Does it take something extra to work in a large city? Evidence from vacancy postings

Harm-Jan Rouwendal & Sierdjan Koster

University of Groningen

Abstract

This paper explores the relationship between demand for skills and agglomeration economies. We question to what extent a jobs in large cities are more complex compared to the same jobs in smaller cities. Most datasets consisting of task and skill descriptions of jobs lack spatial variation in required skills. Using job descriptions from online vacancies, we empirically analyse the spatial variation in skill requirements. The results show that a job in a large city requires more skills than the same job in a small city. Jobs in cities not only require more but also different skills, which indicates a higher level of complexity. In line with a higher specialisation level trough a more extensive the division of tasks, workers are expected to master more skills than workers in the same job in small cities.

1. Introduction

Does it take something extra to work in a large city? A large literature has presented evidence that work in cities is different from work in smaller rural towns. Large cities provide more career opportunities and offer more chances to become a specialist. A journalist in a small town covers all kinds of stories for the local newspaper whereas a journalist at a national newspaper in a large city can specialise in foreign affairs. The same is true for other jobs like doctor, lawyer or accountant. These examples show that the specialisation level and complexity of job contents differs by the size of the market. Large cities have different local industries, different workers, different amenities and also offer a different life. To what extent do the required skills of jobs differ across city size?

The idea that the division of labour is bound by the extent of the market goes back to Adam Smith. Larger markets provide the opportunity for more specialisation through a more efficient division of tasks. Workers choose subsets of activities to specialise in. If a local newspaper has two reporters, they can specialise in half of the topics that should be covered. Empirical evidence shows that scarce occupations are more likely to be performed in large than in small cities (Duranton and Jayet, 2011). Workers in larger cities have significantly more occupational options because there are relatively more vacancies and also in the sense that there are more existing professions present (Papageorgiou, 2021).

But is there also variation within occupations? Some studies have investigated the specialisation levels of jobs in specific industries (Baumgardner, 1988; Garicano & Hubbard, 2009). Another part of the literature has utilised data on education levels, industry concentration to explain the productivity and wage premium of cities (add ref.). Besides a few exceptions (Kok, 2014; Atalay, Sotelo and Tannenbaum, 2021), most research has only paid limited attention to the spatial variation in job contents within occupations. A better understanding of the impact of spatial variation within occupations and industries is needed to further unpack the mechanisms behind agglomeration economies and the increasing spatial inequality between large and smaller cities.

This paper aims to unpack an important aspect of the efficiency of cities by analysing the variation in skill requirements across cities. To overcome the limitation that most datasets on job contents and skill requirements lack spatial information, we exploit online vacancy data with very detailed skill and location information for the Netherlands for the period 2017-2019. Our measure of skills is not limited to education levels or general job tasks but consists of detailed worker tasks, knowledge and characteristics. Our most important result is the stylised fact that the number of required skills increases with city size. This outcome is relevant for debates and policies regarding widening regional inequality.

We focus on the spatial variation in skill requirements in jobs vacancies. We use a detailed measure of skills that is based on the extraction of key words from job descriptions in vacancies and includes both hard and soft skills. This way we are able to measure the tasks (e.g. accountancy), knowledge (e.g. spreadsheets) and characteristics (e.g. self-motivation) that are expected in the job. Proximity enables more specialisation. The level of specialisation, meaning that more workers focus on a specific subset of tasks, is higher within cities than between cities. We argue that more specialisation leads to a higher complexity of jobs tasks.

More specialisation lowers productions costs but increases coordination costs. Coordination costs are also lower within cities than between cities. Combined with the effect of a larger labour force this means that specialisation level of jobs will be higher in large cities than in small cities. Workers in large cities are therefore required to master a smaller range of different tasks than workers in small cities (Kok, 2014). However, despite the number of tasks being lower, the complexity of the tasks is higher. A higher specialisation level requires more (tacit) knowledge. Specialised knowledge needs to be combined in order to create a product. Workers in cities therefore need more (coordination) skills. We expect that workers in large cities are required to possess a higher number of skills than workers in smaller cities.

To test this hypothesis, we use data from online vacancies for the Netherlands for the period 2017-2019. Contrary to most datasets about jobs tasks and skill requirements of jobs, our dataset includes individual skill requirements as well as other job characteristics. Each vacancy in the dataset contains information on, occupation, industry, education level, location and some information about the company. The skills data is constructed based on the appearance of key words mentioned in the job description. Skills are measured in four categories: professional skills, soft skills, IT skills and language skills. The complexity of the job is defined by the number of skills that are mentioned in the job description. The more skills a worker is expected to possess, the more complex the job is. We include occupation fixed effects to filter for spatial variation in jobs.

Results show that jobs in large cities on average require about **?**% of a standard deviation more skills than the same jobs in small cities. Workers for the same jobs need less skills in of all skill types in a small city (<2500 addresses per km2) compared to a large city (>2500 addresses per km2). The results are robust for different measures of complexity and spatial units (**?**). We investigate the spatial variation in skill requirements across sub-samples. Moreover, we find that the diversity in the different skills categories is higher in the large cities(**?**).

The main idea of this paper relates to theories about the distinct nature of urban economies. This extensive literature is focused on explaining the productivity premium of large cities and underlines, among other arguments, the deeper division of knowledge that urban areas offer. One strand of the literature argues that workers in large markets are more productive because of the higher specialisation level (Duranton & Jayet, 2011). Another part of the literature argues that workers in cities are more productive because of the lower coordination costs of specialised workers. In this argumentation the size of the market is less relevant (Becker & Murphy, 1992). In this paper, we empirically analyses whether the extent of the local market has an effect on the complexity of jobs and the skill requirements of workers.

Despite the extensive literature studying agglomeration economies, empirical evaluations of the effect of market size on the content of jobs is limited. There are investigations on specific case studies (Baumgardner, 1988; Garicano and Hubbard, 2009) but most studies focus on the variation *between* jobs instead of the variation *within* jobs (Duranton & Jayet, 2011; Bacolod, Blum & Strange, 2009), sectors (for example Davis & Dingel, 2020) or skil groups (Koster & Ozgen, 2021). Our work is in line with two recent studies. Kok (2014) shows that workers in large cities in Germany perform less subtasks and are thus more specialised. Atalay, Sotelo and Tannenbaum (2021) study vacancy data for the US and find that the intensity of interactive and analytic skills is higher in large cities. Furthermore, they show that task specialization increases with city size. Our contribution to the literature lies in the analyses of the spatial variation of job complexity within occupations. Vacancy data offers the opportunity of a detailed analyse of the spatial variation of demand for skills across space.

The rest of the paper is structured as follows. The next section discusses theory and related literature. Section 3 discusses 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

Agglomeration economies

This paper is related to a vast literature on agglomeration economies, that studies the productivity and wage premia of large cites. A part of this literature assumed that the benefits of a higher density would apply to all types of workers, independent of their education level and skills (Combes, Duranton & Gobillon, 2008). In this framework, the observed level of education of workers is commonly assumed to reveal the skills a workers possess. However, because of widening wage and skill inequalities within education groups and also within occupations groups, the need for more detailed information worker heterogeneity is acknowledged (Koster & Ozgen). Davis and Dingel (2019) argue that the difference between jobs that create tradable and jobs that create non-tradable output is important to explain the wage premium of large cities. Workers in jobs that create tradable output benefit from learning externalities because of the idea exchanges in local interactions. The sorting of this kind of jobs creates an important argument for the difference between urban and rural jobs. This approach also implies a more precise perspective on the abilities of workers. Instead of a degree, specific tasks should be studied to analyse the wage and productivity premia of cities. Some studies have tested if urban wages vary with the task content of jobs. Grujovic (2018) shows that the jobs task content explains the differences in urban wage premia across workers with the same education level. Bacolod et al. (2009) find that large cities contain, to a modest degree, more complex jobs than small cities.

Unlike our paper, this literature is mostly focused on differences between occupations or skill (education) groups. Our contribution relative to this studies is attention for the differences within the same occupation. Moreover, we utilise a more precise measure of the abilities that workers are expected to possess. We focus on the part of this literature that is concerned with explaining the distinct nature of work in large cities.

Job complexity in cities

There are several reasons why jobs in large cities might be more complex. First, high skilled workers might sort themselves into large cities. Over de last decades college graduates have increasingly concentrated into dense urban areas (Berry & Glaeser, 2005). A large part of the spatial variation in wages can be explained by worker characteristics (Combes, Duranton & Gobillon, 2008). Large cities have more specialised skill-intensive complex activities (Davis & Dingel, 2020). Workers in larger cities have significantly more occupational options because there are relatively more vacancies and also in the sense that there are more existing professions present (Papageorgiou, 2021). At the same time, this means that employers in large cities can, for the same job, be more explicit in their skill requirements than their competitors in smaller cities. This may lead to a higher accomplished complexity for the same job.

Secondly, firms specialising in more complex activities might 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 performed in large than in small cities (Duranton and Jayet, 2011). At the same time offer cities greater competition which means that only most productive firms survive.

Thirdly, jobs might 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 might 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.

Differences in complexity within occupations

In the previous paragraph we discussed several reasons why jobs in cities might be more complex. However, parts of this arguments mainly apply to differences between occupations. We argue that there is also a spatial difference of job complexity within occupations.

More specialisation of job tasks lowers production costs because of a better allocation of tasks by the most efficient worker (or firm). 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 he is (Becker and Murphy, 1992). For example, the journalist that specialises in foreign affairs will be more efficient in interpreting the latest geopolitical developments. 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, face-to-face contact still makes is easier to form connections. 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 across and within jobs.

The higher specialisation levels that cities enable is revealed by measuring the number of subtasks that worker perform in the same job (Kok, 2014). Workers in larger cities within the same job performs 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. We therefore expect that workers in large cities are for the same job required to possess a higher number of skills than workers in smaller cities.

There are several reasons which might explain the higher complexity of jobs in cities. Spatial variation in complexity might be causes by the production advantages of cities, but also from the sorting of more talented workers. Because of the difficulty to identify causality it is important to keep in mind that these endogeneity problems might create biases. Data limitations and biases are discus in the next section.

3. Data and method

In this paper, we analyse the spatial variation in job complexity by measuring skill demand in online vacancy data for period 2017-2019 for the Netherlands. The data is provided by TextkKernel, 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 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) and skills. The skills data is extracted from the job description. Using an algorithm, every job description is scanned for skills based on extensive list of thousands of keywords and synonyms. Skills are assigned to one of four categories, professional skills, soft skills, IT skills and language skills. We use the number of skills per skill category that is indicated for each vacancy. The list of skills is consistent over the three years in our dataset.

Vacancy data shows the demand for labour in a certain location. Although this data provides detailed information on the demand side of the labour market it has, like any data source, limitations (Carnevale, Jayasundera, & Repnikov, 2014; Kurekova et al., 2015). It should be noted that online job vacancy data cannot be expected to be perfectly representative of all vacancies in the economy. Alternatives to online job postings tend to be used more in lower-skilled occupations. Vacancies for jobs in fast-food restaurants for example, are less likely to be put online. This creates a bias toward high-skilled occupations. Garasto et al. (2021) use Textkernel data for the United Kingdom adjust their dataset based on an official vacancy survey. However, for this study, it is not so much the occupational but the geographical representativeness that is of importance.

It might be argued that there is a difference in job posting behavior between urban and rural regions. In rural regions, employers might for example rely more on personal networks. However, also the opposite can be argued, namely that in a tight rural labour market companies have to do more effort to find the right worker and therefore post more vacancies online. All in all we do not find persuasive arguments to assume spatial biases in vacancies postings in the dataset. Official information about the spatial distribution of vacancies in the Netherlands is available on the level of the 12 provinces. When correlating the official data with the Textkernel data we find adjusted R^2 between 98,4 and 99,3 for the years in our data, which indicates a good geographical representation.

Unfortunately, detailed data on the supply side is not available and it is unknown if vacancies are filled at the moment they are taken off a website. But since we are interested in the differences of skill demand, this does not disturb our analysis.

Measuring job complexity

We use a detailed skills measure that is based on the extraction of key words from job descriptions in online vacancies. Job descriptions are screened based on a list of thousands of skills and their synonyms. and includes both hard and soft skills. This way we are able to measure the tasks (e.g. accountancy), knowledge (e.g. spreadsheets) and characteristics (e.g. self-motivation) that are expected in the job.

The complexity is a job is in principle defined by the quality of the tasks that a worker performs. However, it is notoriously difficult to measure the quality of tasks. Therefore we use the total number of skills as a measure of complexity. This is based in the assumption that higher quality level jobs require more from a worker. More (tacit) knowledge, more communication and more discipline and independence. Employers manifest this by listing more skills.

An important consideration is the idea that employers assume a large number of skills as given when they post a vacancy for e.g. a software engineer. Applicant are of course expected to have extensive knowledge about computers, software programmes, coding etc. The type and quality of skills that are assumed given a certain job title differs from job to job. However, also within an occupation group, employers list a different number of softs skills and hard skills to make sure that applicants match the needs and working environment of their company.

Table 1. indicates that more complex jobs, here measured by education level, require more skills even though their expected qualities of skills is already higher. Jobs that target applicants with a high school degree list on average 3.8 skills while jobs that targets graduates list on average 9.5 skills.

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

Education level	Skills	SD	Observations
0 Unknown	7.36	8.05	311019
1 Elementary	3.12	2.88	45063
2 High School	3.86	3.13	1073871
3	5.08	3.68	2609608
4	5.87	4.22	676679
5	7.66	5.48	1422070
6	7.72	6.28	656881
7 University	9.46	7.69	409403

Empirical strategy

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. We control for the required education level, the size of the organisation. An occupation is defined as a three-digit ISCO occupation. We use the number of skills per vacancy as a measure of job complexity.

(Add)

4. Results

Descriptive statistics

Table 2 and 3 present descriptive statistics for our data (See the appendix for more descriptive statistics). Vacancies of jobs located in the most densely populated municipalities require on average 6.86 skills whereas vacancies in the rural municipalities mention 4.93 skills. The tables in the appendix indicate important differences in the number of required skills per industry and occupation group. Vacancies for managers and professionals mention about four skills more per vacancy compared to operators and assemblers and workers in agriculture.

(Add)

Table 2a. Urbanisation and skills (CBS municipality definition)

Urbanisation level	Skills	SD	Observations
1 urban	6.86	5.80	2574689
2	5.90	4.88	2500793
3	5.44	4.44	953049
4	5.20	4.33	934292
5 Rural	4.93	4.36	241229

Table 2b.

Urbanisation level	IT	SD	Prof	SD	Soft	SD	Lang	SD
1 urban	1.03	2.87	3.38	3.13	2.01	2.06	0.42	0.76
2	0.62	2.09	3.10	2.82	1.81	1.89	0.35	0.70
3	0.45	1.67	2.95	2.67	1.69	1.83	0.33	0.68
4	0.37	1.48	2.86	2.66	1.62	1.79	0.33	0.69
5 Rural	0.30	1.29	2.73	2.70	1.60	1.80	0.29	0.66

Table 3a.

Urbanisation level	1 analytical non-routine tasks	SD	2 interactive non-routine tasks	SD	3 cognitive routine tasks	SD	4 manual routine tasks	SD	5 manual non-routine tasks	SD
1 urban	8.91	6.95	5.47	4.50	6.68	5.03	4.25	3.80	5.16	3.79
2	8.10	6.15	5.01	4.00	5.99	4.44	3.87	3.29	5.04	3.57
3	7.75	5.71	4.92	3.91	5.61	4.21	3.75	3.05	4.84	3.49
4	7.86	5.64	4.80	3.94	5.35	4.24	3.59	2.99	4.69	3.44
5 Rural	7.75	6.00	4.57	4.01	4.94	4.44	3.41	2.79	4.56	3.38

Regression results

We estimate different models in which we analyse the spatial variation in the number of required skills. Colum one presents the estimates of the simplest model in which we include fixed effects and dummy indication whether the job is located it an urban area or not. As expected, jobs in urban areas require more skills than jobs in small towns.

The number of required skills varies a across other job characteristics as well. The spatial distribution of job vacancies is unequal, large firms are overrepresented in urban areas. The same holds for the spatial distribution of job vacancies for highly educated workers. The second and third column indicate that jobs at larger firms and jobs that require a high education also require more skills.

(City: CBS code 1 (/5), Organization size: > than 50, Education level: > HBO)

Table 4. Regression results.

	Dependent: number of skills per vacancy		
	Model 1	**Model 2**	**Model 3**
(Intercept)	6.354***	6.203***	5.661***
	(0.214)	(0.214)	(0.213)
City (dummy)	0.464***	0.471***	0.426***
	(0.004)	(0.004)	(0.004)
Organization size (dummy)		0.314***	0.314***
		(0.004)	(0.004)
Education level (dummy)			1.137***
			(0.005)
Observations	6557207	6557207	6557207
R2 Adj.	0.192	0.193	0.199

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

5. Further analysis

-Analysis for different occupations groups / (and education levels)

-Analysis for different routine/ non routine groups

-Analysis of alternative spatial units

6. Conclusion

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). AI and jobs: Evidence from online vacancies (No. w28257). National Bureau of Economic Research.

Atalay, E., Sotelo, S., & Tannenbaum, D. I. (2021). The Geography of Job Tasks. Working paper.

Azar, J., Marinescu, I., Steinbaum, M., & Taska, B. (2020). Concentration in US labor markets: Evidence from online vacancy data. *Labour Economics, 66*, 101886.

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

Baumgardner, J. R. (1988). 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.

Blair, P. Q., & Deming, D. J. (2020, May). Structural Increases in Demand for Skill after the Great Recession. *AEA Papers and Proceedings* (Vol. 110, pp. 362-65).

Carnevale, A. P., Jayasundera, T., & Repnikov, D. (2014). Understanding online job ads data. Georgetown University, Center on Education and the Workforce, Technical Report.

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

Davis, D. R., & Dingel, J. I. (2019). A spatial knowledge economy. *American Economic Review, 109*(1), 153-70.

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

Deming, D., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics, 36*(S1), S337-S369.

Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics, 135*(4), 1965-2005.

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.

Harmon, N. A. (2013). Are Workers Better Matched in Large Labor Markets?. Job market paper, Princeton University.

Hershbein, B., & Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review, 108*(7), 1737-72.

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.

Kuhn, P., & Skuterud, M. (2004). Internet job search and unemployment durations. *American Economic Review, 94*(1), 218-232.

Lin, J. (2011). Technological adaptation, cities, and new work. Review of Economics and Statistics, 93(2), 554-574.

Papageorgiou, T. (2020). Occupational Matching and Cities. *American Economic Journal: Macroeconomics*, forthcoming.

Prüfer, J., & Prüfer, P. (2020). Data science for entrepreneurship research: studying demand dynamics for entrepreneurial skills in the Netherlands. *Small Business Economics, 55*(3), 651-672.

Appendix

Descriptive statistics

	% without skills
Total	4.2
IT	78.7
Prof	12.7
Soft	32.3
Language	73.3

Skills per ISCO Code and Education level.

ISCO	Total	SD	Observations
1. Managers	8.25	6.22	505554
2. Professionals	8.09	6.52	1559282
3. Technicians	6.62	4.82	1084860
4. Clerks	5.43	4.30	787042
5. Service and sales	4.36	3.37	762416
6. Agricultural	3.59	2.65	78310
7. Craft and trade	5.77	3.89	1012176
8. Operators and assemblers	3.60	2.84	322155
9. Elementary	3.2	2.65	445412
NA	5.17	4.99	647387

ISCO	**IT**	SD	**Prof**	SD	**Soft**	SD	**Lang**	SD	Observations
1. Managers	0.78	2.20	4.31	3.74	2.64	2.34	0.50	0.85	505554
2. Professionals	1.99	4.01	3.62	3.25	2.07	2.09	0.39	0.73	1559282
3. Technicians	0.60	1.59	3.47	2.87	2.15	2.02	0.38	0.73	1084860
4. Clerks	0.40	0.96	2.72	2.45	1.75	1.88	0.55	0.87	787042
5. Service and sales	0.13	0.63	2.06	1.88	1.82	1.80	0.34	0.71	762416
6. Agricultural	0.06	0.35	1.92	1.63	1.44	1.52	0.16	0.43	78310
7. Craft and trade	0.11	0.69	3.95	2.88	1.43	1.57	0.26	0.58	1012176
8. Operators and assemblers	0.04	0.33	2.21	2.04	1.08	1.36	0.26	0.54	322155
9. Elementary	0.02	0.26	1.83	1.82	1.15	1.38	0.27	0.53	445412
NA	0.53	1.83	2.54	2.78	1.76	1.96	0.32	0.70	647387

Skills per education level

Education level	Skills	SD	Observations
0 Unkown	7.36	8.05	311019
1 Elementair	3.12	2.88	45063
2 High School	3.86	3.13	1073871
9 MBO	5.08	3.68	2609608
10 MBO/HBO	5.87	4.22	676679

11 HBO	7.66	5.48	1422070
12 HBO/WO	7.72	6.28	656881
13 WO	9.46	7.69	409403

Education level	**IT**	SD	**Prof**	SD	**Soft**	SD	**Lang**	SD
0	1.66	4.09	3.30	3.92	1.90	2.39	0.48	0.92
1	0.08	0.79	1.76	1.83	1.00	1.37	0.26	0.57
2	0.08	0.62	2.23	2.15	1.28	1.49	0.25	0.55
9	0.24	0.92	2.89	2.48	1.61	1.71	0.33	0.66
10	0.54	1.47	2.99	2.49	1.94	1.93	0.38	0.73
11	1.25	2.92	3.65	2.99	2.29	2.09	0.46	0.80
12	1.79	3.72	3.43	3.24	2.09	2.13	0.40	0.75
13	1.25	3.30	5.11	4.37	2.59	2.41	0.49	0.85

Skills and firm size

Firm size	Skills	SD	Observations
0 Unkown	5.53	5.56	1049116
1 1-9	6.19	5.03	1519546
2 10-49	6.35	4.90	892403
3 50-199	6.17	4.71	855532
4 200-499	6.69	5.10	513547
5 500-599	6.61	5.07	349315
6 1000+	5.79	5.24	2025135

Firm size	IT		SD	Prof	SD	Soft	SD	Lang	SD
0 Unkown	0.83		2.64	2.72	2.93	1.64	1.97	0.33	0.71
1 1-9	0.82		2.51	3.20	2.81	1.78	1.89	0.38	0.72
2 10-49	0.86		2.55	3.19	2.72	1.88	1.91	0.40	0.74
3 50-199	0.67		2.10	3.22	2.76	1.86	1.87	0.40	0.73
4 200-499	0.69		2.24	3.51	2.98	2.04	1.97	0.42	0.76
5 500-599	0.62		2.04	3.55	3.07	2.10	1.96	0.33	0.68
6 1000+	0.50		1.87	3.08	3.01	1.84	1.96	0.35	0.70