RATIO

Ratio Working Paper No. 256

Migration, Careers and the Urban Wage Premium: Does Human Capital Matter?

Martin Korpi*

William A.V. Clark**

*martin.korpi@ratio.se, The Ratio Institute, P.O. Box 3203, SE-103 64 Stockholm, Sweden..
** California Center for Population Research, UCLA

Migration, Careers and the Urban Wage Premium: Does Human Capital Matter?

Martin Korpi [1]

Ratio Institute, Stockholm, and EHFF, Stockholm School of Economics

William A.V. Clark

California Center for Population Research, UCLA

Abstract: Using detailed Swedish full population data on regional migrants, this paper addresses the question of whether the urban wage premium, and "thick" labor market matching effects, are found only among the higher educated or across all educational groups, and whether the urban population threshold for these type of effects varies by educational category. Estimating initial wages, average wage level and wage growth 2001-2009, we find similar matching effects for all educational groups in the three largest metropolitan areas, but very weak effects for cities ranked 4th - 6th in the urban hierarchy. Our findings suggest that positive urban matching effects are not limited to those with higher education, but that there are distinct population thresholds for these type of effects, regardless of educational background.

Keywords: Human capital; urban wage premium; domestic migration; market thickness; mobility; agglomeration economies

JEL codes: R12; R10; J61; J31

Acknowledgements: This research has been supported by the Regional Studies Association, U.K.

---

[1] Corresponding author; martin.korpi@ratio.se. Ratio Institute, Box 3203, 103 64 Stockholm, Sweden

1. Introduction

In US and European analyses of regional economic growth and development much recent effort has gone into highlighting the role of human capital for per capita income and for job growth. For example, Shapiro (2006) estimates that a 10 percent increase in the university educated population is associated with 0.8 percent overall job growth, while Moretti and Thulin (2013) estimate local multipliers in the order of three for every manufacturing job associated with a longer university education (see also Simon 1998; Cheshire & Magrini 2000; Badinger & Tondl 2003; Faggian & McCann 2006). Human capital also consistently comes out as a significant determinant of innovation and technology absorption in, local industries and firms (Faggian & McCann 2009; Andersson & Lööf 2012), and in the same vein, Moretti (2012) argues that a crucial determinant of the "Great Divergence" in regional development now under way in the US and elsewhere is the regional ability to attract and retain highly educated individuals

This research has led to an increasing focus on migrant motives, and especially on the motives of the highly educated. We here see two strands of the literature; those adopting a labor market perspective – that wages and job availability is the main driver of migration patterns – and those arguing for the role of either amenities, family related issues or consumption possibilities – a 'taste for variety'. In the former strand, labor matching processes have been given a prominent role, both as explaining the urban wage premium and the continued attraction of larger metropolitan labor markets, offering a bigger variety of different types of jobs and more long term career opportunities. These job switches, it is argued, then enable migrants to find which type of activity and which employer where they do best, a search process which over time allows for higher individual productivity also reflected in higher wage gains. For example, Ahlin, Andersson and Thulin (2014) show that job switches among university graduates in Sweden is more prevalent in Swedish large metropolitan regions, finding both higher initial wages and wage growth for these graduates as compared to those moving into city- and more sparsely populated regions. Even studies increasing their scope by including relatively low or medium skilled workers, report these search and matching processes as something which mainly pertains to the higher educated (Bacolod *et al.* 2009; Andersson *et al.* 2014)

Using the same methods as in Ahlin et al (2014), we extend this literature by examining occupational careers and job switching behavior of all migrants, regardless of educational background. Using full population data, we estimate both initial wages, average wage level effects and wage growth for migrants heading into three different types of regions; urban-, city- and sparsely populated regions. Unlike previous studies we find that job-switching in larger metropolitan regions gives rise to higher wage growth for migrants regardless of educational level, and additionally; that the urban population threshold for these effects are more or less equal across education groups. The results suggest that sufficient employer diversity may be an important motive for all domestic migrants, not just the higher educated.

In the following, we discuss the existing literature in section two and in section three our data and statistical model. We provide descriptive statistics and figures on job switching behavior in section four, while section five outlines results and section six concludes.

2. Previous studies

Two bodies of literature are relevant for our study: one concerns the question of drivers and individual motives behind domestic migration, and second, the literature explaining the urban wage premium; why wages are higher in larger cities and local labor markets.

As regards the first of these two, in the past two decades there has been a growing recognition that migration is substantially more complex than the mere simple notion of moving to a better or more generally a higher paid job. This led to a debate about the role of places and whether it is the amenities in a place or jobs in these places which are the driving forces in migration, and by extension regional growth. As examples of the former line of argument, Glaeser *et al.* (2001); Glaeser and Gottlieb (2006) and Partridge (2010) all analyze migration along the lines of a strong correlation between destination choices and the availability of natural (climate) or consumption related amenities (generally meaning the possibility of larger variety and diversity in consumption). Glaeser et al (2001), in particular, emphasize that it is place and consumption which is now driving migration and migration decisions and where once cities were primarily centers of employment opportunities, now successful cities are those that are also centers of consumption.

The counter argument, as represented by for example Storper and Scott (2009), underline the a priori availability of jobs in these places as the prerequisite for these amenities, and therefore give more weight to factors related to the labor market. As they suggest, even though many individuals do have preferences for warm winters or upscale urban amenities, any utility maximizing calculation must be subject to feasibility constraints which means that "most migrants are unlikely to be able to move in significant numbers from one location to another unless relevant employment opportunities are (…) available."

Finally, a third line of argument in the debate on migrant motives has been raised by for example Dixon (2003); Morrison and Clark (2011) and Niedomysl (2011). Based on different types of survey data for a range of countries, these authors point to an approximate estimate of either jobs, amenities or social/family related motives (a desire to be closer to friends and family) as representing about a third each of the main motives that migrants cite when asked about the driving factors behind their decision to move. These authors further argue it's far too premature to hail any one of these three broad motives as coming out on top. When looking at survey evidence rather than using a more macro perspective and analysis of revealed preferences, it is for the individual migrant usually not a question of either or but rather, that these types of motives are often bundled together (see also Niedomysl & Clark 2014).

In this paper we do not distinctly put our foot down in this debate. Rather, we investigate the outcomes of job matching and more longer term career choices. We do however argue that this and other research using a similar labor market perspective highlights a distinct attractive feature of larger metropolitan labor markets, features that are definitely an important part of the reason why larger metropolitan regions continue to grow and smaller regions continue to struggle.

As for the second of these two bodies of literature, highly relevant for our research is also the work on the so-called urban wage premium, i.e., the extent to which workers in larger cities tend to receive higher wages than their counterparts in rural or smaller cities (Kim 1987, 1990; Ciccone & Hall 1996; Glaeser 1998)

The generally accepted interpretation of the urban wage premium is that cities provide a premium because they reduce transport costs, because they are places where technology and knowledge transfers are easily enhanced and because there is a greater access to consumers (which enable economies of scale and scope). Thus, cities and large urban areas generally provide greater opportunities, and migrants to these urban areas will experience greater returns to their relocation.

In addition to these general factors, explanations of the urban wage premium focus on individual productivity of workers (assuming that better able workers are indeed better paid). The sources of this higher productivity can then be related to either learning (sharing knowledge), that is, a situation in which human capital accumulation is faster in urban environments basically due to facilitated social interaction and learning (Glaeser 1999; Glaeser & Maré 2001; Moretti 2004; De la Roca & Puga 2012); or to coordination, the “matching hypothesis” (Kim 1990; Wheeler 2006; Yankow 2006) which suggest that cities create a context in which there is a better chance of bringing about a good match between workers and firms; or, finally, to sorting and self-selection, i.e. the notion that relatively higher worker productivity in larger cities is largely due to different types of innate abilities of workers living in and moving into these larger cities (see Combes *et al.* 2008, 2010)

Complicating matters somewhat, all these three different sources of higher productivity can both affect the static and dynamic urban wage premium, i.e. both the higher initial wage and wage growth over time, and considerable effort has gone into disentangling these effects from one another (for overviews, see Rosenthal & Strange 2004; Puga 2010). Although results here vary considerably a general finding in the literature is that the largest share of the urban wage premium can be ascribed to sorting, i.e. to underlying abilities of workers and relatively less to characteristics of the places themselves that enable matching, knowledge spillovers and learning.

Regardless of these debates, an additional question is here to what extent the premium is universal or something more pertaining to the higher educated. Evidence for the latter is provided in Bacolod *et al.* (2009) and Andersson *et al.* (2014). Bacolod et al (2009) characterize occupations as mainly requiring three broad skill groups; cognitive skills (verbal, numerical/mathematical), people- or interactive skills and, finally, physical skills (strength and motor abilities). By way of estimating series of wage equations for these different skill groups they conclude that the higher returns in larger cities are mainly captured by those with cognitive and interactive skills (the first more than the second), whereas hardly any benefit of dens agglomerations can be traced for the latter group. Similarly, for Sweden, Andersson *et al* equally find the premium as mainly pertaining to those skills required for non-routine jobs, but virtually no effects whatsoever for those doing tasks related to more routine jobs.

In this paper we differentiate migrants along education rather than skills. Our empirical strategy builds upon work by Ahlin et al (2014) and we address the question whether matching effects previously estimated for the university educated can also be found for those with relatively less education. In addition, for all these educational groups, we estimate both initial wages as well as the average urban wage premium over time, estimated by way of fixed effect panel regression thus controlling for unobserved heterogeneity among migrants. Whereas Ahlin et al model outcomes for university graduates initially residing in larger metropolitan regions as well as those moving into these regions, both using pooled and separate samples for these two groups, we focus solely on migrants; in part because of practical reasons and expediency, in part because we approach these questions from a main interest in migration outcomes and migrant motives.

3. Data, Modeling Approach and Variables

In what follows, we utilize full population data from Statistic Sweden's Mona database which offers highly detailed individual level information, such as source and level of income, education, place of birth and residence etc. This individual level data has in turn been merged with employer data on establishment size, type of corporation and ownership, giving us unique possibilities to control for potentially confounding factors when estimating migrant income effects. We study a cohort of those in the age group 22-29 that either receives a university degree in the year 2000, or, who are within that same age span in the year 2000 and have at least primary, secondary or some post-secondary education.[2]

---

[2] The data is then restricted as follows; as we do not have information on working hours and time on the job, we drop all with a yearly incomes below 100 000 SEK (equivalent of around 14 700 in 2005 US dollars). Studies comparing Swedish register and survey data have shown this as adequate for restricting a sample to more or less full time employed (Antelius & Björklund 2000). Second, as we depend upon controlling for job type and occupational categories we also drop individuals without occupational codes. These measures correspond to those in Ahlin et al (2014).

As we are interested in outcomes of migration and locational choice, from this group of younger workers we study active movers, i.e. those workers who migrate long distance at the start of the period and thereby make an active locational choice. More specifically, we focus on those that move between the years 2000 and 2001 who then remain in their destination of choice for the whole time period, 2001-2009. We then compare the outcomes of these migrants to those that switch region types during this period (our reference category). As in Ahlin et. al (2014), migration is defined as those changing region types, these region types being either urban regions (the three major metropolitan areas in Sweden, encompassing some 47 municipalities), city regions, consisting of 46 middle sized cities, and the 197 municipalities defined as country-side regions.

As noted above, we part from Ahlin et. al. (2014) in that we do not only look at university graduates but all migrants of different educational categories. Also as a further extension, we probe the relevance of our definition of urban regions. That is, for all educational groups we test whether matching effects in larger metropolitan regions can also be found in city regions closest to metropolitan regions in terms of population size. This measure is motivated in the sense that local labor market diversity, on which the market thickness approach relies, is strongly linked to local population size both in terms of industrial diversity and types of jobs within these industries (see for example Korpi 2008). Since our 46 city regions differ considerably in this regard, it is motivated to test whether similar matching effects can be found lower in the urban hierarchy, for example also at the fourth or fifth ranked city, and whether threshold population size for these matching effects vary by educational background.

Finally, as we lack information on which universities or educational institutions our migrants have attended, we cannot precisely the equivalent the definition of our university level migrant group. Rather than looking at those having grown up in the country side and then attending a university outside of the bigger metropolitan regions, (as in the Ahlin study) we look at all migrant moves regardless of point of origin for both the highest levels of education as well as our additional educational groups.

As for our empirical strategy and modeling approach, we probe labor market matching effects by estimating the influence of locality, or urban environment, on both initial wages, the average wage level as well as yearly wage growth. Firstly we estimate initial migrant wage income in 2001 by;

$$\ln w_i = \alpha + \Phi_1 D_i^{UrbnRgn} + \Phi_2 D_i^{\text{CtRgn}} + \mathrm{I}_i'\beta \; + \; \Omega_i'\theta + \omega\lambda_i + \varepsilon_i \quad (1)$$

where w_i is the initial wage for individual i, α is the intercept and where the two different D_{it} migrant variables capture moving to an urban- or city region. Country region migrants are here the reference category. The letter I, in turn, represents a matrix of individual level variables, such as age squared, education level and field and first or second generation immigrant. Ω is a matrix of employer level characteristics, including establishment size in terms of number of employees, dummies for public sector and multinational firm as well as sectorial and occupational dummies (see Table 1 for full list of variables). Lastly, λ_i signifies our – by way of probit estimation – derived control for self-selection, the so-called inverse Mill's ratio or Heckman's lambda (see discussion below).

When we then estimate average wage level effects, controlling for individual unobserved heterogeneity among workers, we drop our control for self-selection but add $D_{it}^{CntrRgn}$ and D_{it}^{Mvr}additional migrant destination categories, representing country side migrants and those changing location during the studied time span, 2001-2009. In these estimates those individuals changing region types (D_{it}^{Mvr}) are used as reference category.

$$\ln w_{it} = \alpha + \Phi_1 D_{it}^{UrbnRgn} + \Phi_2 D_{it}^{\text{CtRgn}} + \Phi_3 D_{it}^{CntrRgn} + \mathrm{I}_{it}'\beta \; + \; \Omega_{it}'\theta + \varepsilon_i \quad (2)$$

Finally, when estimating wage growth effects we use a similar model but add controls for initial wage level in 2001, $\ln(w_{it})$, and reintroduce our control for self-selection λ_i . As above, $D_{it}^{Mvr}$is here the reference category.

$$\ln\left(\frac{w_{it+1}}{w_{it}}\right) = \alpha + \rho\ln(w_{it}) + \Phi_1 D_{it}^{UrbnRgn} + \Phi_2 D_{it}^{\text{CtRgn}} + \Phi_3 D_{it}^{CntrRgn} + \; \mathrm{I}_{it}'\beta \; + \; \Omega_{it}' \; + \omega\lambda_i \; + \varepsilon_i \quad (3)$$

When estimating models (1) and (3), we here follow the familiar two-step approach to control for self-selection (Heckman 1979). As is in much of the literature, the aim is here to try to add controls for the fact that migrants, and specifically those that are continuously employed following migration, may not be a representative sample of the population at large, perhaps being more ambitious, motivated or with other innate characteristics affecting their subsequent labor market income. We need to control for this if we are not to confuse environment and locational influence on income with mere intrinsic characteristics of the migrant workers themselves. Our inverse Mill's ratios (our self-selection adjustment term) are estimated using all relevant observable individual characteristics that our data allow for (see Table 1). However, as the question of which variables to include when estimating self-selection is by no means straight-forward, and as we cannot fully replicate Ahlin et al. in this regard, we present our results both with and without these controls for parsimony.

Our selection equation is defined as follows

$$\Pr\ (U_i = 1|x_i) = \Phi\ (x_i'\Gamma) \qquad \text{(4a)}$$

$$x_i'\Gamma = \alpha + \mathrm{I}_i'\beta + \varepsilon_i \qquad \text{(4b)}$$

where Ui is a dummy variable equal to one if the individual is a migrant and employed for all years in either of the regions included in our study, zero otherwise. The selection equation ($x_i'\Gamma$) is then determined by a set of variables (the matrix I) capturing individual level characteristics such as education (since higher educated are assumed to be more prone to migrating and also more likely to have stable employment), marital status of the individual and controls for whether or not an individual is married or living together with someone with a university level education. These latter two variables are included to address the dual worker problem, where married couples in general and those with a higher educated spouse in particular are assumed to be more prone to migrating into a larger urban region, since the likelihood of both spouses finding employment would there be greater. We also include age, male/female and being a first or second generation immigrant, since both the young, women as well as foreign born are more prone to internal migration (see for example Amcoff *et al.* 2011; Niedomysl & Fransson 2014). In contrast to Ahlin et al., we do however not have access to information that to a larger extent captures underlying ability, such as high school grades, parents' educational level, name of university or the higher educational institution and the number of classmates with a job at the migrant destination. Our adjustment variable should instead primarily be interpreted as a composite measure – on the basis of observables – of the degree to which these migrants represent a separate or selected group.

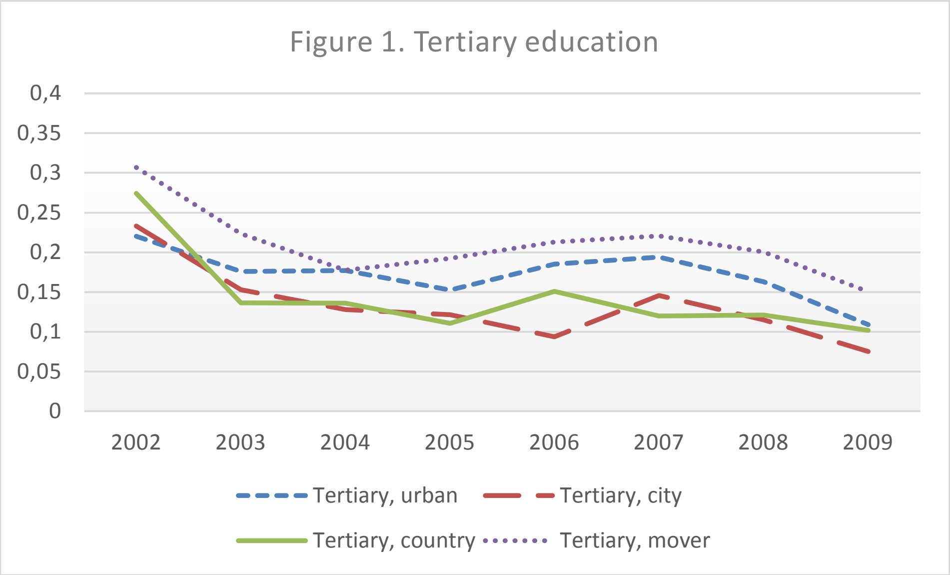
Table 1. Descriptive statistics of migrants by educational category (in 2001)

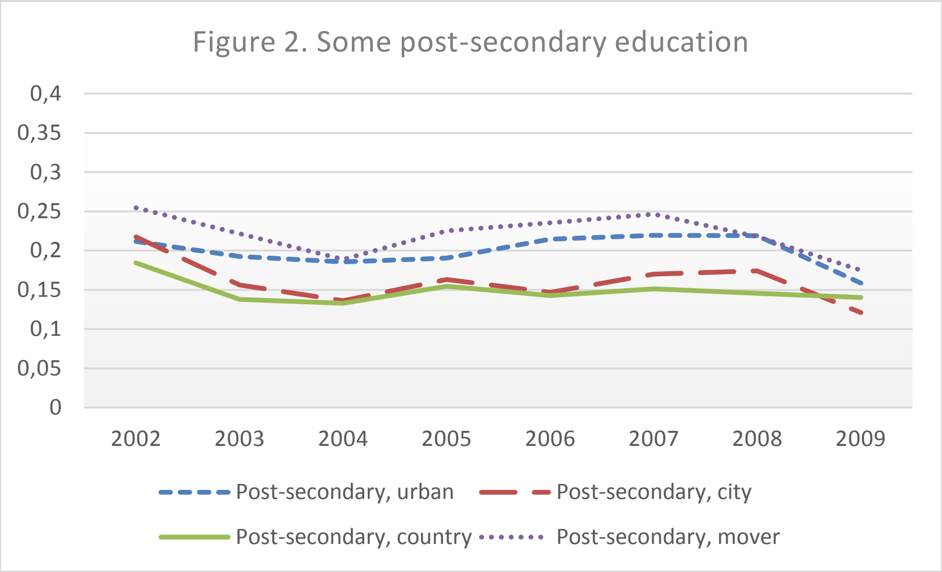
	Tertiary		Post-secondary		Secondary		Primary	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Wage (in EUR)	29030.35	10127.65	23504.18	9523.21	22970.32	8153.11	21203.20	7592.38
Urban migrant	0.33		0.36		0.22		0.22	
City region migrant	0.21		0.14		0.18		0.17	
Countryside migrant	0.12		0.11		0.14		0.15	
Spouse w. univ. edu.	0.06		0.02		0.01		0.01	
Spouse w.o. univ. edu.	0.11		0.06		0.10		0.14	
Male	0.43		0.53		0.63		0.62	
Age	27.54	1.74	26.49	2.07	25.78	2.18	26.47	2.39
Immigrant, 1:st gen.	0.07		0.05		0.07		0.13	
Immigrant, 2:nd gen.	0.03		0.02		0.04		0.05	
Natural science	0.09		0.09		0.01		0.01	
Engineering	0.24		0.28		0.26		0.12	
Social science	0.25		0.27		0.15		0.05	
Private sector	0.52		0.65		0.79		0.78	
Establishment size	349.65	1797.78	454.42	2054.28	588.80	2329.39	675.58	2486.96
MNE	0.30		0.34		0.30		0.28	
Tot. no. observations	2924		5117		6675		1418	

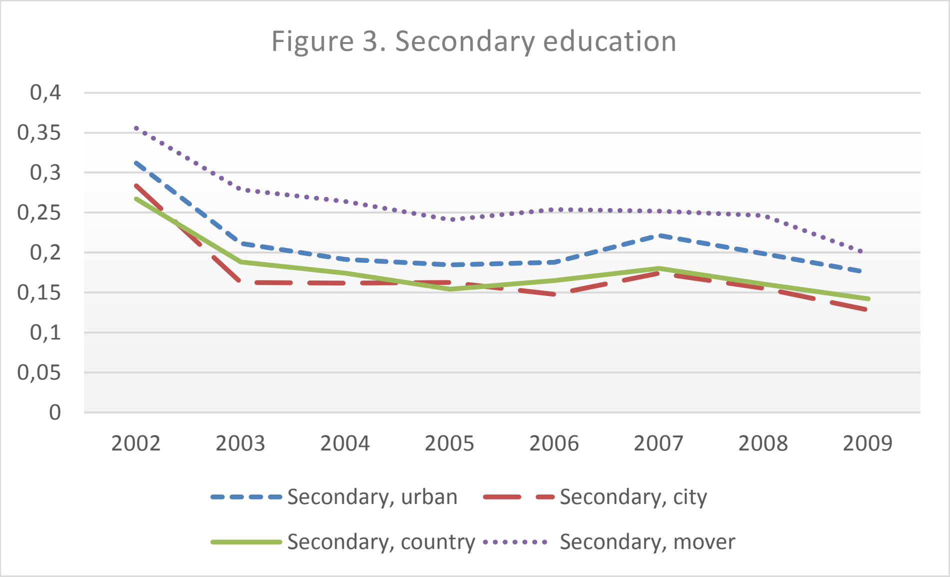
4. Descriptive statistics

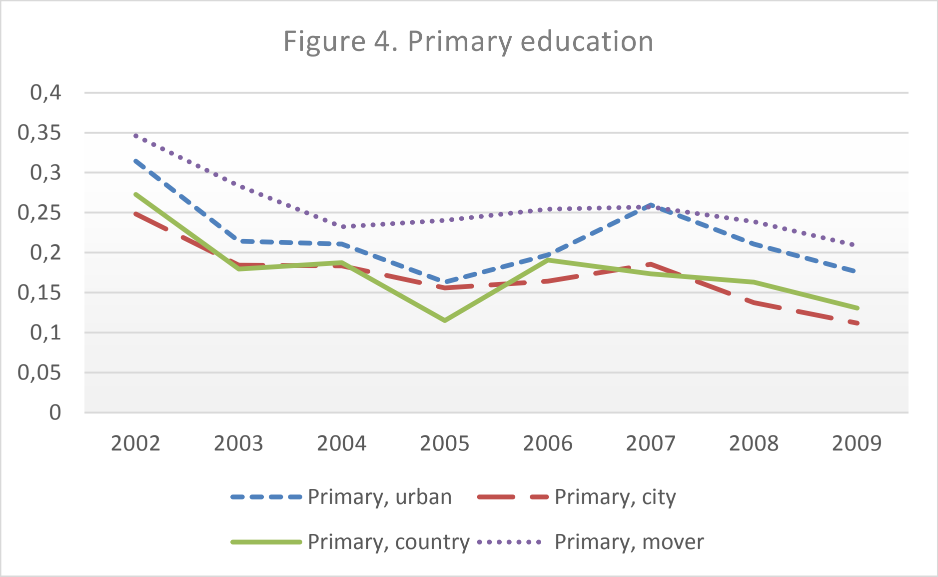
What is the pattern for the frequency of job changes among the migrants in our sample? To get a sense of this, figures 1 to 4 show the number of yearly job switches (by educational group) as a share of the total number of migrants at different regional destinations. As we can readily see from the figures, those changing regional categories ("Movers") show the highest rates of job changes, something which is to be expected since job changes by definition follow moving to a different type of region. However, among those residing at their initial destination, migrants living in large urban areas come out on top showing rates ranging from between 15-20 percent for those with tertiary education to slightly higher rates for our other educational groups. Thus, from sheer numbers we see that relative to those residing in smaller cities and countryside

Figures 1-4. Share of migrants changing jobs, by education and regional category, 2002-2009









regions, our other regional categories, there is definitely more in-between job movement happening over time in the largest urban regions, regardless of educational group.

We now turn to the question of possible consequences of these labor market discrepancies.

5. Results

First, looking at initial urban wage premium, i.e. the initial yearly wage income in 2001 of migrants moving between 2000 and 2001, Table 2 shows significantly higher income for tertiary educated urban migrants with positive but insignificant estimates for our other educational groups. City region migrants also show generally higher estimates compared to those moving to the country side (our reference category), but this effect is captured solely by those with some post-secondary education, significant at five percent level of confidence.

As for our controls, being male is significantly related to higher initial wages, mainly for those with tertiary education. Being foreign born is negative in terms of initial wage level, significantly so for the tertiary educated, while age, type of education (degree in engineering) as well as establishment size and working in the private sector all positively affect migrant initial wages, albeit with considerable variation both in terms coefficient size and level of statistical significance. Our control for self-selection, Heckman's lambda, captures a negative selection effect for the whole sample, this total effect is however less robust when splitting our sample along educational groups.

Following Ahlin et al., as a robust test of these estimates, we also include average wage level estimates for the years that follow (2002-2009), where we use fixed effect panel regression allowing control for unobserved heterogeneity amongst migrants. In Table 3, we here find further evidence that the urban wage premium is mostly a larger metropolis phenomenon, with overall weak or non-statistically significant effects for city region migrants but highly significant effects for their urban region counterparts. Notably, these urban level effects are found for all our educational groups including those with only primary (nine years) education. Further, Table 3 also reveals average wage level estimates that are relatively larger for those urban region migrants with less education than university level. As compared to the insignificant initial urban wage premium for

Table 2. Initial migrant wage in 2001, by educational category [3]

VARIABLES	All	Tertiary	Post-secondary	Secondary	Primary
Urban migrant	0.016*	0.077***	0.001	0.014	0.032
	(0.009)	(0.025)	(0.030)	(0.025)	(0.063)
City region migrant	0.025***	0.028	0.039**	0.012	-0.034
	(0.009)	(0.020)	(0.019)	(0.014)	(0.031)
Spouse w. univ. education	-0.011	-0.067***	0.037	-0.024	-0.000
	(0.020)	(0.025)	(0.039)	(0.049)	(0.106)
Spouse w.o. univ. education	-0.088***	-0.025	-0.098*	-0.128**	-0.049
	(0.011)	(0.034)	(0.056)	(0.052)	(0.132)
Male	0.070***	0.126***	0.025	0.059*	0.152**
	(0.008)	(0.025)	(0.034)	(0.030)	(0.071)
Age (ln)	1.321***	0.384	2.060***	1.243***	0.360
	(0.047)	(0.252)	(0.356)	(0.314)	(0.774)
Immigrant, 1:st generation	0.064***	-0.157**	0.146	0.091	-0.011
	(0.015)	(0.073)	(0.107)	(0.095)	(0.232)
Immigrant, 2:nd generation	-0.034*	-0.011	-0.027	-0.043*	-0.094*
	(0.018)	(0.039)	(0.035)	(0.026)	(0.053)
Natural science	-0.090***	0.047	-0.056	-0.093	-0.289*
	(0.016)	(0.045)	(0.061)	(0.073)	(0.161)
Engineering	-0.005	0.149***	0.005	-0.041	0.008
	(0.010)	(0.035)	(0.047)	(0.041)	(0.104)
Private sector	0.067***	0.046*	0.071***	0.059***	0.065*
	(0.012)	(0.025)	(0.022)	(0.021)	(0.038)
Estblishment size	0.005***	0.009**	-0.001	0.008***	0.005
	(0.002)	(0.004)	(0.003)	(0.002)	(0.005)
Heckman's lambda	-0.323***	0.391*	-0.497	-0.529*	-0.009
	(0.022)	(0.207)	(0.308)	(0.273)	(0.630)
Observations	9,322	1,921	3,105	3,536	760
R-squared	0.309	0.369	0.318	0.272	0.315

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

these groups shown in the previous table (Table 2), these urban migrants thus appear to receive somewhat larger wage growth during the subsequent time period.

[3] Note; as our primary education category includes a limited number of migrants with some short post-elementary education (no more than one year) that are technical/practical or agricultural character, we also get estimates for our dummy variables Natural sciences and Engineering for this educational category. Excluding these migrants does however not affect the outcome.

Other results of interest in Table 3 are that being married or living in a relationship with someone, regardless of the educational status of the spouse (with or without a tertiary education) is negatively related to average wage level. As we are dealing with a sample

Table 3. Wage level effects by educational category, 2002-2009 (FE estimates)

VARIABLES	All	Tertiary	Post-secondary	Secondary	Primary
Urban migrant	0.059***	0.034***	0.058***	0.059***	0.069***
	(0.004)	(0.012)	(0.007)	(0.006)	(0.013)
City region migrant	0.008**	-0.001	0.005	0.014**	0.006
	(0.004)	(0.011)	(0.007)	(0.006)	(0.011)
Spouse w. univ. education	-0.094***	-0.152***	-0.105***	-0.065***	-0.067
	(0.010)	(0.020)	(0.016)	(0.019)	(0.046)
Spouse w.o. univ. education	-0.127***	-0.200***	-0.157***	-0.093***	-0.084***
	(0.004)	(0.011)	(0.006)	(0.006)	(0.011)
Age	2.014***	-1.392*	4.505***	0.815***	0.795
	(0.201)	(0.744)	(0.359)	(0.316)	(0.570)
Private sector	0.013**	0.007	0.020**	-0.015	0.076***
	(0.006)	(0.018)	(0.009)	(0.010)	(0.018)
Tenure	0.088***	0.037***	0.094***	0.076***	0.099***
	(0.002)	(0.007)	(0.003)	(0.004)	(0.007)
Tenure squared	-0.012***	-0.007***	-0.013***	-0.010***	-0.014***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Job change	0.076***	0.052***	0.086***	0.049***	0.067***
	(0.004)	(0.011)	(0.006)	(0.006)	(0.010)
Establishment size	0.003***	0.001	0.004***	0.003***	0.003
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
MNE	0.042***	0.055***	0.036***	0.032***	0.058***
	(0.004)	(0.013)	(0.006)	(0.006)	(0.011)
Observations	67,351	8,354	29,144	22,533	7,320
R-squared	0.223	0.165	0.282	0.205	0.233
Number of IndLpnr	14,028	1,424	7,122	4,401	1,688

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

of relatively young workers, it is possible that some of this reflects being on either paternity or maternity leave but it may also reflect the problems of dual earner households in finding work that match the educational level of both spouses. As for our controls for tenure (time on the job) and changing jobs, both of these are highly significant and positive for all educational categories. For the higher educated the effect of job changes is however larger than tenure, and conversely, the estimates for tenure are somewhat larger than job changes for those with relatively less education. So, even though the differences are by no means substantial, this indicates job changes as entailing relatively larger pay-offs for the tertiary educated.

Turning to our results for yearly wage growth (Table 4), these results further corroborate the findings in Ahlin et al. as regards those with tertiary education. To reiterate, what we analyze here is a select group of migrants that are employed all years following initial relocation into urban regions. As seen in Table 3, column 2, migrants heading into to the three largest areas on average experience a yearly increase in wage income of around two percent.

In line with previous estimates in Table 3 as regards the average wage level, what this analysis points to is that these “thick” labor market matching effects are however not confined to those with tertiary education. Columns three to four, Table 4, highlight wage growth of very similar magnitude (about two percent) also for those with some post-secondary and secondary education. For those with a primary educational level however we get positive but statistically insignificant estimates. As for these insignificant effects, we should note however that our sample size for those with primary education is considerably smaller than for the other groups. When we perform a somewhat less hard test of our hypothesis and increase our sample size by way of analyzing a non-balanced sample, we get highly significant positive estimates also for this educational group (not shown).

As in Ahlin, we can however not find similar matching effects for migrants heading into any of our other region types, regardless of educational background. Instead, across all our educational categories, we get lower – though insignificant – estimates of income development for migrants working in city- and countryside regions compared to our reference group (i.e., compared to those moving in between region types).

Additional significant factors affecting the wage growth (model no. 3) are that men have higher income development relative to women, in ranges of around three to eight percent yearly depending on educational category. Age is strongly positive, implying that the rate of increase goes up as our sample ages from 22-29 to 31-38 years of age. Contrary to estimates in Table 2 and 3 is that being a first generation immigrant is slightly positive.

However, in line with previous results, cohabitation and being married – regardless of the educational level of the spouse – is negatively associated with income development,

Table 4. Migrant wage growth by destination choice and educational category, 2001- 2009

VARIABLES	All	Tertiary	Post-secondary	Secondary	Primary
Urban migrant	0.021***	0.022***	0.018***	0.019***	0.013
	(0.003)	(0.006)	(0.005)	(0.004)	(0.010)
City region migrant	-0.005*	-0.008	-0.009*	0.000	-0.012
	(0.003)	(0.007)	(0.005)	(0.004)	(0.010)
Countryside migrant	-0.006**	0.001	-0.010	-0.004	-0.005
	(0.003)	(0.009)	(0.006)	(0.004)	(0.011)
Lagged wage inc	-0.374***	-0.414***	-0.401***	-0.348***	-0.377***
	(0.005)	(0.011)	(0.009)	(0.008)	(0.018)
Male	0.047***	0.083***	0.037***	0.036***	0.031**
	(0.003)	(0.008)	(0.007)	(0.006)	(0.014)
Age (ln)	0.231***	0.265***	0.185***	0.232***	0.256**
	(0.016)	(0.073)	(0.057)	(0.043)	(0.105)
Spouse w. univ. education	-0.048***	-0.075***	-0.047***	-0.038***	-0.069***
	(0.004)	(0.007)	(0.008)	(0.008)	(0.023)
Spouse w.o. univ. education	-0.065***	-0.085***	-0.078***	-0.054***	-0.078***
	(0.003)	(0.008)	(0.008)	(0.007)	(0.017)
Immigrant, 1:st generation	0.031***	-0.003	0.044**	0.031**	0.072**
	(0.005)	(0.021)	(0.018)	(0.014)	(0.030)
Immigrant, 2:nd generation	0.008	0.014	0.020	0.006	-0.026
	(0.006)	(0.013)	(0.012)	(0.008)	(0.017)
Natural science	-0.027***	-0.031**	-0.020*	-0.032*	-0.083**
	(0.005)	(0.014)	(0.011)	(0.017)	(0.033)
Engineering	-0.017***	-0.013	-0.012	-0.024***	-0.023
	(0.003)	(0.010)	(0.008)	(0.006)	(0.016)
Private sector	0.010***	0.017*	0.020***	0.006	0.030**
	(0.004)	(0.009)	(0.007)	(0.006)	(0.013)
Establishment size	0.004***	0.008***	0.004***	0.002**	0.005**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Tenure	0.003	-0.003	0.007	0.003	0.007
	(0.002)	(0.006)	(0.005)	(0.003)	(0.008)
Tenure squared	-0.000	0.000	-0.001	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Job change	0.009**	0.022**	0.032***	-0.007	-0.010
	(0.005)	(0.011)	(0.009)	(0.007)	(0.014)
Heckman's lambda	-0.076***	0.049	-0.091**	-0.121***	-0.184**
	(0.007)	(0.053)	(0.043)	(0.035)	(0.078)
MNE	0.021***	0.023***	0.015***	0.024***	0.013
	(0.002)	(0.007)	(0.005)	(0.003)	(0.008)
Observations	51,450	11,441	15,584	20,568	3,857
R-squared	0.203	0.211	0.254	0.184	0.218

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

while working in the private sector and size of establishment is positive for all educational categories. Further, using this model, tenure is insignificant for all groups, while job change is significantly positive for those with tertiary and some post-secondary education but insignificant for the secondary or primary educated. Finally, our controls for self-selection (Heckman's lambda) show significant negative effects for our lower educational categories, indicating that our migrant sample is indeed a select group. We also find positive effects of working at a multinational company (MNE) for all but those with lowest educational levels (primary).

Again, to repeat; all these estimates capture effects on wage development that go beyond effects related to the business cycle (year dummies), type of workplace ownership (private/public) as well as controls for industry type and occupation.

We now turn to our last research question, that is, whether or not these labor market matching effects are solely confined to the largest metropolitan regions, and whether this is true for all educational categories. To gauge this, Table A2 shows results of model number three on our main variables of interest, i.e. our different migrant categories, however, in contrast to previous estimates we here add dummy variables for migrants moving into labor markets that are ranked fourth, fifth and sixth in terms of population size (Linköping, Örebro and Västerås, respectively). This additional analysis mainly corroborates our previous findings; neither of these additional migrant destination categories capture anything additional in terms of income development regardless of educational background.

To be sure, this conclusion is somewhat dependent on modelling approach: For example, when including these lower ranked labor markets in our original categories for urban migrants (and dropping them from the city region category) we still find positive and significant estimates for urban region migrants, though somewhat smaller in magnitude. However, our sample is sufficiently large that if these migrant destinations were also truly associated with this type of urban wage premium, we would most likely capture these effects using separate categorical dummy variables as in Table A2.[4]

[4] Note: When we increase sample size by using an unbalanced sample, and then test model number 3 adding dummies for lower ranked cities, this does not affect the outcome; these variables are still statistically insignificant (NOT SHOWN). Our conclusions in this regard are thus robust to concerns of too small sample size.

6. Concluding discussion

This paper has highlighted labor market matching effects for migrants of different educational categories moving into Swedish urban-, city- and country side regions, respectively. As in most previous literature, we find these effects as mainly – almost exclusively – happening in the bigger city metropolitan regions (in the Swedish case; Stockholm, Gothenburg and Malmö). Somewhat contrary to the previous literature – which has pointed to the urban wage premium as mostly pertaining to the higher educated, or those with skills more associated with university level education – we find these type of matching effects of be of similar magnitude for all educational groups. That is not to say that there is no variation; as for the initial wage premium of migrants, measured the year of the move, we can only find significant positive estimates for those with university level education. Measuring income development over time however, looking at the average nine year wage level as well as yearly wage growth, this generally gives a picture of stronger increases for those with relatively lower formal education. Admittedly, this conclusion is somewhat less robust for those with primary education but we need to keep in mind that when testing wage growth for full employed during nine years (as in Table 4) our sample size is considerably smaller for the lower educated, and using an unbalanced sample gives strong significant estimates wage growth also for this subgroup of migrants.

Our additional tests for the relevance of our destination categories (urban, city and country side regions), originally used in Ahlin et al (2014), also reveals the results from our main models as robust across different geographical categories; when adding controls for city regions that are just below the large metropolitan category in terms of population size, this points to very similar outcomes, and we cannot find significant effects at normal levels of confidence for any of our additional geographical categories. This suggests rather exact population thresholds for these type of matching effects across educational categories.

As to causes of this migrant urban wage premium, we should note that our conclusions follow from theory in the sense that we assume that a good match – whether happening initially or over time when individuals subsequently switch jobs leading to better employer-employee matches – is something that results in higher individual productivity which is then also reflected in the wages paid to the individual. In other words, our empirical approach does not imply measuring matching effects directly, which is hard to do. Rather we control for all other factors effecting individual income development (including year-, industry- and occupational dummies, plus controls for self-selection and unobserved heterogeneity) and add migrant locational dummies to capture where we can find effects that go beyond what we can capture with our other variables.

Finally, we should note that our results do not imply that migrants heading into city- or country side regions experience a loss from that relocation. In our research design, the negative or statistically insignificant coefficients estimated for these non-urban migrants only pertain relative to other migrant categories, not to those staying behind and not moving at all.

7. References:

Ahlin, L., Andersson, M., Thulin, P., 2014. Market Thickness and the Early Labour Market Career of University Graduates: An Urban Advantage? Spatial Economic Analysis 9, 396-419

Amcoff, J., Östh, J., Niedomysl, T., Moberg, U., 2011. Vart tar invandrarna vägen? Vidareflyttning under 00-talet bland nyanlända flykting-, arbets- och äktenskapsinvandrare. In: Demografisk rapport. Landstingsstyrelsens förvaltning, Tillväxt, miljö och regionplanering, Stockholm

Andersson, M., Klaesson, J., Larsson, J.P., 2014. The sources of the urban wage premium by worker skills: Spatial sorting or agglomeration economies? Papers in Regional Science 93, 727-747

Andersson, M., Lööf, H., 2012. Small business innovation: firm level evidence from Sweden. The Journal of Technology Transfer 37, 732-754

Antelius, J., Björklund, A., 2000. How reliable are register data for studies of the return on schooling? An examination of Swedish data. Scandinavian Journal of Educational Research 44, 341-355

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

Badinger, H., Tondl, G., 2003. Trade, human capital and innovation: the engines of European regional growth in the 1990s. Springer.

Cheshire, P., Magrini, S., 2000. Endogenous processes in European regional growth: convergence and policy. Growth and Change 31, 455-479

Ciccone, A., Hall, R.E., 1996. Productivity and the Density of Economic Activity. The American Economic Review 86, 54-70

Combes, P.-P., Duranton, G., Gobillon, L., 2008. Spatial wage disparities: Sorting matters! Journal of Urban Economics 63, 723-742

Combes, P.-P., Duranton, G., Gobillon, L., 2010. The identification of agglomeration economies. Journal of Economic Geography, lbq038

De la Roca, J., Puga, D., 2012. Learning by working in big cities CEPR Discussion Paper No. DP9243. Available at SSRN: http://ssrn.com/abstract=2210212

Dixon, S., 2003. Migration within Britain for job reasons. Labour Market Trends 111, 191-202

Faggian, A., McCann, P., 2006. Human capital flows and regional knowledge assets: a simultaneous equation approach. Oxford Economic Papers 58, 475-500

Faggian, A., McCann, P., 2009. Human capital, graduate migration and innovation in British regions. Cambridge Journal of Economics 33, 317-333

Glaeser, E.L., 1998. Are Cities Dying? The Journal of Economic Perspectives 12, 139-160

Glaeser, E.L., 1999. Learning in cities. Journal of urban Economics 46, 254-277

Glaeser, E.L., Gottlieb, J.D., 2006. Urban Resurgence and the Consumer City. Urban Studies 43, 1275-1299

Glaeser, E.L., Kolko, J., Saiz, A., 2001. Consumer city. Journal of economic geography 1, 27-50

Glaeser, Edward L., Maré, David C., 2001. Cities and Skills. Journal of Labor Economics 19, 316-342

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica: Journal of the econometric society, 153-161

Kim, S., 1987. Diversity in urban labor markets and agglomeration economies. Papers in Regional Science 62, 57-70

Kim, S., 1990. Labor heterogeneity, wage bargaining, and agglomeration economies. Journal of Urban Economics 28, 160-177

Korpi, M., 2008. Does size of local labour markets affect wage inequality? a rank-size rule of income distribution. Journal of Economic Geography 8, 211-237

Moretti, E., 2004. Human capital externalities in cities. Handbook of regional and urban economics 4, 2243-2291

Moretti, E., 2012. The new geography of jobs. Houghton Mifflin Harcourt.

Moretti, E., Thulin, P., 2013. Local multipliers and human capital in the United States and Sweden. Industrial and Corporate Change 22, 339-362

Morrison, P.S., Clark, W.A.V., 2011. Internal migration and employment: macro flows and micro motives. Environment and Planning-Part A 43, 1948

Niedomysl, T., 2011. How migration motives change over migration distance: evidence on variation across socio-economic and demographic groups. Regional Studies 45, 843-855

Niedomysl, T., Clark, W.A.V., 2014. What matters for internal migration, jobs or amenities? Migration Letters 11, 377-386

Niedomysl, T., Fransson, U., 2014. On Distance and the Spatial Dimension in the Definition of Internal Migration. Annals of the Association of American Geographers 104, 357-372

Partridge, M.D., 2010. The duelling models: NEG vs amenity migration in explaining US engines of growth. Papers in Regional Science 89, 513-536

Puga, D., 2010. The Magnitude and Causes of Agglomeration Economies*. Journal of Regional Science 50, 203-219

Rosenthal, S.S., Strange, W.C., 2004. Evidence on the nature and sources of agglomeration economies. Handbook of regional and urban economics 4, 2119-2171

Shapiro, J.M., 2006. Smart cities: quality of life, productivity, and the growth effects of human capital. The review of economics and statistics 88, 324-335

Simon, C.J., 1998. Human capital and metropolitan employment growth. Journal of Urban Economics 43, 223-243

Storper, M., Scott, A.J., 2009. Rethinking human capital, creativity and urban growth. Journal of economic geography, lbn052

Wheeler, C.H., 2006. Cities and the growth of wages among young workers: Evidence from the NLSY. Journal of Urban Economics 60, 162-184

Yankow, J.J., 2006. Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. Journal of Urban Economics 60, 139-161

8. Appendix

Table A1. Main variables of interest and other controls; definitions

Urban migrant	Coded one if residing in an urban region; Stockholm, Gothenburg or Malmö
City region migrant	Coded one if residing in a city region (46 city regions in total)
Countryside migrant	Coded one if residing in a countryside region (197 in total)
Mover	Changing regional category post initial migration, 2000-2001
Male	Coded one if male
Age (ln)	Individual's age squared
First generation immigrant	Born outside of Sweden
Second generation immigrant	Both parents foreign born
Spouse with higher education	Spouse with tertiary education
Spouse without higher education	Spouse without tertiary education
Lagged wage income	Previous year's wage income
Natural science	Degree or diploma in the natural sciences
Engineering	Degree or diploma in engineering
Private sector	Working in the private sector (public sector reference category)
Establishment size	No. of employed at place of work (ln)
Tenure	Time on the job (no. of years)
Tenure squared	Time on the job squared
Job change	Change of jobs (both of workplace and employer)
MNE	Working within a multi-national firm
Heckman's lambda	Adjustment term for self-selection

Table A2. Wage growth by destination choice and educational category, 2001- 2009, including separate dummies for cities ranked 4th to 6th, respectively.

VARIABLES	All	Educ. 4	Educ. 3	Educ. 2	Educ. 1
Urban migrant	0.021***	0.022***	0.018***	0.019***	0.013
	(0.003)	(0.006)	(0.005)	(0.004)	(0.010)
Linkoping	-0.009	0.021	-0.017	-0.027*	0.004
	(0.009)	(0.018)	(0.015)	(0.016)	(0.022)
Orebro	-0.011	-0.034	0.004	-0.011	-0.016
	(0.008)	(0.021)	(0.014)	(0.012)	(0.029)
Vesteras	0.005	0.009	0.035**	-0.005	-0.015
	(0.008)	(0.025)	(0.016)	(0.011)	(0.017)
City region migrant	-0.006**	-0.009	-0.014**	0.002	-0.014
	(0.003)	(0.007)	(0.006)	(0.004)	(0.011)
Countryregion migrant	-0.005*	0.000	-0.009	-0.002	-0.002
	(0.003)	(0.009)	(0.007)	(0.004)	(0.011)
Laged wage income	-0.374***	-0.415***	-0.401***	-0.349***	-0.377***
	(0.005)	(0.011)	(0.009)	(0.008)	(0.018)
Male	0.047***	0.083***	0.038***	0.036***	0.031**
	(0.003)	(0.008)	(0.007)	(0.006)	(0.014)
Age	0.231***	0.266***	0.187***	0.231***	0.254**
	(0.016)	(0.073)	(0.057)	(0.043)	(0.105)
Spouse w. univ. education	-0.048***	-0.075***	-0.047***	-0.039***	-0.069***
	(0.004)	(0.007)	(0.008)	(0.008)	(0.023)
Spouse w.o. univ. education	-0.065***	-0.086***	-0.078***	-0.054***	-0.078***
	(0.003)	(0.008)	(0.008)	(0.007)	(0.017)
Immigrant, 1:st generation	0.031***	-0.002	0.044**	0.031**	0.071**
	(0.005)	(0.021)	(0.018)	(0.014)	(0.030)
Immigrant, 2:nd generation	0.008	0.014	0.021*	0.007	-0.026
	(0.006)	(0.013)	(0.012)	(0.008)	(0.017)
Natural science	-0.027***	-0.032**	-0.020*	-0.031*	-0.083**
	(0.005)	(0.014)	(0.011)	(0.017)	(0.033)
Engineering	-0.017***	-0.013	-0.012	-0.024***	-0.023
	(0.003)	(0.010)	(0.008)	(0.006)	(0.016)
Private sector	0.010***	0.018*	0.021***	0.005	0.029**
	(0.004)	(0.009)	(0.007)	(0.006)	(0.013)
Establisment size	0.004***	0.007***	0.004***	0.002**	0.005**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Tenure	0.003	-0.003	0.007	0.003	0.007
	(0.002)	(0.006)	(0.005)	(0.003)	(0.008)
Tenure squared	-0.000	0.000	-0.001	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Job change	0.009**	0.022**	0.032***	-0.007	-0.010
	(0.005)	(0.011)	(0.009)	(0.007)	(0.014)
Heckman’s lambda	-0.076***	0.048	-0.092**	-0.120***	-0.183**
	(0.007)	(0.053)	(0.043)	(0.035)	(0.078)
MNE	0.021***	0.022***	0.015***	0.024***	0.013
	(0.002)	(0.007)	(0.005)	(0.003)	(0.008)
Observations	51,450	11,441	15,584	20,568	3,857
R-squared	0.203	0.211	0.255	0.184	0.218

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1