Does it take extra skills to work in a large city?

-Working paper-

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Abstract
This paper explores the relationship between demand for specific skills and agglomeration economies. We assess to what extent jobs in large cities are more demanding compared to similar jobs in smaller cities. The use of online job vacancy data allows us to empirically analyse the spatial variation in skill requirements within instead of between occupations. Results show that jobs in dense areas require extra skills compared to similar jobs in sparsely populated areas. Moreover, we show that jobs in large cities require a more diverse skills set. Results hold for both high and low skilled occupations and indicate more efficient matching in dense areas, which enables a higher level of job specialisation and complexity. These findings help explain the productivity premium of cities and the growing spatial inequality between urban and rural labour markets.

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1. Introduction

Does it take extra skills to work in a large city? It is well known that work in cities is different from work in small towns. Large cities provide for example more opportunities to become a specialist. A small village can often only support a general practitioner with a broad but relatively shallow skill-set, while a larger city also supports medical specialists with deep but narrower skill sets. The existence of urbanization and localization economies in cities is then demonstrated in the occurrence of specific and relatively rare occupations that need the scale of the city to sustain themselves (Duranton & Jayet, 2011). Workers in these occupations are likely to perform more specialized and complex tasks. Following the same reasoning, one could expect that the complexity of job content within occupations will reflect the same phenomenon. In other words, does an urban environment also affect the complexity level of the activities of a job *within* occupations? This effect should be particularly present for occupations that are supposed to respond to urbanization economies. The skillset that is required for primary school teachers might be independent of their location, but lawyers and accountants in a large city may perform more specialised and complex compared to those on the countryside.

In this paper, we study the relationship between urbanisation and skill requirements. In doing this, we aim to unpack an important aspect of the productivity premium of cities (Rosenthal & Strange, 2004) and provide insights on the mechanism behind agglomeration economies. One of the explanations for the productivity premium of large cities is the deeper division of knowledge that urban areas offer. Workers choose subsets of activities to specialise in. Empirical evidence shows that scarce occupations are more likely to be performed in large than in small cities (Duranton and Jayet, 2011; Papageorgiou, 2022). Workers in larger cities also have significantly more occupational options which makes the search and match process different. Large cities allow for a more efficient matching between workers and firms (Dauth et al., 2022) which enables a higher job levels.

The benefits of a higher density that large cities offer may apply to all types of workers, independent of their education level and skills (Combes, Duranton & Gobillon, 2008). However, because of widening wage and skill inequalities within education and occupations groups, the need for more detailed information on worker heterogeneity is clear (Van der Velde, 2020; Koster & Ozgen, 2021). Until now, the number of empirical evaluations of the effect of market size on the content of jobs is limited Baumgardner, 1988a). There are investigations on specific case studies like doctors and lawyers (Baumgardner, 1988b; Garicano and Hubbard, 2009) but most studies focus on the variation *between* occupations instead of the variation *within* occupations (Duranton & Jayet, 2011; Bacolod, Blum & Strange, 2009), sectors (for example Davis & Dingel, 2020) or education groups (Koster & Ozgen, 2021). We analyse the job content of narrowly defined occupation groups that cover virtually all jobs in the economy. With this goal, this paper builds on two related studies. In the first, Kok (2014) shows that workers in large cities in Germany perform less subtasks and are thus more specialised. In the second, Atalay et al. (2022) study vacancy data for the US and find that the intensity of interactive and analytic skills is higher in large cities and that task specialization increases with city size.

We hypothesize that cities enable a more efficient match and therefore a higher job level, meaning that the complexity of the activities in the job is higher. More specialisation, meaning that workers focus on a specific subset of tasks, lowers productions costs but increases coordination costs (McCann, 2008). These coordination costs are lower within cities than between cities. Combined with the effect of a larger labour force this leads to a higher level of specialisation of jobs in large cities. Specialisation is by definition a concentration on specific tasks. Specialisation can therefore lead to the performance of less (sub)tasks (Kok, 2014) but likely increases the level of demands that come with these tasks. Furthering the argument that workers in cities are likely to be more specialised we focus on the quality, i.e. the level of complexity of a job.

We study differences in job levels by investigating the complexity of the activities that are required for a job. It has been shown that workers expect higher wages for more complex jobs (Ophem et al., 1993) and that differences in the complexity levels of production process can explain inter-firm wage differentials (Pekkarinen, 2002). Wood (1986) distinguishes between three dimensions of complexity: component, coordinative and dynamic complexity. Component complexity refers to the number of distinct acts that are needed to perform a task. A higher specialisation level requires more (tacit) knowledge of that task. Specialised knowledge needs to be combined in order to create a product. Coordinative complexity covers the nature of the relationship between task inputs and task products. Workers in cities would therefore need more (coordination) skills. Dynamic complexity describes the changes workers need to made during the task performance. Complex tasks require more information processing, more coordination and are more adaptions during the process of execution. We expect that workers in large cities are required to possess a higher number of skills and also more specific combinations of skills than workers in smaller cities within a given occupation and given their tasks. The job descriptions with specific skill requirements in online job vacancies provide a way to measure the complexity of the activities and therefore the level of the job.

To test whether urbanisation has an effect on the level of jobs, we use a unique database of Dutch online vacancy postings with detailed skill and location for 2018. The skills data is constructed based on the extraction of key words from job descriptions in vacancies and is measured in four categories: professional skills, soft skills, IT skills and language skills. Furthermore, the dataset provides information on job location, occupation, education level and company size.

We investigate spatial differences in job levels in three ways, by looking at (I) the number of skills, (II) the diversity of skills and (III) the type of skills that are required. These measures are based on the assumption that higher quality jobs require more from a worker: more (tacit) knowledge, more communication and more discipline and independence. Employers manifest this by listing more skills and more skill combinations for a given occupation. We control for a large degree of specialisation by using occupation fixed effects to filter for spatial variation between occupations.

Our contribution to the literature is threefold. First, we unpack an important aspect of the urban wage premium and provide evidence for the relationship between urbanisation and skill requirements in the Netherlands. Second, we measure skill requirements at the level of the individual job instead of the occupation, education or firm level. This allows us to control for occupation and firm characteristics. Third, we add to the growing number of studies which use job vacancy data and provide new insights about the demand for work across locations.

Our most important result is the stylised fact that the number of required skills per job increases with city size. The number, the diversity and the type of skills that are required reflect that jobs in urban areas are more demanding. This outcome is an important insight for debates and policies regarding agglomeration economies and the increasing spatial inequality between large and smaller cities (Baum-Snow & Pavan, 2013; Autor, 2019) as it shows that workers with specific skills or specific skills combinations have, regardless of their occupation type, a better chance of finding a job in larger cities.

The rest of the paper is structured as follows. The next section discusses theory and related literature. Section 3 describes the data and our empirical approach. Section 4 presents the results on the spatial variation in job content. Section 5 concludes.

2. Theory and related literature

2.1 Job levels in cities

There are several reasons why jobs in large cities can have a higher complexity level. First, high skilled workers sort themselves into large cities. A large part of the spatial variation in wages can be explained by worker characteristics (Combes, Duranton & Gobillon, 2008). For workers with the same education, the task content of the occupation explains a large part of the urban wage premium (Grujovic, 2018). Working in a large city is also interesting for (high skilled) workers because they have significantly more occupational options because there are more existing professions present (Papageorgiou, 2022). In short, cities offer workers the opportunity to find jobs that match their skill requirements. For workers with highly specialised skills sets, cities may be the only places where the jobs are on offer. Over de last decades college graduates have increasingly concentrated into dense urban areas (Berry & Glaeser, 2005). Cities offer more complex jobs as reflected in the number of skills mentioned to described the job. Given the larger pool of workers, however, employers can be more explicit in the formulation of job offers of a similar job in an area with a thinner labour market. This process than reinforces itself because works with scarce skills sets have a higher chance of finding a job in a large city.

Secondly, firms specialising in more complex activities may sort themselves into large cities (Behrens, Duranton & Robert-Nicoud, 2014), for example because of the larger talent pool. Highly specialised employers like business-service firms, research universities, laboratories and hospitals are located in large cities. This implies that cities have, at least on average, more complex jobs and different kind of occupations than small ones. Empirical evidence shows that scarce occupations are more likely to be located in large than in small cities (Duranton and Jayet, 2011). Cities offer at the same time greater competition which means that only most productive firms survive.

Thirdly, jobs may be more complex because of agglomeration economies. Large cities may accelerate new idea creation and complementarity among knowledge and resources. This implies that jobs in cities are more diverse and more complex. Literature investigating this idea has shown that particularly diverse cities generate innovations and entrepreneurial progress (Duranton & Puga, 2001; Davis & Dingel, 2020).

A fourth, overlapping reason why jobs in cities may be more complex is the faster adaption of technological change. When technological innovations are introduced, workers have to adapt their skills to the new technology. Since not every firm is adopting new technology at the same pace, even though they might produce the same service or product, and better performing firms concentrate in cities, workers in cities are expected to adapt faster.

Finally, a higher degree of coordination is a fifth reason in for the higher complexity of jobs in cities. This is discussed in more detail in the next paragraph.

2.2 Differences in complexity within occupations

In the previous paragraph we discussed several reasons why jobs in cities may be more complex. However, there are two ways in which this higher complexity can be manifested. In the form of specialisation between distinct occupations and within an occupation. In this section, we focus on the latter option.

More specialisation of job tasks lowers production costs because of a better allocation of tasks by the most efficient worker (or firm) (unless these lower production costs directly translate into higher wages). Every worker possesses a subset of the total number of skills. The more time a worker uses to produce a specific output the more specialised the worker is (Becker and Murphy, 1992). For example, the doctor that specialises in cardiology will be more efficient in treating rare heart conditions. Specialisation leads to more efficient production per worker. However, at the same time, coordination costs increase. Coordination and communication are required to combine the work of different specialists into a product. Journalists that write about national politics and foreign affairs should coordinate their activities to produce a consistent newspaper. Coordination and communication may be difficult, especially when it comes to implicit norms and tacit knowledge.

Large cities have an important advantage when it comes to coordination costs. Cities enable human interactions and make it easy to coordinate, plan, consult and evaluate. Despite the possibilities of online communication, virtual contact has been shown to be complementary to face-to-face contact instead of forming a replacement. Large cities enable knowledge spillovers. Performing highly specialised tasks is easier when specialised colleagues are close by and can be spontaneously consulted. This means that it is more efficient to specialise within a location than across locations. Large cities therefore enable a higher level of specialisation between and within occupations. If this is indeed the case we can expect that soft skills and language skills in cities are important especially in combination with professional skills.

The higher specialisation levels that cities enable is revealed by measuring the number of subtasks that workers perform in the same job (Kok, 2014). Workers in larger cities within the same job perform less subtasks and can therefore focus on more specialised core tasks. In today's knowledge economy this specialisation is only attractive if it increases the quality of the output (unlike assembly line work where specialisation only increases efficiency). This means that the overall level of the job is higher, which indicates that workers are expected to master skills at a higher level. A higher specialisation level requires more (tacit) knowledge that needs to be combined in order to create a product. This leads to even more concentration of complex jobs in dense areas (Koster & Ozgen, 2021). In other words, jobs in cities have a higher level of complexity. Kok (2014) focuses on professional job tasks (for example: manufacturing of goods, repairing, teaching, consulting) whereas jobs also require other soft, language and IT skills which together give an indication of the level or complexity of a job. Looking at the number of skills that are mentioned in the job description, we therefore expect that workers in large cities are expected to possess a higher number of skills than workers in smaller cities for a similar job.

3. Data and method

3.1 Data

To analyze the spatial variation in job levels, we exploit the skill demand in online vacancy data for 2018 for the Netherlands. The data is provided by Textkernel, an Amsterdam-based tech company which uses Artificial Intelligence to collect online job vacancies. The technique to scrape vacancies from webpages is advanced to a level in which virtually all online vacancies in the Netherlands are captured. Since vacancies are often posted multiple times and on several online platforms, Textkernel has developed a deduplication algorithm and classifies the information from the job description in variables like job type, location and required education level. We removed vacancies with missing information regarding job location, job type (ISCO), education level and skills. The skills data is extracted by Textkernel from the job description. Using an algorithm, every job description is scanned for skills based on extensive list of about 8000 unique skills and their synonyms. Skills are assigned to one of four categories: professional skills (e.g. consultancy, nursing), soft skills (e.g. teamwork, adaptability), IT skills (e.g. big data, JavaScript), and language skills (e.g. English, Dutch). We use the total number of skills per skill category that is indicated for each vacancy. In total we analyze about 2 million vacancies.

Vacancy data shows the demand for labour in a certain location. Given this property, vacancy information complements existing empirical information on job levels and task complexity in cities that typically focuses on the supply of labour (educational level for example) and realized labour market matches (occupational information). At the same time, the data compromise on some factors (Kurekova et al., 2015). For example on the fact that we do not know whether the vacancy has been filled. We can therefore not observe to what extent skill requirements are met by applicants and if spatial differences exist in the willingness of employers to hire candidates with sub-optimal skillsets. However, since we focused on the differences of skill demand, this does not disturb our analysis. Similarly, online vacancies tend to be biased towards more highly educated positions. Empirically, it is then important to assess the variation in skill requirements within occupations and control for educational level.

3.2 Measuring job complexity

The level or complexity of a job is in principle defined by the quality of the tasks that a worker performs. However, there is no commonly accepted measure of job level or job complexity. We therefore use the total number of skills as an indication of this quality and thus as a measure of the job level. This is based on the assumption that higher quality level jobs require more from a worker: more (tacit) knowledge, more communication and more discipline and independence. Employers reveal this by listing more, and more varied, skills for a given occupation. We use a detailed skills measure that is based on the extraction of key words from job descriptions in online vacancies to measure job complexity. A vacancy mentions on average 6 skills.

We empirically test the hypothesis that vacancies in a given job in large cities require more skills compared to vacancies for the same job in small cities or towns:

$$S_i = \alpha_i + \beta_{j(i)} + \delta_{l(i)} + \alpha_2 E_i + Y_{l(i)}\, E_i + F_i a_3 + \epsilon_{i.}$$

S_i refers to the total number of skills, i.e. the complexity level, of vacancy *i* with occupation j in city l. $\beta_{j(i)}$ are occupation fixe effects controlling for the average number of skills in the occupation. $\delta_{l(i)}$ refers to the variable we are most interested in, the effect of population density. Furthermore, we control for the required education level E_i and firm size F_i. An occupation is defined as a four-digit ISCO occupation.

In the empirical analysis we use the population density of the 380 Dutch municipalities in 2018 as in indicator of urbanisation. We use three education levels, low (lower than Secondary education), medium (Secondary or Higher Vocational Education) and high (Higher Vocational Education or University). Firms with more than 200 employees are defined as large firms. Appendix A.1 and A.2 provide further information on the definitions and measurement of the variables.

We are interested in the quality or complexity levels of jobs in large cities. The idea behind this is that employers in urban labour markets can be more specific because of the larger number of potential applicants (Modestino et al., 2020). They can afford to be 'picky' and selective whereas rural employers would get too few applicants when listing too many skills requirements. However, we cannot be certain that differences the number of potential applicants lead to a higher number of skills and therefore to a higher job level. Ideally, information on the number of applicants is needed to control for this. Since we lack this type of information we control for vacancy density: the number of vacancies in the same labour market areas in a comparable occupation (ISCO 2 digit) per 1000 existing jobs in that region. This means that for a vacancy for a journalist, the number of vacancies for the group Legal, Social and Cultural Professionals compared to the total number of jobs in that labour market areas is taken into account. This way we aim to isolate the effect of job complexity.

4. Results

This section first shows that the number of skills in a vacancy is linked to the level of a job. Then, we examine to what extent spatial differences in skill demand exist. Ultimately, we test the hypothesis that urbanisation is linked to job level by investigating the (I) number of skills, (II) the diversity of skills and (III) the type of skills in several models.

4.1 Descriptive analysis

Table 1 shows the average number of required skills by educational level. There is a clear and consistent pattern visible: vacancies that require higher educational levels include more skills, with 3-4 skills mentioned at the lower end of the educational ladder and 8-10 at the higher end. Though not unexpected, the result is important since it gives credence to the interpretation that the number of skills indeed reflects the level of the job on offer.

Table 1. Number of skills per education level (low to high)

Education level	Skills	Observations
1. Elementary	3.18 (2.72)	13851
2. High School	4.02 (3.09)	321715
3. Secondary Vocational Education	5.36 (3.68)	757217
4. Secondary or Higher Vocational Education	6.42 (4.21)	190408
5. Higher Vocational Education	7.45 (5.07)	407421
6. Higher Vocational Education or University	8.69 (6.56)	170292
7. University	10.01 (7.84)	114816

*Standard deviation between brackets

Next, we take the spatial dimension into account. Table 2 presents the average number of skills per urbanisation category[1] (urban to rural). This unconditional analysis indeed shows that vacancies in cities typically have more skill requirements, which is to say that they are more complex. For all skills taken together (second column), vacancies for jobs located in the most densely populated municipalities require on average 6.8 skills whereas vacancies in the rural municipalities mention 5.1 skills. The other columns show that this difference is present in all four skill types. Although the average number of IT and Language skills is small in absolute numbers, the difference between urban and rural areas is large in relative terms. This in an indication that the level of a job in related to the level of urbanisation.

[1] Here we follow the classification of the Dutch Bureau of Statistics which distinguishes five categories of municipalities. Each category contains a more or less equal amount of the population. Urbanisation categories: 1: > 2500 addresses per km2 , 2: 1500 – 2500 addresses, 3: 1000 – 1500 addresses, 4: 500 – 1000 addresses , 5: <500 addresses.

Table 2. Urbanisation and skills

Urbanisation level	All skills	IT skills	Professional Skills	Soft skills	Language skills
1. Urban	6.85 (5.40)	0.93 (2.64)	3.45 (3.02)	2.03 (1.99)	0.43 (0.74)
2.	6.12 (4.74)	0.62 (2.05)	3.23 (2.78)	1.88 (1.87)	0.37 (0.70)
3.	5.83 (4.42)	0.48 (1.73)	3.16 (2.70)	1.80 (1.82)	0.36 (0.69)
4.	5.48 (4.21)	0.37 (1.42)	3.04 (2.65)	1.70 (1.78)	0.35 (0.70)
5. Rural	5.11 (4.18)	0.29 (1.26)	2.83 (2.63)	1.67 (1.79	0.31 (0.65)

*Standard deviation between brackets

Table 3 provides further support for the idea that the number of skills is a valid indicator of the level of the level of a job. Occupations with analytical non-routine tasks, which can be expected to have the most complex activities, have the highest number of required skills compared to occupations with manual and routine tasks. The tables in appendix B indicate that these differences in the number of required skills are also apparent in industry and occupation groups. Vacancies for managers and professionals mention about four skills more per vacancy compared to operators and assemblers and workers in agriculture. Furthermore, the results follow the urban hierarchy as expected, vacancies in urban municipalities show a higher number of skills. Spatial differences in sector structures and the thickness of the labour market are likely to play a role in the difference of the required number of skills in vacancies, it is therefore important to analyse job levels within specific occupations and control for other effects.

Table 3. Urbanisation and skills in routine / non routine occupations

Urbanisation level	1. Analytical non-routine tasks	2. Interactive non-routine tasks	3. Cognitive routine tasks	4. Manual routine tasks	5. Manual non-routine tasks
1. Urban	8.83 (6.49)	5.51 (4.22)	6.61 (4.76)	4.29 (3.57)	5.39 (3.73)
2.	8.17 (5.92)	5.19 (3.86)	6.05 (4.33)	4.07 (3.27)	5.21 (3.56)
3.	8.12 (5.58)	5.32 (3.86)	5.69 (4.15)	4.02 (3.13)	5.17 (3.54)
4.	8.05 (5.32)	5.15 (3.81)	5.33 (4.16)	3.76 (2.92)	4.99 (3.42)
5. Rural	7.69 (5.55)	4.92 (3.89)	4.77 (4.31)	3.54 (2.72)	4.81 (3.35)

*Standard deviation between brackets

4.2. Job complexity and agglomeration: the number of skills

Table 4 includes the baseline results for the association between urbanisation and job complexity as measured by the number of skills formulated in the vacancy posting. Throughout the model specification, we find a positive and consistent association between urbanisation and the number of required skills. The first column shows the result for the empty model that includes only the occupational fixed effects (ISCO four digit) and population density. As expected, jobs in dense areas require more skills than similar jobs in small towns. An increase of population density by 1000 people per km2 is associated with an increase of 0.09 skills. The explanatory power of the estimations is rather high given that we use individual observations.

In the second and third column we control for job characteristics that may also affect the number of required skills. The spatial distribution of job vacancies is unequal, vacancies for highly educated workers large firms are for example overrepresented in urban areas. The same holds for the spatial distribution of large firms. Results show that these factors have indeed a positive effect the number of skills. Jobs that require a medium (Secondary or Higher Vocational Education) or higher education (Higher Vocational Education or University) require more skills compared to jobs for which a lower education is sufficient. The reference unit are the vacancies that aim to attract low educated workers. The same holds for jobs at larger firms (more than 200 employees). Although the estimate of the population density effect declines in size, it remains significant.

Table 4. Job complexity and agglomeration

	Dependent variable: total number of skills per vacancy				
	(1)	(2)	(3)	(4)	(5)
	FE	FE	FE	FE	IV
Population density	0.088***	0.068***	0.069***	0.063***	0.093***
(x1000)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Education middle		0.522***	0.528***	0.534***	0.529***
		(0.007)	(0.007)	(0.007)	(0.007)
Education high		1.827***	1.834***	1.830***	1.808***
		(0.012)	(0.012)	(0.012)	(0.012)
Firm size (>200)			0.342***	0.343***	0.355***
			(0.007)	(0.007)	(0.007)
Vacancy density				0.012***	0.012***
				(0.000)	(0.000)
Observations	1975720	1975720	1975720	1975720	1895650
Adjusted R-squared	0.224	0.235	0.236	0.237	0.238
F Test					2173658

Note: All regressions include occupation fixed effects. Robust standard errors are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

In the fourth column we address the concern that the total number of skills that are listed in a vacancy is the result of a larger applicant pool in cities which gives employer the possibility to be more specific (see method). The estimated effect of the city location is indeed smaller than in the earlier models. A higher vacancy density seems indeed related to the number of skills in a vacancy. This is in line with our expectations that employers in dense areas can be more explicit in their skill requirements. We use this extended model to study the relationship between job complexity and urbanization in specific occupation groups (table 5-7).

A possible concern can be that population density may be correlated to unobserved factors that influence job levels. To address this implied endogeneity, we use population density in 1830 as an instrument for population density in 2018.[2] Here we make the (strong) assumption that population density in 1830 is unrelated to unobserved factors that influence job levels in 2018 but causally related

[2] Note that the number of municipalities declined strongly between 1830 and 2018. We merge the municipalities of 1830 to the boundaries of the municipalities in 2018. This means that we lose some observations because of the creation of municipalities on new land which did not exist in 1830 (Meer & Boonstra, 2006).

to population density in 2018.[3] Results in column five show a higher estimated effect of population density on the number of required skills per vacancy.

Because the use of population density per municipality as indicator of urbanization is inevitably somewhat arbitrary, we estimate the models presented in table 4 also with another measure of urbanization based on address density. The results presented in appendix C.1 are in line with the findings in table 4. The number of required skills increases with population density.

4.3. The diversity of skills

Secondly, we look at combinations of skill groups to gain further insights in the relationship between urbanisation and higher job complexity. The results in table 4 indicate that a higher number of skills are required in cities. But is this higher demand concentrated in one of the four categories or spread out over the different kind of skills? Following the argumentation that coordination is more important in city jobs we expect that the diversity of skill will be higher in cities. This would than indicate a higher job complexity because workers need to master not only more but also more diverse combinations of skills.

Table 5 Skill combinations: Herfindahl index

	(1)	(2)
Population density (x1000)	0.002***	0.001***
	(0.000)	(0.000)
Education middle		0.009***
		(0.000)
Education high		0.017***
		(0.000)
Firm size		0.000
		(0.000)
Vacancy density		0.000***
		(0.000)
Observations	1333111	1333111
Adjusted R-squared	0.114	0.1164

Note: All regressions include occupation fixed effects. Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We use a Herfindahl index to study this question. The Herfindahl index is a measure of concentration and is calculated for each vacancy based on the distribution of the number of skills across the four skills categories (professional, soft, IT and language skills). The index is calculated by squaring the share of each skill category and summing the resulting numbers. We subtract the scores from 1 to make the interpretation more intuitive. A Herfindahl of 0 indicates that only one out of four skills categories is mentioned while a score of 1 indicates a perfectly equal division . Higher values indicate more diversity in the types of skills that are required. We only include vacancies that have a least four skills to create a fair comparison between urban and rural areas, as we have shown that rural areas have less skills for

[3] First stage regression result, coefficient for population density 1830: 3.908*** (0.002).

similar vacancies. Table 5 shows that the Herfindahl in large cities is significantly higher in the urban municipalities compared to all other municipalities. This means that the diversity of skills that workers in cities are expected to master is higher and indicates a higher job level.

4.4. The type of skills

Thirdly, some skill groups may respond more strongly to urbanization economies than others, for example because occupations in cities may require more interaction and coordination. Therefore, we test if there are spatial differences in the type of skills that are required. To find out if the results presented in table 4 are driven by one skill category, the specification of model 5 in table 4 is used with the distinct skill categories (professional, soft, IT and language skills) as dependent variable. Table 6 shows that the number of required skills is higher in cities for each skill category. This indicates that jobs in cities have a higher complexity level than similar jobs elsewhere since it is not one category that is more important in cities.

Table 6. Regression results across different skill categories

	Dependent variable: number of skills per category			
	Professional	Soft	IT	Language
Population density	0.025***	0.008***	0.023***	0.008***
(X1000)	(0.001)	(0.001)	(0.001)	(0.000)
Education middle	0.258***	0.181***	0.048***	0.047***
	(0.005)	(0.003)	(0.002)	(0.001)
Education high	0.929***	0.487***	0.316***	0.098***
	(0.007)	(0.005)	(0.004)	(0.002)
Firm size	0.285***	0.079***	0.006***	-0.027***
	(0.004)	(0.003)	(0.003)	(0.001)
Vacancy density	0.005***	0.001***	0.006***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1975720	1975720	1975720	1975720
Adjusted R-squared	0.185	0.082	0.431	0.084

Note: All regressions include occupation fixed effects. Robust standard errors are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

4.5. Decomposition by occupation groups

The association between city-size and complexity of the job may differ across occupational groups. Some occupations – knowledge intensive ones – may respond to urbanization economies in a stronger way than others. Also, some occupations may require a relatively fixed set of skills for example because of strict regulations and requirements for such occupations (teachers or doctors for example). In this subsection, we look at the relationship between city size and skill requirements at the level of specific occupation groups. Table 7 presents the results for routine and non-routine occupations groups. Like in the first table, all regressions include fixed effects on the four-digit ISCO level. Results show a positive and significant relationship between the total number of skills and city size for all routine classes. Interestingly, the effects are less strong for non-routine occupations than for routine occupations. This means that the higher job complexity is not limited to typical high skilled jobs but also present in lower skilled occupations. This might indicate that urban employers can use higher requirements for jobs that face the threat of automation. Appendix C.2 presents the results for one-digit ISCO occupation groups, which shows a similar picture. In all occupation groups, the number of required skills is higher in larger cities.

Table 7. Regression results across routine / non routine occupation groups

	Dependent variable: total number of skills				
	Analytical Non routine	Interactive Non routine	Cognitive routine	Manual routine	Manual Non routine
Population density	0.047***	0.018***	0.062***	0.087***	0.051***
(x1000)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Education middle	0.624***	0.543***	0.818***	0.347***	0.485***
	(0.048)	(0.018)	(0.019)	(0.015)	(0.010)
Education high	2.171***	1.741***	1.766***	1.943***	1.940***
	(0.048)	(0.024)	(0.025)	(0.048)	(0.035)
Firm size	0. 841***	0.123**	0.220***	0.030**	0.120***
	(0.016)	(0.014)	(0.015)	(0.014)	(0.010)
Vacancy density	0.020***	0.014***	0.009***	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	571309	322523	407321	193492	481075
Adjusted R-squared	0.142	0.136	0.187	0.194	0.181

Note: All regressions include occupation fixed effects. Robust standard errors are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

Wage inequalities across different skills groups are widening between large and small cities (Baum-Snow & Pavan, 2013). Although there has been attention for the relationship between wages and urbanisation, the effects of density on job content within occupations remain unclear while this may be an important explanation of the urban wage premium. In this paper, we study the relationship between urbanisation and skill requirements using data of online job vacancies for The Netherlands.

Results indicate a higher job level, a higher specialisation and complexity level of activities in large cities, Jobs in dense areas require extra skills compared to similar jobs in sparsely populated areas. This result is not limited to the total number of skills but also present in the skill categories: professional, soft, IT and language skills. We further show that the diversity of skills that workers in cities are expected to master is higher than in rural areas, which also indicates a higher job level. This result is only partly explained by a higher number of potential applicants in cities and through education level and firm size. Interestingly, the higher job level in cities is not limited to typical high skilled occupations like lawyers or accountants but also present in typical low skilled occupations that require manual labour. This indicates that agglomeration economies have an effect on all type of workers.

Our findings indicate that wage differences between locations at least partly reflect differences in the skills that workers need to perform their tasks, even within occupations. Given that cities allow for more efficient matching and high educated workers have a better chance of finding jobs that match their skills in large cities, the spatial difference in job levels within occupations may even further increase (wage) inequality. This is an important insight for policy and scientific discussions about growing regional (wage) inequality as it shows that more productive workers with more specialised skill sets have, regardless of their occupation, a better a better chance of finding a job in larger cities.

References

Atalay, E., Sotelo, S., & Tannenbaum, D. I. (2022). The Geography of Job Tasks (No. w30421). National Bureau of Economic Research.

Autor, D. H. (2019). Work of the Past, Work of the Future. In *AEA Papers and Proceedings* (Vol. 109, pp. 1-32).

Bacolod, M., Blum, B. S., & Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics, 65*(2), 136-153.

Baum-Snow, N., & Pavan, R. (2013). Inequality and city size. *Review of Economics and Statistics, 95*(5), 1535-1548.

Baumgardner, J. R. (1988a). The division of labor, local markets, and worker organization. *Journal of Political Economy, 96*(3), 509-527.

Baumgardner, J. R. (1988b). Physicians' services and the division of labor across local markets. *Journal of Political Economy, 96*(5), 948-982.

Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics, 107*(4), 1137-1160.

Behrens, K., Duranton, G., & Robert-Nicoud, F. (2014). Productive cities: Sorting, selection, and agglomeration. *Journal of Political Economy, 122*(3), 507-553.

Berry, C. R., & Glaeser, E. L. (2005). The divergence of human capital levels across cities. *Papers in regional science, 84*(3), 407-444.

Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters!. *Journal of urban economics, 63*(2), 723-742.

Dauth, W., Findeisen, S., Moretti, E., & Suedekum, J. (2022). Matching in cities. *Journal of the European Economic Association, 20*(4), 1478-1521.

Davis, D. R., & Dingel, J. I. (2020). The comparative advantage of cities. *Journal of International Economics, 123,* 103291.

Duranton, G., & Jayet, H. (2011). Is the division of labour limited by the extent of the market? Evidence from French cities. *Journal of Urban Economics, 69(*1), 56-71.

Duranton, G., & Puga, D. (2001). Nursery cities: urban diversity, process innovation, and the life cycle of products. *American Economic Review, 91*(5), 1454-1477.

Garicano, L., & Hubbard, T. N. (2009). Specialization, firms, and markets: The division of labor within and between law firms. *The Journal of Law, Economics, & Organization, 25*(2), 339-371.

Kok, S. (2014). Town and city jobs: How your job is different in another location. *Regional Science and Urban Economics, 49*, 58-67.

Koster, H., & Ozgen, C. (2021). Cities and Tasks. *Journal of Urban Economics 126*, 103386

Kureková, L. M., Beblavý, M., & Thum-Thysen, A. (2015). Using online vacancies and web surveys to analyse the labour market: a methodological inquiry. *IZA Journal of Labor Economics, 4*(1), 1-20.

McCann, P. (2008). Globalization and economic geography: the world is curved, not flat. *Cambridge Journal of Regions, Economy and Society, 1*(3), 351-370.

Meer, A., & Boonstra, O. W. A. (2006). Repertorium van Nederlandse gemeenten, 1812-2006. Den Haag: DANS, Data Archiving and Networked Services.

Modestino, A. S., Shoag, D., & Ballance, J. (2020). Upskilling: Do employers demand greater skill when workers are plentiful?. *Review of Economics and Statistics, 102*(4), 793-805.

Ophem, H. van, Hartog, J., & Vijverberg, W. (1993). Job complexity and wages. *International Economic Review*, 853-872.

Papageorgiou, T. (2022). Occupational matching and cities. *American Economic Journal: Macroeconomics, 14*(3), 82-132.

Pekkarinen, T. (2002). Complexity, wages, and the O-ring production function: evidence from Finnish panel data. *Labour Economics, 9*(4), 531-546.

Rosenthal, S. S., & Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In *Handbook of regional and urban economics* (Vol. 4, pp. 2119-2171). Elsevier.

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational behavior and human decision processes, 37*(1), 60-82.

Velde, L. van der (2020). Within occupation wage dispersion and the task content of jobs. *Oxford Bulletin of Economics and Statistics*, *82*(5), 1161-1197.

Appendix

A1. List of included variables

	Measurement	Mean	S.D.
Skills	Number of skills per vacancy, out of 8000 unique skills	6.22	4.89
Population density	Number of inhabitants per km2 per municipality (x1000)	2.09	1.77
Education low	Dummy variable indicating whether a vacancy requires a diploma lower than Secondary education	0.17	0.38
Education middle	Dummy variable indicating whether a vacancy requires a diploma of Secondary or Higher Vocational Education	0.48	0.49
Education high	Dummy variable indicating whether a vacancy requires a diploma for Higher Vocational Education or University	0.35	0.47
Firm size	Dummy variable indicating whether the firm has more than 200 employees	0.44	0.49
Occupation	Four-digit ISCO occupation group (376 unique occupations)		
Vacancy density	The number of vacancies in the same labour market areas in a comparable occupation (ISCO two digit) per 1000 existing jobs in that region (x1000)	30.2	18.0

A2. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Skills	1.00					
(2) Pop density	0.10	1.00				
	(0.00)					
(3) Education middle	-0.13	-0.09	1.00			
	(0.00)	(0.00)				
(4) Education high	0.30	0.18	-0.71	1.00		
	(0.00)	(0.00)	(0.00)			
(5) Firm size	-0.03	-0.02	-0.00	-0.04	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)		
(6) Vacancy density	0.15	0.06	-0.03	0.08	-0.08	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Note: n= 5547175. P-values are in parentheses.

B. Descriptive statistics

B.1. Skills per ISCO 1-digit group.

ISCO	Total	IT	Prof	Soft	Language	Observations
1. Managers	8.16 (5.84)	0.71 (1.96)	4.28 (3.58)	2.65 (2.25)	0.50 (0.84)	145423
2. Professionals	8.22 (6.20)	1.92 (3.83)	3.73 (3.20)	2.15 (2.06)	0.40 (0.73)	441967
3. Technicians	6.68 (4.60)	0.58 (1.50)	3.52 (2.78)	2.18 (1.98)	0.38 (0.72)	337202
4. Clerks	5.32 (4.10)	0.37 (0.91)	2.66 (2.37)	1.74 (1.81)	0.54 (0.84)	251895
5. Service and sales	4.65 (3.27)	0.13 (0.63)	2.18 (1.86)	1.95 (1.78)	0.37 (0.72)	218310
6. Agricultural	3.91 (2.67)	0.05 (0.33)	2.04 (1.66)	1.61 (1.52)	0.19 (0.46)	23181
7. Craft and trade	5.89 (3.84)	0.11 (0.63)	4.06 (2.88)	1.50 (1.59)	0.30 (0.60)	316394
8. Operators and assemblers	3.81 (2.90)	0.04 (0.33)	2.31 (2.07)	1.17 (1.38)	0.28 (0.54)	101112
9. Elementary	3.45 (2.62)	0.02 (0.25)	1.90 (1.81)	1.22 (1.38)	0.29 (0.54)	140236

B.2. Skills and education level

Education level	Total Skills	IT	Prof	Soft	Language	Observations
1. Elementary	3.18 (2.72)	0.04 (0.56)	1.86 (1.75)	0.99 (1.34)	0.27 (0.57)	13851
2. High School	4.02 (3.09)	0.07 (0.62)	2.33 (2.14)	1.33 (1.47)	0.27 (0.56)	321715
3. Secondary Vocational Education	5.36 (3.68)	0.25 (0.95)	3.03 (2.49)	1.69 (1.70)	0.36 (0.68)	757217
4. Secondary / Higher Vocational Education	6.42 (4.21)	0.59 (1.55)	3.28 (2.56)	2.11 (1.93)	0.43 (0.76)	190408
5. Higher Vocational Education	7.45 (5.07)	1.21 (2.82)	3.58 (2.76)	2.21 (2.02)	0.44 (0.78)	407421
6. Higher Vocational Education /University	8.69 (6.56)	2.00 (3.93)	3.90 (3.50)	2.33 (2.18)	0.45 (0.79)	170292
7. University	10.01 (7.84)	1.37 (3.47)	5.38 (4.49)	2.73 (2.44)	0.51 (0.85)	114816

C. Regression results

C.1 Additional regressions

The use of population density per municipality as indicator of urbanization is inevitably somewhat arbitrary and many workers in the Netherlands commute into different municipalities. To account for this, we estimate the models in table 4 also with the urbanization classification of Dutch Bureau of statistics, which is based on address density and distinguishes five categories. Each category contains a more or less equal amount of the population. In the main analysis the 19 most urban municipalities, with more than 2500 addresses per km² and in total about twenty percent of the Dutch population are compared to all other municipalities. The large city effect is thus defined as the 19 most densely populated municipalities. [4] Results are in line with the findings of table 4. Municipalities with a higher address density tend to have higher job requirement.

To study the urban hierarchy in more detail we estimate in column four the level of urbanisation in five urbanisation categories instead of in one dummy variable. The reference unit are the most rural municipalities with less than 500 addresses per km2. The estimated effect of urbanisation on the number of required skills follows the urban hierarchy but appears to be non-linearly, the effect becomes stronger as density increases. The estimated effect of the city is in this estimation higher because municipalities with less than 500 addresses per km2 form the reference category instead of all municipalities with less than 2500 addresses per km2.

	Dependent variable: total number of skills				
	(1)	(2)	(3)	(4)	(5)
City	0.336***	0.263***	0.264***	0.363***	0.237***
(>2500 addresses)	(0.004)	(0.004)	(0.004)	(0.009)	(0.004)
1500-2500 addresses				0.143***	
				(0.009)	
1000-1500 addresses				0.052***	
				(0.009)	
500 -1000 addresses				0.042***	
				(0.009)	
Education middle		0.455***	0.463***	0.461***	0.468***
		(0.004)	(0.004)	(0.004)	(0.004)
Education high		1.850***	1.853***	1.849***	1.851***
		(0.007)	(0.007)	(0.07)	(0.007)
Firm size			0.381***	0.380***	0.381***
			(0.004)	(0.004)	(0.004)
Vacancy density					0.012***
					(0.000)
Observations	5547175	5547175	5547175	5547175	5547175
Adjusted R-squared	0.223	0.234	0.236	0.236	0.236

Note: Data for 2017-2019. All regressions include occupation fixed effects. Robust standard errors are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

[4] Municipalities with more than 2500 addresses per km²: Groningen, Utrecht, Amsterdam, Beverwijk, Haarlem, Hilversum, Delft, Dordrecht, Gouda, Den Haag, Leiden, Rotterdam, Rijswijk, Schiedam, Vlaardingen, Zoetermeer, Eindhoven, Tilburg, Leidschendam-Voorburg.

C.2. Regression results across occupations (ISCO)

Dependent variable: total number of skills

	Managers	Professionals	Technicians	Clerks	Service workers	Agricultural workers	Craft workers	Operator	Elementary occupations
Pop dens (x1000)	0.072***	0.026***	0.053***	0.037**	0.027***	0.123***	0.055***	0.016***	0.083***
	(0.009)	(0.005)	(0.004)	(0.005)	(0.004)	(0.014)	(0.005)	(0.006)	(0.005)
Edu middle	0.646***	-0.011	0.559***	0.799***	0.731***	0.130**	0.618***	0.155***	0.466***
	(0.077)	(0.050)	(0.042)	(0.018)	(0.016)	(0.033)	(0.014)	(0.017)	(0.016)
Edu high	2.352***	1.312***	1.692***	2.127***	1.758***	2.245***	2.673***	1.145***	1.017***
	(0.079)	(0.048)	(0.044)	(0.029)	(0.032)	(0.138)	(0.047)	(0.086)	(0.048)
Firm size	0.703***	0.810***	0.676***	-0.275***	0.144***	0.735***	-0.063***	0.232***	-0.054***
	(0.031)	(0.018)	(0.017)	(0.016)	(0.014)	(0.035)	(0.014)	(0.017)	(0.014)
Vacancy-	0.058***	0.019***	0.013***	0.009***	0.004***	0.007	0.000	0.003***	0.001
density	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)	(0.001)
Observations	145423	441967	337202	251895	218310	23181	316394	101112	140236
Adjusted R^2	0.085	0.193	0.116	0.196	0.077	0.087	0.136	0.153	0.069

Note: All regressions include occupation fixed effects. Robust standard errors are in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$