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Non-routine activities and the within-city distribution of jobs

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Abstract

Externalities are believed to drive the productivity benefits of cities, and also of dense sub-parts within cities, e.g. the central business district (CBD). Recent research claims that density externalities accrue mostly to non-routine activities, and that their effects - e.g. human capital spillovers - attenuate sharply with distance. Consistent with these claims, I demonstrate strong clustering tendencies in non-routine professions as evidenced by job-switching patterns, specifically switchers' distances moved between employers. Individual-level geo-coded data for switchers within Sweden's metropolitan areas are used to illustrate that employees hired to non-routine occupations tend to switch to jobs close to the previous work establishment, while blue collar workers show dispersion. The differences are chiefly explained by i) non-routine activities concentrate in the CBD (the strongest effect) and local employment centers, ii) non-routine activities cluster also outside of centers, and iii) industry-specific effects. The patterns are consistent with the importance of sharply attenuating non-market interactions (e.g. knowledge spillovers) in the production of non-routine products and services.

1. INTRODUCTION

Cities are increasingly understood as arenas for reducing interaction costs, as opposed to units economizing on the transportation costs of goods (Glaeser & Kohlhase, 2003). One suggested reason for this development is the alleged increased role of human capital externalities in production - a role that emphasizes the benefits of productive interaction, the extent of which is often proxied by local density levels.

The city has public good like characteristics in the mediation of knowledge, but the magnitude varies across the urban landscape, and also matters differently depending on whether the task to be performed is intensive in its use of knowledge as an input. The empirical literature on human capital externalities has established two main stylized facts: first, spillovers attenuate sharply with distance, and second, local density matters more in so-called non-routine - or interactive - occupations (Andersson, Klaesson, & Larsson, 2014; Bacolod, Blum, & Strange, 2009; Rosenthal & Strange, 2008).

These findings imply a spatial equilibrium where knowledge-intensive[1] occupations cluster to each other and to the central business districts (CBDs) to take advantage of productivity gains that depreciate with space, and hence imply increasing returns to local density. Such clustering is consistent with an internal city structure where e.g. financial districts almost invariably are located in the center of cities, while capital intensive production is generally located in the outskirts of urban areas. If these arguments are correct, there is a built-in mechanism favoring stronger spatial concentration and CBD orientation in non-routine occupations, owing to the spatial concentration of the spillovers. Hence, theories of human capital externalities and their attenuation with space predict within-region clustering of functions at the neighborhood level.

If central land is a commodity that contributes to the production function of workers in non-routine professions, then within-city clustering of such work tasks is predicted by a simple bid-rent framework. The original bid-rent observation that capital-intensive production requires space and is pushed to the outskirts by rents (cf. Alonso, 1960) is observationally equivalent with knowledge-intensive production being pushed to the center by increasing returns to density. If non-routine workers and activities are employed in tighter within-city clusters, then workers switching jobs should find prospective employers closer to their current employer, all else equal. The empirical section of this paper tests this prediction using data on job-switching distances from the old to the new employer, by occupation group, in Sweden's metropolitan areas: Gothenburg, Malmö, and Stockholm. Switchers' distances are used as

[1] A "knowledge-intensive" production process may simply be thought of as one that intensively utilizes human capital (or knowledge more generally) as an input.

dependent variable, under the assumption that such flows inform about clustering tendencies by occupation. I also include variables to investigate how the between-occupation differences relate to the CBDs and local density, local employment centers, clustering outside the CBD, and industry-specific effects, among other determinants in the pertinent metropolitan landscape.

Why is this question important? First, occupation clustering at the neighborhood level has implications for planning of the built environment, zoning laws, infrastructure projects and so on. Second, the issue bears directly on the productivity of cities. Job-switching overlaps two micro foundations of agglomeration economies (e.g. Duranton & Puga, 2004): i) learning: the knowledge flows that individual workers bring with them to their new employer, and ii) matching: increased productivity through specialization in thick markets, implying a feedback mechanism. To the extent that job-switching is a neighborhood phenomenon (the best matches are nearby) then so is, at least in part, externalities contingent on job-switching, including human capital spillovers. If sharp attenuation of human capital spillovers induces clustering and localization of the labor force, then localized job-switching rates follow and could in fact further contribute to the within-city clustering. We may thus understand localized job-switching as part of a circular causation, driving clustering of interactive activities and workers.

A job-switch in a database registers the flow that over time makes up the city's geography of jobs. Why not simply use the resulting distribution? First, there is inertia in full distributions, due to e.g. costs of relocation, meaning that powerful posterior distributions may conceal interesting year-by-year dynamics. Second, job-switchers may serve as an indication of optimization decisions (for all matched parties) based on current market conditions. From this point of view, the creation of some number of new matches says more about an area than does knowledge of the existence of the same number of pre-existing matches. Cluster development (e.g. formation) related issues are generally better analyzed in a flow, compared to a stock, framework.

1.1 Background and motivation

The 20th century has seen a relative decrease of blue collar jobs performed in cities, and a corresponding increase of professions involving thought, communication, and analytical tasks (Rauch, Michaels, & Redding, 2013). Such job tasks are sometimes referred to as "non-routine", meaning that they require induction to be solved, and cannot in general be routinized by *if-then* type algorithms (Autor, Levy, & Murnane, 2003; Levy & Murnane, 2004). Consistent with interdependence in the development of non-routine job tasks on the one hand and agglomeration gains on the other, Glaeser and Kahn (2001) show that the introduction of the automobile to the broad masses tended to decentralize American employment, with the exception of knowledge-intensive industries. Common for tasks carried out in such industries is that they tend to be non-routine, intensive in the degree to which they benefit human capital externalities, and that they consistently exhibit higher returns to density (Andersson et al., 2014; Bacolod et al., 2009) These tasks are aptly performed in dense environments, because such environments facilitate knowledge accumulation, implying that fewer inputs have to be replicated in production. If an input (knowledge) can be replicated without cost, homogeneity of degree one is no longer a binding assumption about the production function, and constant returns to scale no longer a constraint on growth (cf. Romer, 1986).

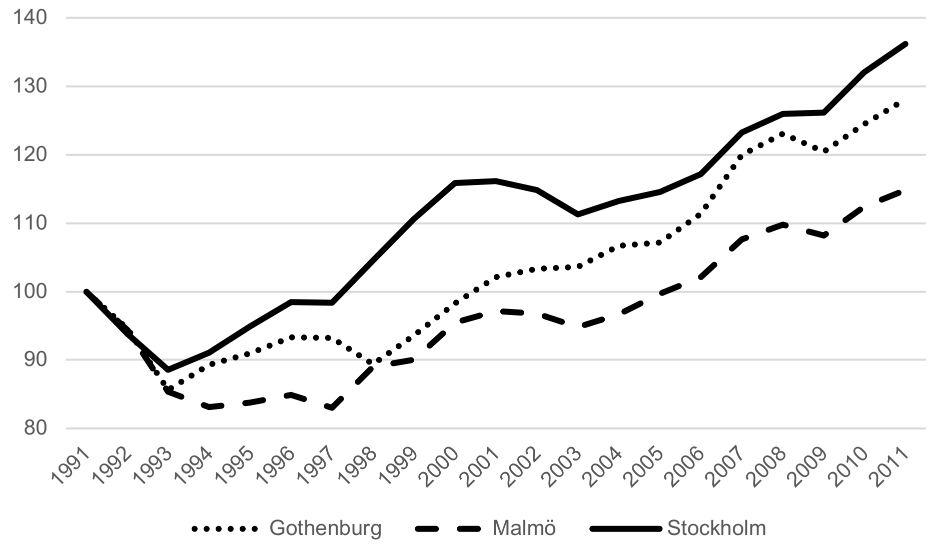
Early estimates that indicate depreciation with space of human capital externalities are found in Rosenthal and Strange (2001), who compare estimates on the zip code and state levels. Subsequent approaches have moved to using individual data and towards abandoning the idea of an administrative region as a homogenous unit of observation (e.g. Rosenthal & Strange, 2008). The main conclusion derived from these results is that there is spatial friction of knowledge diffusion, since the value of non-market interactions depreciates with space. The diffusion is limited by the extent of the interaction arena, which has increasingly proven to be quite small in spatial terms. Included in the rather vague concept of non-market interactions is any unpriced interaction of productive value, including observation and imitation (cf. Durlauf, 2004); the interaction arena can be thought about as naturally constrained by what can be heard, seen, and felt (Glaeser, 2000). This narrative begs the question of whether workers who benefit productively from hearing, seeing, and feeling have higher returns to density (cf. Bacolod et al., 2009), and it also explains why the effect's attenuation are particularly sharp for such workers.

A growing body of evidence suggests that the attenuation of human capital externalities is sharp. Using Swedish data, Andersson et al. (forthcoming) document spillovers that dissipate after less than one km for university educated workers. Larsson (2014) estimates that an average Swedish worker may increase his or her wage by almost 10 percent by moving from an average-density neighborhood to the densest neighborhoods. Arzaghi and Henderson (2008) analyze the advertising industry on Manhattan and conclude that spillovers dissipate already after a few blocks. Koster et al. (2013) document evidence consistent with substantial *within-building* agglomeration gains.

Needless to say, firm and employment misallocation can prove quite costly. If the depreciation is sharp enough, location differences of only a few blocks may have profound consequences in terms of production. If the externalities are important for productivity, then agents locating in close proximity to each other will be more productive. Since such a process will render switchers spatially sticky, this will also be true of embodied knowledge flows. If the embodied flows are localized, say, to the CBD, then learning will be more pronounced there relative to other areas (Glaeser, 1999).

Figure 1 displays an employment index (1991=100) plotting growth in terms of employment less than 5 km from the Stockholm, Gothenburg, and Malmö metropolitan CBDs, defined as the neighborhood housing the largest number of 5-digit industries in the central local municipality. The initial decline is due to the crisis that hit the Swedish economy hard in the early 1990's.

Figure 1. Central business district (CBD) employment growth (1991=100), 5 km radii around the CBDs in Malmö, Gothenburg, and Malmö.



Note: Total CBD employment, 1991 (2011): Malmö 96 000 (110 000); Gothenburg 137 000 (175 000); Stockholm 307 000 (418 000). CBD employment density per km², 2011: Malmö: 1398; Gothenburg: 2234; Stockholm: 5324.

Though this picture does not inform about the nature of the jobs created, a few things stand out. First, employment growth in Stockholm has been substantially higher than in Gothenburg, where it has been substantially higher than in Malmö, *even in relative numbers* and disregarding the fact that Stockholm's CBD was substantially denser in 1991. Second there are marked differences in the speed of recovery after the crisis. The Stockholm CBD was back at its pre-crisis level in 1998, Gothenburg in 2001, Malmö not until 2006. Third, the absolute numbers are impressive, too. Together these three CBDs with a combined area of a little over 230 km^2 added a thousand net jobs per km^2 on average, between the crisis low in 1993 and 2011. This figure represents 40 percent of net job growth in the metropolitan regions over the time period on less than 2 percent of the metro surface area. It also represents almost 25 percent of national net job growth during the same time period.

2. DATA, VARIABLES, AND ESTIMATION

The data source is a publicly audited matched employer-employee dataset, maintained by Statistics Sweden. Excluded from the data are workers in the public sector, mining and agriculture. The full population of private sector employees in the metropolitan areas of Sweden who were registered as employed full-time in November of each year between 2003 and 2010 are included, subject to data availability.

Sweden has 61 metropolitan area local municipalities, aggregated into three metropolitan regions, each of which is integrated in terms of commuting flows (Johansson, Klaesson, & Olsson, 2003). The empirical analysis focuses strictly on within-variation in these three areas. The metropolitan regions are: Gothenburg (16 local municipalities), Malmö (15 local municipalities), and Stockholm (30 local municipalities). Associated with each metropolitan region is one regional center (CBD) and several (non-principal city) municipal centers, referred to as local employment centers. The data do not cover individuals who changed their place of residence *between regions* during the period, although they do include individuals who lived in different local municipalities *within regions*. This operation has three main motivations: first, distance as the crow flies is not a good measure of functional distance across regions that are located in different parts of the country. Second, switches between regions are not indicative of cluster formation within regions. Third, the average of the dependent variable would be dominated by outliers. In total, cutting out between-region switchers excludes 304,428 individual-year observations. The resulting unbalanced panel contains 3,539,713 individual-year observations and tracks 970,994 metropolitan employees. In 2010, the number of individual observations is 568,447, and out of this population 77,227 changed jobs within their metropolitan area during that year (in total, the data track 685,219 within-metro switches over 8 years). The overall probability that a random employee in the population becomes a within-metro job-switcher during an average year is about 15 percent, although varying slightly with the business cycle and reaching its maximum at 17 percent in 2007.

Each worker is registered as employed in a certain work establishment, all of which belong to a firm, but each firm may of course have many work establishments (a worker must be associated with a new *firm* to be considered a switcher). Each worker and each work establishment are geo-coded down to a point in the south-west corner of a square (referred to as a *neighborhood*), within a uniform, exogenously determined grid of squares, all of which are sized 0.25-by-0.25 km (a base of about 0.16 miles).

2.1 Identification using geocodes and occupations

An issue in the literature concerns how to separate between workers' skills or, crudely speaking, how to drive wedges between classes of workers who by some logic are considered different (in this case routine vs. non-routine). Andersson et al. (forthcoming) analyze university-educated workers, conclude that the returns to density are higher for such workers, and that the attenuation effect is sharper. But education level is a crude proxy if the aim is to differentiate between skill sets in the domain specific sense. The underlying identifying assumption in this paper is that skills are rewarded differently in cities, and that a worker's occupation says something about his or her skill set[2]. A rigorous empirical treatment of this question is found in Bacolod et al. (2009), who conclude that market pricing of cognitive skills - as proxied by occupation - is increasing with local population in all of their specifications, and that social (or people) skills are also being rewarded more highly by density. This finding is further evidence suggesting marginally increasing returns to density for interactive and non-routine employees.

Why analyze occupations and not industries? First, the relatively crude industry classification in the Swedish registry data is based on the SIC code of the majority of the firm's output, meaning that a large fraction of the employees can be - and often are - assigned to an inappropriate industry. Second, many firms registered as manufacturing firms in reality produce a considerable amount of services, and many service firms produce a wide array of different services, and so on. Being able to differentiate functions *within* firms (and even within establishments within firms) is therefore desirable. The variables included in the empirical part do however include industry-specific effects.

In this paper, I represent[3] non-routine workers by managers, legislators, and senior officials (ISCO-88, 1), and by professionals, including engineers and scientists (ISCO-88, 2). Both of these groups are also highly educated (see table 1). These workers are contrasted with employees in blue-collar professions, who are more dependent on strength and motoric skills, and who have been shown to reap smaller, or no, benefits from density (Andersson et al., 2014; Bacolod et al., 2009). These are found in crafts and trades related occupations (ISCO-88, 7) and in occupations relating to operating of machinery and assembly (ISCO-88, 8). Table 1 summarizes these occupations, including a cautious estimate of the extent of non-routine work tasks associated with each broad occupation group (adapted from Hakkala, Heyman, & Sjöholm, 2008).

[2] For a discussion of this assumption in connection with routine and non-routine work tasks, see e.g. Andersson et al. (2014).

[3] All occupation measures in this article are based on the International Standard Classification of Occupations (ISCO). Under ISCO, jobs are specifically grouped together based on similarity of skill requirements.

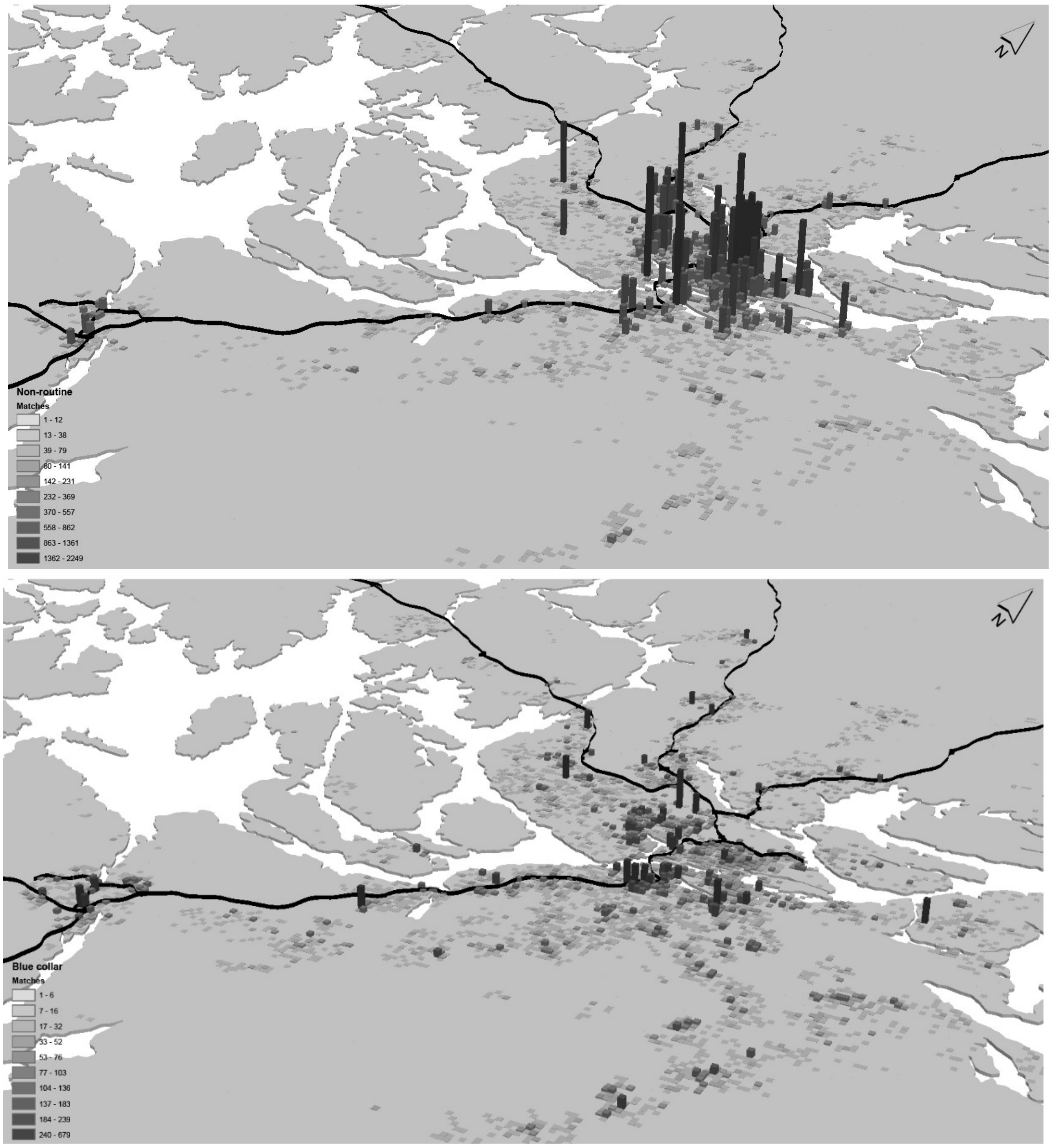
Table 1. Included occupation types, and average share of non-routine work tasks.

(ISCO-88) Occupation	Type	Avg. non-routine work tasks (%)	Avg. years of schooling (2011)
(1) Managers, legislators, senior officials	Non-routine	60	13
(2) Professionals, incl. engineers and scientists	Non-routine	79	15
(7) Crafts and related trades workers	Blue collar	30	11
(8) Machinery operation and assembly	Blue collar	23	11

Note: the "average non-routine work tasks" column is the unweighted average of two-digit occupations under each category, adapted from Hakkala et al. (2008). The average years of schooling column is a population-weighted mean derived from Statistics Sweden's registry data.

The empirical relevance of this division is illustrated in figure 2, which shows new matches by neighborhood in the Stockholm metropolitan region. The top panel shows matches for non-routine workers, while the bottom panel shows matches for workers in blue collar professions.

Figure 2. Labor market matches, by neighborhood (250*250 meter squares), in the Stockholm metropolitan area. The maps show matches for non-routine workers (including engineers, scientists, and managers, top) and for blue collar workers (including crafts, and machine operation, bottom).



Note: the bar height represents the (absolute) number of job switches. The figure excludes employees who worked for a firm that went out of business in t-1, and/or firms that were bought up. 250 meters is about 0.16 miles.

First, note how concentrated both pictures are relative to the surrounding lands. Second, note how non-routine workers find jobs chiefly in close proximity to the central business district and also to a corridor to the north, heading to the industrial districts and research hubs of Solna and Kista. Notably, most of the densest neighborhoods in terms of matches are within the borders of the central local municipality. The blue collar workers' picture is more dispersed, with local clusters scattered in the surrounding local municipalities (such as Södertälje to the south-west and Järfälla to the north), but still with the bulk of matches taking place in proximity to the region center of Stockholm. Taking the perspective of new matches as optimization decisions, those decisions do appear to favor the CBD, and most notably so in non-routine professions.

Certainly, these patterns are consistent with the bid-rent predictions reviewed above, where firms that derive benefits (and profits) from density pay higher rents for access to density. This notion is investigated in the regression analysis part of this paper, where I make some attempts at discriminating between occurrences in the metropolitan landscape. In addition to basic observables, the empirical section contains a number of key variables sorted into three categories: bid-rent, clustering, and industry specific effects.

Bid-rent variables

One reason why we a priori would expect patterns such as in figure 2 is simply that non-routine workers have their productivity determined as an increasing function of local density. If we expect the city center to be a hub for recruitment of such workers, then we should expect them to move short distances as they shop around for jobs near the city center. This class of variables include distances to the CBD, defined as the neighborhood in the central municipality that is home to the largest number of 5-digit industry codes, distance to local employment centers, and local neighborhood employment density.

Clustering variables

There is also the possibility of clustering of functions across the geography unrelated to the central business districts. In fact, powerful non-market interactions predict multiple equilibria across space, as clusters grow powerful by internalizing knowledge. Such a case could be driven e.g. by large within-occupation specialization gains, and the clusters may be based on natural advantages, historical accidents, local cultures (see e.g. Andersson & Larsson, fortcoming, who demonstrate local feedback effects in entrepreneurship) and so on. This step includes controls for "hotspots" (places in space where the largest number of similar workers are employed, a measure independent of CBDs and local employment centers) and also overall clustering measures (the number of neighborhoods employing similar workers relative to the total number of active neighborhoods per region, and local municipality).

Industry-specific effects

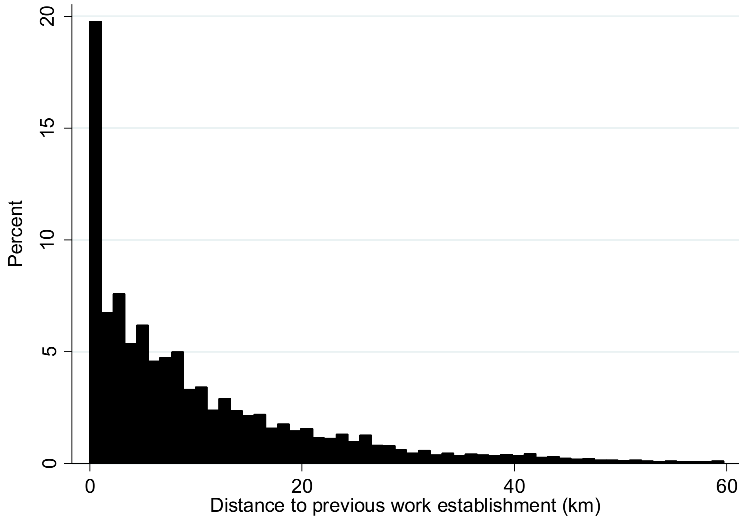
There are also likely to exist industry-specific linkages that are not picked up by occupation based variables. There is potentially an industry-specific effect localizing workers, where the industry is bound to stay close to input suppliers, complementary services and so on, meaning that the average length of a move may be an effect of the *industry* in which the worker is employed. These variables include industry dummies at the 2-digit level and controls for the book value of capital stocks per firm.

All variables are defined and discussed in further detail in section 2.4 below.

2.2. Dependent variable: job-switching distances by occupation

An overview picture of the dependent variable for all private-sector workers is displayed in figure 3 (switches from defunct firms and workplaces are excluded), where switchers' distances between current and previous work establishments are plotted along the x axis.

Figure 3. Distance decay in within-region job-switching: distance in kilometers between new establishment and establishment in year t-1. N=293,965.

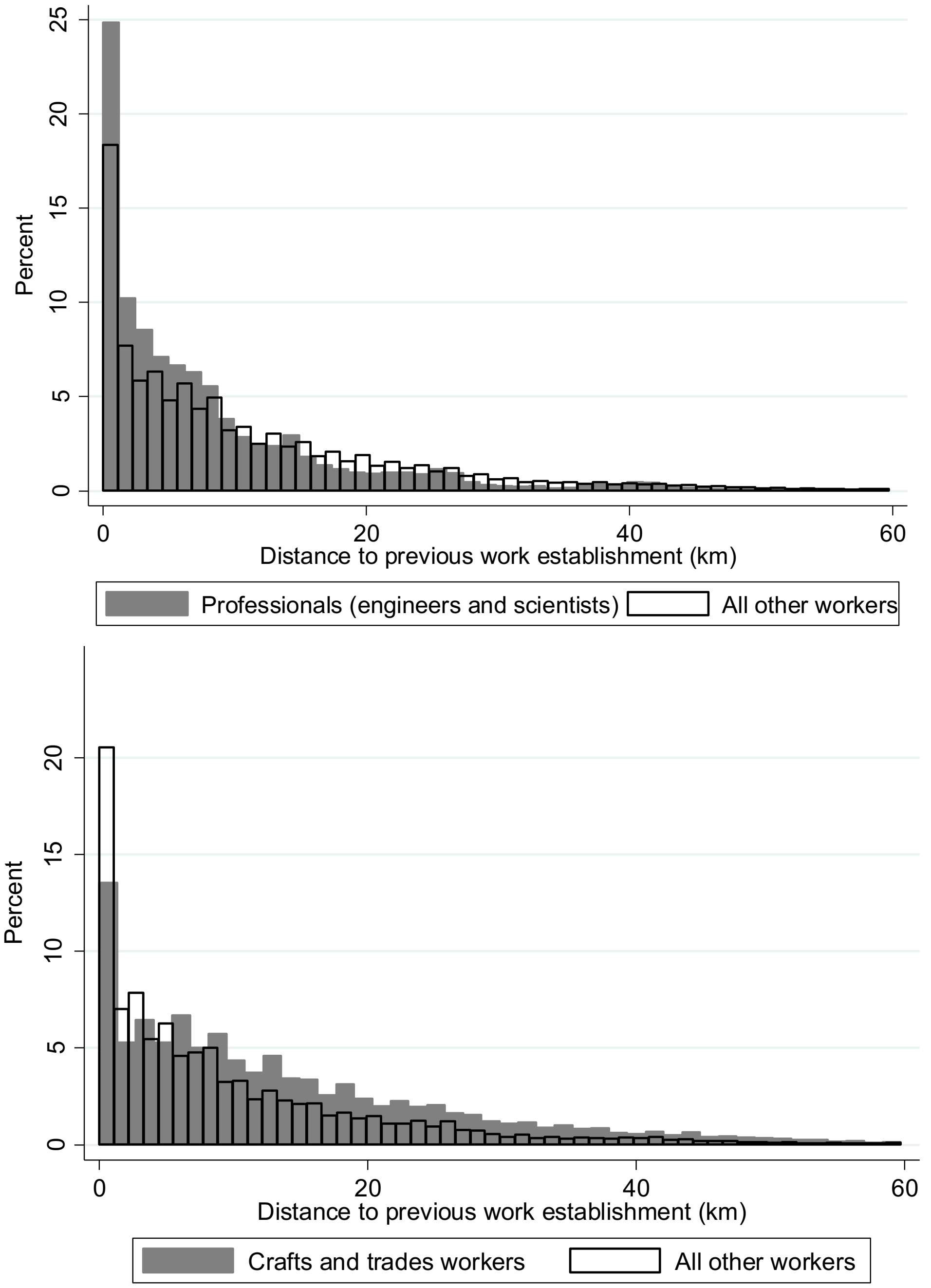


Note: the figure excludes workers who worked for a firm that went out of business in t-1, and/or firms or workplaces that were bought up. Workers who moved longer than 60 kilometers (0.008 percent of cases) are excluded from the figure.

There is a clear tendency towards "distance decay" of matching in these metropolitan labor markets. In fact, in almost 20 percent of the cases, the workers locate within about one km from where they were employed in year t-1 (do note that this figure excludes those employees that left the region).

The graphs in figures 1-3 do not speak of the sources of this behavior, nor are they informative in terms of between-occupation differences. In figure 4, the same data are reproduced for professionals (e.g. engineers and scientists, upper panel), and crafts and trades workers (lower panel). These occupation-specific graphs are contrasted against all other workers, represented by the outline-only bars in the foreground. Following the discussion above about matches as optimizations decisions by both agents, the occupation code used is simply the one at time *t*, i.e. the occupation switched to.

Figure 4. Distance decay in within-region job-switching: distance in kilometers between new establishment and establishment in year t-1.



Note: the figure excludes workers who were employed by a firm or workplace that went out of business in t-1, and/or for a firm that was bought up in t-1. Workers who moved farther than 60 kilometers (0.008 percent of cases) are also excluded.

The fraction of professionals who find a new employer in the same neighborhood is nearly twice as large as the fraction of crafts and trades workers who locate to the same neighborhood. The fraction of professionals is larger than all other workers for each distance-bar approximately up until the 10 km mark, after which the pattern is reversed. For crafts and trades workers, the pattern is quite different (in fact, it is close to the inverse), as such workers consistently appear to move farther than the average. The average distance between the old and the new workplace is just over 7 km, but there is substantial between-occupation variation as is depicted in table 2.

Table 2. Average distances for within metropolitan regions private-sector job switchers, in km, between workplace in time t, and various points in the pertinent urban landscape.

(ISCO-88) Occupation	**Average distance in km, from new workplace, to:**			
	Previous work est.	Regional CBD	Local emp. center	Home
(1) Managers, legislators, senior officials (N= 52,459)	6.00	10.06	3.82	17.89
(2) Professionals, including engineers and scientists (N=134,601)	5.57	7.50	3.40	16.43
(7) Craft and related trades workers (N=60,229)	10.50	16.42	5.07	22.10
(8) Plant and machine operators and assemblers (N=58,464)	9.87	16.85	5.19	17.92

Note: The occupations correspond to the ISCO-88 standard in parentheses. The statistics exclude workers who live more than 200 kilometers from their workplace. Workers in mining and related industries are excluded from category (7).

The two first rows describe non-routine professions, while the second two rows describe blue collar professions. Non-routine workers move shorter distances between jobs, and their tendencies towards the central areas are stronger. The workers that move the shortest distances between workplaces also tend to be the workers that are employed close to the CBDs or close to the local employment centers. With professionals (including engineers and scientists), the tendency is even stronger than for managers. This may be seen in the marked difference between the previous and the latter group in terms of proximity to the CBD.

At first glance, the differences may seem immaterial, but two things should be noted. First, numerous studies using disaggregated data sources have concluded that a city’s public good like characteristics depreciate quickly with space, where some of those characteristics seem to be internal to a few blocks, or even a building. Second, when thinking about the differences as proxies for search ranges, a circle with radius 10.5 is actually about three and a half times as large in terms of surface area, compared to a circle with radius 5.6.

2.3 Estimation issues

This section describes the estimation procedure used to discriminate between the effects listed above. The most straightforward strategy may be to simply run an OLS regression on the workers that switched jobs. This practice would however assume that job switchers are a random subset of the population. Selection could be a concern if certain workers are more prone to switching jobs, while simultaneously exhibiting correlation with the variables of interest. To account for such selection, I use a Heckman selection model, which in a first step estimates the probability of an individual switching jobs. The variables of the selection equation and their coefficients are presented in appendix 1. The full set of variables included in the selection equation are displayed in table A1.1. The table also contains variable definitions, descriptions, and also summary statistics for each variable. The corresponding probit coefficients obtained by estimating (1) are displayed in table A1.2. Formally the selection equation is defined as:

$$\Pr\left(N_{i,t} = 1 \middle| \mathbf{x_{i,t-1}}\right) = \Phi\left(\mathbf{x'_{i,t-1}\Gamma}\right) \tag{1}$$

where $N_{i,t}$ is a dummy, indicating 1 if individual *i* switched jobs between t-1 and *t*. Further, $x_{i,t-1}$ contains lagged individual control variables, and Φ denotes the cumulative density function. Previous studies provide evidence that individuals of certain attributes (e.g. short tenure and young age) are more likely to become job switchers, providing a general idea of standard control variables (see e.g. Andersson & Thulin, 2013). Agents in employer-employee pairs that are productively matched in period t-1 are less inclined to look for a new match in period t. An important variable in this regard is tenure[4]
, i.e. number of consecutive years spent with the same employer (Farber, 1994). Here, tenure is measured from 1991 (i.e. for up to 19 years).

The baseline outcome equation to be estimated is then specified as:

$$y_{i,t} = \alpha + \sum_{p=1}^{4} O'_{i,p,t}\,\beta_p + Z'_{i,t}\,\delta + D_t + D_R + D_{R,t} + \lambda_i + \varepsilon_{i,t} \tag{2}$$

where $y_{i,t}$ is the number of km that individual *i* moved between employers between periods *t-1* and *t*, β contains the coefficient of the main variables of interest, relating to individual *i*'s occupation type (*p)* at time t. Further, *Z* is a matrix of control variables, as outlined below. The *D* variables are dummies, relating to year, labor market region, and region-year pairs, respectively. Finally, λ_i is the inverse Mills ratio obtained through (1), and $\varepsilon_{i,t}$ is a white noise error term.

2.4. Variables

The variables in the outcome equation are defined in table 3.

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[4]In this empirical framework, tenure is also an example of an exclusion restriction in a Heckman selection framework, since it is a powerful predictor of a job switch (the standard error in table A1.2 corresponds to a t-value in excess of 100), while there is no apparent link between tenure and distance moved. The pairwise correlation between a one-year lag of the tenure variable and switchers' distances is 0.01.

Table 3. Variables used in in the outcome equation. The selection equation variables are displayed in table A1.1.

Main and baseline variables	
Distance to previous employer	Distance in km between the employer in year t, and the employer in year t-1. Dependent variable in the outcome equation.
Occupation (dummy)	1-digit ISCO-88 dummy denoting occupation at time t.
Region (dummy)	Dummy variables indicating the metropolitan region.
Basic observables	
Wage change (%)	Percentage change in yearly wage between year t and year t-1
Workplace employee size (ln)	Plant size in terms of the natural logarithm of the number of employees.
Distance to home	Distance in km to the worker's place of residence.
Discontinued workplace	Dummy variable denoting whether the previous work establishment had discontinued its operations.
Discontinued firm	Dummy variable denoting whether the previous employer had discontinued its operations.
Female	Dummy denoting whether the worker is female (1) or male (0)
Immigrant	Dummy denoting whether the worker is an immigrant (1) or not (0)
Years of schooling	Years theoretically associated with the worker's achieved degree.
Education specialization	Dummies, denoting the 1-digit ISCED 97 standard.
Experience	Age less years of schooling, less 6 (cf. Rauch, 1993).
Bid-rent	
Distance to CBD	Distance in km between the new employer, and the central business district, defined as the geo-code where the largest number of 5-digit SIC industries are present. The CBD is the center of the central municipality in each of the three labor market regions.
Distance to local emp. center	Distance to local employment center, defined in the same way as regional CBD, but for the local municipality.
Employment density (1km^2 neighborhood, ln)	Number of employed individuals in the exogenously assigned 1 km^2 square that the new work place belongs.
Clustering	
Occupation clustering (region)	Number of neighborhoods (250-by-250 meter squares) employing workers with the same 1-digit ISCO-88 standard classification, relative to the total number of neighborhoods with economic activity.
Occupation clustering (local)	Defined in the same way as region clustering, but calculated for the local municipality.
Distance to hotspot (region)	Distance in km between the new employer, and the local hotspot, defined as the geo-code where the largest number of workers sharing the same 1-digit ISCO-88 standard classification are employed.
Distance to hotspot (local)	Defined in the same way as region hotspots, but calculated for the local municipality.
Industry-specific	
2-digit SIC dummy	42 dummies indicating industry belonging (2-digit SIC) of the new employer.
Capital/worker (ln)	Natural logarithm of the book value of capital, relative to the total labor force of the firm in question.

Note: Region dummies are included in all regressions. Year dummies are also included in to control for time trends, as well as region*year dummies, to control for region-specific, time-variant shocks.

The variables are separated by five levels, and the regressions are run for each level separately to assess the contribution from each set of variables. Summary statistics for each variable is presented in table 4.

Table 4. Descriptive statistics for variables used in in the outcome equation.

	Mean	St.Dev.	Min.	Max.
Main and baseline variables				
Distance to previous employer (dep. variable)	7.05	11.72	0	166
Managers, legislators, senior officials	.08	.27	0	1
Professionals, including engineers and scientists	.20	.40	0	1
Craft and related trades workers	.09	.28	0	1
Plant and machine operators and assemblers	.09	.28	0	1
Region: Gothenburg	.27	.44	0	1
Region: Malmö	.15	.36	0	1
Region: Stockholm	.58	.49	0	1
Discontinued workplace	0.08	0.27	0	1
Discontinued firm	0.56	0.50	0	1
Basic observables				
Wage change from previous year (%)	.09	.55	-7.18	7.20
Workplace employee size (ln)	4.53	2.29	0	10.24
Distance to home	16.97	20.69	0	200
Female	0.39	0.49	0	1
Immigrant	0.19	0.39	0	1
Years of schooling	12.53	2.17	9	22
Experience	18.53	10.91	0	49
Bid-rent				
Distance to CBD	10.83	14.31	0	126
Distance to local employment center	3.93	4.06	0	48
Employment density (1km^2 neighborhood, ln)	10.43	1.12	4.75	12.05
Clustering				
Occupation clustering (region)	0.12	0.02	0	0.17
Occupation clustering (local)	0.13	0.02	0	0.29
Distance hotspot (region)	13.45	13.77	0	129
Distance to hotspot (local)	6.56	5.68	0	56
Industry-specific				
2-digit SIC dummy	N/A	N/A	N/A	N/A
Capital/employee (ln)	9.85	3.27	-5.55	23.37

Note: N=685,219 (total number of job-switches). The selection equation variables are displayed in table A1.1.

The main variables of interest are the occupation dummies in the top part of the table. The estimation process advances in five steps, and the main idea here is to study the change in the dummy variables, as more controls are gradually included. To address concerns that the variables we add introduce collinearity issues to the model, steps 3-5 (containing the variables of interest), below are also estimated individually in appendix 2, Table A2.1.

Step 1: baseline

First, baseline occupational differences are estimated without controls. These contain the "main and baseline variables" from tables 3 and 4, including dummies for year, labor market region, and region-year pairs.

The baseline model also include indicators reflecting whether the previous work establishment was discontinued (slightly more than half of switches), which includes simple exit (e.g. through bankruptcy), but also whether the firm was bought up and continued as a 'new' firm under different ownership. The occupation dummies used are for ISCO-88 1-digit occupation levels 1, 2, 7 and 8 at time t, as outlined above (see e.g. table 2). As can be seen from table 4, all categories contain slightly less than 10 percent of the total each, except for professionals, which contains 20 percent. The implication is that the base category is all other private-sector job-switches included in the dataset, stemming from any other category. This step finally includes dummy variables indicating the metropolitan region. More than half of the switches took place in Stockholm, a little over one fourth in Gothenburg, and 15 percent in Malmö.

Step 2: basic observables

The next set of coefficients are obtained controlling for sorting on basic observables. This equation includes variables describing processes that could conceivably constrain or encourage a worker's movement across space, but also variables that are likely to correlate with such processes, such as immigration status, and sex. This category includes the yearly percent wage change between *t-1* and *t*, since a higher yearly wage may act as a compensating differential and induce workers to move farther distances. Further, this step contains controls for distance to the home location[5], as well as the establishment's number of employees, since location in space is in part a product of residence location, and of sheer workplace size.

The second step also includes controls for observable human capital: schooling, and experience, as suggested by Mincer (1974). This step allows us to observe the differences, keeping a common measure of human capital constant, allowing subsequent steps to analyze what is not captured by such a measure, including non-routineness of work tasks.

Step 3: bid-rent variables

The next step includes controls for bid-rent positioning, wherein profitable firms are hypothesized to outbid their competition for attractive locations. The variables include distances to CBDs, and to local employment centers. These spots are defined as distance from the new employer to the point that is home to the largest number of 5-digit industries in each local municipality and in each metropolitan region, respectively. This is an empirical definition. It may seem most intuitive to simply use the densest points in terms of employment. A problem is that some work places outside the cities are so massive that they employ workers over a larger area than the squares (while still having all workers registered at

[5] Workers' location choices relative to their home locations are depicted in appendix 3. It is well in line with predictions about commuters' responses to distances, as it essentially represents a curve showing willingness to commute. At first, the fraction is increasing slightly with distance, reflecting higher rents near the city center where a large fraction of new jobs are created. After a threshold the pattern is a rather smooth, convex, curve. When the distance to the workplace extends beyond 100 km, the fraction is essentially zero.

the same point). This operationalization would give nonsensical locations of some CBDs. Such is the case e.g. in Gothenburg, where the scale of the automotive industry would move the "CBD" to the outskirts of the city.

The distance variables are complemented by local density measures, corresponding to employment density in the 1 km^2 square that each workplace belongs to (the fact that each workplace belongs to a 0.25-by-0.25 km square implies that 16 such squares make up one km^2).

Step 4: clustering variables

The fourth step includes clustering variables, controlling for the geographic concentration of employment for workers with the same 1-digit ISCO-88 standard classification, but these measures are independent of CBDs, local employment centers, and neighborhood density.

The occupation clustering measure is defined as the total number of 0.25-by-0.25 km squares where similar workers are employed, relative to the total number of squares with economic activity, per local municipality and metropolitan region, respectively. The variable ranges from a theoretical high of 1 (implying that the occupation is represented literally everywhere where there is economic activity) to a low of almost zero (meaning that the occupation is only available in few spots). Table 4 informs that in practice this variable stretches from (close to) zero to 29 percent locally, and 17 percent regionally.

Finally, the step includes distances to local and regional hotspots, defined as the neighborhood where most workers sharing the same 1-digit ISCO-88 standard classification are employed. The hotspots are sometimes - but not necessarily - identical to the CBDs and local employment centers for some occupation groups.

Step 5: industry-specific effects

Industry-related effects, such as capital intensity, accessibility to input suppliers and customers are likely to play a role. This phenomenon is controlled for using 2-digit NACE dummies corresponding to the industry that employed the worker at time *t*. Additionally, this step controls for the natural logarithm of the book value of capital per worker in the firm.

3. RESULTS

The coefficients from the outcome equation (2) for the five steps described above are displayed in table 5. The first step presents baseline estimates, conditioned only on selection. The second step adds basic observables (personal characteristics), while the three subsequent estimations investigate the occupation parameters as variables describing bid-rent, clustering, and industry-specific factors are sequentially added as covariates. The base category among the occupations is all private sector job switchers who do not belong to any of the four groups discussed in the previous section.

Table 5. Occupation differences in job switching distances.

Variable / Step (see section 2)	(1)	(2)	(3)	(4)	(5)
	Baseline	**Observables**	**Bid-rent**	**Clustering**	**Industry**
Managers, legislators, senior officials	-.621**	-.474**	-.362**	-.307**	-.356**
	(.0834)	(.0790)	(.0783)	(.117)	(.115)
Professionals, including engineers and scientists	-1.690**	-1.424**	-.870**	-.638**	-.542**
	(.113)	(.0932)	(.0912)	(.181)	(.178)
Crafts and related trades workers	2.975**	2.096**	.876**	.606**	.202
	(.174)	(.160)	(.153)	(.212)	(.211)
Plant and machine operators and assemblers	2.769**	2.642**	1.131**	1.001**	.901**
	(.260)	(.226)	(.221)	(.228)	(.253)
Region: Malmö	-.161	-.300	-1.613**	-1.637**	-1.656**
	(.523)	(.483)	(.472)	(.469)	(.459)
Region: Gothenburg	-1.158**	-1.221**	-1.739**	-1.790**	-1.799**
	(.423)	(.402)	(.526)	(.520)	(.487)
Discontinued firm	-6.842**	-5.911**	-6.566**	-6.550**	-6.637**
	(.274)	(.295)	(.227)	(.225)	(.191)
Discontinued workplace	3.117**	3.080**	3.126**	3.125**	3.121**
	(.224)	(.211)	(.224)	(.225)	(.219)
Years of schooling		-.137**	-.0526**	-.0542**	-.0649**
		(.0179)	(.0184)	(.0179)	(.0175)
Experience		-.0723**	-.0839**	-.0847**	-.0855**
		(.00405)	(.00360)	(.00360)	(.00322)
Wage change from previous year (%)		.313**	.274**	.272**	.247**
		(.0398)	(.0391)	(.0389)	(.0384)
Distance to home (km)		.0982**	.0874**	.0870**	.0863**
		(.00359)	(.00318)	(.00313)	(.00310)
Female (dummy)		-.567**	-.341**	-.364**	-.380**
		(.0663)	(.0672)	(.0656)	(.0547)
Immigrant (dummy)		-.252**	-.0108	.00898	.0502
		(.0587)	(.0583)	(.0584)	(.0574)
Workplace employee size (ln)		-.209**	-.151**	-.153**	-.175**
		(.0347)	(.0327)	(.0317)	(.0308)
Distance to CBD (km)			.175**	.157**	.153**
			(.0124)	(.0215)	(.0209)
Distance to local employment center (km)			.0407*	.0468	.0432
			(.0183)	(.0282)	(.0270)
Employment density (1km^2 neighborhood, ln)			-.897**	-.930**	-.919**
			(.117)	(.114)	(.117)
Distance hotspot (km, region)				.0221	.0202
				(.0227)	(.0216)
Distance to hotspot (km, local)				-.0104	-.00589
				(.0216)	(.0213)
Occupation clustering (region)				25.87**	22.90**
				(6.878)	(6.731)
Occupation clustering (local)				-26.42**	-25.26**
				(6.983)	(6.594)
Capital/employee (ln)					.111**
					(.0171)
2-digit SIC dummies	NO	NO	NO	NO	YES
Year dummies	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES
Constant	10.24**	12.10**	19.35**	19.81**	19.23**
	(.332)	(.494)	(1.413)	(1.550)	(1.622)
Observations	3,539,713	3,539,713	3,539,713	3,539,713	3,539,713
Individuals	970,994	970,994	970,994	970,994	970,994
R-squared	.11	.14	.22	.22	.22
$\frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$	.0338*	.0728**	.0268*	.0272*	.0174
	(.0137)	(.0150)	(.0112)	(.0110)	(.00929)
$\lambda = (\sigma * \rho)$	.3710**	.7838**	.2766*	.2802*	.1792
	(.1518)	(.1651)	(.1163)	(.1143)	(.0957)

Note: Robust standard errors are clustered at the level of neighborhoods (0.25-by-0-25 km square). All variables are defined in section 2. ** p<0.01, * p<0.05. The parameters are estimated using a Heckman selection model (selection equation in appendix A1). Period: 2003-2010. Dependent variable: job switchers' distances in km between work establishment in year t, and year t-1. The last two lines offer selectivity estimates, investigating correlations between the residuals from the first stage, with the residuals from the second stage. Regressions adding all sets of variables individually are presented in table A2.1.

The baseline regression essentially confirms the patterns from the descriptive table 2: the difference between non-routine (the managers, and professionals categories) and blue collar (the crafts, and plant categories) workers is considerable. The difference in average distance between previous and current employer is about 4 km between someone hired as a professional and someone hired as a crafts worker. The picture confirms that non-routine workers switch jobs over much more concentrated areas of land, compared to blue collar workers.

In the second step, Mincer's (1974) classic determinants of human capital, schooling and experience, are included together with an array of variables describing each worker's characteristics, e.g. in terms of sex and immigration status. This step also includes an estimate of establishment size in terms of number of workers, and the distance in km to the location of residence. The most notable result in this step is how little these characteristics contribute to the between-occupation differences, considering that schooling is controlled for at this stage. However, this set of variables do indeed explain some of the distance covered, foremost by crafts and trades workers.

Step three adds controls for bid-rent behavior, in terms of distances to the CBD, and to the local employment centers, respectively. This step also contains a control for employment density of the 1 km^2 neighborhood to which the work establishment belongs. Bid-rent theory predicts that more profitable firms will be located closer to the city center, since they will outbid less profitable competition for attractive locations. Knowledge-intensive firms are thought to become more profitable *because* they locate close to city center, as discussed above.

Adding these controls pushes all variables of interest closer to the zero bound, and reveals that a substantial part of the differences are produced by non-routine workers finding new jobs primarily in and around the CBDs (cf. Glaeser, 1999) and by blue collar workers primarily finding new jobs outside of the city centers.

The lion's share of the effect here is produced by distance to the CBD and by density of the new neighborhood. Distance to the local employment center is statistically speaking less important, as is evidenced by the lower level of significance. The coefficient becomes statistically indistinguishable from zero in subsequent steps. This result may be appreciated as further evidence of the importance of the CBD and local density in providing knowledge-intensive employment. In addition, the unstandardized coefficients actually understate the relative differences since a one standard deviation change is more than three times as large for the distance to CBD variable (see table 4).

On average, moving to a workplace an additional km away from the CBD is associated with about a 0.15 km longer move between employers. Just outside of the 5 km cutoff used in figure 1, moves would on average be close to one km farther on average, more than enough for much of human capital externalities to dissipate in non-routine industries, such as the advertising industry described in Arzaghi and Henderson (2008). 5 km correspond to slightly more than one standard deviation in table 4.

Step four further includes controls for clustering, owing to the possibility of cluster formation outside of the metropolitan cores. The occupation clustering variables are statistically significant, both locally and regionally, albeit with coefficients of different signs. The results indicate that there is indeed some clustering outside of the centers, associated (at least statistically) with the tendency for non-routine workers to be more spatially concentrated (note the decreases in all variables of interest). The shifting signs of the clustering coefficients indicate that occupations clustered in the local municipality are associated with shorter moves, while regional clustering exhibits an inverse relationship. Hence: if similar jobs are clustered in the local municipality, the moves are shorter. Overall, a one standard deviation (0.02 in table 4) increase in clustering is associated with about 0.5 km *longer* moves on the level of metropolitan regions, and about 0.45 km *shorter* moves on the level of local municipalities.

The fifth and final step adds controls relating to industry. In this step, dummies at the 2-digit NACE industry level are introduced, as is a variable indicating the size of the capital stock per employee (size in terms of the number of employees are controlled for since the second step). On average, a one percent increase in capital per employee, is associated with 0.1 km longer moves on average, indicating that capital intensive production is dispersed around the city, and often concentrated to the outskirts. This step further pushes the between-occupation differences closer to zero (except for in management occupations). After this step and after accounting for all control variables, the only occupation group that moves farther than a km than the other groups is plant and machine operators and assemblers. It may also be noted that the selectivity statistics (the last two rows of the table) are close to zero at this stage, indicating low degrees of non-random sorting in the fully-specified model.

Comparing steps 1-5 in table 5, reveals that about three fourths of the span in between-occupation differences are explained by the variables introduced, where bid-rent related variables - foremost distances to the CBDs and employment density - appear most important.

To assess the relative contribution of each category of variables, as well as issues of collinearity between them, the model is estimated for all categories individually in appendix 2. Columns 1-2 are identical for reference and steps 3-5 estimates separately the effect of the bid-rent, clustering, and industry categories. By studying the change in the coefficients in columns 4 and 5, it is revealed that clustering and industry-specific factors do contribute less than the bid-rent variables (additionally, some of the effect of clustering here is driven by the fact that these clusters are sometimes located close to, or in, the CBDs). It appears, then, that the lion's share of the clustering behavior observed is driven by a high proportion of non-routine workers finding new jobs close to their old place of work in the metropolitan areas' main central business districts, local employment centers, and other dense areas.

4. CONCLUSION

This paper demonstrates that there is substantial variation across occupations in terms of how they cluster within cities. Using job-switching data for Sweden's three metropolitan regions, I analyze clusters of different economic activities as evidenced by clustering of occupations, by analyzing job-switchers' length of moves between previous and current employers. I show that workers in non-routine type occupations move substantially shorter distances than other workers when they switch jobs, indicating that they on average find new employment in local labor markets, while blue collar, non-interactive, jobs do not show nearly as high levels of concentration. This finding corroborates theoretical arguments about clustering behavior as a function of attenuating human capital externalities. It also has the power to explain the increasingly important role of the central business district (CBD) in economic geography. The sharper is the depreciation with space of knowledge spillovers, the stronger are the incentives for strong clustering in space. The more intensive an occupation utilizes knowledge inputs in production, the more likely we are to observe that occupation in the CBD. Further, with more knowledge-intensive production and more non-routine work tasks comes more powerful incentives to form parts of clusters.

Using regression analyses with switchers' distances between employers on the left hand side, I show that - even though general clustering and industry-specific effects do play a role - the most powerful predictor of this behavior is clustering towards the centers and the locally dense parts of the metropolitan regions. The effect is nowhere as strong as with non-routine type professions, such as engineering, science, and upper-management occupations.

As the share of knowledge in production increases, the role of human capital externalities is gaining in importance, and so is the tendency towards powerful CBDs. The density driven employment growth documented in this paper has clear policy implications. This phenomenon e.g. means that there is a direct link between zoning laws and building height regulations on the one hand, and the productivity and future growth prospects of cities on the other. Some occupations may indeed *require* a certain frequency of interaction in order to stay competitive. Measures to keep down building height, for instance, may have indirect consequences on employment growth, specifically in knowledge-intensive industries.

Since non-routine occupations seem to have close proximity to human capital externalities (and therefore economic density) as an important input in the production process, this research lines up with a growing body of evidence suggesting a strong link between the density of cities - as well as neighborhoods *within cities* - and long-run growth prospects.

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APPENDIX 1

Table A1.1. Variable included in the Heckman selection equation

Variable	Description	Mean	St.Dev.	Min.	Max.
Job switcher (dummy)	Dummy denoting if a worker spent year t with a new employer, compared to year t-1. Dependent variable.	.15	.35	0	1
Schooling$_{t-1}$	Number of theoretical years of completed schooling.	12.4	2.3	9	22
Education specialization$_{t-1}$	9 dummies denoting the 1-digit ISCED 97 standard.				
Experience$_{t-1}$	Years between graduation and year t-1, less 6, following Rauch (1993).	22.3	11.2	0	48
Occupation type $_{t-1}$	9 occupation type dummies as indicated by the 1-digit ICSO-88 standard.				
Wage$_{t-1}$ (ln)	Wage earnings, yearly, in SEK.	8.01	.59	.69	12.6
Tenure$_{t-1}$	Number of consecutive years with the same employer, since 1991.	5.7	4.4	1	19
Firm size $_{t-1}$ (ln)	The natural logarithm of the number of employees. Proxies for within-firm specialization.	5.3	2.5	0	10.24
Capital/employee$_{t-1}$ (ln)	Book value (SEK) of physical capital, divided by the number of employees.	10.9	2.8	-3.4	22.75
Discontinued firm	Dummy denoting whether the worker's employer discontinued its operations in year t-1.	.086	.28	0	1
Discontinued work establishment	Dummy denoting whether the worker's work establishment discontinued its operations in year t-1.	.018	.13	0	1
Industry$_{t-1}$	Industry belonging of the firm, as indicated by 42 2-digit NACE dummies.				
Market potential$_{t-1}$ (ln)	Time distance-weighted market potential per urban region, following Johansson et al. (2002, 2003)	12.6	.64	9.4	13.2
Region$_{t-1}$	3 dummies, indicating the metropolitan region in which the worker is employed.				
Immigrant	Dummy, denoting whether the worker is an immigrant.	.17	.37	0	1
Female	Dummy, denoting whether the worker is female.	.36	.48	0	1
Married$_{t-1}$	Dummy, indicating whether the worker is married or in a domestic partnership.	.44	.50	0	1
Children staying at residence$_{t-1}$	Dummy denoting whether the person has children staying in the place of residence.	.53	.50	0	1

Note: Total population size is 3,539,716 individual-year observations, based on 970,994 individuals.

Table A1.2. Determinants of job-switching. Heckman selection equation, probit coefficients.

Variable	**Coefficient**
Schooling$_{t-1}$	-.00858** (.000742)
Experience$_{t-1}$	-.0156** (.000128)
Wage$_{t-1}$ (ln)	-.0782** (.00217)
Tenure$_{t-1}$	-.0346** (.000321)
Market potential$_{t-1}$ (ln)	.0311** (.00210)
Discontinued firm	3.297** (.00534)
Discontinued workplace	.231** (.00891)
Firm size $_{t-1}$ (ln)	.0131** (.000527)
Capital/employee$_{t-1}$ (ln)	-.0050** (.000421)
Malmö metropolitan region (dummy)	-.069** (.00358)
Gothenburg metropolitan region (dummy)	-.089** (.0028)
Female (dummy)	-.0379** (.0027)
Immigrant (dummy)	.00646* (.0030)
Married$_{t-1}$ (dummy)	-.00206 (.00260)
Children staying at residence$_{t-1}$ (dummy)	-.00218 (.00239)
Managers, legislators, senior officials (dummy)	.110** (.00580)
Professionals, incl. engineers and scientists (dummy)	.0581** (.00521)
Craft and related trades workers (dummy)	-.00963 (.00584)
Plant and machine operators and assemblers (dummy)	-.000541 (.00598)
Pseudo R-squared	.44
Observations	3,539,716
Individuals	970,994

Note: Standard errors in brackets. The regressions include year dummies to control for season effects, education type dummies, industry dummies at the two-digit level, and an additional six occupation dummies (1-digit ISCO-88). All variables are defined in table A1.1. ** p<0.01, * p<0.05

APPENDIX 2

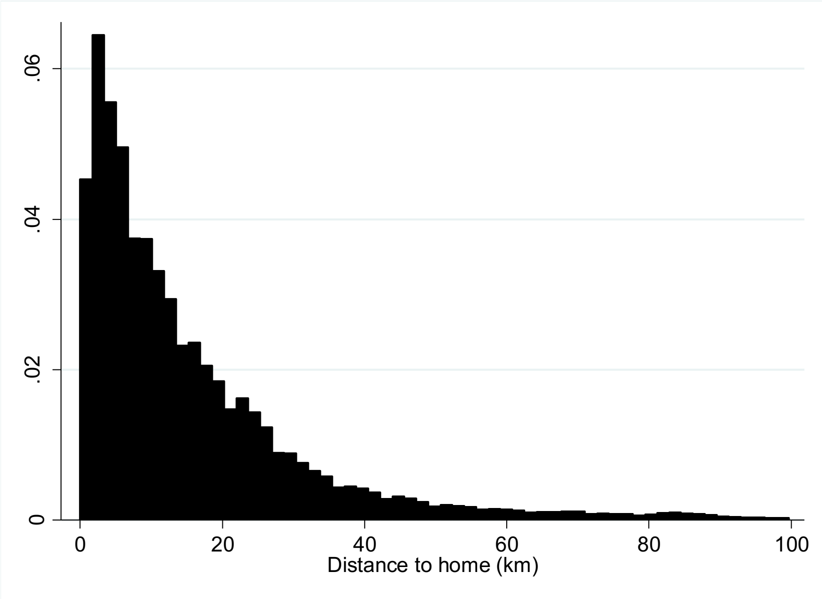
Table A2.1. Occupation differences in job switching distances.

Variable / Step (see section 2)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Baseline	**Observables**	**Bid-rent**	**Clustering**	**Industry**
Managers, legislators, senior officials	-.621**	-.474**	-.362**	-.661**	-.555**
	(.0834)	(.0790)	(.0783)	(.123)	(.0774)
Professionals, including engineers and scientists	-1.690**	-1.424**	-.870**	-1.320**	-1.041**
	(.113)	(.0932)	(.0912)	(.183)	(.0939)
Crafts and related trades workers	2.975**	2.096**	.876**	1.196**	1.076**
	(.174)	(.160)	(.153)	(.212)	(.153)
Plant and machine operators and assemblers	2.769**	2.642**	1.131**	1.280**	2.094**
	(.260)	(.226)	(.221)	(.239)	(.218)
Region: Malmö	-.161	-.300	-1.613**	-.607	-.464
	(.523)	(.483)	(.472)	(.440)	(.445)
Region: Gothenburg	-1.158**	-1.221**	-1.739**	-1.750**	-1.289**
	(.423)	(.402)	(.526)	(.522)	(.383)
Discontinued firm	-6.842**	-5.911**	-6.566**	-6.406**	-6.544**
	(.274)	(.295)	(.227)	(.230)	(.209)
Discontinued workplace	3.117**	3.080**	3.126**	3.204**	3.013**
	(.224)	(.211)	(.224)	(.220)	(.210)
Years of schooling		-.137**	-.0526**	-.0854**	-.154**
		(.0179)	(.0184)	(.0187)	(.0166)
Experience		-.0723**	-.0839**	-.0794**	-.0752**
		(.00405)	(.00360)	(.00364)	(.00336)
Wage change from previous year (%)		.313**	.274**	.295**	.221**
		(.0398)	(.0391)	(.0392)	(.0394)
Distance to home (km)		.0982**	.0874**	.0913**	.0957**
		(.00359)	(.00318)	(.00318)	(.00344)
Female (dummy)		-.567**	-.341**	-.618**	-.456**
		(.0663)	(.0672)	(.0674)	(.0531)
Immigrant (dummy)		-.252**	-.0108	.0231	-.116*
		(.0587)	(.0583)	(.0594)	(.0566)
Workplace employee size (ln)		-.209**	-.151**	-.152**	-.276**
		(.0347)	(.0327)	(.0333)	(.0307)
Distance to CBD (km)			.175**		
			(.0124)		
Distance to local employment center			.0407*		
			(.0183)		
Employment density (1km² neighborhood, ln)			-.897**		
			(.117)		
Distance hotspot (km, region)				.212**	
				(.0103)	
Distance to hotspot (km, local)				-.113**	
				(.0140)	
Occupation clustering (region)				14.61*	
				(6.844)	
Occupation clustering (local)				-2.28**	
				(7.325)	
Capital/employee (ln)					.175**
					(.0169)
2-digit SIC dummies	NO	NO	NO	NO	YES
Year dummies	YES	YES	YES	YES	YES
Region-year dummies	YES	YES	YES	YES	YES
Constant	10.24**	12.10**	19.35**	11.54**	11.54**
	(.332)	(.494)	(1.413)	(.634)	(.634)
Observations	3,539,713	3,539,713	3,539,713	3,539,713	3,539,713
Individuals	970,994	970,994	970,994	970,994	970,994
R-squared	.11	.14	.22	.16	.20
$\frac{1}{2}\ln\left(\frac{1+\rho}{1-\rho}\right)$	.0338*	.0728**	.0268*	.0420**	.0250**
	(.0137)	(.0150)	(.0112)	(.0104)	(.0108)
$\lambda = (\sigma^* \rho)$	.3710**	.7838**	.2766*	.4369**	.2665*
	(.1518)	(.1651)	(.1163)	(.1092)	(.1158)

Note: Robust standard errors are clustered at the level of neighborhoods (0.25-by-0-25 km square). All variables are defined in section 2. ** p<0.01, * p<0.05. The parameters are estimated using a Heckman selection model (selection equation in appendix A1). Period: 2003-2010. Dependent variable: job switchers' distances in km between work establishment in year t, and year t-1. The last two lines offer selectivity estimates, investigating correlations between the residuals from the first stage, with the residuals from the second stage.

APPENDIX 3

Figure A3.1 Distance in kilometers between new establishment and home.



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