Master Urban and Economic Geography
Master thesis: guided research abroad

Final version

Demand for high-skilled workers concentrates in large cities

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ABSTACT Cities are skill magnets. Over the last decades college graduates have sorted themselves in large cities, resulting in growing spatial inequality. But why do high-skilled individuals increasingly move to large cities? This study utilizes online vacancies as a new data source to test the hypothesis that demand for high-skilled workers disproportionately concentrates in large cities. We advance scaling analysis by using the number of jobs instead of population size as scaling measure. Results strongly confirm our hypothesis. In general, labour demand concentrates in cities, but findings reveal significant differences between low- and high-skilled workers. Spatial concentration of demand in cities increases as skill levels increase. Demand for workers with a master's degree disproportionally concentrates in larger cities compared to demand for workers with a high school diploma. Findings suggest that the growth of spatial inequality is connected to education and skill-levels.

KEYWORDS: scale, skills, concentration, cities, vacancies

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1. Introduction

Cities are skill magnets. While knowledge and skills have become increasingly important in thriving economies, the workforce which embodies this knowledge and capabilities have become increasingly mobile. However, this has not led to economic convergence but rather to a growing spatial divergence (Florida, 2017, Moretti, 2012). In the Netherlands for example, large cities are growing substantially while border areas are confronted with population decline. Technological development, globalization and the reorganization of production and service firms are not only reshaping the labour market (Autor & Dorn, 2013) but also the role of (large) cities as focal points of economic growth and human capital cumulation. Some scenarios about the future of work predict mass unemployment as a result of skill mismatch (Autor, 2010; Moretti, 2012), but we know that larger cities are likely to emerge as the winners of this development if they attract enough skills and talent. In today's knowledge-intensive global economy, cities can only compete by accessing a global labour market and attracting and retaining high-skilled workers (Glaeser & Resseger, 2010). This suggests a growing divergence in demand for skilled workers between large and small cities. Empirical evidence supports this hypothesis. Over the last decades college graduates have increasingly moved to high-wage, high-rent cities (Diamond, 2016; Berry & Glaeser, 2005).

But why do high-skilled individuals concentrate in large cities? We build upon recent work (Balland et al., 2020) that combines insights from economic complexity literature with work on urban scaling to unpack this question. In the first stream of literature, the complexity of economic activities is pointed out as the driver of economic growth (Hidalgo & Hausmann, 2009; Hidalgo, 2015). 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 (Bettencourt et al, 2007; Bettencourt & West, 2010; Bettencourt, 2013; Youn et al., 2016; Van Raan et al., 2016). However, this superlinear scaling differs across economic activities.

Empirical evidence suggests that the concentration of economic activities increases with their complexity (Balland et al., 2020). More complex activities require more specialization, forcing workers to focus their skills and expertise. This deepening division of knowledge creates high coordination costs as it becomes more difficult to find and combine workers with the required highly specialised skills. Larger cities are better in solving these coordination problems by creating more matching opportunities between workers and companies, which also causes productivity premiums (Dauth et al., 2018; Andersson et al, 2007; Scott & Storper, 2015; Bettencourt, 2013).

This leads to the assumption that high skilled individuals move to larger cities because urban systems create better matches between their skills and complex knowledge intensive jobs. As a result, demand for high-skilled labour will be larger in larger cities. Furthermore, urban economies thrive on knowledge spill-over mechanisms that are dependent on the availability of a high-skilled workforce (Glaeser et al., 1992, Neffke & Henning, 2013, Neffke, Hartog, Boschma & Henning, 2018). Spin-offs and innovation are unthinkable without a high skilled labour pool (Klepper, 2001; Leiponen, 2005). Moreover, specialized institutions for both public and private research and development, which train and attract high-skilled workers, are concentrated in cities (Feldman & Florida, 1994). Together these forces lead to the hypothesis that there is a difference in the demand for low-skilled and high-skilled workers between large and small cities. Whereas demand for low-skilled workers is spread out over both small and large cities, demand for high-skilled workers will disproportionately concentrate in larger cities because of their ability to specialize in skill intensive activities. We expect linear or sublinear scaling in demand for low skilled workers and superlinear scaling in demand for high skilled workers.

In labour economics, a matching function is often used to describe the process of jobseekers finding a vacancy that matches their capabilities. Usually it is found that this function has constant returns to scale: when the unemployment rate and the vacancy rate increase with the same percentage the number of employment contracts also increases with this percentage (Petrongolo & Pissarides, 2001). Petrongolo and Pissaridedes (2006) for example, did not find evidence for a scaling effect of the size of the local labour market. The suggestion that there is no difference between urban and rural job markets has caused curiosity because of the assumption that urban labour markets are more efficient because of their density (for example: Gautier & Teulings, 2009). We expect scaling effects in the number of vacancies in urban areas because of the higher specialization and expertise levels that can be reached in cities because of their density.

In the next sections we introduce the dataset and explore the link between spatial concentration and skill levels by using information from two million online vacancies. We use the required education levels to measure the skill intensity and utilize the locations of the vacancy to measure concentration. In scaling literature, it is common to use population size as a measure of scale (e.g. Bettencourt, 2013). However, because we are using vacancy data, the number of jobs in a city is more relevant as a scaling measure to investigate the relationship between skill level and concentration. We extend our analysis by investigating scaling laws by using the number of vacancies and the number of current workers in 12 occupations groups.

Our findings show that demand for all types of workers concentrates in cities. However, significant differences are found in the spatial concentration of demand for low- and high-skilled workers. Spatial concentration in demand increases as skill levels increase. Demand for workers with a university degree concentrates disproportionally in larger cities compared to demand for workers with elementary education or a high school diploma. These findings contribute to our understanding of the growing spatial division between high- and low-skilled workers. Differences in education levels contribute to growing spatial inequality, this urges policymakers and planners to consider the role of (access to) education in growing spatial inequality.

2. Data and methods

This study analyses the spatial concentration of demand for labour by using online vacancy data for the years 2017 and 2018 for the Netherlands. The terms cities and urban areas are used interchangeably but refer to the 35 labour market areas of the Netherlands which are used in the analysis. These labour market areas are, like Core Base Statistical Areas (CBSA's) 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 Netherlands is a relatively small and densely populated country, which is why the differences between cities and their surrounding areas is relatively small compared to for example the United States. Given this dataset, analysis at the level of labour markets is more reliable than using municipalities because agglomerations like Amsterdam and Rotterdam cover more than one municipality. Moreover, workers are highly mobile and commute from one municipality to another but less so between labour market areas.

Online vacancy data is provided by TextKernel, an Amsterdam-based company which uses Artificial Intelligence to collect online vacancies. The technique is advanced to a level in which virtually all online vacancies are captured. Extensive data cleaning was needed to remove multiple postings (both time and platform wise) of the same vacancy. Furthermore, we removed vacancies with missing information regarding location and required education. In total, we analyse 2.218.776 vacancies. Original vacancy data observations included fourteen education levels, we combined all six different high-school diplomas into one variable, resulting in a total of eight ascending education levels. The data does not differentiate between bachelor and master's degree, but it is common to require a master's degree in vacancies in the Netherlands.

Although vacancy data provides detailed information on the demand side of the labour market it has, like any data source, limitations (Carnevale, Jayasundera, & Repnikov, 2014). In this case, the dataset might be slightly biased towards high-skilled labour because vacancies for low-skilled jobs, for example in fast-food restaurants, are less likely to be put online. This limitation is unlikely to have a large effect on our results since there is no reason to assume spatial patterns in vacancies that might be underrepresented in the dataset. Furthermore, a growing number of people (over a million workers) in the Netherlands is (solo)self-employed. For these types of jobs, no vacancies are put online. Instead, many of these workers offer their services to find assignments through personal networks. However, the fact that there is other demand for labour in the form of specific tasks does not influence scaling relationships between vacancies and the number of jobs. Vacancy data shows the demand for labour in a certain location. Detailed data on the supply side is not available and it is unknown if vacancies are filled at the moment they are taken of the website. However, because we removed double postings for the same job, analysis of demand for labour is not affected.

We use employment data from LISA, which provides the number of workers per municipality per year and aggregate this data to labour market areas. For employment in specific occupations (Fig 2.), 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. We use the International Standard Classification of Occupations (ISCO) information to compare the demand and the existing number of workers in different occupations classes in figure 2. However, the presented occupation classes are not ISCO classes but follow the division of the information on existing employment data for labour market areas in the Netherlands.

3. Results

Our first main finding is that vacancies disproportionally concentrate in cities. Scaling laws in cities can be written in the form $y = x^{\beta}$. x represents the number of jobs in labour market areas, y is the number of vacancies while β is the scaling exponent. The number of vacancies grows as the $\beta=1.09$ ($R^2=0.94$ std. err 0.04) power of the number of jobs. This means 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: there are 505 vacancies per 1000 jobs in the labour market area Amsterdam compared to 293 vacancies per 1000 jobs for the rural labour market area Drenthe. We unpack this result by utilizing vacancy information about required education levels and occupation types.

Figure 1 shows scaling relationships between vacancies divided in 8 ascending levels of required education and the total number of jobs in 35 labour market areas in the Netherlands. For the three lowest education levels we observe sublinear scaling. The number of vacancies requiring elementary education (Fig. 1a) grows as the $\beta=0.68$ power of the number of jobs. The exponent for high school education (Fig. 1b) is $\beta=0.91$ while the exponent for Intermediate Vocational Education (Dutch: MBO) (Fig. 1c) lies close to 1 ($\beta=0.98$). The number of vacancies per 1000 jobs for these lower-skill education levels is lower in urban areas than in rural area.

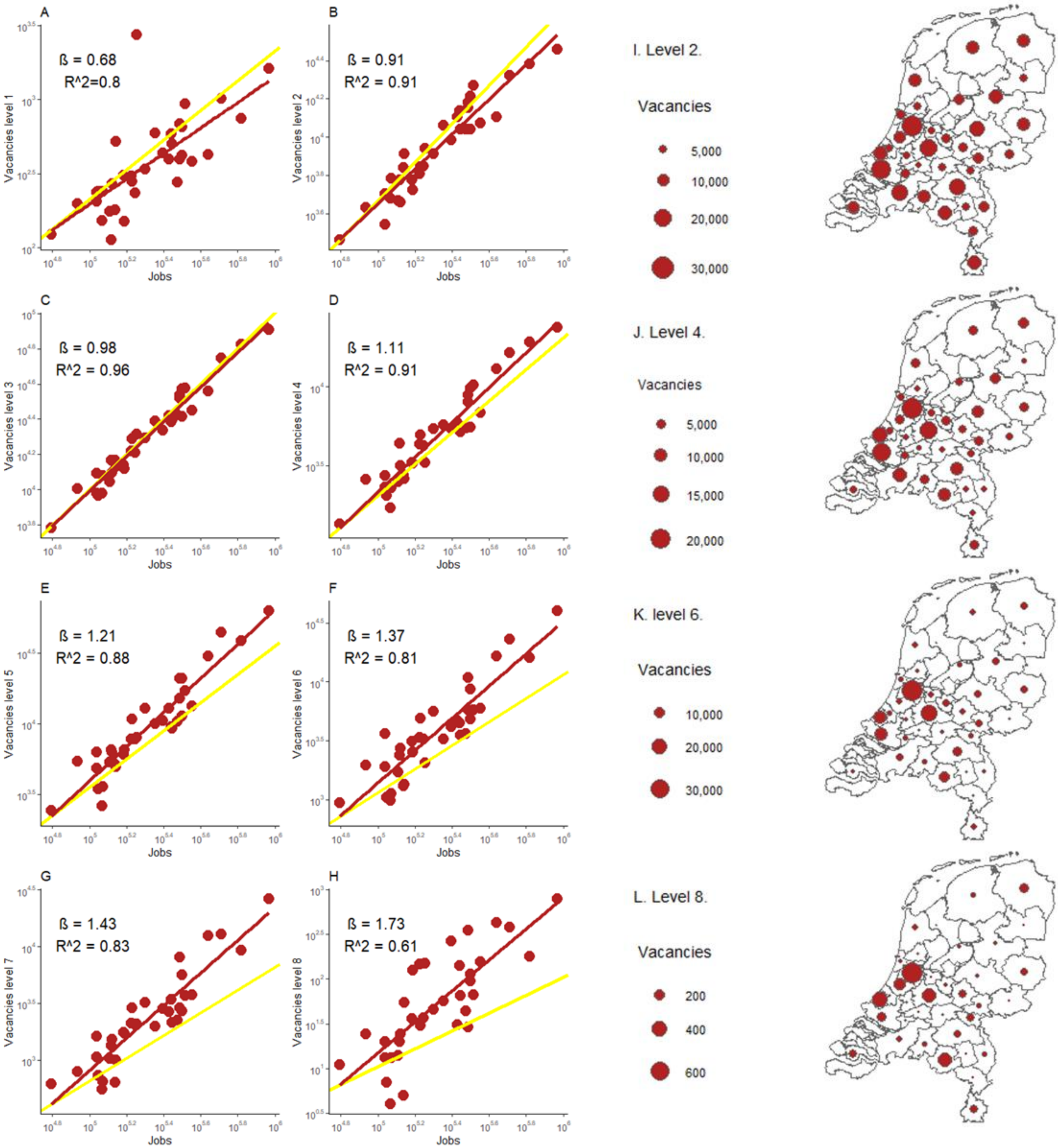

Fig. 1. **Spatial concentration of demand**. **a-h,** scaling relationships between 8 ascending levels of required education in vacancies per labour market areas and the total number of jobs in 2018 in the Netherlands: level 1: Elementary (**a**), level 2: high school (**b**), level 3: Intermediate vocational education (Dutch: MBO) (**c**), level 4: Intermediate vocational education / Higher Vocational Education (Dutch: MBO/HBO) (**d**), level 5: Higher Vocational Education (Dutch: HBO) (**e**), level 6: Higher Vocational Education / University degree (Dutch: HBO/WO) (**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 level 2 (**i**), 4 (**j**), 6 (**k**), and 8 (**l**).

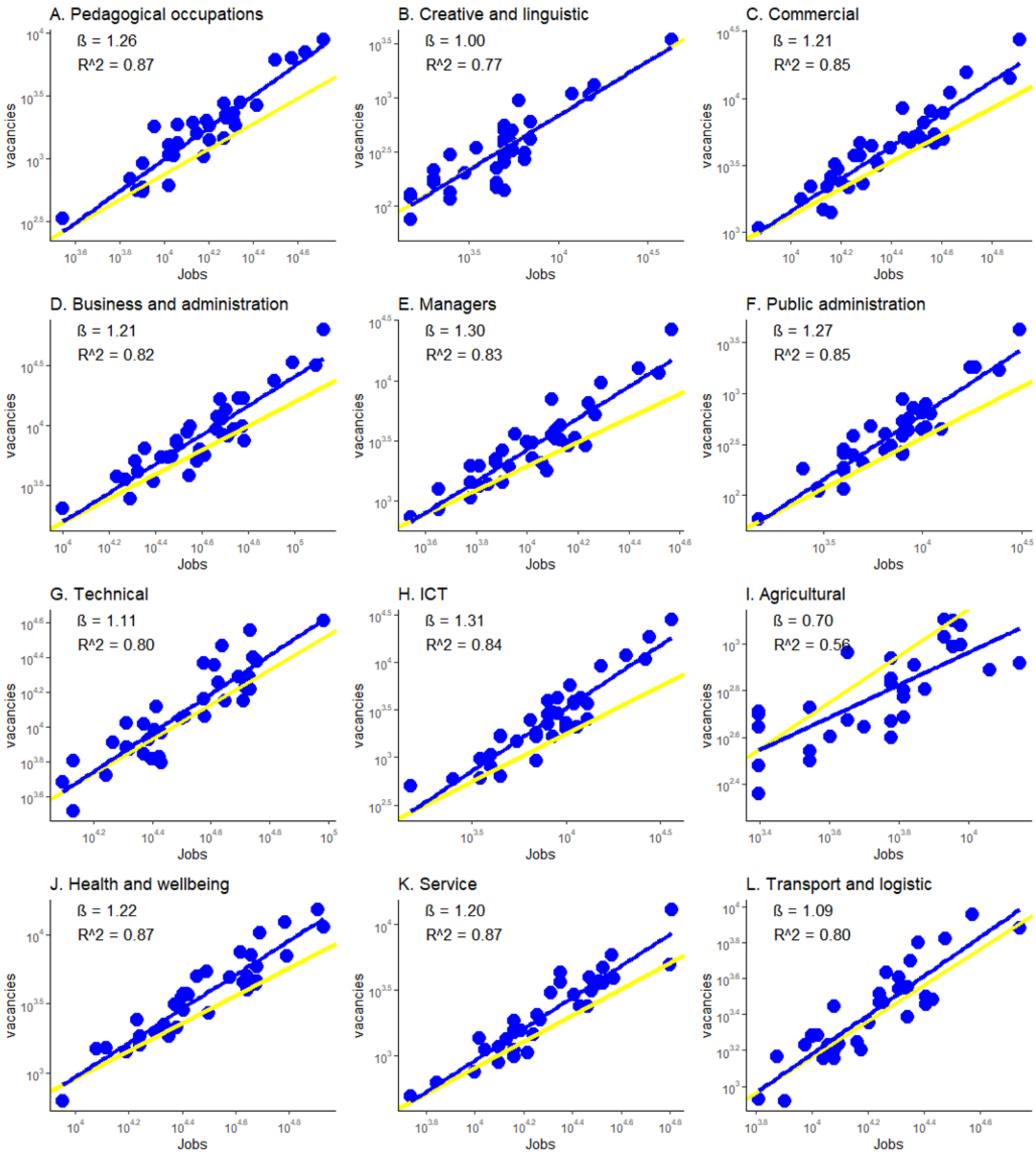

Fig. 2. Spatial concentration of demand for specific sectors. **a-l**, scaling relationships between the number of vacancies in a sector and the number of existing jobs in that sector per labour market area in the Netherlands (average for 2017-2018). The yellow lines show the situation in which the scaling relationship is linear.

The five remaining education levels show increasing concentration effects as the level of education increases. Scaling increases from β=1.11 for vacancies in either Intermediate vocational education or Higher Vocational Education (Dutch: MBO/HBO) (Fig. 1d), β=1.21 for Higher Vocational Education (Dutch: HBO) (Fig. 1e), β=1.37 for Higher Vocational Education or a university degree (Dutch: HBO/WO) (Fig. 1f), to β=1.43 for University degree (Fig. 1g). Although the number of vacancies that requires a PhD is relatively small, the scaling effect is large as the demand for workers with a PhD degree grows with an exponent of β=1.73. Scaling levels of vacancies increase with the required level of education.

Figure 1 i-l shows the spatial concentration of demand for 4 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.

It might by argued that urban labour markets are different from rural labour markets in the sense that it is more difficult to fill certain vacancies because of greater competition between firms, especially for job openings requiring high education levels. To control for this effect, we included the average duration in days that a vacancy is kept online as an explanatory variable. Results show negligible differences in scaling exponents.

We extend our analysis by studying scaling laws for specific occupation groups. Figure 2 shows the scaling relationships between the number of vacancies and the number of existing jobs for twelve occupation groups. 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. For a precise analysis we use existing number of jobs per occupation as scaling measure instead op population or the total number of jobs. Because of data availability we use the average number of workers and vacancies for the years 2017 and 2018.

Ten out of twelve occupation groups show superlinear scaling. Vacancies in sectors which can be intuitively expected to require high education levels like ICT (β=1.31), managing (β=1.30) and public administration (β=1.27) concentrate most. Vacancies in transport and logistics (β=1.09), creative and linguistics (β=1) and agriculture (β=0.7) concentrate least. Sublinear scaling for vacancies in agriculture is in line with expectations since jobs in this sector are almost by definition located outside urban areas. In addition to Figure 1, Figure 2 shows that the number of vacancies per 1000 workers in a specific sector is higher in 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.

In the appendix we show scaling relationships between vacancies in 38 occupation groups and the total number of all jobs in labour market areas. The findings are in line with the results presented in figure 2. 26 groups show superlinear scaling. Occupation groups that show sub-linear scaling typically require lower skill levels and/or manual labour.

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

4. **Discussion**

The central idea of this study is that the required skill levels explain the variations in the degree to which demand for labour agglomerates. Our findings show this hypothesis to be true for labour demand measured in vacancies in the Netherlands. In contrast with a matching function that assumes constant returns to scale, we find that vacancies disproportionally concentrate in cities. We observe sublinear scaling for low skilled-workers and superlinear scaling for high-skilled workers. Demand concentration increases as required skill levels increase. The results are in line with theories which suggest that economic activities tend to concentre in cities because they require more specialisation (Balland et al., 2020). Tasks are increasingly too complex to be performed by a single worker or a single team, instead, the required knowledge and skills are spread out over multiple workers or teams. Large cities are better in creating a match between highly specialised tasks and actors with the required skills and expertise (Hidalgo, 2015).

In a world of digital communication, the location of a vacancy does not necessarily have to match the location where the actual work is carried out. However, demand for workers in the occupation group which can be assumed to be most footloose, ICT, shows strong scaling effects. The companies that offer work which can be carried out remotely still concentrate, which suggest that local communication and face to face contact is important in accomplishing complex tasks. More generally, the strong observed concentration in demand for the highest skilled workers points towards the importance of local knowledge spill overs. The knowledge to perform complex tasks is often tacit and spread best over relative short distances through social networks (Hidalogo, 2015, Farinha et al., 2019) and job changes (Neffke & Henning, 2013). Innovation and productivity growth are driven by these local spillover mechanisms. This means that cities, in which these mechanisms can thrive through public and private research institutions, are the focal point of future economic development.

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 mechanism behind the relative higher number of all vacancies in urban areas is not yet explained. We briefly mention three complementary explanations which should be the topic of further investigation. Firstly, it might be that workers in urban areas change jobs more often than workers in rural areas, which is in line with the better matching function of cities. Secondly, it can be that companies in urban areas generate and terminate more jobs per worker than companies in rural areas, this is in line with the finding that firms with fluctuating employment tend to cluster (Overman & Puga, 2012). A third explanation might lay in replacement hiring. Vacancies that are filled create often new vacancies. In urban areas this vacancy chain can grow longer because of the larger labour pool (Mercan & Schoefer, 2020).

The finding that demand for labour concentrates which education levels raises important questions for planner and policy makers. On an individual level, it means that access to higher education is and will become increasingly decisive for the workforce of the future. On a collective level, this study confirms the hypotheses that the economic efficiency that cities bring, comes with growing spatial inequality. Demand for labour does not only concentrate in cities, but sparsely populated areas have also relatively more vacancies for low skilled workers while demand for high-skilled labour is higher in cities. This means that cities have 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. When it is attractive for high-skilled workers to move to large cities, there will be fewer high-skilled workers in rural areas. This creates inequality between rural and urban areas. At the same time, the share of high-skilled workers in cities is likely to grow, as cities have relatively fewer jobs for low skilled workers. This means that inequality is also growing within cities.

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. This might mean that current (urban) policies on housing, transportation, densification and access to amenities that assume equal growth over space and do not consider growing spatial inequality, need rethinking. Some scenarios of the future of work predict mass unemployment as the result of technological change, automation and skill-mismatch (Autor, 2010; Moretti, 2012). The results of this study confirm the assumption that these developments will be unequal across space (Shutters et al., 2015). Policy should therefore aim to control spatial inequality and anticipate both positive and negative outcomes on the (inter)national, regional and local level.

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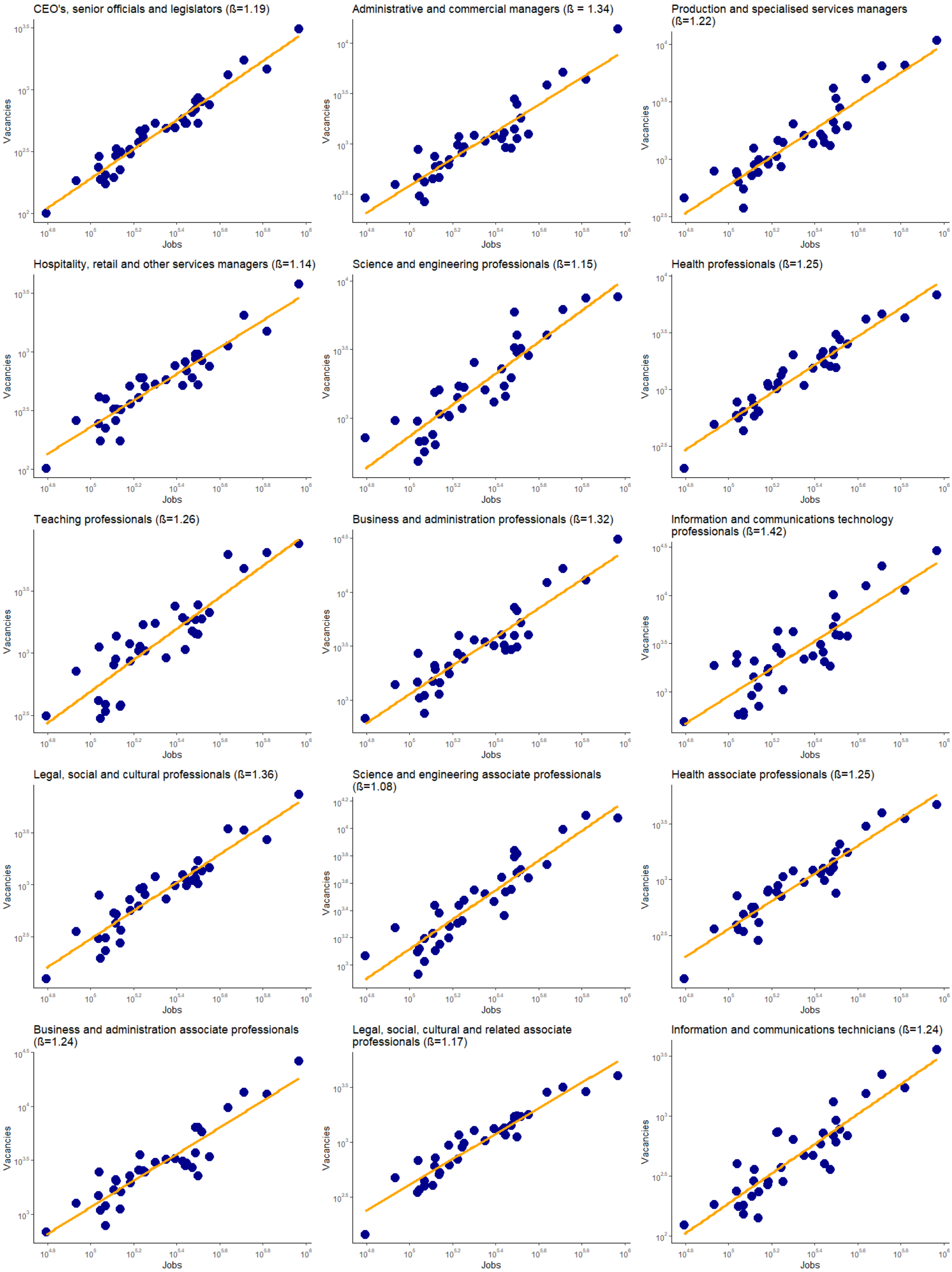
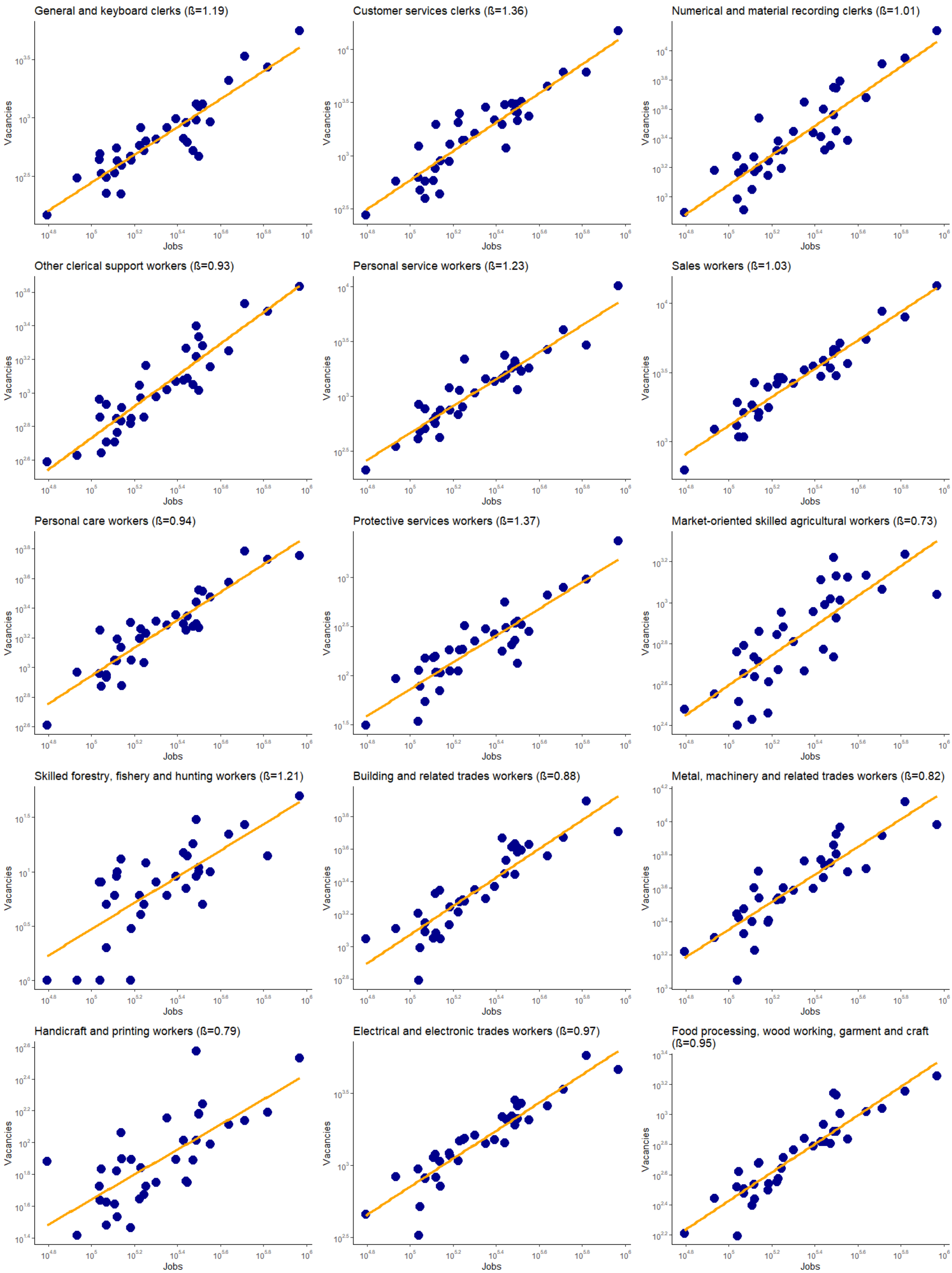
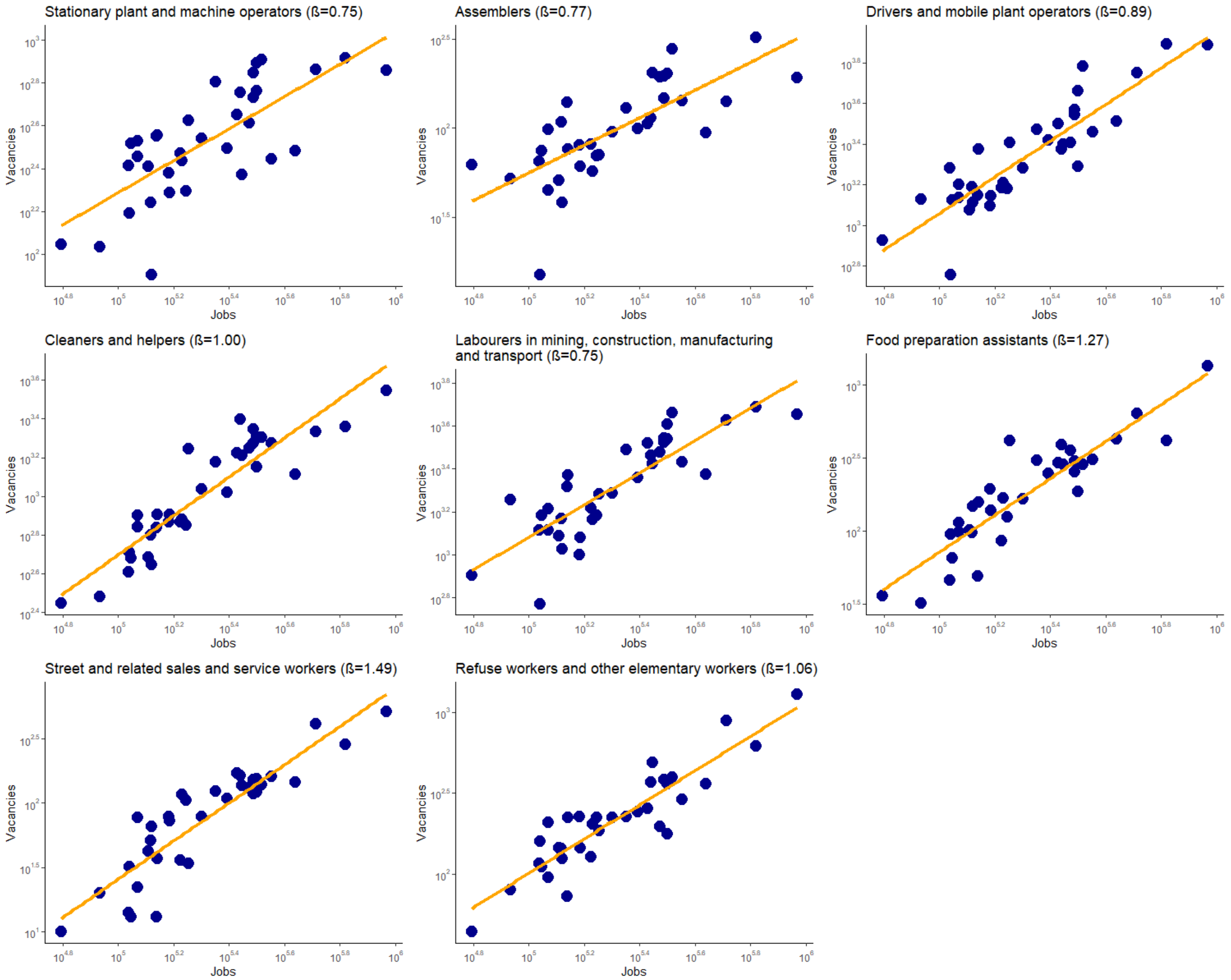
Appendix

Urban scaling of specific occupation groups

The scatter plots show the relation between the number of workers in an labour market area and the number of vacancies in 2-digit ISCO occupations for 2018.




General and keyboard clerks (ß=1.19)
Customer services clerks (ß=1.36)
Numerical and material recording clerks (ß=1.01)
Other clerical support workers (ß=0.93)
Personal service workers (ß=1.23)
Sales workers (ß=1.03)
Personal care workers (ß=0.94)
Protective services workers (ß=1.37)
Market-oriented skilled agricultural workers (ß=0.73)
Skilled forestry, fishery and hunting workers (ß=1.21)
Building and related trades workers (ß=0.88)
Metal, machinery and related trades workers (ß=0.82)
Handicraft and printing workers (ß=0.79)
Electrical and electronic trades workers (ß=0.97)
Food processing, wood working, garment and craft (ß=0.95)
Vacancies
Jobs


Stationary plant and machine operators (ß=0.75)
Assemblers (ß=0.77)
Drivers and mobile plant operators (ß=0.89)
Cleaners and helpers (ß=1.00)
Labourers in mining, construction, manufacturing and transport (ß=0.75)
Food preparation assistants (ß=1.27)
Street and related sales and service workers (ß=1.49)
Refuse workers and other elementary workers (ß=1.06)
Vacancies
Jobs