Source: Authors' own calculations.

jobs. This suggests that urban labour markets are more efficient in allocating workers to jobs. Empirical studies suggest that this is related to higher job mobility of young workers. The greater efficiency of urban labour markets is at odds with the consistent finding of constant returns to scale for matching functions, which suggest that the

advantage of a large number of vacancies in dense places is cancelled out by the large numbers of job seekers. However, a consistently higher vacancy-to-employment ratio would imply an advantage for urban on-the-job searchers.

Using online job vacancy data for the Netherlands for the period 2017–2018 we find that urban areas indeed generate disproportionally more vacancies. This is not only true relative to all employment but also relative to employment in 10 out of 12 occupation groups. Moreover, results indicate that compared to all employment, concentration of labour demand increases with required skills levels.

Although the concentration of high-skilled jobs in cities is a well-known phenomenon, the higher *vacancy-to-employment rates* for occupations requiring skilled workers which comes on top of it has, as far as we know, not been observed before. The results show that faster employment growth in the total number of jobs or in specific occupation groups in urban areas does *not* explain the relatively higher number of vacancies in cities. We have offered an alternative explanation in the form of a vacancy chain model and show that under plausible conditions the interaction among spatial labour markets that differ in size will result in higher vacancy rates in the larger markets. Vacancy chains in larger cities tend to become longer as there are more potential workers.

The findings of this study contribute to our understanding of mechanisms behind the productivity gains of cities. In urban labour markets it is less risky to quit a job with a suboptimal match between capabilities and requirements because there are disproportionally more opportunities to switch jobs (which is complementary to the findings of Andersson and Thulin 2013). This means that urban labour markets can reach a superior quality of job-worker matches and this could well explain the higher mobility of especially younger workers in cities. This mechanism in itself may lead to an even higher number of vacancies through vacancy chains. This finding is not explained by the fact that firms with fluctuating employment tend to cluster and thus generate and terminate more jobs per worker (Overman and Puga, 2010) since we find disproportionally more vacancies in urban areas within almost all occupation groups.

This study is limited in the sense that it presents a descriptive and cross-sectional analysis. This means that the dynamics of labour demand concentration remain a topic for further investigation and that the exact mechanism behind the relative higher number of all vacancies in urban areas is not yet explained. We have proposed a mechanism that operates via vacancy chains that are likely to end up or stay in urban markets, but our empirical work does not provide direct evidence on its validity.

The finding that vacancy rates are higher in cities raises important questions for planners and policy makers. Demand for labour does not only concentrate in cities, but cities also offer substantially more job opportunities for high-skilled individuals than rural areas. The implication of this is growing spatial inequality, both between urban and rural areas and within cities (Autor, 2020; Wheatley, 2021). Even in the Netherlands, a relatively small and densely populated country with a good (public) transportation infrastructure, large differences between urban and rural areas exist, which can be expected to be larger in less densely populated countries like France and Germany but even more so in the United States and China. Policymakers should acknowledge that forces that drive economic progress are likely also driving the growth of inequality between urban and rural areas and also within cities. Policy measures should incorporate theses effects and aim to control spatial inequality by anticipating both positive

and negative outcomes on the (inter)national, regional and local level.

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Notes

1. Andersson and Thulin (2013) find that a higher employment density increases the probability of job switches, but while they look at job switching we focus on the demand for labour.
2. There is a relationship with the literature on spatial mismatch, which has convincingly shown that better job accessibility shortens the duration of job search, see for instance Andersson et al. (2018) and Johnson (2006).
3. An important early contribution is Jackman et al. (1989).
4. We assume that unemployment is positive in both local labour markets. Then the probabilities that a vacancy is filled by an on-the-job searcher, $\pi_{uu} + \pi_{ur}$ and $\pi_{ru} + \pi_{rr}$ are both strictly smaller than 1. Therefore we have: $(1 - \pi_{rr})(1 - \pi_{uu}) > \pi_{ru}\pi_{ur}$.
5. We will in each case only discuss the deviations of the probabilities π that vacancies are filles by on-the-job searchers from the values given in (4). It may be observed that changes in these probabilities will in general be associated with changes in the probabilities that vacancies in either area will be filled by unemployed job seekers from either area. However, since these changes will have no impact om vacancy chains, there is no need to discuss them explicitly. Apart from the restriction that the probabilities that a particular vacancy should be all non-negative and add up to one, they can take on arbitrary values. Note that the adding up restriction imposes a ceiling on the multiplication factors k, m and n that will be introduced below.
6. There is abundant evidence for the importance of informal networks for finding jobs, for example, Cingano and Rosolia (2012). The weak ties emphasised by Granovetter (1973) are often colleagues, see Ra'jkumar et al. (2022) for recent evidence on their importance for job mobility.
7. The large majority of workers realise commutes that take at most 45 minutes one-way travel time. See, for example, Van Ommeren and Fosgerau (2009) on the (considerable) marginal cost of commuting.
8. One could also think about the creative class with a strong preference for urban living who are an important determinant of urban productivity and growth, see Florida (2002).
9. It has been shown in the literature that workers who realised wage increases in cities will take the higher wages with them when accepting a job in other areas. See for example, Glaeser and Maré (2001).
10. It is beyond the scope of this paper to develop a fully fledged model of two interacting labour markets. In such a model the spatial aspects of matching have to be elaborated. In such a setting also the assumption

that quits are always followed by the creation of new jobs can be relaxed.
11. Mooij et al. (2020) investigate the regional dimension of vacancies in health care but do not compare this to the official vacancy questionnaire.
12. See Appendix B for a correlation matrix.
13. This terminology originates from the work of physicists who applied some of their methods to biological and social phenomena. See for instance Bettencourt (2013) and West (2017).
14. Controlling for the percentage of job growth over a longer period (since 2015) hardly changes the estimation results.
15. Another possible concern is that the number of vacancies could be influenced by the distribution of self-employed workers in the Dutch economy. However, we found no significant association between the percentage of self-employed workers and the number of vacancies on the level of the municipalities.
16. Correlation between employment in 2010 and employment in 2018: 0.98. First stage regression result, coefficient for population in 2010: 0.888*** (0.060).
17. And restricted by the requirement that COROP regions had to add up to provinces.
18. Vacancy rates for a specific education level are expressed.
19. Note that some occupational classes are likely to be filled almost exclusively by higher educated workers.
20. See for more information: https://www.cbs.nl/en-gb/our-services/methods/surveys/brief-survey-description/dutch-labour-force-survey–lfs–
21. The share of these workers is very small.

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Appendices

Appendix A. Were newly hired workers more than proportionately employed in the same labour market area?

In our theoretical model, we consider spatial areas that can be divided into an urban and a rural part as a single labour market and show that systematic deviations from random matching are required to generate the concentration of vacancies in the urban area. We consider three possibilities. According to the first mechanism, workers who recently accepted a job in the urban (rural) part of the labor market should disproportionally have been working in that same area before. We investigate the empirical relevance of this mechanism in this appendix.

To do so we use the Dutch labour force survey (LFS) (EBB in Dutch)[20] for the year 2018. The LFS is a recurring survey that collects information on the relationship between individuals and the labour market. As such, the LFS offers a representative sample of the Dutch population. For each respondent the municipality of residence and of work (if there is a fixed work location) are reported, as is the date at which a worker started in his present job. This allows us to compare the locations of the workers who have recently accepted their current job to the total of workers in a region.

The LFS does not inform us about the location of the former job, but we can make a reasonable estimate of this share by assuming that the workers who have recently accepted a job (and whose residential location we know) had the same spatial distribution of work locations over rural and urban areas as the total number of workers in the LFS. The LFS also provides information about workers who recently accepted another job and moved house in relation to that job. We leave them out because their former residential location is unknown.[21]

Labour markets

We considered a number of labour markets consisting of urban and rural parts. In the first analysis, the total of the Netherlands is viewed as a single labour market. The western part of the country, the Randstad area, is the urban part, while the remainder is the rural part. Although the Netherlands is relatively small and the Randstad may be considered to be a single, multi-centred agglomeration comparable to, say, New England in the US or the Ruhrgebiet in Germany, commutes from the far periphery, for example Groningen or Maastricht, to the Randstad are difficult to realize. Moreover, the Randstad area itself includes municipalities that are predominantly agricultural in land use. In the second analysis we therefore consider the four largest municipalities of the Netherlands, Amsterdam, Rotterdam, the Hague and Utrecht, to be the urban core of the Randstad, while the remainder is treated as the more rural fringe. In a third analysis, we focus on three medium sized urban areas located outside the Randstad area that may be considered as spatial labor markets that are (more or less) separated from the rest of the country: Groningen in the north, Zwolle in the east and Eindhoven in the southeast. Since the number of newly appointed workers for these relatively small area is low, we are not able to present the results for each of these labour markets separately, but had to aggregate them.

Table A1. Test of the first mechanism.

Area	(1) s_u^n	(2) S_u
Randstad	0.58	0.36
Rest of the Netherlands	0.74	0.64
Four largest cities	0.84	0.24
Rest of Randstad	0.84	0.75
Groningen, Zwolle and Eindhoven	0.90	0.55
Surroundings	0.70	0.45

Method

We confine the analysis to workers for which residential and job locations are known. For those who accepted their current job less than a year ago, we exclude workers who indicated having moved house because of work. We compare the share of workers who had recently accepted their current job in the urban (rural) part of the market from a previous job in the same part of the market, with the total share of workers employed in the urban (rural) part of the market.

Formally, we estimate the share of workers who recently accepted a job in the urban part of the labour market and also previously worked in the urban part, s_u^n as:

$$s_u^n = \sigma_{u|u}^n S_{u|u} + \left(1 - \sigma_{u|u}^n\right) S_{u|r} \qquad \text{(A.1)}$$

where $\sigma_{u|u}^n$ denotes the share of newly appointed workers in the urban part of the labour market that are also living in that part, $S_{u|u}$ is the share of the total number of workers living in the urban part of the labour market that are also working there and $S_{u|r}$ is the share of workers living in the rural part of the labour market that are working in the urban part. Our hypothesis is confirmed if s_u^n exceeds the share of total workers in the labour market employed in its urban part, S_u.

The method is completely analogous hypothesis for s_r^n, the share of newly appointed workers in the rural area who previously had a job in that area, and S_r, the share of workers employed in the rural area.

Table A2. Decomposition by education.

Area	(1) s_u^n	(2) S_u
Lower educated		
Randstad	0.49	0.26
Rest of the Netherlands	0.80	0.74
Medium educated		
Randstad	0.60	0.38
Rest of the Netherlands	0.74	0.62
Higher educated		
Randstad	0.79	0.63
Rest Netherlands	0.57	0.37

Results

The results presented in Table A1 confirm the hypothesis for all labour markets considered. The share of workers who recently accepted a job in the urban (rural) part of the labour market and also previously worked in the urban (rural) part, s_u^n, is higher than the share of the total number of workers employed in the urban (rural) part of the labour market, S_u.

Since the LFS is a survey and the number of workers switching jobs is relatively small, our possibilities for decomposing the labour markets on the basis specific groups are very limited. One decomposition we could make is for education. In Table A2 we present the results for three educational groups in which the whole of the Netherlands is considered as a single labour market with the Randstad its urban area. The results again confirm our hypothesis.

Conclusion

In this appendix we have shown that newly hired workers are more than proportionately employed previously in the labour market area in which their new job is located. This confirms the presence of the first mechanism for a disproportionally higher number of vacancies as proposed in the main text in the Dutch labour market.

Appendix B. Correlation matrix

Variable	Total vacancies	Jobs	Job growth %	Area	Duration	Large firms %	Below age 35%
Total vacancies	1						
Jobs	0.95	1					
Job growth %	0.16	0.18	1				
Area	0.24	0.33	0.18	1			
Duration	−0.12	−0.04	0.09	−0.00	1		
Large firms %	0.11	0.09	0.07	−0.10	0.09	1	
Below age 35%	0.47	0.52	0.32	0.16	−0.16	−0.06	1

Appendix C. Alternative geographical areas

Table C1. Municipalities.

Variable	(1) OLS	(2) OLS	(3) 2SLS
Jobs (log)	1.263***	1.310***	1.346***
	(0.045)	(0.083)	(0.077)
Job growth %		−0.008	−0.008
		(0.016)	(0.016)
Large firm (>200) %		−0.000	−0.001
		(0.004)	(0.004)
Young people (<35) %		−0.000	0.000
		(0.000)	(0.000)
Duration (log)		−0.253*	−0.241
		(0.152)	(0.150)
Area (log)		−0.209***	−0.216***
		(0.040)	(0.039)
Observations	355	355	355
Adjusted *R*-squared	0.803	0.822	0.822
Wald test (Jobs(log)=1) Chisq	34.779***	13.857***	19.936***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C2. Labour market areas.

Variable	(1) OLS	(2) OLS	(3) 2SLS
Jobs (log)	1.071***	1.237***	1.369***
	(0.072)	(0.116)	(0.167)
Job growth %		−0.014	0.023
		(0.046)	(0.046)
Large firm (>200) %		0.009	0.009
		(0.011)	(0.011)
Young people (<35) %		−0.013	−0.028
		(0.021)	(0.025)
Duration (log)		−0.398	−0.417
		(0.562)	(0.594)
Area (log)		−0.214**	−0.270**
		(0.95)	(0.116)
Observations	35	35	35
Adjusted *R*-squared	0.787	0.822	0.818
Wald test (Jobs(log)=1) Chisq	0.962	4.160**	4.900**

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Appendix D. Control variables

Table D1. Control variables for existing employment in 12 occupation groups.

Variable	Pedagogical	Creative and linguistic	Commercial	Business and administration	Dependent variable: total number of vacancies per occupation group (log)							
					Managers	Public administration	Technical	ICT	Agricultural	Health and wellbeing	Service	Transport and logistics
Jobs (log)	1.511***	0.996***	1.377***	1.466***	1.266***	1.163***	1.347***	1.271***	0.751***	1.392***	1.224***	1.577***
	(0.098)	(0.095)	(0.118)	(0.179)	(0.117)	(0.131)	(0.189)	(0.182)	(0.284)	(0169)	(0.089)	(0.193)
Job growth %	0.025***	0.0070*	0.014**	0.000	0.004	0.006*	0.012	0.008	0.005	0.0011	0.009**	0.001
	(0.006)	(0.003)	(0.007)	(0.000)	(0.005)	(0.003)	(0.009)	(0.005)	(0.008)	(0.010)	(0.004)	(0.006)
Large firms (>200) %	0.002*	0.000	0.003	0.003***	0.003	0.003	−0.003	0.004	−0.005	−0.001	0.006***	0.003**
	(0.001)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.004)	(0.003)	(0.008)	(0.002)	(0.001)	(0.002)
Young people (<35) %	0.011	−0.036	0.025	−0.003	0.029	0.009	0.019	0.018	0.062	0.012	0.016	−0.013
	(0.020)	(0.023)	(0.020)	(0.029)	(0.018)	(0.024)	(0.026)	(0.039)	(0.049)	(0.028)	(0.013)	(0.029)
Area (log)	−0.246***	−0.027	−0.204***	−0.120	−0.105	−0.261***	−0.092	−0.121	0.223	−0.273**	−0.005	−0.110
	(0.068)	(0.111)	(0.070)	(0.087)	(0.075)	(0.082)	(0.111)	(0.113)	(0.215)	(0.115)	(0.052)	(0.114)
Duration (log)	0.604	0.386***	−0.107	−0.012	−0.055	0.555	0.946	0.427	0.917*	−0.386	−0.694*	−0.366
	(0.611)	(0.546)	(0.404)	(0.617)	(0.730)	(0.517)	(0.556)	(1.246)	(0.533)	(0.469)	(0.406)	(0.532)
Observations	35	33	35	35	35	35	35	35	29	35	35	35
Adjusted R^2	0.901	0.734	0.823	0.782	0.808	0.817	0.673	0.753	0.399	0.745	0904	0.740
Wald test, Jobs (log)=1	26.929 ***	0.002	10.152***	6.791***	5.190**	1.541	3.347*	2.221	0.767	5.404***	6.358**	8.936***

Note: *$p < 0.1$, **$p < 0.05$,***$p < 0.01$.

Table D2. Control variables for all employment for eight education levels.

	Dependent variable: total number of vacancies per education level (log)							
Variable	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Jobs (log)	1.459***	1.109***	1.175***	1.255***	1.279***	1.374***	1.511***	1.808***
	(0.178)	(0.001)	(0.140)	(0.140)	(0.145)	(0.182)	(0.135)	(0.296)
Job growth %	−0.159	0.001	0.008	0.027	0.006	0.059	−0.053	−0.084
	(0.143)	(0.053)	(0.054)	(0.036)	(0.062)	(0.070)	(0.092)	(0.201)
Large firms (>200) %	0.027	−0.005	0.010	0.005	0.010	0.011	0.008	0.017
	(0.022)	(0.011)	(0.014)	(0.010)	(0.010)	(0.010)	(0.008)	(0.016)
Young people (<35) %	−0.086*	−0.038*	−0.028	−0.006	0.019	0.038	0.047	0.118**
	(0.048)	(0.022)	(0.025)	(0.021)	(0.029)	(0.033)	(0.033)	(0.057)
Duration (log)	−1.402**	−0.656**	−0.311	−1.573***	1.651*	−1.740**	0.347	−1.439**
	(0.551)	(0.271)	(0.313)	(0.302)	(0.829)	(0.820)	(0.759)	(0.651)
Area (log)	−0.031	−0.302	−0.182	−0.375	−0.469	−0.595	−0.059	−0.191
	(0.896)	(0.374)	(0.645)	(0.455)	(0.539)	(0.512)	(0.601)	(0.716)
Observations	35	35	35	35	35	35	35	35
Adjusted R^2	0.554	0.776	0.753	0.836	0.786	0.806	0.817	0.701
Wald test, jobs (log)=1	6.615**	1.469	1.564	3.338*	3.71*	4.236*	14.373***	7.469***

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.