Selection on Temporary Migration: the Role of Ethnic Networks

Majlinda Joxhe*

June 21, 2013

Abstract

This paper attempts to identify the peer effects of ethnic networks on the migration process among temporary migrants in the UK labor market. Exploring a simple theoretical model I show how the presence of the network may determine a diverse selection process on the composition of the migration distribution skills, in case some of the already established migrants return home. The model predicts that in presence of migration networks, there will be positive selection on out-migration among low-skilled migrants (*the best of the worst*) and negative selection among high-skilled migrants (*the worst of the best*).
Using data from Understanding Society[1] with Minortiy Ethnic Boos Sample and the Census (2001) in UK, the empirical evidence reconfirms the theories advocated by Hanson (2005) and Borjas (1997) regarding self-selection on the migration process.

JEL classification: F22; J31; R12

Keywords: Migration; Wage Differential; Ethnic networks

*I am grateful to Mark Taylor, Brigita Rabe and all the ISER department of the University of Essex for their useful suggestions and for the data provision. A special thank goes to my Professor Giuseppe De Arcangelis. I want thank also all the useful comments that came from ERSA Conference Bratislava 2012 and my advisor Maria Cristina Rossi.

[1]Understanding Society in UK (2009-2011)

1 Introduction

The increasing inflow of migrants in developed countries has raised recently the attention on modeling the economic impact of migration or analyzing the migrant's performance on the hosting labor market. Dustmann (1997) emphasizes, that "one of the main forms in which migration occurs in Europe is through the *temporary migration*".

Differently from permanent migration, the decision on staying temporary in a hosting country may influence in the meantime the decisions on consumption, human capital accumulation and labor supply of the migrants. There is enough empirical evidence[2] indicating that migrants return home after an experience of migration abroad[3]. Temporary migration is also recognized as one of the main channels that involve migration and development in home country and hence becomes important to examine the socio-demographic characteristics of temporary migrants. Research on the out-migration, as pointed out by Constant and Massey (2003), is important for at least four reasons.

First, temporary migration is essential to understand the relative success of migrants in the host country labor market. If the immigrants are positively or negatively selected, the selective character of out-migration amplifies their initial selection and can, therefore, weaken the validity of cross-sectional studies to yield erroneous estimates about the assimilation processes (Borjas 1985).

Second, it is also important to underline selective temporary migration when measuring the economic effect of immigration on natives. Third, selective patterns of temporary migration may have important fiscal implications (Reagan and Olsen 2000; Duleep 1994), as the characteristics of immigrants are tied to use the social welfare system. Finally, more precise research on temporary migration can improve the ability to forecast trends in immigration.

The main question being tackled by the existing literature is explaining how the flows of the migrants are positive or negative self-selected in their skills and the results are quite different.

[2]Dustmann Ch., Weiss Y. 2007. "Return Migration: Theory and Empirical Evidence from the UK" British Journal of Industrial Relations, 45 (2), 236–56

[3]In the framework of the research activities of the RDP, return migrant refers to a person who returns to his/her country of origin, in the course of the last ten years, after having been an international migrant (whether short-term or long-term) in another country. Stay in the country of return must be longer than three months. Return may be permanent or temporary. Source: Return migration and Development Platform (RDP): European University Institute: Robert Schuman Centre for Advanced Studies)

The theoretical analysis of Borjas and Bratsberg (1994) argues that the direction of selection in out-migration depends on whether the immigrants themselves were positively or negatively selected originally. Using data from the 1980 Census of U.S they emphasize that out-migration rates suggest that immigrants tend to return to wealthy countries that are not too distant from the United States. In addition, empirical evidence points out that the return migration process accentuates the type of selection characterizing the immigrant population left in the United States.

Ramos (1992) verified the theoretical predictions of Borjas in his study about the Puerto Ricans migrants in the U.S and he found that migrants from the island were generally negatively selected, but the returnees were drawn from the most skilled.

These theoretical predictions assume that time-equivalent migration costs (all migration costs are proportional to wages at home) do not determine self-selection.

As many authors argue, the international migration is costly, involving monetary, search and psychological costs and these costs tend to be differ across level of skills. Migration is sometimes the result of a complex decision-making process and influenced by uncertainty, the plan of the migrants can be often revised in case new information and recent foreseen opportunities arise[4].

The existence of *"migration networks"* can greatly affect migration plans and provide more information about the destination country[5].

The *"migration networks"* may play a fundamental role also on decreasing the costs of migration as the established migrants can provide both personal support and job information[6]

There are a lot of findings in economic literature that emphasize the role of the networks on employment opportunities as a valid alternative of employment source (Granovetter, 1974; Corcoran 1980; Wahba and Zenou, 2005; Pattachini e Zenou 2011). This literature has figure out that members of a particular ethnic group concentrate in specific jobs and when new employment opportunities become available at their workplace, they pass this information along to social contacts, often of the same race and ethnic background (Conley and Topa 2002).

Return migration is a decision based at least partly also on the employment opportunities, and thus the aim of this study is to analyze if connections to an ethnic network (*migration network*)

[4]see N. Coniglio, G. De Arcangelis and L. Serlega 2010

[5]Constant and Massey (2003)

[6]W. Carrigton 1996

may influence also the decision on out-migration. Ethnic minorities usually experience a high rate of unemployment and the decision on return is subjective to the employment opportunities in the hosting country.

The contribution of this paper is to identify the role of the ethnic networks on the out-migration process exploring a simple theoretical model based on the models proposed by McKenzie, Rapoport (2010)and Cuecuecha (2005). I expand the model originally proposed by Borjas and then by D. Mckenzie including network effects in case some of the already established migrants return home. The return decision is incorporated as an opportunity for the migrant to have higher rewarding of his skills at home because during the migration process he can improve (i.e. increase) his level of skills. I try to answer to two research questions: At first, does the size of the network increase the probability of out-migration[7]? Second, how the selection process is correlated among different ethnic networks, (i.e Do the ethnic network effect the distribution of skills among migrants? The model predicts that in presence of networks that there might be positive selection on out-migration among low-skilled migrants (the best of the worst) and negative selection among high-skilled migrants (the worst of the best). The data of Understanding Society with Minority Boost Sample for the United Kingdom and the UK Census of 2001 are used to implement econometric estimation. The remainder of the paper is structured as follows. Section I explore the related literature with the study. Section II sets out the model of self selection including decreasing migration cost through networks. Section III describes the data and the estimation strategy. Section IV concludes.

2 Theoretical framework

2.1 Literature Background

Saajstad (1962) explains migration as an investment decision based on the net discounted value of income streams across countries[8]. Given that the incentives and the costs to migrate may

[7]Out-migration and return migration are not perfectly substitute in these paper. Due to the avaliablity of the data the out-migration refers also to migrants that make several trips (i.e circular migration; for further see Dustman(2003)

[8]In a neoclassical economics framework, international migration is considered only as a process to overcome wage differentials between countries and the migration decisions are induced by the labor market. In this view, the implicit assumption is that migration is permanent and the wage gap between two countries is the key variable explaining migration

vary across age, gender and education levels, immigrants are self-selected from the population and, as Borjas (1987) indicates this selection is not random.

In general,the migration selection model affirms that, given sufficiently high difference of skills between the home and foreign country and time-equivalent migration costs, labour migrants are negatively (positively) selected on unobservable characteristics, such as abilities, when the home country has more (less) dispersion in its earnings distribution. Otherwise, the migrants are negatively (positively) selected on observable skills, such as education, if the returns from educational attainment in the home country is relatively higher (lower) than the foreign country. That is the reward for people with higher skills would be less (more) to migrate than for those with lower skills [9]. In both cases, that is self-selection in observable or unobservable characteristics, the implications for the existing stock of migrants is that the return (temporary) migration accentuates the selection that characterises the initial migration flow. If migrants were positively selected then the return migrants tend to be the worst of the best; in case they were negatively selected they tend to be the best of the worst.

These predictions assume that the time-equivalent migration costs are constant through individuals with different skills therefore do not determine selection, that is the migration costs don't determine selection.

As argued in recent contributions the migration is costly, both in monetary and psychologically terms.

Carrington (1996) explains migration between the South and the North in U.S during the Great Migration of southern blacks to the North between 1915 and 1960 through a dynamic model assuming endogenous moving costs. Introducing decreasing moving-cost as a function of the established networks of migrants in the North explain why the South-North migration continued even if the wage differential between regions narrowed.

Chiuqiuar and Hanson (2005) propose decreasing migration cost at different level of skills concluding that selection of migrants in terms of observable skills depends on the distribution of schooling in the source country. They argue that migrating legally in U.S implicates dealing with bureaucratic requirements, involving intense paperwork's and repeated interactions with

[9] Rooth D.-O, Saarela. J. (2007). "Selection in migration and return migration: Evidence from micro data." Economics Letters 94: 90–95.

U.S. immigration authorities. More-educated individuals may be able to meet these requirements more easily. Even though there is a large service industry of lawyers and other specialists helping migrants manage the U.S. admissions process and given the cost of these services is more or less fixed, the time-equivalent cost of migration will be lower for individuals with higher hourly wages. Credit constraints may raise migration costs for low-income individuals, who are also likely to be less educated.

Coniglio, De Arcangelis and Serlenga (2010) using two surveys of microdata for Mexico and Italy find empirical evidence that the intention to return to the home country is more likely for highly skilled illegal immigrants than skilled legal migrants. The effects are weaker when migration takes place within consolidated networks of already established migrants, as for the case of Mexicans in the US.

The theoretical model proposed here, emphasise the role of the established networks on the out-migration selection process. Larger networks increase the probability of positive selection among low-skilled workers (the best of the worst) and increase the probability of negative selection among high-skilled workers (the worst of the best). In the next section a simple theoretical framework is developed to explain the theoretical predictions.

2.2 The Model

The aim of this simple framework is to identify the relationships between the individual level's skills, network and the return plans of migrants coming from a low-income country to a high-income country.

Following Borjas (1987) assume a population with heterogeneous level skills from the same source country that consider the possibility of migrating permanently or temporarily to a destination country. The earnings distribution in both countries depend on the country wage profile, based on the individual level of skill given by the following wage equations:

$$lnw_{0i} = \mu_0 + \delta_0 s_i + \epsilon_{0i} \tag{1}$$

$$lnw_{1i} = \mu_1 + \delta_1 s_i + \epsilon_{1i} \tag{2}$$

where $w_0 i$ and $w_1 i$ are the individual wage levels in home(0) and host country (1); $\mu_0 > 0$ and $\mu_1 > 0$ are the minimum wage obtained in absence of skills in each country; $\delta_0 > 0$ and $\delta_1 > 0$ are the return to skills both at home country and host country; ϵ_{0i} ϵ_{1i} are an iid random variable distributed with zero mean and finite variance that reflects some uncertain component of the both labor markets and s is the level of skill of each individual i.

Following McKenzie and Rapoport (2010) and Cuecuecha (2005)assume that: $\delta_0 > \delta_1$ so that the return to skills in the home country is higher due to the scarce supply of skills; and $\mu_0 < \mu_1$ which refers to the minimum wage differential between two countries indicating that the minimum wage at home is lower. The migrant knows that a temporary stay in the host country must improve his economic options that he has at home as like accumulating human capital or improving his skills. After spending a fraction of time γ at the host country he may increase his level of skills by κ.

Define C the cost of migration and in line with the migration networks literature, is decreasing in individual skills and network size[10]:

$$C = C(n, s) \tag{3}$$

where n is the size of the network and s is the level of skill and $C'(n) < 0$

The time-equivalent migration cost can be written as:

$$\pi = \pi(n, s) = C_0/w_o \tag{4}$$

Define the π as in McKenzie (2010):

$$\ln \pi = \mu_\pi - \phi_1 s - \phi_2 n \tag{5}$$

[10]The time-equivalent migration costs can decrease with schooling because higher wages require fewer hours of work to pay a fixed fee.Evidence is provided by Cuecuecha (2005), who describes a number of other channels leading to this decreasing relationship, including the better ability of more educated individuals to assimilate

where ϕ_1 and $\phi_2 > 0$ and μ_π is the fixed cost of migration that is independent of the level of skill and the network size. The π is given by:

$$\pi = e^{\mu_\pi - \phi_1 s_i - \phi_2 n_i} \tag{6}$$

A potential migrant will decide to migrate if:

$$(lnw_1) - (lnw_0 + C) \cong (lnw_1) - (lnw_0) - \pi > 0 \tag{7}$$

Initially the network size is normalized to zero and a potential migrant will face a wage profile at the destination country based only on his level of skills[11].

$$D = \mu_1 + \delta_1 s_i + \epsilon_{1i} - e^{\mu_\pi - \phi_1 s} \tag{8}$$

Before the networks begin to expand, two thresholds can be distinguished, s_L and s_H between which the migration is optimal. Below s_L the migration costs are higher than the incentives to migrate and above s_H the returns to skill at home is higher and disincentive migration. Introducing expanded networks at the destination country can be translated as an increase in the wage profile at each level of skills. The new wage profile is given by:

$$D' = \mu_1 + \delta_1 s_i + \epsilon_{1i} - e^{\mu_\pi - \phi_1 s - \phi_2 n} \tag{9}$$

Thus, as in McKenzie (2010) larger migration networks will increase the migration incentives and more at low-skill level. A change in migration incentives (in wages at destination net of migration costs) defines two new threshold values of s_L, s'_L and s_H s'_H. As migration networks expand, more people are willing to migrate at both tails of the migrants' skill distribution. Larger networks will reinforce, or increase the chances of obtaining negative self-selection. If the migrant decides to stay temporarily in the hosting country he will increase his level of skill[12] by κ and

[11] See Figure.1

[12] For simplicity I assume that the level of skills increase equally

at home will face a new wage equation given by:

$$lnw_{01} = \mu_0 + \delta_0(s_i + \kappa_i) + \epsilon_{01i} \tag{10}$$

The new wage equation can be translated as a shift of the wage country upper. Two new thresholds for migration to be optimal in presence of networks and temporary migration are ruled out: s''_L and s''_H. A change in the migration incentives (that is the rewarding of higher skills is higher at home relative to cost) increases the out-migration flow but more at high-skilled level. That is, the presence of networks increases the incentives of negative selection and accentuates this type of selection in the out-migration process. Figure.1 shows that the out-flows of low-skilled are positive selected and high-skilled are negative selected. These predictions affirms again the theoretical analysis made by Borjas (1994) and then by Hanson (2005)regarding self-selection on international migration.

3 Data and Empirical Strategy

3.1 Data

The migration in UK, quite long and diversified, is considered as one of the main contributing feature of the population change of the country in the recent years. The cohort of the present immigrants are mainly from the former colonies and recent waves, mostly from Eastern Europe. The recent international migration trends [13]show an increasing of non-uk born workers from 8.5% in the 2002 to 13.9% in the 2011, that means 1,7 million increase of non-uk born workers since 2002.

The main data source for the analysis is Understanding Society, a world leading study of social and economic circumstances and attitudes of 100.000 individuals in 40.000 British households. Starting from January 2009, all the adult household members are asked detailed questions about a range of subjects: family structure, employment, income, health etc. Each member of the sample is then re-interviewed a year later to see how things have changed over the past 12 months and this 'longitudinal' approach provides much clearer evidence about the processes underlying

[13]ONS: Non-UK born workers in the UK and the level of their skills May 2011

social and economic change, and enables analysts to make inferences about causation which cannot be supported by one-off, cross-sectional surveys[14]

. From the first wave the survey oversamples households from minority ethnic groups. Its General Population sample is the representation of the population of the UK including members of ethnic minority groups. The Ethnic Minority Boost Sample screened an additional households from areas of moderate to high ethnic minority density (i.e. covering over 80 per cent of the minority group population) to provide a sample of around 1000 adult respondents in each of the following groups: Indians, Pakistanis, Bangladeshis, Caribbeans and Africans. The aim is to enable detailed comparisons of social and economic experiences across ethnic groups, as well as to study issues of special relevance to ethnic minorities.

Table.1 highlights summary statistics regarding the sample composition for natives and migrants[15] from the total Understanding Society dataset regarding demographics, education and the occupation status. Migrants tend to be younger than natives, around 90% of them live in couple and the typical U-shaped education level for migrants is confirmed by the data; that is a higher tendency to be drawn from the tail of the distribution of education. Around 23 % of the non-uk born have no qualification and 24 % have a first or a higher degree. Approximately, 38% has a managerial or a technical job, 34% are engaged in a skilled job and on average the non uk-born earn relatively less then natives.

Understanding Society is household survey, which allows me to get rich individual-level information and merge this information with the respondent's local area[16], i.e.the local authority, as well as information on ethnicity at a level of disaggregation suitable for estimation purposes.

The Local Authority Districts are a finer level of spatial disaggregation of the English local government structure, that captures the local spatial characteristics of the country geography.

Due to important cultural (and language) differences between ethnic groups, at first, I define ethnicity in a very narrow way, e.g. density of Indian people living nearby cannot be a good

[14]Design of the Understanding Society; Ethnic Minority Boost Sample;(Richard Berthoud,Laura Fumagalli, Peter Lynn, Lucinda Platt)ISER, University of Essex 2009

[15]migrant is defined as a non uk-born; weights are used to enable the comparisons

[16]Local Authority Districts (non-metropolitan districts, unitary authorities, London Boroughs, metropolitan districts, Scottish council areas, Northern Irish district council areas).Local authority (LA) is a generic term for any level of local government in the UK. Local Authority Districts comprise a number of different geographies which evolved historically according to the local government structure that existed for the different parts of England and the other countries of the UK. See Birgitta Rabe "Geographical identifiers in Understanding Society, Version 1";*Understanding Society Working Paper Series No. 2011 – 01 March 2011*

approximation of the social contacts of a Asian person[17].Therefore, in order to have a relative cultural homogeneity within each ethnic group, the study conducts analysis separately for each ethnic minorities that can be identified in our data, namely “Black Caribbean”,“Black African”, “Indian”, “Pakistani”, “Bangladesh” and “Chinese”.

Furthermore, a precise test for the ethnic networks requires detailed information on all social contacts between individuals over time, which is unfortunately not available. Since ethnic communities tend to be more socially cohesive, a reasonable conjecture is that the density of people living in the same area is a good approximation for the number of direct friends one has, especially if the areas are not too large and if people belong to the same ethnic group.This mechanism approximate the social proximity by the geographical proximity. Data on ethnic minorities[18] at Census level of United Kingdom 2001 are used to overpass this issue. Since the networks and the percentage of ethnic minorities may evolve over time, a good assumption is that these changes can be quite small, as new people move in and some of them move out the same District. With the assumption of “statistic networks” I merge the Understanding Society with Census 2001 over Local Authority Districts. Performing an estimation based on ethnic densities I restrict the sample to local areas that have population less 250.000 people, excluding also low ethnic densities, I am left with a sample size that consist of 9,289 individuals[19].

Table 2. reports the summary statistics for the different groups.

The Indians have the highest share of the total sample population (7%) and 28,4% of the total ethnic population. The Chinese is the group that has the smallest share of the sample only 1% and 5.6% of the total ethnic population.

3.1.1 Measuring Temporay Migration

In most empirical analysis, identifying temporary and returned migrants is important as enable estimation. Identification is complicated and most of the studies base their analysis following the same individuals over time and observe which of the migrants will return within a given interval of time and this type of analysis requires longitudinal data analysis. Rooth and Saarela(2006)use longitudinal linked micro data from Sweden and Finland and confirm the predictions of migration

[17]for the same reason the mixed ethnicity are excluded
[18]the percentage of ethnic groups based on Census 2001
[19]including also natives:British ethnicity

selection theory. Migrants were found to be negatively selected and return migrants positively selected on observable skills, whereas there is only minor selection on unobservable skills. Cohen(2001) analyzes self-selection of returning immigrants applying it to Israeli-born immigrants who arrived in the United States during 1970–79 and returned to Israel during 1980–89. He conclude that those who return from the United States to Israel have reached a higher level at school than those who remain in the United States.

Understanding Society is a rich dataset and the Minority Ethnic Boost Sample includes the migration history module where all the non-uk born are asked: *whether have ever returned to country of birth to live?*. I use this variable to identify temporary migration[20].

I focus the analysis on male and female in working age[21], between 25 and 65 living in a Local District for each minority. I modify the sample restricting only to people migrating in UK after 1960. Table.3 describes some summary statistics. The return migrants tend to be males, older and have spent more years in UK than those who are left. In average the return migrants have lower wages than the non returns. The Pakistani migrant report the highest percentage on return migration, the 33% of all the returned.

Figure.2 describes the distribution for each level of the education by return profile showing how the return migrants are drawn from the tail of the distribution.

3.1.2 Wage Equations

One method for exploring only the selectivity in return migration and not in its direction on selectivity is to examine data on income dispersion between the home and destination country. Random return migration would indicate either no change or an increase in income dispersion among immigrants. A decline in the variance in the incomes of immigrants (relative to natives) over time reflects a situation in which returnees are drawn from one or both tails of the income distribution (Bloom and Gunderson 1990). Income distribution in both countries need to be estimated and following Dustman(2003)I estimate wage equation for home and destination country. Since I do not observe the wage for the home country, one feasible way is to approximate it by

[20] Different for "absolute" returned migrants, the circular migration involves the migrants making different trips between home and destination country, here the return migrants are those who have migrated in UK and returned to their home country to live and re-migrated again in UK.

[21] I exclude the students: as reported on the literature a major part of the students stay temporary in the hosting country and return back home after finishing the studies

estimating the potential wages of the returns given by the equation:

$$W_i = \alpha X_i + \beta yedu_i + \gamma ethnic_i + \lambda yedu_i * ethnic_i \tag{11}$$

where X_i is a vector of individual characteristics such as age, agesq, gender, $yedu_i$ are the year of schooling of each individual returned, and $ethnic_i$ are dummy variables for ethnic groups. Including all the For the UK country wage equation I estimate wages using the same equation including all the sample of the migrants. Report of the wage equation are shown on table 4. In this way I estimate wage equations for all non-ukborn (wage hosting country) and for those who have ever returned (wage home) and the predicted wage for each group are used to as control variables in the empirical model[22]

[22]See next section

3.2 Estimation

3.2.1 Probability to Return

The aim of the study is to test whether the extent of network size impacts on the individual probability of out-migration, as well as to find out if there is a selection in skills among different ethnic groups. In order to test these implications, first I estimate the following equation:

$$Prob(return_i | w_i^{home} - w_i^{host}, n_i, s_i, X_i) = \Phi[\alpha(\Delta w) + \beta(n_i) + \gamma(s_i) + \delta(X_i) + \epsilon_i)] \qquad (12)$$

where $return_i$ is a dummy variable that takes the value 1 if the migrant has ever returned to his country to live, $network_i$ is the district with ethnicity prevalence.
X_i are the control variables that capture the individual[23].
The individual characteristics include age dummies, a dummy for being married, a dummy for gender and for the employment status. I also include a measure of the knowledge for the language of English (a dummy variable for individuals that declare to have no difficulties on speaking English).Furthermore, a past migration experience generally lowers the non-monetary cost and the psychological cost of a subsequent migration, hence I include a dummy variable if the individuals declare that have been in other countries before entering the UK. As mentioned above, I use the density of own-ethnic migrants workers living nearby as a proxy for the size of each individual social network.
The main problem is the possible presence of unobservable area characteristics that can be responsible for an endogenous sorting of individuals into areas. For example, if the more able ethnic minority workers manage to live in more dynamic labour markets, with higher employment rates, and if these individuals are also the ones who benefit the most from job information provided by friends, and make them staying in UK. In this way the estimates will be upward biased. In this paper, I address these concerns in two ways.
First I include area fixed effects. The spatial unit of analysis is the local authority and I use

[23] In the meantime, characteristics of the country origin may influence the decision to stay or to return such as the occurrence of the social conflicts or economic crisis, push factors that are difficult to be captured in the dataset. In this case I try to introduce a proxy variable for the level of development of the origin country (The Income Index reported by the United Nation as a component of the HDI *Human Development Index*) and expect to have a positive effect on the return outcome. The estimated wages for home and host country are included and the log of geographical distance as a proxy for the migration cost is included

fixed effects at the level of NUTS3[24] area, which are wider areas.In this way, large number of unobserved differences between areas are controlled. Second, out-migration history rate is used in a two stage regression framework, using migration history rate as an instrument.

3.3 Conclusion TBA

[24]Government Office Regions

Table 1: Descriptive statistics: Understanding Society

	(1) Migrants		(2) Natives	
	mean	sd	mean	sd
Age	41.20	10.44	43.53	10.75
Male%	0.57	0.50	0.53	0.50
Married%	0.90	0.29	0.85	0.36
Employed%	0.70	0.46	0.76	0.43
No qualification	0.23	0.42	0.20	0.40
0 level	0.22	0.42	0.40	0.49
No College Degree	0.10	0.29	0.10	0.30
College Degree	0.21	0.41	0.20	0.40
University Degree	0.24	0.42	0.10	0.31
Professional Occupation	0.10	0.29	0.07	0.26
Managerial Technical Occupation	0.38	0.49	0.43	0.49
Skilled non manual	0.18	0.38	0.20	0.40
Skilled Manual	0.16	0.37	0.16	0.37
Partly skilled occupation	0.15	0.36	0.12	0.32
Unskilled Occupation	0.03	0.17	0.03	0.16
Real Wage*	922.50	1198.68	1120.27	1303.77
N	2582		10864	

Notes: Individuals in working age between 25 and 65 for male; 25 and 59 for female
Notes: * Real monthly wage deflated by CPI

Table 2: Return Profile:
According to Age, Demographics, Ethnicity and Occupation

	(1) Non Returned		(2) Returned	
	mean	sd	mean	sd
Male%	0.58	0.49	0.60	0.49
Age	40.69	10.20	41.70	10.57
Age at entry	22.24	10.73	19.76	12.31
Years since migration	18.52	13.89	22.02	14.19
Married	0.92	0.27	0.92	0.27
Indian	0.37	0.48	0.28	0.45
Pakistani	0.20	0.40	0.33	0.47
Chinese	0.05	0.21	0.03	0.18
Bangladeshi	0.14	0.35	0.13	0.34
Caribbean	0.06	0.24	0.06	0.23
African	0.17	0.38	0.17	0.37
Self employed	0.11	0.31	0.19	0.39
Employed	0.57	0.49	0.51	0.50
Unemployed	0.10	0.30	0.07	0.26
English First language	0.28	0.45	0.27	0.44
Difficulty speaking English	0.18	0.38	0.16	0.37
Real wage	851.19	1157.14	721.93	889.79
Remitter family	0.29	0.45	0.27	0.45
Moved direct from country of birth	0.91	0.29	0.94	0.24
N	1561		162	

Source: Understanding Society waves 2009-2011

Table 3: Summary statistics: Ethnicity Sample

	(1) Indian mean	(2) Pakistani mean	(3) Bangladeshi mean	(4) Chinese mean	(5) Caribbean mean	(6) African mean
In Total Sample	0.07	0.06	0.05	0.01	0.04	0.03
In Total Ethnic Population	2.84	2.20	1.82	0.56	1.83	1.65
Age	39.28	38.16	36.78	40.97	41.37	39.30
Age at entry	22.81	21.35	18.27	26.84	17.56	25.25
Returned	0.08	0.15	0.09	0.07	0.09	0.10
No Qualification	0.15	0.30	0.33	0.21	0.24	0.09
0 level	0.22	0.25	0.29	0.13	0.41	0.18
No College Degree	0.10	0.10	0.14	0.05	0.09	0.12
College degree	0.25	0.20	0.10	0.20	0.16	0.28
University Degree	0.28	0.16	0.14	0.41	0.10	0.33
Real wage	1034.11	560.40	631.95	1240.65	990.18	1100.93
Difficulty English Speaking	0.08	0.25	0.29	0.11	0.65	0.03
Remitter family	0.20	0.19	0.22	0.15	0.20	0.47
N	915	785	693	104	549	467

Source: Understanding Society 2009-2011: UK Census 2001

Table 4: OLS Estimation for Home and Host Wages

	(Home) Log of Wage	(Host) Log of Wage
Age	0.0805	0.152**
	(0.0579)	(0.0474)
Agesq	-0.000873	-0.00180**
	(0.000685)	(0.000556)
Married	-0.573**	-0.0865
	(0.193)	(0.148)
Male	0.371+	0.573***
	(0.186)	(0.118)
No Qualifications	0.294	-0.0411
	(0.300)	(0.124)
No College Degree	1.051**	0.380*
	(0.325)	(0.171)
College Degree	0.811**	0.575***
	(0.242)	(0.160)
University or Higher Degree	0.764***	0.263
	(0.213)	(0.244)
Indian	-6.348*	0.623
	(2.891)	(0.803)
Pakistani	-6.345*	0.115
	(2.746)	(0.828)
Bangladeshi	-7.735**	0.364
	(2.754)	(1.051)
Caribbean	-4.112+	1.667*
	(2.330)	(0.844)
African	-5.853*	0.685
	(2.348)	(0.805)
English	.	0.995
	(.)	(0.667)
_cons	11.35***	2.697*
	(2.644)	(1.300)
N	65	1198

Standard errors in parentheses
Notes: Understanding Society 2009-2012;
O level is the omitted educational category dummy variable;
Dummy variables are included as interaction
between years of schooling and ethnicity not reported
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Probit estimation for Return Migrants across Networks

	(1) Probit	(2) Probit RD	(3) Probit Low Population	(4) Probit RD and Low Population
Male (=1)	-0.0119	-0.0940	-0.342	-0.554*
	(0.231)	(0.226)	(0.266)	(0.258)
Age	0.0183*	0.0192*	0.0114	0.0143
	(0.00760)	(0.00772)	(0.00922)	(0.00964)
Married (=1)	-0.199	-0.207	-0.394	-0.501
	(0.314)	(0.302)	(0.352)	(0.354)
Predicted Wage-Home	-0.225	-0.356	-0.562	-0.874+
	(0.362)	(0.376)	(0.417)	(0.465)
Predicted Wage-Host	0.0215	0.123	0.986*	1.307**
	(0.399)	(0.403)	(0.490)	(0.492)
Self employed (=1)	0.284	0.390	0.241	0.490
	(0.274)	(0.264)	(0.320)	(0.325)
Employed (=1)	-0.0643	0.00477	-0.325	-0.172
	(0.202)	(0.190)	(0.249)	(0.237)
Unemployed	-0.134	-0.145	-0.168	-0.0955
	(0.232)	(0.234)	(0.267)	(0.278)
Difficulty speaking English	-0.0418	-0.0497	-0.156	-0.243
	(0.172)	(0.170)	(0.213)	(0.215)
Moves directly from country of birth	0.421	0.403	0.566+	0.219
	(0.291)	(0.306)	(0.342)	(0.356)
No qualification	-0.143	-0.120	0.136	0.269
	(0.264)	(0.259)	(0.290)	(0.310)
O level	-0.157	-0.214	-0.103	-0.0147
	(0.333)	(0.330)	(0.385)	(0.394)
A level	-0.208	-0.155	0.0697	0.294
	(0.292)	(0.295)	(0.322)	(0.343)
College degree	0.174	0.169	-0.102	-0.119
	(0.244)	(0.244)	(0.265)	(0.278)
Indian-Network	-0.0279*	-0.0205	-0.0421*	-0.00539
	(0.0138)	(0.0166)	(0.0182)	(0.0216)
Pakistani-Network	-0.0323+	-0.0427+	0.0605	-0.0173
	(0.0184)	(0.0252)	(0.0427)	(0.0505)
Bangladeshi-Network	0.000385	0.00224	-0.0140	-0.00766
	(0.00912)	(0.00937)	(0.0113)	(0.0120)
Chinese-Network	0.00518	0.00834	0.454+	0.449
	(0.197)	(0.206)	(0.270)	(0.330)
Caribbean-Network	-0.0637	-0.0565	-0.116+	-0.0382
	(0.0390)	(0.0421)	(0.0656)	(0.0609)
African-Network	0.0468	0.0591+	0.0404	0.0363
	(0.0293)	(0.0313)	(0.0395)	(0.0403)
Log of Distance	-0.401	-0.330	-1.410*	-1.258*
	(0.506)	(0.494)	(0.556)	(0.595)
Inequality-adjusted income index	2.802**	2.809**	2.465*	3.099*
	(1.078)	(1.045)	(1.253)	(1.366)
Regional Dummies	No	Yes	No	yes
Observations	1073	1071	729	716

Standard errors in parentheses
Notes: All variables Understing Society 2009-2011 University degree is the omitted variable
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

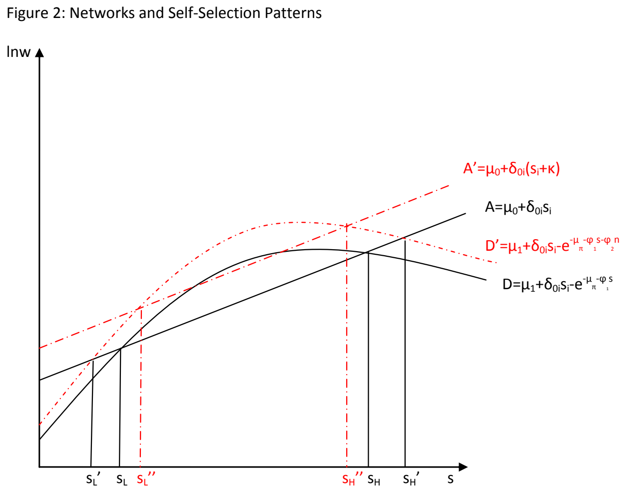

Figure 1: Networks and Self-Selection Patterns

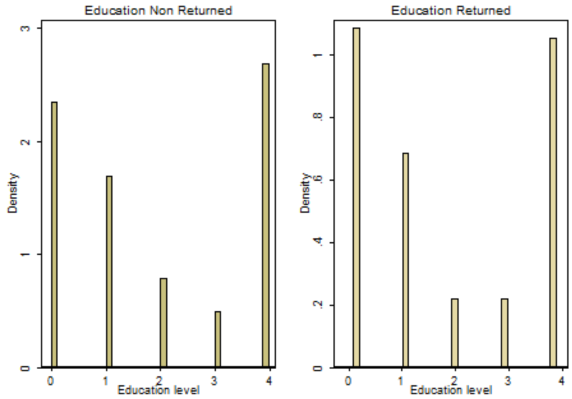

Figure 2: Education level of Non Returned and Returned Migrants

References

[1] Bellemare, Ch. 2007. "A Life-Cycle Model of Out-migration and Economic Assimilation of Immigrants in Germany." European Economic Review, 51, 553-76.

[2] Borjas, G.J. 1987. "Self-Selection and Earnings of Immigrants." The American Economic Review, 77 (4), 531-53.

[3] Card, D. 2001. "Immigrant Inflows, Native Outflows, and the Local Market Impacts of Higher Immigration." Journal of Labor Economics, 19 (1), 22-64.

[4] Carrington W. J., Detragiache E., Vishwanath T. 1996. "Migration with Endogenous Moving Costs." The American Economic Review, 86 (4), 909-30.

[5] Costant A., Massey D. M. 2002. "Return Migration by German Guest Workers: Neoclassic Versus New Economic Theories," Blackwell Publisher

[6] Damm, A. P. 2009. "Determinants of Recent Immigrants' Location Choices: Quasi-Experimental Evidence." Journal of Population Economics, 22, 145-74.

[7] Dustmann Ch. 2003. "Return Migration, Wage Differentials, and the Optimal Migration Duration." European Economic Review, 47, 353–69.

[8] Dustmann Ch., Weiss Y. 2007. "Return Migration: Theory and Empirical Evidence from the UK." British Journal of Industrial Relations, 45 (2), 236–56

[9] Harris J. R., Todaro M. P. 1970. ”Migration, Unemployment and Development: A Two-Sector Analysis ” The American Economic Review, 60 (1), 126-42.

[10] Hill J. K. 1987. ”Immigrant Decisions Concerning Duration of Stay and Migratory Frequency.” Journal of Development Economics, 25, 221-34

[11] Magris F., G. Russo. 2009. ”Selective Immigration Policies, Human Capital Accumulation and Migration Duration in Infinite Horizon.” Research in Economics, 63, 114-26.

[12] McKenzie D, and Rapoport H., 2010 ”Self-Selection Pattern in Mexico-U.S. Migraiton: The Role of Migration Networks” Review of Economics and Statistics, 92(4): 811–821

[13] Mesnard A. 2004. ”Temporary Migration and Capital Market Imperfections.” Oxford Economic Papers, 56, 242–62.

[14] Osili U. O. 2007. ”Remittances and Savings from International Migration: Theory and Evidence Using a Matched Sample.” Journal of Development Economics, 83, 446–65.

[15] Rooth D.-O., Saarela J. 2007. ”Selection in Migration and Return Migration: Evidence from Micro Data.” Economics Letters, 94, 90–95.

[16] Stark O., Helmensteinc Ch., Prskawetzd A. 1998. ”Human Capital Depletion, Human Capital Formation, and Migration: A Blessing or a “Curse”?” Economics Letters, 60, 363–67.