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Human capital theory and internal migration: do average outcomes distort our view of migrant motives?

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Abstract

By modelling the distribution of percentage income gains for movers in Sweden, using multinomial logistic regression, this paper shows that those receiving large pecuniary returns from migration are primarily those moving to the larger metropolitan areas and those with higher education, and that there is much more variability in income gains than what is often assumed in models of average gains to migration. This suggests that human capital models of internal migration often overemphasize the job and income motive for moving, and fail to explore where and when human capital motivated migration occurs.

Keywords: migration; human capital; labor mobility; urban rural.

Introduction

Models of inter-labor market migration have documented the average gains that accrue from moving from one labor market to another. In the human capital model of migration, with its emphasis on how movers self-select to take advantage of skill specific wages at alternate locations, these average nominal gains are then routinely used to explain continuing migration up the urban hierarchy and especially to larger cities in the hierarchy. This basic idea has been pervasive and continues to be a mainstay of research and policy making.

However, in contrast to average returns we know much less about the *distribution* of income gains from labor market migration. To place the notion of average gains in context, we might think of the following outcome. In a cohort of movers, the cohort overall might have an average income gain that could well be related to a selection of movers who do very well from the move, but the cohort could also

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contain a subset of movers who make no gains or even losses. Thus, while the average may be positive it is an incomplete picture of the returns to migration.

Survey research on migrant motives also provides a potential explanation for why there should be a wide range of economic outcomes. It suggests that when employment is relatively ubiquitous across an array of locations, employment may enter the decision making matrix but it is not necessarily the primary motivation (Chen & Rosenthal 2008). In these situations we might well expect income gains to be quite variable, as is also highlighted in for example Morrison and Clark (2011) and Niedomysl (2011) where only about one third of respondents list employment related reasons as their main motive for moving.

To explore the variation in migrant outcomes we pose two questions about the nature of labor market migration and its pecuniary returns: Firstly, how large a share of those moving actually experience a percentage increase in nominal income, and how many experience a loss? Second, how does this outcome depend on the characteristics of migrants and the time-frame of analysis?

Using a five percent sample of the Swedish working age population, 2001-2009, and distinguishing between migrant groups in terms of educational background and direction of migration, we analyze these research questions by estimating a multinomial logit model of the placement of migrants in different income growth categories, short and long term. The results suggest that it is primarily the higher educated and those heading into the bigger metropolitan areas that receive larger pay-offs from internal migration.

The paper is organized as follows; section two discusses previous research and section three our research methods and data. Section four and five provide detailed figures of the distribution of migrant outcomes and our model results, respectively, while section six concludes.

Previous Research

In human capital models of migration, the focus is on the individual's decision to move and that this decision is conditional upon the return he/she expects to receive from moving in contrast to what is expected from staying (Kan 1999; Khwaja 2002). These ideas still motivate much contemporary analysis of migration, and since Hicks (1932) the argument has reiterated that differences in net economic advantages, chiefly wages, are the main cause of migration. The theme is continued in Sjaastad (1962), and Harris and Todaro (1970), and more recent research including Nakosteen and Westerlund (2004), Newbold (1996; 2012), Blackburn (2010), Böheim and Taylor (2007), and in the New Zealand context by Maré and Timmins (2003), who continue to treat the decision to move from one labor market to another as primarily a human capital *investment*.

However, some recent work on human capital investment also suggest that the returns to migration are more differentiated along for example age and education than shown in previous studies. Yankow (1999) provides two conclusions for 25-32 year old workers, both relevant for our approach – (*i*) that indeed, young interstate migrants generate positive returns, especially those in their early career stages who change employers, and (*ii*) that time is important; the rewards accumulate over a five year period so obviously time dependent outcomes become important (see also Farber, 1994). Similar differentiation of returns is highlighted in Rodgers and Rodgers (2000), where, looking only at continuously employed, real earnings were 20 percent above expected levels six years after moving, and younger men had the most returns while there was little or no benefit for older movers. Yankow (2003), also shows quite clearly that it is the highly educated movers make the highest gains, again with a lag of about two years before the gains become apparent. Thus, there is increasing evidence that the returns to migration are focused on a sub-set of movers; younger migrants, the more skilled and moves that explicitly involve changing jobs.

Despite the evidence in support of a human capital investment approach, several papers have also suggested that increasingly cities offer not just employment opportunities but a vast array of consumption opportunities from housing to cultural life (Glaeser *et al.* 2001). In this conceptualization, migrant motives are more complex than evaluating only the best job and moving as a response (Berger & Blomquist 1992). Glaeser et al point to the fact that urban rents go up faster than urban wages in growth cities as a demonstration that there is a demand for living in cities for reasons *beyond* wages, and a recent paper using Swedish data found similar results (Korpi *et al.* 2011).

If it is true that cities offer more than employment opportunities and equally allow households to meet other demands than increasing their returns to labor, we would in fact expect a wide distribution in the returns to migration. As mentioned previously, this expectation is also in line with survey studies which suggest that migrants are as much concerned about adjusting consumption and/or realigning social relationships as they are about making specific economic gains (Chen & Rosenthal 2008; Morrison & Clark 2011; Niedomysl 2011). See also Cassarino (2004) and De Haas (2010).

Thus, we here draw attention to a long standing argument that migration is not only about pecuniary gains, and by examining the determinants of the distribution of outcomes rather than estimating average returns, we can better elaborate on both the returns to migration and the possible underlying motivations. To reiterate though, it is not that economic factors do not underlie the migration outcomes, certainly, there is also evidence that costs of living are important in the decision to move (Withers & Clark 2006), and the unemployed often still move to improve their job prospects. But in between there are a wide range of social outcomes inter-related with migration decisions. Here, we therefore seek a way to bridge the gap between qualitative and quantitative approaches to migration, and ask the question; does focusing on average outcomes distort how we interpret migration, and can examining the whole range of proportional gains enlarge our understanding about its motives?

Data and Research Methods

Our paper utilizes a five percent sample from Statistics Sweden's full population database (LISA) for the years 2001-2009. These data detail place of residence and work plus a series of individual-level data, including educational and occupational status as well as source and level of income. The data (unbalanced) totals 194 661 individuals, ages 20-64, out which 32 462 are internal migrants.

Since we are not in interested in student related migration and also seek to avoid having to interpret outcomes related to tied movers, we define migrants as all non-student single households, i.e. persons not married or living in a registered partnership, that move in between Swedish local labor markets. According to the definition of local labor markets that we use here, Sweden can be divided into 82 such labor markets (comprising some 290 municipalities), where the main separation criteria for these is the share of working age population commuting out of a municipality on a daily basis (Statistics Sweden 2003).

To enhance robustness and make our estimates less model-dependent, we match migrants and non-migrants on age, geography and education. Rather than using the more conventional PSM-techniques, we here utilize so-called CEM-matching (coarsened exact matching). Where propensity score matching aims to match treated and the non-treated on the basis of an average estimated score for the covariates, CEM seeks to emulate the ideal – but impractical – exact matching.[1] Further, as to limit any outsized influence on our estimates emanating from the tails of the distribution, we also set the outliers of our income growth estimates equal to either the 1st or 99th percentile of the distribution (using Stata's winsorize command).

Our modeling approach can then be described as follows. Firstly, we calculate the interquartile range of percent yearly change in disposable income and assign each individual to either one of the three resulting categories. That is, as either belonging below the 25th, in-between the 25th and the 75th or above the 75th percentile of yearly income gain (which on average correspond to -98 to -3, -3 to 16 and 16 to 448 percent, respectively). Second, we specify a multinomial logit model where we estimate the determinants of the log odds of belonging to the first and third of these three categories (our low and high income growth category), using our "average" growth category as reference.

Formally, these logistic regressions are of the form:

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[1] For a detailed review of this methodology and a comparsion with propensity score matching, see for example Iacus *et al.* (2011a, 2011b), King and Nielsen (2016).

$$\text{logit (y=1)} = log\left(\frac{p(y=1)}{1-(p=1)}\right) = \beta_0 + \mathbf{RM'}_{i,t}\beta_1 + \mathbf{MM'}_{i,t}\beta_2 + \mathbf{X'}_{i,t}\,\beta_3 + \varepsilon_{i,t} \quad (1)$$

$$\text{logit (y=3)} = log\left(\frac{p(y=3)}{1-(p=3)}\right) = \beta_0 + \mathbf{RM'}_{i,t}\beta_1 + \mathbf{MM'}_{i,t}\beta_2 + \mathbf{X'}_{i,t}\,\beta_3 + \varepsilon_{i,t} \quad (2)$$

where y=1 and y=3 are the income growth categories one and three, respectively, β_0 is the intercept and $RM'_{i,t}$ and $MM'_{i,t}$ are two matrices including binary variables for regional and metropolitan migration. Each individual migrant is here characterized as belonging to any one of four separate educational categories (see Table 1).

Table 1. List of variables

Migrant categories:
TERTIARY *regional* = Coded one if a regional migrant has at least a bachelor's degree
POST SECONDARY *regional* = regional migrant with some post-secondary education
SECONDARY *regional* = regional migrant with completed secondary education, at least 12 years of schooling
PRIMARY *regional* = Coded one if an individual migrant has up to nine years of mandatory education, or is either a high school or gymnasium level drop-out.
TERTIARY *metropolitan* = Coded one if an metropolitan migrant has at least a bachelor's degree
POST SECONDARY *metropolitan* = metropolitan migrant with some post-secondary education
SECONDARY *metropolitan* = metropolitan migrant with completed secondary education, at least 12 years of schooling
PRIMARY *metropolitan* = Coded one if a metropolitan migrant has up to nine years of mandatory education, or is either a high school or gymnasium level drop-out.
Other controls:
FEMALE = Coded one if female
AGE = Individual's age
AGE2 = Individual's age squared
EDUC = Educational ordinal variable that assumes values one to four, where these categories correspond to migrant's educational types as listed above (tertiary, post-secondary, secondary & primary)
NON EU 15 = Coded one if born outside of Sweden or any of the original 15 European union members
EMPLOYMENT = Going from unemployment to employment
UNEMPLOYMENT = Going from employment to unemployment
EDUCHANGE = Acquiring a higher level of education
JOBCHANGE = Accumulated number of job changes
YEAR = Binary variable for each year 2001-2009 (2001 used as base year)

Regional migration (RM) is defined as migration between non-metropolis local labor markets (i.e. all migration outside of the three biggest metropolitan regions, Stockholm, Gothenburg and Malmö), and metropolitan migration (MM) as migration into any of these three regions. Non-migrants are the reference category.

Finally, the matrix $X'_{i,t}$ includes controls for additional observable characteristics assumed to determine income development (see Table 1 for a list of explanatory variables), while β_1, β_2 and β_3 are parameters to be estimated. $\varepsilon_{i,t}$ is the stochastic error term.

Descriptives: The distribution of outcomes

The graphs below, depicting the distribution of percent gains from migration, are to our knowledge the first to examine and plot individual migrant outcomes, and by comparison also for stayers. Rather than focus on average outcomes, in these figures we show the extent to which outcomes vary. The figures readily confirm that there is considerable variability in the proportional gains and losses from relocating.

For our purposes, there are three main points to be derived from this type of descriptive analysis; (*i*) the overall nature of gains and losses, (*ii*) the distributions of these gains and losses by sub-categories such as education and direction of migration, and (*iii*) the comparison with the equivalent gains and losses of stayers.

First, looking only at the migrant distributions (shaded areas, figures 1 and 2), these distributions are approximately normal with modest right skews, that is, overall more movers make gains than losses. Depending on education and direction of the move, between 60 and 77 percent of migrants make a gain related to their move.

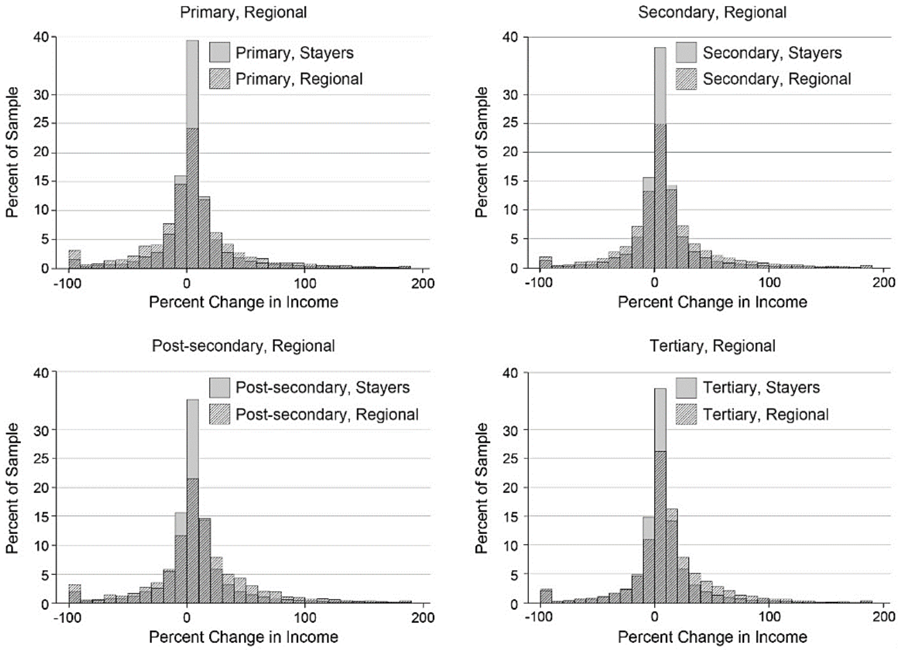
The greatest proportion of these migrant gains are rather modest: Regardless of educational background about a quarter of all migrants make gains in the 0-10 percent range, depicted in the first positive bar of the distribution. Some movers make very large proportional gains but the absolute number of these migrants is relatively small.

Further, more than half of all positive outcomes are in the first three bars of the distribution, i.e. corresponding to positive gains of up to 30 percent in income. The results are similar for regional and metropolitan movers although for the latter group they are somewhat skewed towards gains of less than 20 percent.

The flip-side of these numbers, in turn, mean that a substantial share of migrants make a loss from migration. We routinely think of movers making gains and certainly the migration literature tends to take the positive view of migration and its outcomes. Of course those taking an income loss may still be satisfied from the migration decision, but – varying somewhat by education – more than a quarter (28-40 percent) of movers make a loss from their move. Whether these moves are failed migration, social in nature (family or friends) or simply the willingness to trade income for amenities, it is clear that migration is much less systematically positive than is generally portrayed.

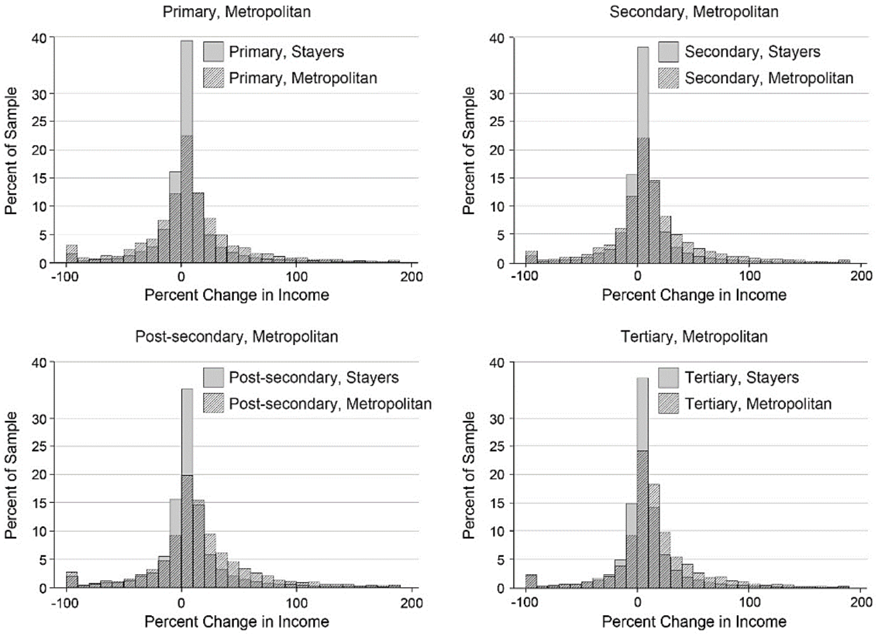
As for the variation of gains and losses by educational level, visually the distributions shift to the right and the share of migrants making gains, increases as education level changes from primary to tertiary (see Figure 1 and 2). This is true for both regional and metropolitan migrants, but is more pronounced for the latter group, and for both regional and metropolitan migrants those with post-secondary and tertiary education overall are more likely to make percentage gains.

Figure 1. Histograms of percent change in disposable income by educational category; regional migrants, 2001-2009



Finally, we compare the distribution of income gains for migrants with the equivalent distributions for stayers. These distributions are also approximately normally distributed, but compared to those of migrants they are *i)* considerably more centered around small and modest gains and losses, i.e. compared to migrants, stayers in general show less variation in outcomes. Of the gains to stayers, nearly 40 percent have increases in the 0-10 percent range and another 15 percent have losses of the same order. Further, *ii)* the distributions for stayers are somewhat less skewed upwards, especially if we look at outcomes for the higher educated and compare this distribution with the higher educated migrants heading into metropolitan regions (Figure 2).

Figure 2. Histograms of percent change in disposable income by educational category; metropolitan migrants, 2001-2009



Results: Modeling the Migration Outcome

In Table 2 below, we show to which extent this basic descriptive picture holds up when we ad controls. To repeat, what we model are the effects of different types of migration on the likelihood of making either a loss or a bigger gain related to internal migration. As we could also see in figures 1 and 2 above, what the estimates tell us is that there is a substantially larger spread in the outcomes for those migrant categories with relatively lower levels of education as compared to those with tertiary education. For all but the highest educated, these migrant groups are about as likely to make as loss as they are of making a substantial gain related to their move.

As for the tertiary educated regional and metropolitan migrants, these are the only categories for which we cannot estimate any likelihood whatsoever of ending up in the loss category. In other words, here also, the fact the income distributions for these migrants are relatively more skewed towards the right is also born out in model estimates.

Behind this general picture, there are however some noteworthy differences. For the primary and secondary educated *regional* migrants, the likelihood of making a loss is actually larger than making any bigger gains, whereas for the regional migrants with some post-secondary education chances of a loss or bigger gain are about equal. As for the metropolitan migrants, equally, those with primary and secondary education are just as likely to make a loss as they are of making any bigger gains. For those with post-secondary or tertiary education, however, chances of bigger gains are markedly higher.

To conclude, the picture we get from Figure 1 and 2 in the descriptive section basically holds when adding our controls. In other words, the variation in migrant outcomes do not in any substantial way reflect differences in terms measurable migrant characteristics, such as age, male/female or foreign born.

Our control estimates are as follows: as we would expect, educational level, getting employed and receiving additional formal education increases the likelihood of making it into the high income growth category. Somewhat surprisingly, however, age does not affect the likelihood of making a loss or a bigger gain in any discernable pattern (both below and above IQR estimates are negative), and this also goes for being female. In other words, women are much more likely than men of ending up in middle income growth category (i.e. between the 25^{th} and 75^{th} percentiles of the distribution). Job-changes and immigrant status, in turn, are a hit-or miss; i.e. they seem to affect the likelihood of individuals ending up in the loss or high growth category symmetrically, although the coefficient size is larger for immigrant status than for job-changes. Finally, unemployment has a large negative effect, as expected.[2]

As stated earlier in the text, these estimates reflect average yearly income growth over a nine year period, but what are the differences between the short- and long run of migration outcomes? To address this, in Table 3, we present the equivalent model estimates but using two samples; one divided into those with three years post-migration or less, and another for those with at least eight years post migration (average time post- migration is five years for the sample as a whole).

Comparing these outcomes, we see that our short-run outcomes much more closely resemble our year-average estimates presented in Table 2 previously, except coefficient sizes are larger both on the positive and negative side. A conclusion readily at hand is therefore that for most migrants the largest income growth effects happen in a relatively short time frame after migration. Turning to our long run estimates, this observation is however not valid for the highest educated migrants; both regional and metropolitan tertiary educated migrants are those that are most likely to make it into the highest income growth category in the longer run.

[2] To gauge to what extent our outcomes and conlusions depend on our choice of income growth categories, we also run our model using percetiles 20-80, and 30-70 as alternative cut-offs to the inter quartile range. These different specifications do not affect the outcome to any significant degree and do not alter conclusions drawn from our main approach using the inter-quartile range. The tables are available from the authors but cannot be included here.

Table 2. The effect of migration on placement within the inter quartile range of yearly percent growth in disposable income, 2001-2009

Migrant categories:	Below IQR	Above IQR
PRIMARY *regional*	0.600***	0.498***
	(0.022)	(0.023)
SECONDARY *regional*	0.314***	0.193***
	(0.019)	(0.019)
POSTSCNDRY *regional*	0.405***	0.418***
	(0.025)	(0.024)
TERTIARY *regional*	0.002	0.173***
	(0.025)	(0.022)
PRIMARY *metropolitan*	0.504***	0.528***
	(0.036)	(0.037)
SECONDARY *metropolitan*	0.274***	0.319***
	(0.028)	(0.027)
POSTSCNDRY *metropolitan*	0.230***	0.474***
	(0.033)	(0.029)
TERTIARY *metropolitan*	-0.221***	0.161***
	(0.034)	(0.027)
Controls:		
Age	-0.069***	-0.212***
	(0.002)	(0.002)
Age2	0.001***	0.002***
	(0.000)	(0.000)
Educ	-0.012***	0.070***
	(0.003)	(0.003)
Employment	0.403***	0.796***
	(0.013)	(0.011)
Unemployment	1.347***	0.630***
	(0.015)	(0.019)
Female	-0.170***	-0.165***
	(0.006)	(0.006)
NonEU15	0.493***	0.460***
	(0.010)	(0.010)
SumJobChange	0.199***	0.199***
	(0.004)	(0.004)
EduChange	0.172***	0.406***
	(0.011)	(0.010)
Observations	773,144	773,144

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

Table 3. Short and long run migrant outcomes, 2001-2004 and 2001-2009, respectively

Short run, 2001-2004:		
Variables	**Below IQR**	**Above IQR**
PRIMARY regional	0.735***	0.666***
	(0.077)	(0.083)
SECONDARY regional	0.445***	0.299***
	(0.065)	(0.066)
POSTSCNDRY regional	0.636***	0.751***
	(0.094)	(0.088)
TERTIARY regional	0.207**	0.458***
	(0.092)	(0.083)
PRIMARY metropolitan	0.504***	0.528***
	(0.036)	(0.037)
SECONDARY metropolitan	0.274***	0.319***
	(0.028)	(0.027)
POSTSCNDRY metropolitan	0.230***	0.474***
	(0.033)	(0.029)
TERTIARY metropolitan	-0.221***	0.161***
	(0.034)	(0.027)
Long run, 2001-2009:		
Variables	**Below IQR**	**Above IQR**
PRIMARY regional	0.577***	0.267***
	(0.074)	(0.072)
SECONDARY regional	0.361***	0.031
	(0.070)	(0.062)
POSTSCNDRY regional	0.480***	0.455***
	(0.096)	(0.070)
TERTIARY regional	0.512***	0.654***
	(0.098)	(0.068)
PRIMARY metropolitan	0.708***	0.588***
	(0.128)	(0.112)
SECONDARY metropolitan	0.616***	0.545***
	(0.113)	(0.090)
POSTSCNDRY metropolitan	0.571***	0.657***
	(0.130)	(0.089)
TERTIARY metropolitan	0.292**	0.840***
	(0.141)	(0.085)

*Note: Sample size for short and long run estimates are 82 469 and 62 272 observations, respectively. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Concluding discussion

In this research we disaggregate the returns to internal migration. Our focus hereby is not on modeling the average gains across migrants, as is standard in most econometric models of income related migration, but rather on the distribution of outcomes. We do not seek to address whether the human capital model fits the data or not – on average it clearly does – but instead focus on the question if the model provides a better fit better for certain migrant groups more than others.

Our analysis examines who makes gains, how big the gains are as well as the factors that determine the placement of individual migrants within this distribution, primarily educational background and direction of migration. This approach points to a more dual picture of the migration process, suggesting that the human capital model generally provides a better fit for higher educated migrants: Those with post-secondary and tertiary education have the highest likelihood of making it into the top income growth category, in the short and longer run respectively. At the same time however, the evidence also shows that quite large proportions of movers do not make gains whatsoever.

In the econometric analysis, we model distributional outcomes by estimating the likelihood of migrants belonging to either an above or below average income growth category, defined by the interquartile range of percent disposable income growth. Distinguishing between different types of educational and directional migrant categories, and controlling for competing factors such as age, immigrant status and movements in and out of employment, we conclude that the picture arrived at in the descriptive section basically holds when adding demographic controls. The higher educated and those moving into the largest metropolitan areas are those that have the highest likelihood of making big gains related to internal migration. For our other migrant categories, the likelihood of belonging to either the below or above average categories are about the same.

Further, despite gains for a majority of migrants the fact is that there is significant spread in these outcomes, and that about 25 to 40 percent have negative returns to migration. Even though we cannot make direct inferences as regards motives from this type of analysis (a possibility is of course that moves associated with these losses are in fact human capital motived but 'failed' migrations), we argue that this type of analysis represents a more realistic interpretation of the complexity internal migration.

In sum, these outcomes suggest that a focus on distributions – rather than averages – provides a way to encompass both qualitative and quantitative interpretations of migration. They emphasize how important it is to re-think how we interpret the outcomes from decisions to move; they are far from the mere simple notions of moving for higher income.

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