Essays on Immigration

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Abstract

The first chapter explores the role of income in the decision of native-born individuals to enroll in college when the local labor market is affected by inflows of immigrant labor. I develop a unified theory of the decision to acquire schooling taking into account that immigration influences both the returns to education and income available to finance this decision. In addition I theoretically show how household income affects the impact of immigration on natives' college enrollment decisions. Using U.S. Census microdata from 1970 to 2000, I empirically investigate these predictions. I correct for possible non-random selection of immigrants into labor and geographic markets. I find evidence of a positive relationship between relatively unskilled migration and native college enrollment for individuals who come from poorer households and of a negative one for individuals from richer households. The results vary by age and race as they are most pronounced for young natives and African-American and Caucasian natives.

In the second chapter using a unique household level dataset that allows us to draw comparisons between 30 transition economies in Eastern Europe and Central Asia my co-authors and I assess potential gains from various types of mobility to those who are currently immobile. We also identify proportion of current immobility that can be explained by lack of economic incentives. This proportion varies significantly across the regions but can be as high as 92 percent for countries in the former Yugoslavia region. To further strengthen our results and identify the direction of the potential selection bias we employ an instrumental variable that exploits unique nature of privatization of real estate in transition countries. We find evidence of possible negative self-selection into mobility for in countries that belong to the region of extended Commonwealth of Independent States (CIS). Lastly, having data on household expenditures we adjust the income for cost of living to control for increases in nominal versus real income. When latter measure is used gains to certain types of mobility, in particular relocation to urban areas, are significantly deflated.

Index words: International Migration, Geographic Labor Mobility, Immigrant Workers, Human Capital, Education

Dedication

The research and writing of this dissertation is dedicated to my wonderful and very loved parents, my brother, Dalia Bahous, Luz Leyva, Navruz Avloni, Dariya Fadeeva and all those who made this process possible and enjoyable.

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Chapter 1

Immigration and the educational choices of native-born workers: the role of income.

1.1 Introduction

Immigration is a hotly debated and controversial topic in the policy realm of the United States. One of the dimensions of this phenomenon that has received most attention is its impact on natives' labor market opportunities. The standard labor-economics model predicts that immigration should negatively affect wages and employment outcomes of native-born workers. However, several studies[1] find that immigration has an insignificant impact on natives' labor market opportunities. This might be explained by the fact that native-born workers can adjust to immigration along several dimensions. One of these possible adjustments is natives' decision to change skill level via staying in or going back to school in response to immigration. This is the topic this paper focuses on.

To the best of my knowledge, while this channel has received attention mostly at the level of high school enrollment and completion, there is only one paper (Jackson 2011) that analyzes this response at the post-secondary education (college) level. I take the analysis one step further. Building off the econometric framework introduced in Jackson (2011), I estimate the effect of immigration on natives' decision to enroll

[1] Card (1990), Card (2009), Ottaviano and Peri (2012).

in college accounting for the fact that the actual decision to apply and enroll ultimately depends on one's ability to finance college education. I develop a theory of the schooling decision where immigration influences both the opportunity cost of and the gains from getting an education. Additionally, I assume that individuals can be credit constrained and that their educational outcome depends on their ability to finance their schooling decision.

Educational upgrade is not free. The cost of being in school or going back to school consists of two parts: the *explicit* cost of education (tuition, room and board, books, etc) and the *implicit* cost of foregoing wage income while being enrolled in school. Low-skilled immigration can lower the unskilled wage – and thus decrease the opportunity cost of going back to school – and can increase the skilled wage – and thus raise the gains from schooling. At the same time, if unskilled wages are lower or competition displaces unskilled native-born individuals out of work, their incomes are also reduced. Thus college education becomes harder to afford. Depending on which one of these effects dominates, an increase in relatively unskilled immigration can lead to either an increase in native college enrollment (which corresponds to the case of "crowding in") or to a decrease (which corresponds to the case of "crowding out"). Moreover, an individual's ability to enroll in college might depend on her access to a source of additional income besides her earnings. This is the case if, for example, parents finance their child's education. I theoretically analyze how this exogenous source of income, i.e. household income, affects the impact of immigration on natives' college enrollment decisions. I find that an effect of a decrease in low skill depens on individual's exogenous income as well as on the relationship between high skill wages and tuition. Additionally, I find that once the effect of the decrease in the unskilled wage on native college enrollment is positive its magnitude declines as native's exogenous income increases.

Using U.S. Census microdata from 1970 to 2000, I empirically investigate these predictions. I correct for possible non-random selection of immigrants into labor and geographic markets using a supply-push based instrument (Card 2001, Ortega and Gonzales 2008). The instrument exploits the idea that existing immigrant enclaves and networks are important in the choice of destination by new immigrants. My results provide evidence of a positive relationship between relatively unskilled migration and native college enrollment for individuals who come from poorer households and of a negative one for individuals from richer households. Based on my findings, there is some evidence that in fact the poorer workers – who can potentially gain the most by enrolling in school – are in fact the ones who are more likely to do so. I find that, when total pre-tax household income net of personal pre-tax income is controlled for, a 1 percent increase in relatively unskilled immigrant labor raises the rate of native college enrollment by 1.1 percent for a household with an average median income. But a 1 percent increase in exogenous household income reduces the magnitude of this effect by about 0.15 percent. Thus, native-born individuals from more well-off families are less likely to be "crowded in" into college.

When results are broken down by age group the youngest individuals, i.e. those aged 18 to 22, are the ones for which the above results are most pronounced. There is variation of results by race too. "Crowding in" is strongest for poor Caucasian native-born individuals with a 2.8 percent increase in enrollment associated with a 1 percent increase in the relative unskilled immigrant flow into local markets. For poor African-American individuals an increase of only 0.86 percent in enrollment is associated with a 1 percent increase in the relative unskilled immigrant flow, which is almost a 3 time reduction in magnitude compared to poor Caucasian natives. Furthermore, there seems to be no effect for Asian-American native-born. Lastly, for both Caucasian and

African-American native-born individuals, there is evidence in favor of individuals from richer households being less likely to be "crowded in" into college.

This chapter is organized as follows: Section 1.2 presents a brief review of the relevant literature, Section 1.3 outlines a simple conceptual framework, Section 1.4 develops a theoretical motivation behind the question, Section 1.5 presents the empirical strategy used to test the predictions. The data and results are described and discussed, respectively, in Sections 1.6 and 1.7. Conclusions follow.

1.2 Literature Review

According to the standard labor-economics model, immigration has a negative impact on wages and employment opportunities of similarly skilled native-born workers. Several studies in the existing literature look for such a negative effect using the "spatial-correlation" framework. This type of analysis exploits variation in the number of immigrants and in natives' labor-market outcomes across different geographical units within a country. As mentioned in the Introduction, the studies following the "spatial-correlation" approach find evidence of an insignificant or small negative impact of migration on natives' labor market opportunities. While this result is surprising, it might be explained by the fact that native-born workers can adjust to immigration along several dimensions. In other words, through different channels, the negative impact of migration can be mitigated.

Among these channels, one of the most important ones pointed out and analyzed by the existing literature is internal migration (Card 2001, Borjas 2003, Borjas 2006). The "spatial-correlation" approach is based on the assumption that each geographical unit within the country is a closed economy. However, if this assumption is not true, then native-born workers can move across city lines in response to the immigration shock to their skill category, thereby alleviating the impact of migration into a specific geographical unit.

Other channels through which the negative impact of migration can be mitigated are: the adjustment of production technologies towards more labor intensive ones (Lewis 2010), task specialization (Peri and Sparber 2009), and human capital investment decisions (Hunt 2012, Betts and Lofstrom 2000, Llull 2010, Eberhard 2012, Jackson 2011). This paper contributes to the literature which focuses on the latter channel – i.e. human capital investment decisions – by analyzing the decision of native-born individuals to enroll in college. To the best of my knowledge, this type of analysis has only been carried out in Jackson (2011). I extend the results in Jackson (2011) by addressing the potential of low-skilled immigration to not only alter the net benefit of college education but also the income available to finance this education.

The adjustment of human-capital in response to unskilled immigration is an important issue to address in light of the assumption – which characterizes most of the existing migration literature – that the relative size of skill cells of native-born workers is fixed. This assumption is made in one of the most influential studies in the migration literature, Borjas (2003). The latter paper proposes an alternative to the spatial-correlation approach, which should correct for the bias associated with internal migration. Borjas (2003) exploits the national-level variation of the immigrant shock over time and across different skill/experience cells. His approach relies on the assumption that native-born workers do not move across skill cells in response to immigration:

> "...Most importantly, the size of the native workforce in each of the skill groups is relatively fixed, so that there is less potential for native flows to contaminate the comparison of outcomes across skill groups...." Borjas (2003).

However, if native born workers can react to the impact of immigration on their local labor market by "voting with their feet" – as pointed out by Borjas (2003) – maybe they can also react to it by upgrading their education and thus migrating out of the impacted skill cell. As pointed out in Llull (2010) and Eberhard (2012), the decision to invest in one's human capital is an endogenous one that happens in response to the current or anticipated (Eberhard 2012) situation in a local labor market. Thus there will be spillover effects of immigration on wages along skill categories and this could be another reason why the negative effects on unskilled wages are harder to detect in the data.

The fact that immigration can alter natives' human capital investment decisions has been pointed out as early as 1989, but only few articles feature theoretical models that can potentially account for these effects (Chiswick (1989), Razin and Sadka (1999), Casarico and Devillanova (2003)). The topic has received a lot more attention recently, both empirically and theoretically (Lull (2010), Jackson (2011), Eberhard (2012), Hunt 2012). However, none of these papers considers the ability of immigration to influence schooling decisions through credit constraints.

Chiswick (1989) proposes a setting with a social planner and defines human capital as occupation specific skills. In her model the immigration flow is endogenous, however, and the social planner is collecting rents from immigrants. Razin and Sadka (1999) and Casarico and Devillanova (2003) present a dynamic model where human capital accumulation of natives happens in the setting of an overlapping-generations two-period model of a welfare economy with a pay-as-you-go pension system. In the absence of credit constraints, the decision to acquire schooling boils down to a budget maximization problem and there is no heterogeneity in responses for a fixed ability level. Additionally, these papers are not focused on the human capital accumulation decisions of natives and do not empirically test the predictions in regards to them.

Among the more recent contributions, the closest paper to my work is Jackson (2011), which presents the effect of both immigrant labor and immigrant students on demand for and price of schooling under various assumptions about the elasticity of supply of college seats. He finds that, on net, the effect of immigration on college enrollment of low-skill native-born individuals is positive and is strongest for the younger cohorts. However, while immigrant students are allowed to "crowd out" natives out of education – through raising college demand and thus potentially college tuition – the effect of immigrant workers on the income available to finance college education is not analyzed.

Empirically his results are close to Hunt (2012). The latter paper analyzes both the positive effect of immigrant labor and the negative effect of immigrant students – using U.S. Census data from 1940 to 2010 – on high school completion. It finds that, on net, the effect is positive and strongest for native born African-American students and almost not present for native-born Hispanics.

Both Eberhard (2012) and Lull (2010) present results on the impact of immigration on human capital investment decisions using general equilibrium models and simulation of counterfactuals. Eberhard (2012) finds that, while immigration has a small negative direct effect on earnings, it has a positive and relatively large impact indirectly through human capital accumulation and educational attainment. Lull (2010) also finds evidence of the presence of human capital adjustment in response to immigration but, as opposed to Eberhard (2012), in his setting it is not big enough to offset the decrease in earnings due to immigration.

Lastly, with the exceptions of Jackson (2011) and Lull (2010), none of the above papers includes a cost of schooling that is different from the opportunity cost. Furthermore, even when this cost is included, the possibility of credit constraints becoming more pronounced with the arrival of low-skilled immigrants is not considered.

1.3 Conceptual Framework

An increase in the relative share of unskilled immigrants has two opposite effects on natives' probability of college enrollment. I label them the *income* and *opportunity cost* effects. First, an increase in the relative share of unskilled immigrants can raise the wage differential between skilled and unskilled labor, thereby reducing the opportunity cost of going to school while increasing the expected benefit. This effect, labeled the *opportunity cost effect*, is expected to increase the probability of college enrollment for the native-born. However, by lowering wages of low skilled workers or displacing them out of work, immigration is likely to reduce their income and thus ability to finance their education. Through this channel, labeled the *income effect*, an increase in the relative share of unskilled workers reduces the probability that native-born workers enroll in college.

It is unclear which effect will dominate and in fact it is likely to depend on the initial income level of the native-born. In addition and more importantly, the sign of the relationship between migration and native college enrollment should depend on the income level of the household, which I consider to be an additional source of financing for college, not affected by immigration. Thus in this paper I analyze the role of *exogenous income*, i.e. household income net of individuals' own earnings, in shaping the impact of migration on the probability of native college enrollment.

It is possible that the *income effect* is dominant for people with relatively low levels of exogenous income. Since labor income represents a bigger share of their total income available to finance college education, they might be more sensitive to its actual or anticipated decrease. In fact it can make schooling (or even taking out a loan for schooling) completely unaffordable and thus rule it out as a choice.

On the other hand as long as the credit constraint is not binding, individuals with lower levels of exogenous income might be more responsive to increased returns of schooling due to immigration, since their marginal utility of each additional dollar of income is higher than for those from richer households. Similarly, the "opportunity cost" effect might not be as strongly pronounced for unskilled natives from rich backgrounds who, due to their preferences, were not already likely to go to school as it represents a smaller portion of their total income. Thus we might see *the opportunity cost effect* to be dominant for natives from poorer backgrounds.

The sign on the interaction term between the logarithm of exogenous income and the logarithm of the share of unskilled immigrants can provide an insight into which effect, the *income* or *opportunity cost* one, in fact dominates, depending on one's level of exogenous income. Additionally it can show the relationship between exogenous income and magnitude of the human capital adjustment response to an increase in low skill immigration.

1.4 Theoretical Framework.

I am starting with the simplest framework for evaluation of human capital adjustment response to immigration in a setting with only two skill levels: low and high skill. This model allows me link increase in relative unskilled share of immigrants to changes wages for each skill category and to identify how these induced changes can alter human capital investment choices of natives depending on their preferences and exogenous income.

I present a two period closed economy model with low and high-skilled workers. Their total supply in the economy is denoted by P_{Lt} and P_{Ht} respectively. The periods are denoted by $t \in 1, 2$. I assume there is no discounting between periods.

I assume that individuals are heterogenous in terms of their initial endowment/assets y_i, which is distributed uniformely between $\underline{y}$ and $\bar{y}$. Additionally at each fixed level of exogenous income individuals are assumed to be heterogeouns in terms of their intertemporal preferences denoted by α, distributed uniformely on the interval between 0 and 1, with higher α corresponding to more patient individuals that put more value on their future consumption.

Each individual makes his/her educational decision in period 0 (not observed in the model) with full knowledge of his/her net benefits from schooling given current labor market conditions. This decision is realized in period 1, which is the first period observed in the model.

Production in this closed economy is assumed to be carried out by an aggregate profit-maximizing firm that uses capital and two types of labor (low and high skilled) as inputs.

1.4.1 Production and Wages.

Following closely the spirit of the model in Card (2001)[2] there is a single output good Y_t produced in both periods. This good is sold in a competitive market for a price q, which is the same across periods. I assume that production function is the same for both periods and is represented by the following equation:

$$Y_t = F(K, L_t), \tag{1.1}$$

where K is a vector of non-labor inputs that is assumed to be non-changing over time, and L_t is a vector of labor inputs.

The vector of labor inputs is represented by the following functional form in each

[2]This set up but without variation in time can be found in Card (2001), pages 25-26, but I repeat it in detail here.

period:

$$L_t = [\sum_{j=1}^{2} (u_j N_{jt})^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}, \tag{1.2}$$

where N_{jt} is the number of people with skill level j *employed* at time t; u_j is an economy wide skill- specific demand shock, and σ is the elasticity of substitution between different skill groups.

The first order condition equating the wage of each skill group with its marginal product of labor is the following:

$$\log N_{jt} = \sigma \log[qF_L(K, L_t)L_t^{\frac{1}{\sigma}}] + (\sigma - 1)\log u_j \tag{1.3}$$

Denote $\sigma \log[qF_L(K, L_t)L_t^{\frac{1}{\sigma}}]$ by θ_t, where θ_t is a common factor shared by all the skill groups.

On the labor supply side, participation rates are decided according to the following equation[3]:

$$\log(\frac{N_{jt}}{P_{jt}}) = \varepsilon \log w_{jt}, \tag{1.4}$$

where ε is positive and represents factor supply elasticity. Combining equations (1.3) and (1.4) we get the following expressions for wage rate and participation for people of skill j living in period t:

$$\log w_{jt} = \frac{1}{\varepsilon + \sigma}[(\theta_t - \log P_t) + (\sigma - 1)\log u_j - \log(\frac{P_{jt}}{P_t})] \tag{1.5}$$

$$\log(\frac{N_{jt}}{P_{jt}}) = \frac{\varepsilon}{\varepsilon + \sigma}[(\theta_t - \log P_t) + (\sigma - 1)\log u_j - \log(\frac{P_{jt}}{P_t})] \tag{1.6}$$

The main insight that I take away from these two equations is that both wages and participation rates depend on the relative proportion of workers of each skill in the local labor market and are decreasing in this proportion.

This paper is particularly concerned with equation (1.5) and I assume full participation rate.

[3]Worker's education decision though is based on the full employment, i.e. full hours of work assumption by a worker.

1.4.2 Immigration.

I allow for both skilled and unskilled immigration. Thus it is their relative share that will be defining the change in wages. For example, an increase in relative unskilled share of immigrants is expected to lower unskilled wages.

I assume that immigration shock happens in period 0 not observed in the model and that consumers make their schooling choices after observing the relevant change in wages.

1.4.3 Consumer's Maximization: Demand for schooling.

On the consumption side workers take w_L and w_H as given. From equation (1.5) we know that these will be affected by both low and high skill immigration, and in particular by their relative proportion. Hence I am mostly interested in comparative statics of solutions to the consumer optimization problem with respect to changes in w_L, w_H and how degree of responsiveness to decreases in unskilled wage varies with the level of y_i.

Set Up

Assume that consumers have Leontieff preferences $U(c_1, c_2) = min[\alpha c_1, c_2]$, where α represents the weight individual i puts on consumption tomorrow relative to consumption today. As was said earlier I assume that at a given level of exogenous income individuals are distributed uniformly with respect to their intertemporal preferences α, with α being a draw from uniform distribution $(0, 100)$.

In period 1 everyone starts with assets y_i and earning a low skill wage w_L. In period 2 only labor income is available: there is no additional exogenous non-labor income. I allow for saving in between of two periods at an interest rate normalized to zero. To model credit constraints I assume that borrowing is costly. Specifically, the interest rate for borrowing is $\delta \in (0, +\infty]$. An outcome where $\delta = +\infty$ corresponds to no borrowing being allowed.

In period zero individual makes a decision to acquire schooling in period 1, which comes at a fixed cost s and opportunity cost $0.5 * w$, corresponding to part-time work.[4]If an individual obtained schooling in period 1 then in period 2 she recieves a high skill wage w_H, which is strictly higher than low skill wage w_L. If she did not go to school she continues earning low skill wage.

Figure 1 shows the implied budget constraints. The budget constraint without schooling has a vertical intercept at $y_i + 2w_L$, horizontal intercept at $w_L + y_i + \frac{w_L}{1+\delta}$, and is kinked at $(w_L + y_i, w_L)$. The budget constraint with schooling has a vertical intercept at $w_H + 0.5w_L + y_i - s$ and a horizontal intercept at $y_i + 0.5w_L - s + \frac{w_H}{1+\delta}$. It has a kink at $(y_i + 0.5w_L - s, w_H)$.

For values of y_i such that $y_i + 0.5w_L - s + \frac{w_H}{1+\delta} > 0$ (i.e. schooling is affordable at least with a loan) if $\frac{w_H - w_L}{1+\delta} - 0.5w_L > s$ then schooling budget constraint dominates the one without schooling. Thus all individuals, regardless of preferences, will choose schooling (see Figure (1.1)). If on the other hand $w_H - 1.5 * w_L < s$ then no schooling budget constraint dominates the one with schooling and option to go to school is never chosen regardless of intertemporal preferences (see Figure (1.2)).

The more interesting scenario and one more relevant for my analysis is when the two budget constraints intersect, which means that $\frac{w_H - w_L}{1+\delta} - 0.5w_L \leq s \leq w_H - 1.5w_L$. This is the case when individual's intertemporal preferences will matter in his/her choice of schooling over no schooling. Note that if there is no credit constraint and thus $\delta = 0$ this case vanishes. Thus, the credit constraint (i.e. $\delta > 0$) is necessary

[4]Heterogeneity with respect to opportunity cost could have captured differences in learning abilities but it complicates the model unnecessarily without adding extra insights.

Budget constraint with schooling always dominates budget constraint without schooling if $(w_H-w_L)/(1+\delta)-0.5w_L>s$. This holds for realizations of y_i such that $y_i+0.5w_L-s+(w_H/(1+\delta))>0$, i.e. schooling is affordable at least with a loan. Dashed lines represent budget constraints once borrowing is not available (i.e. $\delta=+\infty$).

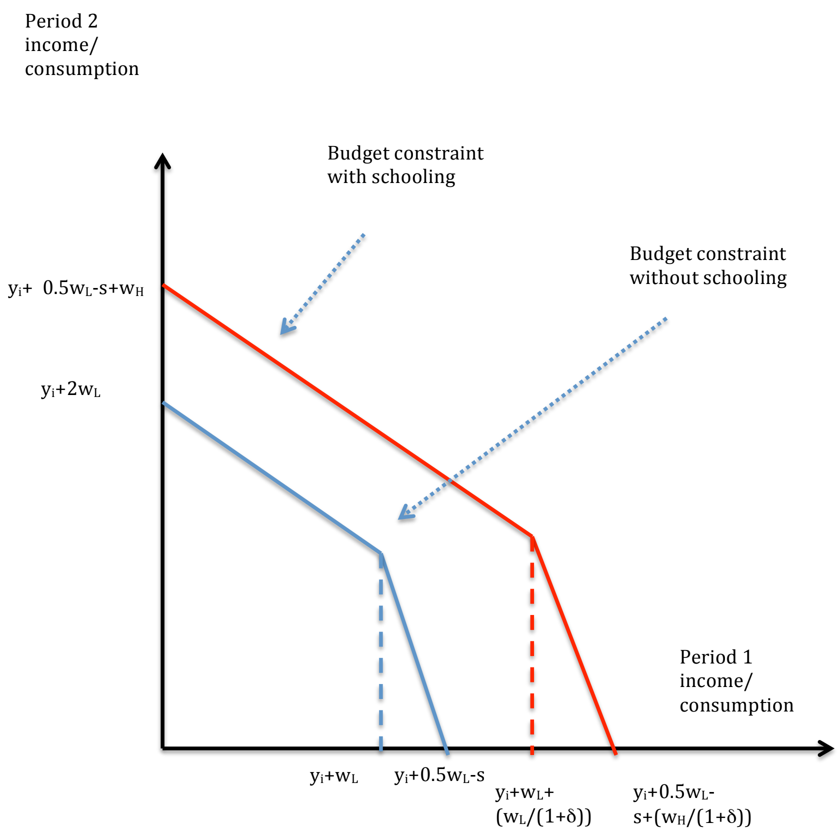

Figure 1.1: Budget constraint with schooling dominates the one without schooling.

Budget constraint without schooling dominates the one with schooling if $s>w_H-1.5w_L$. In this picture it is implicitly assumed that schooling is affordable at least with a loan given the realization of y_i (i.e. $(/(1+\delta))>0$, but as opposed to Figure 1 this is not a crucial assumption. Dashed lines represent budget constraints when borrowing is not available (i.e. $\delta=+\infty$).

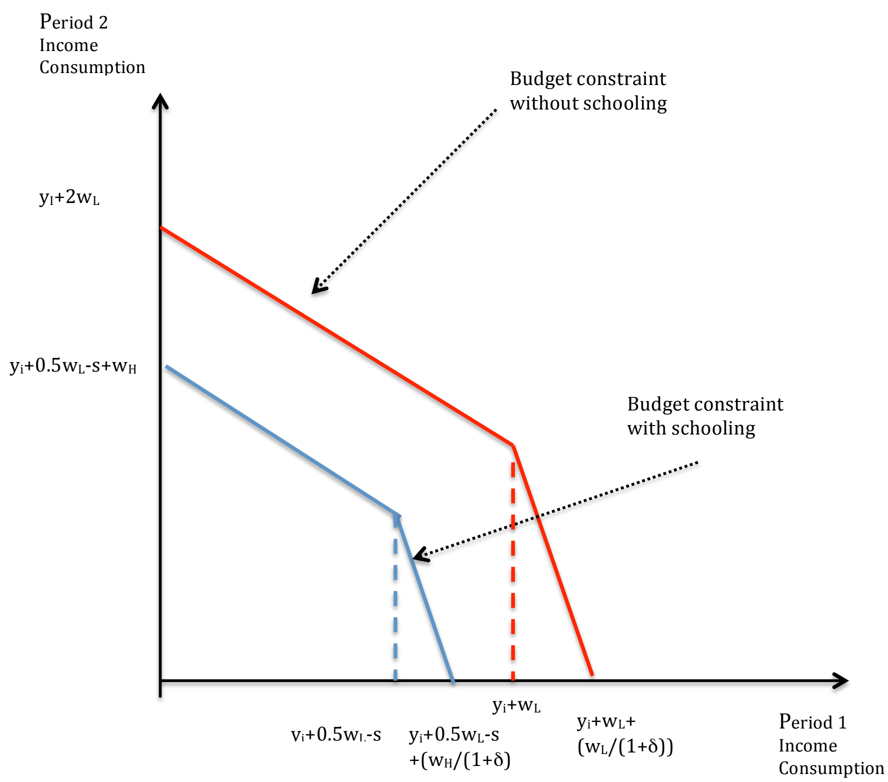

Figure 1.2: Budget constraint without schooling dominates the one with schooling.

for the schooling decision to depend on preferences. The fact that preferences matter allows for a non-uniform human capital investment response to changes in wages even for individuals with the same exogenous income.

Comparative Statics.

Given Leontieff preferences for fixed values of y_i, δ, s, w_L, and w_H there will be a cutoff level of intertemporal preferences α^* such that an individual with this value of α will be indifferent between going to school with a loan and not going to school and not borrowing (See Figure (1.3)). For the same exogenous income level y_i everyone with a value of $\alpha > \alpha^*$ will choose schooling and everyone with a value of $\alpha < \alpha^*$ will choose no schooling.

The assumption that these preferences are distributed uniformly for each level of y_i allows me to use the sign of the partial derivative of α^* with respect to w_L , w_H and the cross-partial of α^* with respect to both w_L and y_i to identify how proportion of native-born enrolled in college changes with decrease in low and increases in high skill wages and how exogenous income affects the magnitude of this change.

I start by solving for the value of α^*. It depicts intertemporal preferences such that individual who has them is indifferent between a point on the budget line that corresponds to schooling with a loan and a point on the budget line that corresponds to no schooling without borrowing. Thus c_1^* that chosen by this individual is such that:

$$(1+\delta)(y_i + 0.5w_L - s) + w_H - (1+\delta)c_1^* = y_i + 2w_L - c_1^*$$

Solving for associated values of c_1^* and c_2^* gives the following value of α^*:

$$\alpha^* = \frac{1.5(1-\delta)w_L - w_H + (1-\delta)s}{\delta * y_i - 0.5(3-\delta)w_L + w_H - (1-\delta)s} \tag{1.7}$$

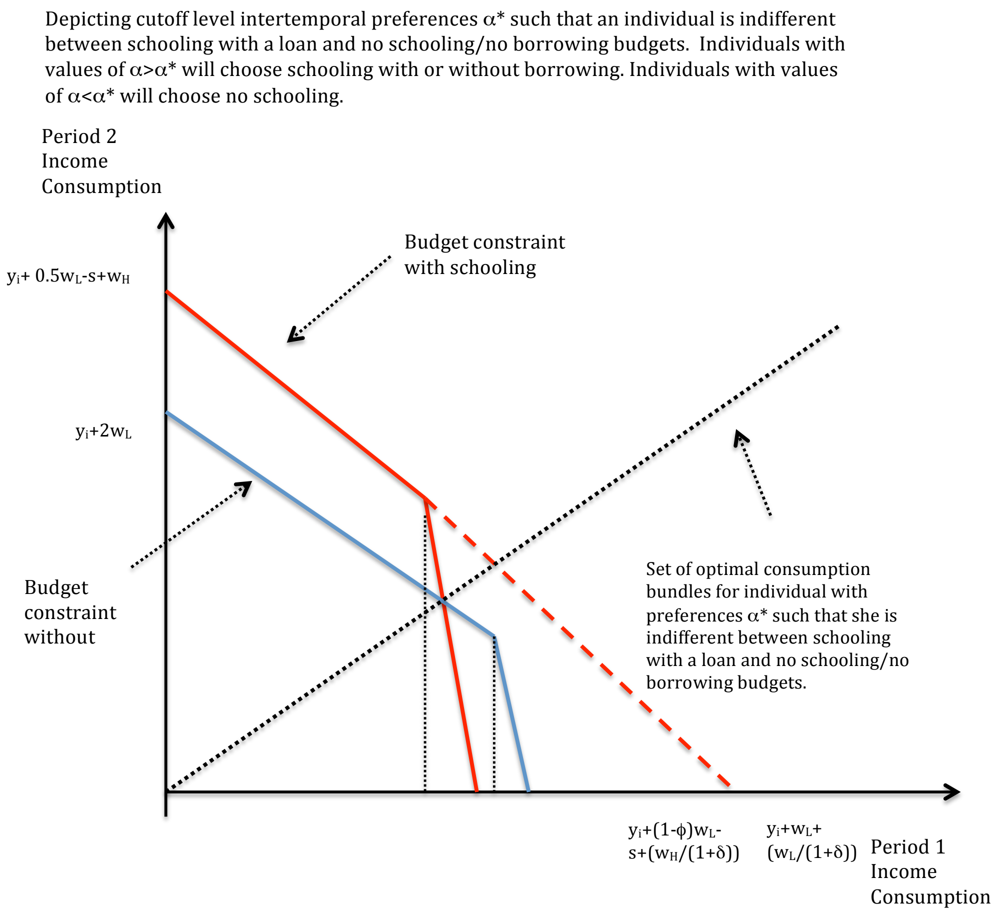

Figure 1.3: Cutoff intertemporal preferences α^*.

Partial derivative of α^* with respect to w_L is:

$$\frac{\partial \alpha^*}{\partial w_L} = \frac{\delta(1.5(1-\delta)y_i - w_H + (1-\delta)s)}{(\delta * y_i - 0.5(3-\delta)w_L + w_H - (1-\delta)s)^2} \tag{1.8}$$

The sign of (1.8) depends on the sign of the numerator and in particular on the sign of: $1.5(1-\delta)y_i - w_H + (1-\delta)s$. This expression is positive if:

$$y_i > \frac{w_H - (1-\delta)s}{1.5(1-\delta)} \tag{1.9}$$

The main takeaway from this equation is that there's a cutoff level of exogenous income such that decrease in w_L increase the proportion of the population choosing schooling when income is above the cutoff. In more detail there are three cases to consider:

1. Assuming $\delta < 1$ and $w_H > (1-\delta)s$ (1.8) implies that a decrease in low skill wage will be associated with a decrease in enrollment through increasing α^* for low levels of y_i and increase in enrollment for values of y_i above the threshold specified in (1.9).

2. If on the other hand $w_H < (1-\delta)s$ and $\delta < 1$ then decrease in low skill wage w_L will be associated with an increase in enrollment for all levels of y_i.

3. Lastly if $\delta > 1$ then same as in scenario above a decrease in low skill wage w_L will be associated with an increase in enrollment for all levels of y_i.

Thus a response to a decrease in w_L will depend on the value of exogenous income y_i and on the relation between w_H and s. But taking in account that a sign of partial derivative is positive in both cases 2 and 3 and that cutoff value specified in scenario 1 above is rather small (as it equals discounted difference between high skill wage minus fraction of tuition), it is likely that we will observe an increase in enrollment associated with increase in relative unskilled immigration for most of the exogenous income levels besides very low ones.

Partial derivative of α^* with respect to w_H is the following:

$$\frac{\partial \alpha^*}{\partial w_H} = -\frac{\delta(y_i - w_L)}{(\delta * y_i - 0.5(3-\delta)w_L + w_H - (1-\delta)s)^2} \tag{1.10}$$

Therefore with the exception of very low level of exogenous income that is below unskilled wage as w_H increases proportion of those choosing schooling increases.

To see how the magnitude of this response varies with y_i I look at cross-partial of α^* with respect to w_L and y_i:

$$\frac{\partial \alpha^*}{\partial w_L \partial y_i} = \frac{\delta(-1.5\delta(1-\delta)y_i + (3-\delta)(0.5w_H - 0.75(1-\delta)w_L - 0.5(1-\delta)s))}{(\delta * y_i - 0.5(3-\delta)w_L + w_H - (1-\delta)s)^3} \tag{1.11}$$

The sign of (1.11) depends on the signs of both numerator and denominator with the numerator being positive if:

$$y_i < \frac{(3-\delta)(w_H - 1.5(1-\delta)w_L - (1-\delta)s)}{3\delta(1-\delta)} \tag{1.12}$$

and the denominator being positive if:

$$y_i > \frac{(1-\delta)s + 0.5(3-\delta)w_L - w_H}{\delta} \tag{1.13}$$

There are a few cases to consider.

1. Assuming $\delta > 3$ then denominator is always negative, numerator is always positive and thus the sign of (1.11) is negative meaning that as y_i increases responsiveness to changes in w_L decreases.

2. Assuming $1 < \delta < 3$ denominator is then always positive, while the sign of the numerator depends on if $(1-\delta)s - w_H + 0.5(3-\delta)w_L$ is positive or negative. If $w_L < \frac{w_H - (1-\delta)s}{0.5(3-\delta)}$ then numerator is always positive and therefore responsiveness

to changes in w_L increases with y_i. Otherwise there is a part of the range of y_i for which numerator is negative and responsiveness to changes in w_L decreases as y_i increases. This fraction corresponds to higher incomes. However as exogenous income level decreases and finally y_i passes the threshold indicated in (1.12) enrollment becomes more responsive to changes in w_L as income increases. So we will see higher responsiveness to for higher incomes but in the lower income levels and the opposite for the higher income levels.

3. Assuming $\delta < 1$, which is probably the most realistic case, creates a few sub scenarios.

   (a) If $w_H < (1-\delta)(s+1.5w_L)$ then denominator is always negative, while numerator is positive for high levels of exogenous incomes[5]. Thus for low levels of y_i the responsiveness of enrollment to changes in w_L will increase with y_i, but for levels of y_i satisfying (1.13) and assumptions on w_H above responsiveness of the schooling decision to changes in w_L will decrease with income.

   (b) The denominator will be always positive if $w_H > (1-\delta)s + 0.5(3-\delta)w_L$. Then numerator will be positive for low values of y_i, such that (1.12) is satisfied but will be negative otherwise. Thus starting with some level of y_i such that (1.12) is not true the responsiveness of enrollment to changes in w_L will be decreasing with income.

   (c) Lastly assuming w_H lies in between of the values indicated above, so that neither denominator, nor numerator are always positive, threshold indicated in (1.13) will be higher than (1.12) Thus for exogenous income

[5]However, note that once $w_H < s + 1.5w_L$ no schooling budget line always dominates and therefore I am unsure that this statistics will be relevant.

levels high enough such that (1.13) is satisfied the cross partial will be negative and therefore the responsiveness to changes in w_L will decrease for higher levels of income.

Therefore while there might be variation in relationship between y_i and magnitude of responsiveness to changes in w_L for low levels of income, once the exogenous level of income y_i is high enough we are the most likely to observe that as exogenous income increases individuals are less responsive to changes in w_L in terms of their schooling decisions.

1.4.4 Empirical Implications.

The model above generates the following empirically testable predictions.

- An increase in the relative share of unskilled immigrants will lower wages of unskilled natives by increasing the relative share of unskilled people in the population.

- The effect of changes in w_L on the schooling decision depends on exogenous income, high skilled wages and schooling costs. Specifically, there is a cutoff level of exogenous income y_i^*, such that decreases in w_L will increase the proportion of the population with incomes above y_i^*. This cutoff y_i^* increases in high skilled wage w_H and falls in schooling costs s. Altogether, the model predicts that an increase in low skilled immigration should increase the proportion of native-born choosing to go to college.

- Lastly the relationship between the magnitude of this change and exogenous income will depend on the relationship between wages and schooling costs. But overall for higher levels of exogenous income the responsiveness to decreases in unskilled wage will decrease as income level increases. Thus we are likely to observe less "crowding in" for higher levels of exogenous income.

1.5 Empirical Specification.

To test the empirical implications above and to more broadly assess the effect of immigration on the schooling decisions of the native-born individuals I employ the empirical specification below. This approach builds on the empirical framework proposed in Jackson (2011).

Dependent variable is the change in logarithm of the enrollment ratio of the native-born individuals ages between 18 and 34 [6]. The native-born are grouped according to their gender, race, state of residence and year into age-gender-race-state-year cells.

I assume that immigrants of different race, age and gender affect all native born in any given cell in the same way. Thus explanatory variables are unique at the state-year level with exception of income, which varies by the group and estimated by the median income measure for each group.

The initial specification is as follows:

$$\begin{aligned} ln\frac{Native^{CE}}{Native}_{argjt} = \beta_1 ln\frac{Immig^U}{Immig^H}_{jt} + \beta_2 lnIncome_{argjt} + \beta_3 lnIncome_{argjt} \\ * ln\frac{Immig^U}{Immig^H}_{jt} + \alpha ln(Immig^{CE})_{jt} + \sigma_t + \omega_j + \theta_g + \rho_r + \mu_a + \epsilon_{rgjt}, \end{aligned} \tag{1.14}$$

where a denotes age, j denotes state, t denotes year, g denotes gender, r denotes race. CE stands for college enrolled, U for unskilled (i.e. high school education or less), S for skilled (i.e. some college education or more), σ represents year fixed effects, ω state fixed effects, θ gender fixed effects, ρ race fixed effects and μ age fixed effects.

[6] I exclude those that are older than 34 year due to incredibly low enrollment levels.

It is very possible that there is some serial correlation in native enrollment rates. While in Jackson (2011) the standard errors are clustered at the state level to allow for state-specific variance-covariance matrices, I cluster the standard errors at state-year level as I believe it is more likely that variance-covariance matrices vary at this level.

To account for time invariant fixed effect the following first differences regression is used:

$$\begin{aligned}\Delta ln\frac{Native^{CE}}{Native}_{rgjt} &= \beta_1 \Delta ln\frac{Immig^U}{Immig^H}_{jt} + \beta_2 \Delta Income_{rgjt} \\ &+ \beta_3(\Delta Income_{rgjt} * \Delta ln\frac{Immig^U}{Immig^H}_{jt}) \\ &+ \alpha \Delta ln(Immig^{CE})_{jt} + \Delta\sigma_t + \Delta\epsilon_{rgjt},\end{aligned} \tag{1.15}$$

Note that all the time-invariant fixed effects are differenced out.

I use household pre-tax income net of personal pre-tax income as proxy for exogenous income. I do not include personal income as it is likely to be correlated with the enrollment due to allocation of time from income generating activities to schooling.

Coefficient β_1 is supposed to capture the effect of "crowding in". Positive sign of β_1 indicates that *opportunity cost effect* of immigration is stronger than *income* effect and thus probability of native enrollment increases as relative share of unskilled immigrants increases. Negative sign of β_1 indicates the opposite. Coefficients on β_2 and β_3 capture the effects of exogenous income on enrollment probability and variations in magnitude of "crowding in" effect depending on income. Positive sign of β_3 indicates that people with more exogenous income are more likely to be "crowded in" as they possible have smaller financial constraints, while negative sign indicates the opposite suggesting that native-born individuals from poorer households are more likely to enroll in response to increase in unskilled immigration.

Also note that while I do not discuss it in the conceptual framework or theoretical model parts of my paper I do control for the possible effects of the presence of immigrant students in my regresssions.

Potential Endogeneity. There are two main problems that a researcher can encounter while performing the analysis above using immigrant flows that are reported in the Census. These problems are:(i) endogenous selection of immigrants into either schooling or labor market; and (ii) endogenous selection of immigrants into certain geographical labor markets based on returns to their skills. The former problem is supposed to be mitigated by using predicted immigrant enrollment versus realized one, where prediction is based on the logistic model ran on Census data from 1960. The latter problem is mitigated by the use of the two stage least squares with a standard instrumental variable that exploits immigrant networks.

Assigning immigrants to enrollment. To exogenously determine which immigrants will enroll in college and which will choose to be in the labor force following Jackson (2011) I use logit model of college enrollment on individual characteristics for the data from 1960 as follows:

$$Immig_{ij}^{CE} = \beta_0 + \beta_1 Age_{ij} + \beta_2 Age_{ij}^2 + \beta_3 Female_{ij} + Race_{ij}'\beta_k + Country_{ij}'\beta_h + \epsilon_{ij} \quad (1.16)$$

where *Age* is age in years, *Female* is a dummy variable for women, and *Race* and *Country* are vectors of race and country dummies, respectively. According to Jackson (2011) if market shocks are not correlated with any of these chosen characteristics, this equation will consistently estimate how each of the covariates affects college-enrollment via change in underlying demand. Using the coefficient estimates, college enrollment for individuals from 1970-2000 sample is predicted. Then it is broken down into quintiles and those from the top quintile are assigned to be enrolled in college, while the other immigrants are assumed to have stopped their education and are assigned to be in the low or high skill groups of the labor force depending on their reported level of education.

Instrument. It is possible that there might be a problem of reverse causality due to skill-complementarities. For example, in booming economies higher-skilled natives are likely to provide more jobs for lower-skilled immigrants and thus we might be observing positive sign on β_1 but not due to change in educational patterns of low-skilled native-born. Following the literature I use a supply-push based instrument (Card 2001, Ortega and Gonzales 2008). It exploits the idea that existing immigrant enclaves and networks are important in the choice of destination by new immigrants.

The instrumented variable looks as follows:

$$\sum_h \frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}} \Delta ImmigrantType_{ht} \tag{1.17}$$

where h is countries of origin included in the 1960 US Census, $\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}$ is the percentage of all immigrants from country h in the 1960 census who were living in state j, and $\Delta ImmigrantType_{ht}$ is the difference between year t and year $(t-10)$ immigrants of a given type from country h. The three types of immigrants are as outlined above: (1)immigrant students, (2)unskilled immigrant labor, (3) skilled immigrant labor. Predicted immigrant flows are used for the construction of the instrument which is applied to the variable that uses realized values of these. As an extra robustness check I also use this instrument applied to the realized values of immigrants in each of the three groups. Both instruments pass the check for being a strong instrument using the first stage first stage values of Kleibergen-Paap rk statistics.

1.6 Data

The analysis uses population samples from the Integrated Public Use Microsamples (IPUMS) of decennial U.S. census for the 1970 to 2000 period and 1960 for the creation of probabilistic weights for the assignment of enrollment probabilities and creation of instrumental variable. I use 1 percent samples for both native and immigrant population. Initial data set contains individuals ages 18 to 34. Following Borjas and Peri data excludes those who are self-employed, those living in group quarters (besides those that are education related), and those in military service. Education is measured by the highest level of school or degree completed by the time of the interview. Individuals for whom schooling variable is missing are excluded from the sample. I use a standard definition of immigrant as one who was born abroad (with the exception of the ones born to American parents).

Labor force versus schooling. Immigrant population is broken down into three non-overlapping groups: low skilled individuals (high school degree or less), high skilled individuals (some college and more), and those enrolled in college. It is assumed that if one is in school she is not in the labor force[7].

Skills Skills are limited to the formal education and are assigned in the following way. I use the EDUC variable in the Census data that gives me information on the highest level of education completed by the time of the survey. I initially break the population down into the following four skill groups:

- 0- high-school dropout
- 1- high school graduate
- 2- some college
- 3- Bachelors degree or more (which is approximated by 4 years of college and more, as well as enrollment in graduate school)

[7] This might cause some measurement errors as at least judging by my descriptive statistics it looks like that for some age groups those groups overlap due to part time work.

These are further aggregated into two main groups: *skilled* and *unskilled*. Unskilled are those who have not completed high school or only have high school degree. Skilled are those who have some college and more. Again this aggregration can be refined depending on if people with some college are closer in their labor market characteristics to high-school or to college grads.

There are a few ways one can approach assigning education levels to immigrants, due to the fact that not all foreign education is recognized in the United States. One approach is to just look at the education levels of immigrants as given. Second is to assign them the education level by occupation. This can be done if one looks at the average level of education for natives in the same occupation that immigrant has.[8] For simplicity I use the reported values of education since these will matter only for the portion of those who will be predicted to be in the labor force.

Gender and Race. I also create indicator variable for being female and for belonging to either one of the three major racial categories: African American, Asian or Caucasian- with default category being what Census denotes as "Other", which includes mixed races.

1.7 Results

Tables with results can be found in Appndix A. Thus I just refer to them by number for the rest of the section. When household pre-tax income net of personal pre-tax income is included (Table 1) there is evidence of about 1.4 to 2 percent increase in native enrollment ratio associated with 1 percent increase in relative share of unskilled

[8]There are of course other more sophisticated ways such that are used by Card (2001) that I do not use yet, primarily because the way is constructed for the probability to be in a certain occupation as opposed to the schooling level.

immigrants, and about 0.11 to 0.21 percent decrease in native enrollment ratio associated with 1 percent increase in immigrant enrollment. The coefficient on exogenous income variable is positive indicating that increase in income is associated with increased probability of college enrollment. The coefficient on interaction term is negative. This can be interpreted as: (i) with increase in income the positive effect of "crowding in" is less strong (which is consistent with the story of people with lowest income levels gaining the most via educational upgrade); and (ii) with increase in relative share of unskilled immigrants the positive effect of income on probability of low-skill native-born individuals to be enrolled in college decreases. This can be consistent with the idea that if increase in low skilled immigration is perceived as a threat to households income or stable employment opportunities then each dollar is more likely to be used for other needs in household consumption besides education.

To find out if these results are driven by observations from some specific groups I split the sample into three age groups: (i) those ages 18 to 22; (ii) those ages 23 to 27; and lastly those that are 28-32 years old. Results from these regressions are presented in Tables 2-4. It looks like the results are driven primarily by those of normal college enrollment age, which corresponds to the youngest group in my partitioned sample. There is strong evidence of "crowding in" for the youngest group with about 0.64 percent increase in enrollment ratio corresponding to 1 percent increase in relative unskilled immigrant labor. However, coefficient on "crowding in"parameter is not significant in older with exception of the instrumented one for those ages 23 to 27. The signs on income and interaction terms are not statistically significant for the older groups either.

Finally when analysis is done for three major races,-Caucasian (Table 5), African-American (Table 6), and Asian/Asian-Pacific (Table 7), - the following results emerge. Evidence of "crowding in" effect is the strongest for Caucasian native-born individuals.

Corresponding to about from 2.3 to 2.8 percent increase in enrollment ratio in response to 1 percent increase in relative unskilled immigration, which is more than twice the size of the effect for the African-American segment of population, while there is no evidence of any effect on Asian-American/Pacific native-born at all. Income on the other hand is statistically significant only for this latter group. However, for all groups the coefficient on the interaction variable is negative. This might indicate that the more well off native-born low-skilled individuals are more insulated from competition with immigrants. This also completely works with the empirical implications of my theoretical model.

1.8 Conclusions

It is reasonable to assume native-born might adjust their human capital in response to immigration. Yet magnitude and even presence of this response are not clear. This is possibly so due to immigration affecting both the returns to immigration and the means to finance it. Thus the magnitude of "crowding in" will depend on the presence of credit constraint and on the initial distribution of incomes in the population especially for households with low-skilled workers.

My results so far are supportive of the hypothesis that there is overall a positive effect of an increase in low-skill immigration on college enrollment of native born even controlling for presence of immigrant students and for the effect of immigration on income. Since the effect is the greatest for the poorest households, it would be good to extend this work and to see if there is an associated increase in uptake of student loans. This can be done using data from National Center for Education Statics and in particular National Postsecondary Student Aid Study.

Lastly while there is literature showing there are positive effects of low-skill immigration in terms of “crowding in” of native-born into higher education there is almost no research that addresses the fate of those marginal students after enrollment. For example, it is likely that they were not enrolled due to their lower educational ability or high distaste for schooling and thus they might be more likely to drop out of school. Taking in account that an increase in college enrollment is predicted to happen concurrently with an increase in uptake in students loans it might be that we will observe higher enrollment but concurrently with higher drop out rates of those who have taken out loans for college.

Chapter 2

Is There Really Too Much Immobility in Transition Economies? Identifying Potential Gains to Geographic Mobility in Eastern Europe and Central Asia.

2.1 Introduction

[1]

There is a common perception that rates of mobility in European and transition economies are low, with them being exceptionally low in Eastern Europe and Central Asia region even despite quite significant variation in rates and even when compared to majority of Western European countries. These high rates of immobility represent a major challenge for economic theories since they suggest that - aside from explaining why certain people move, - economic theory also has to explain, why, despite substantial potential gains from geographical mobility, so many individuals remain immobile.

IZA report on "Geographic Mobility in the European Union: Optimizing its Economic and Social Benefits" from 2008 presents comparison of the lifetime mobility rates [2] in EU25 countries using Eurobarometer data. The difference between mobility rates in Eastern European members of the EU25 and the rest is striking. While in the overall sample the rate of lifetime mobility varies from 40-90 percent, with exception

[1] This chapter is a part of an on-going work with Erwin Tiongson, Caglar Ozden and Peter Huber.

[2] Non-mover is defined as someone who has never relocated from his/her place of birth in span of his/her entire life.

of Latvia and Lithuania, mobility rates in Eastern European members are in the 40-50 percent range on average being at the bottom of the distribution with only Mediterranean countries being close to these lower rates (IZA 2008).[3] This is consistent with earlier findings from Vandenbrande et al (2007) based on Eurobarometer data that suggest that the share of those that have never moved after leaving their family is 27 percent in the EU countries and that it may reach up to around 1/3 in high unemployment EU countries such as Greece. But, as one can notice, from comparison with data above these shares are still significantly lower than in the Eastern European region, where this would turn out to be as high as 50 or 60 percent. To further substantiate this statistics in the Life in Transition Survey (LITS) which covers a sample of 38900 households in 35 countries (with 30 of them being transition economies in Eastern Europe and Central Asia) more than half (58.6 percent) of the respondents state that they have lived in their current place of residence [4] for their whole life, and even among those that have moved at least once the median duration of residence in their current community (i.e. village, town or city) is 21 years. For comparison in the United States according to the data from Census Bureau about 35 percent of population report to have moved at least once in the past 5 years when asked this question in 2010, which is already a decrease from about 40 percent in 2005. But on the other hand Fischer et al (2000) find that 87 percent of the Swedish population does not move residence over a 15 year period.

Nevertheless, while number wise there is clearly a lot of variation in immobility rates and while Eastern European countries are very likely to be at the bottom of the distribution, even more fundamentally it is unclear if mobility rates are low compared to some “desirable" level (and how does one estimate this “desirable” level) or if they

[3] In fact it is Malta that has the lowest rate of lifetime mobility in the sample at 38 percent.

[4] Current place of residence is defined as village/town/city.

are low just in comparison with developed economies like Western Europe and United States. While one can address this question from the position of a benevolent planner and a link between economic growth of a country and higher rate of mobility (which can be noted even from the statistics above), our paper addresses this question from the position of potential individual economic gains that can or cannot be reaped by those who are currently immobile in case of various relocation options. Thus using LITS II data focusing primarily on 30 transition economies in Eastern Europe and Central Asia we answer the following questions, which to the best of our knowledge have not been addressed for this set of countries before: What are the potential gains from mobility to those who do not move? What share of current immobility can be explained by lack of economic incentives to move and what share can be explained by other factors in light of possible economic gains? What are the target populations that could have gained by relocation in light of potential gains for them?

LITS allows us to draw comparisons between different countries and regions and to use rigorous sets of controls and possible instruments based on information about attitudes, social capital and real estate ownership. Furthermore, it allows us to potentially capture income from non-market activities, which plays a significant role in transition and developing countries, and might not be captured by datasets and studies that rely on nominal earnings information. Lastly it allows us to use data on expenditures and create a proxy for a location specific CPI to make sure that increases in income are not just associated with move to a more expensive location.

We first present the analysis of changes in income associated with different types of relocation in transition and comparator countries while controlling for human capital and other relevant characteristics of both movers and non-movers in the sample. We proceed to create counterfactuals for those currently immobile to deduce potential gains from different relocation options controlling for their individual/household characteristics. Counterfactual scenarios are based on coefficients from those who are currently mobile and thus rely on assumptions of wage rigidity, selection only on observable characteristics and no congestions in the destination labor markets. Thus simulated gains are likely to be upper bounds on possible gains and thus negative numbers are more informative. We find that in some regions like former Yugoslavia and Commonwealth of Independent States (CIS) from 17 to 53 percent of immobility can be explained by lack of monetary gains to any type of relocation given individual's labor market characteristics.

To address potential selection bias and to strengthen our results we employ instrumental variable technique. We find that there are likely downward bias due to negative self-selection into mobility for urban dwellers in countries that belong to CIS extended region.

The chapter proceeds as follows. Section 2.2 presents review of the literature on consequences of mobility and impediments to mobility/determinants of immobility with regards to our contribution. Section 2.3 presents our conceptual framework and empirical specification. Section 2.4 describes data set used and the construction of relevant variables. Section V discusses results and Section 2.5 concludes.

2.2 Literature Review

There are two main strands of literature that are relevant to our work. The first addresses the consequences of migration/mobility both internal and international from both micro and macro perspectives. While research on consequences of mobility addresses gains/losses from relocation to those who moved, our paper contributes to the existing literature by identifying consequences of immobility via assessing potential gains/losses from various relocation options for those who are currently immobile accounting for their characteristics. The second strand of literature we draw on focuses on determinants of immobility/mobility and impediments to mobility and thus helps us identify potential instruments to address selection bias.

2.2.1 Literature on Consequences of Mobility.

Much of the economic literature and many public policy debates consider lacking regional labor mobility an impediment to both long and short run economic growth as well as a cause for high and persistent regional labor market disparities[5]. The reason for this view is that countries with low labor mobility are unlikely to take full advantage of the positive effects of urbanization on productivity and income growth (see World Bank (2009) for a powerful argument in this direction) and because in low labor mobility environments (adverse) region specific shocks to labor demand also lead to a higher persistence of regional unemployment rates. Furthermore, in the face of large regional disparities in terms of income, unemployment and poverty, regional mobility is obviously also a possibility for individuals (and/or households) to improve their individual well being and to escape from unemployment and/or poverty.

However, this view does not go unchallenged. Lall et al (2006) present a good overview of literature including both theoretical and empirical work mentioning that even relocation from rural to urban areas is not always unambiguously beneficial. Rural to urban migration is thought to be especially beneficial for economic growth via urbanization and agglomeration effects. However, one has to take in account such factors as congestion, which combined with wage rigidity can lead to the so called Harris-Todaro paradox (Todaro 1969, Harris-Todaro 1970). In this case under certain

[5] Lall et al (2006), Janiak and Wasmer (2008), Quispe-Agnoli and Zavodny (2002), Mas et al. (2008) and Huber and Tondl (2011)

circumstances a policy that increases employment in the urban areas can induce too much migration, which in turn will lead to increased urban unemployment.[6]

In some other cases such as Ortega (2002) and Sato (2004) rural to urban migration is positive for overall welfare. However, one has to notice that this is so only under certain circumstances and is not a universal truth.

From the individual perspective according to the standard neo-classical migration theories (see Todaro 1969, Harris and Todaro 1970, Sjaastab 1962) migrant's move from places with low expected income to regions with high expected income in order to maximize their lifetime utility. While it is worth mentioning that it has been observed that some types of migration, for example, rural to urban happen even in cases when it is not economically justified by the wage differential (Katz and Stark 1986a), there is vast body of literature researching economic gains to mobility (in particular in the United States) both internal and international.

Lall et al (2006) presents a good overview of the literature addressing individual level consequences of migration to date. They highlight that the empirical literature has mainly tried to estimate the monetary returns to migration focusing on wage comparisons or using current earnings as a proxy for the stream of future income to deduce the dynamics of migrants wages. These might not be the best methodology for transition and developing countries where a relatively significant share of income comes from black market or subsistence farming activities.

[6] It is unclear though who bears the burden of this unemployment: the urban dwellers, potential migrants from other urban locations or rural migrants. So while aggregate effect is clear its distribution across different types of individuals is ambiguous.

2.2.2 Literature on Impediments to Mobility.

We draw on the second strand of research focusing on impediments to mobility and determinants of immobility to identify instrumental variables to use, so that we can correct for potential endogeneity due to self-selection into migration decision.

The literature in this direction can be classified into four major groups: (i) the one focusing on the macroeconomic and demographic factors: (ii) the one addressing income compression, matching and the role or labor market institutions; (iii) the one looking at non-labor market institutions as determinants of mobility; and lastly (iv) a vast strand of relatively new literature on the role of social capital and networks in the migration decision.

The first group focuses on macroeconomic conditions and demographic factors as impediments to mobility. In case of transition economies it highlights the role of informal market income that is location specific as an impediment to mobility. For example, Abdulloev et al. (2011) find evidence that persons with good access to black market activities are less likely to migrate in Tajikistan. Furthermore, to the degree that such unmeasured income components are earned in kind, rather than in case, this may make it difficult for persons to move if case payments are needed for migration costs. Thus for instance Friebel and Guriev (2000) show that in kind payments of firms to Russian workers reduce their willingness to move, a similar role could also be played by in kind transfers within family.

Strong presence of in kind payment and black market activities in the region of analysis makes LITS a better dataset for our analysis as we do not have to rely on official labor income earnings. However, even though there is a question that does address these sources of income this is unlikely to be a good instrument as it will be affecting the level of income.

As far as macroeconomic characteristics there is some evidence that in fact high national level of unemployment might be a deterrent to immigration (Gordon 1985, Pissarides and Wadsworth 1989, Bentolila 1997.) Additionally, demographic characteristics such as age, gender and marital status are shown (even though not always convincingly) to be determinants of migration decisions with older people, women and married couples being less likely to migrate. In particular older people have a lower probability of migrating, because for them the time to earn the returns on the original investment of migration is lower (Becker 1964) or because of higher psychological costs of migration (Schwartz 1976) or due seniority rights to older workers in many countries (David 1976). However, this is not so when tested on the U.S. data (Bodvarson and Hou 2010). Coincidentally these are also the characteristics that are often considered to be determinants of earnings/income.

The second group identifies inefficiencies in matching as a result of which job searchers in the labor market facing substantially higher probability of being hired per unit of time spent searching in their region of residence, than in a region, where they do not live. They additionally address the role of labor market institutions and labor market policies, such as unemployment protection in migration decisions.

The third group focuses on non-labor market factors that might be connected to mobility. We draw on this strand of literature to identify the instruments used. In this literature the most prominent place is taken by “Oswald hypotheses” (Oswald 1996), which states that high rates of homeownership are connected to the lower rate of mobility. However, one of the biggest criticisms of homeownership being analyzed as a determinant of mobility is potential endogeneity of ownership in its relationship to the mobility decision. Furthermore, more relevant to the transition countries, is the role of housing market inefficiencies and of relatively cheap government provided or subsidized housing as deterrents to mobility (Monchuk et al 2010).

Lastly there is a relatively new but numerous research on the role of social capital and networks in migration decision. Networks have been shown to play a role in both returns to migration (via location and occupation choices/outcomes) and in decisions to migrate. The literature is quite developed in terms of theory. On the empirical side there are two successful papers that stand out. First is Munshi and Rosenzweig (2009) who show that social networks play a role in the migration decision in India and serve as an impediment to mobility even when there are clear monetary gains to it. The second one is Belot and Ermisch (2006), where authors use the information on frequency of contact with individual's three closest friends as one of the proxies for local social capital. However, identifying proper proxies for "social capital" and "local networks" remains an area where more development can be used.

We derive mostly on the strand of literature concerned with real estate ownership. To disentangle it from potential endogeneity with regards to relocation decision or from being strongly correlated with income we use an instrument that exploits a rather sporadic nature of real-estate privatization in transition countries where it has been mixed with ad hoc land grants, bureaucratic assignment of real estate and most importantly where many countries have implemented it in some but not all regions.

2.3 Empirical Framework

It is true that number wise mobility is strikingly low in the transition countries. Just looking at Figure (2.1), which depicts a proportion of current country's residents that have ever moved[7] in their life the difference in mobility rates between select Western European countries (with exception of Italy) is striking. So why do people not move? Are there impediments to mobility implicitly and explicitly created by the government and society? Is majority of non-movers possibly already located in local

[7]Moving being defined as relocation between two different geographic units.

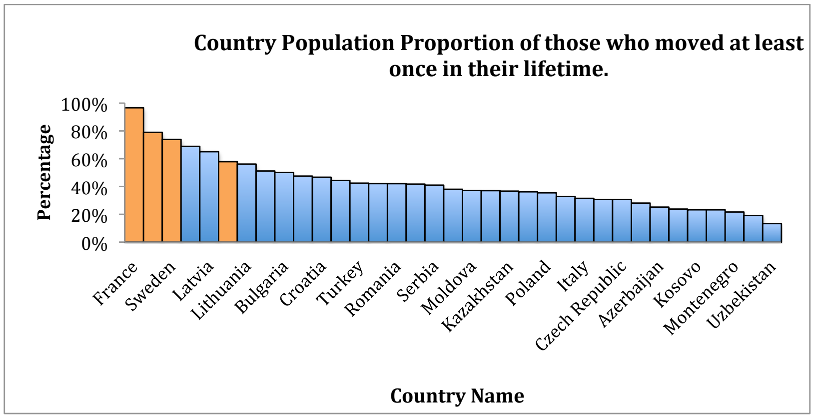

Figure 2.1: Distribution of lifetime mobility across 35 countries in LITS II sample. Bars for Western European comparator countries are color-coded in orange. Source: LITS II survey.

metropolitan or booming areas and therefore do not gain anything by the move? Or are the characteristics of immobile so different from the ones of successful movers that they are unlikely to gain? A brief glance at data suggests that it might be a combination of all those.

Looking at Figure (2.2) one can notice that in the past 20 years some of the transition countries have been catching up in terms of their mobility rates, which suggests that maybe some lack of mobility can be explained by the past of living in a command economy. This will be in accordance with the last explanation. And this it might wise to differentiate between those who moved whenever and the new/recent movers i.e. those that have been mobile in the past 20 years past the collapse of Soviet Union.

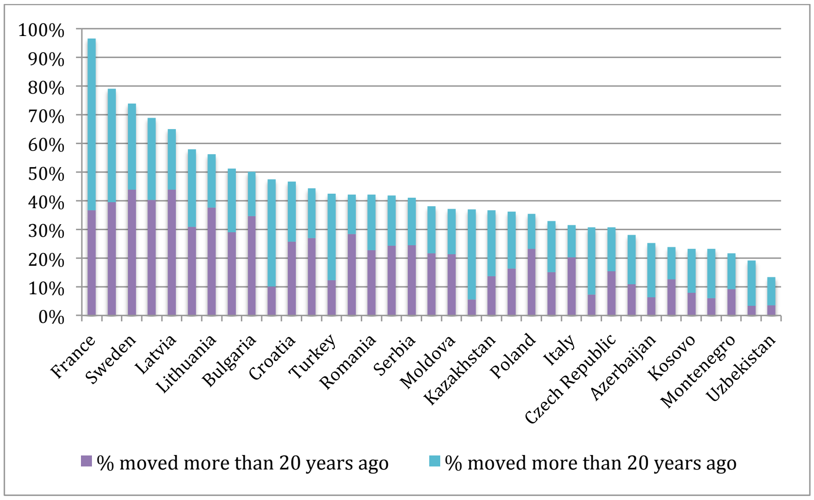

Figure 2.2: Break down of country level mobile into: (i) those who moved in the past 20 years and (ii) those who moved more than 20 years ago. Source: LITS II survey.

Additionally, it is very possible that consequences of relocation will vary with the type of relocation. For example in some countries it is likely that if you are born in a metropolitan area your income is likely to be highest if you stay there due to these areas featuring the highest number of job options and the best educational opportunities. Also it is likely that in the long run there might be an increase in income associated with relocation from rural to an urban area, while changes in income associated with relocation between two rural areas are unclear.

Thus we create the following seven different categories of mobility behavior. Three of them are for people who are considered immobile and four describe different types of relocation.

1. A person (household) that was born in a rural area and did not move from this rural area ever in his/her life. This person is labeled "*rural non-mover*".

2. A person (household) that was born in an urban area and did not move from this area ever in his/her life. This person is labeled "*urban non-mover* ".

3. A person (household) that was born in a metropolitan area and did not move from this area ever in his/her life. This person is labeled "*metro non-mover.*"

4. A person (household) who moved between two rural areas. This type of movement is labelled "*rural to rural*" relocation.

5. A person (household) who relocated from a rural to an urban area. This type of movement is labeled "*rural to urban*" relocation.

6. A person (household) who moved between two urban areas. This type of relocation/movement is labeled as "*urban to urban*" relocation.

7. A person (household) who relocated from an urban to a rural area. This type of relocation/movement is also labeled "*urban to rural*" relocation.

Figure (2.3) and Figure (2.4) represent the distribution of lifetime and recent movers with respect to different types of relocations. A few things stand out on these pictures. First of all, generally relocation towards urban areas dominates with exception the countries that belong to EU 10 region, which rural and urban oriented mobility seem to be quite balanced. There is a striking tendency towards urbanization among movers in the comparator Western European countries. Same is true for the residents of CIS region, while the opposite holds for EU10. Lastly one can notice that a bar representing former Yugoslavia stands out among the other by being about 20

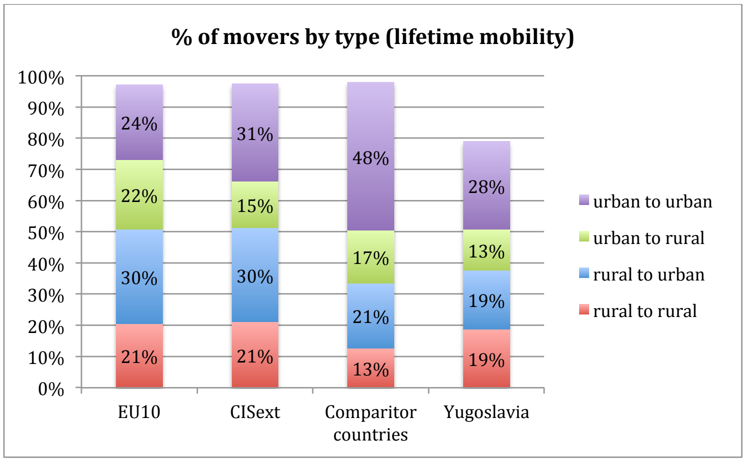

Figure 2.3: Distribution of lifetime movers by type of mobility. If the bar doesn't reach 100 percent mark it means the respondent declined to disclose his or her place of previous residence. Source: LITS II survey.

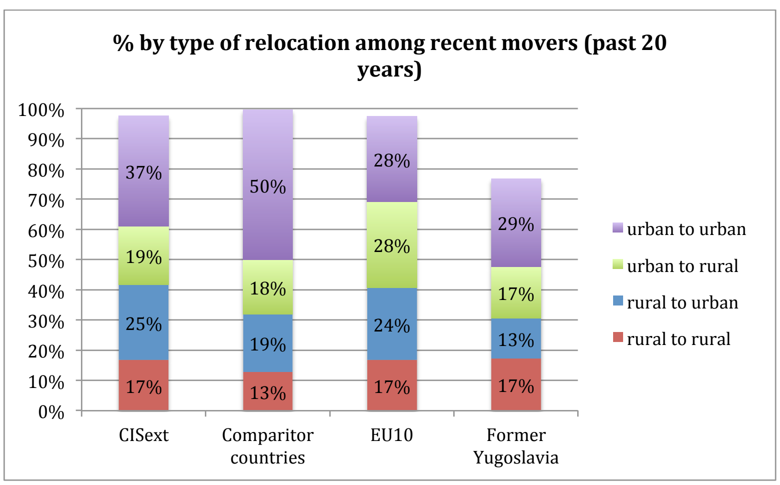

Figure 2.4: Distribution of recent (less than 20 years ago) movers by type of mobility. If the bar doesn't reach 100 percent mark it means the respondent declined to disclose his or her place of previous residence Source: LITS II survey.

percent shorter. These lost 20 percent represent those who declined to state their previous location. A bit proportion of them relocated due to the conflict.

Additionally as was stated before there is very likely a difference in job market characteristics of those who remain immobile and those who move. To analyze if this is in fact so we compare the two groups across the following dimensions:

- age
- percentage female
- percentage employed
- educational characteristics
- average household size
- real estate ownership
- attachment to friends
- risk taking behavior
- attitudes towards labor migration

See Table 2.1 for results of this comparison. One thing that absolutely stands out is that there is a drastic difference between characteristics of recent versus all movers in transition countries but not in the Western European countries. This might indicate that there were in fact impediments to mobility 20 years ago and that more recent movers match those in Western Europe more closely in terms of their attitudes towards labor migration and risk, in terms of their education and age. Another trend that stands out is that as opposed to the Western European countries in transition countries women tend to be more mobile.

Table 2.1: Comparative characteristics of movers and non-movers.

		EU 10 (lifetime mobility)	EU 10 (recent movers)	CIS extended (lifetime mobility)	CIS extended (recent movers)	Former Yugoslavia (lifetime mobility)	Former Yugoslavia 10 (recent movers)	Comparitor countries (lifetime mobility)	Comparitor countries (recent movers)
1. average age (years)	nonmovers	50**	53**	49**	51**	51**	53**	51**	55**
	movers	53	42	51	44	53	46	53	46
2. % female	nonmovers	57%**	60%	61%**	63%**	52%**	54%**	58%**	57%**
	movers	65%	61%	72%	72%	66%	64%	55%	54%
3. % employed	nonmovers	56%**	50%**	49%**	48%**	45%**	42%**	59%	52%**
	movers	47%	62%	46%	50%	40%	49%	58%	60%
4. % with college and more	nonmovers	17%	17%**	24%	24%**	12%**	12%**	15%**	20%**
	movers	18%	22%	25%	28%	14%	16%	30%	35%
5. % High School grad	nonmovers	31%	31%	33%**	31%	42%	40%**	37%**	29%**
	movers	30%	32%	26%	31%	39%	44%	21%	21%
6. % High school dropout	nonmovers	21%**	21%**	15%	15%**	15%	14%	28%**	26%**
	movers	19%	18%	15%	13%	13%	14%	22%	19%
7.Average Household size (# people)	nonmovers	2.6**	2.4**	3.7**	3.5	3.4**	3.3	2.4**	2.2**
	movers	2.4	2.7	3.2	3.5	3	3.4	2.3	2.5
8. % owning their dwelling through privatization	nonmovers	11.3%**	16%**	29%**	32%**	6.20%	6.9%**	17.3%**	13.2%**
	movers	18.30%	8%	35%	26%	6.30%	3.20%	7%	5%
9. % who sees friends at least once a week	nonmovers	59%**	56%**	54%**	51%	75%**	72%	71%**	67%**
	movers	52%	60%	47%	50%	65%	70%	62%	61%
10. % willing to take a risky job	nonmovers	31%**	27%**	27%**	25%**	27%**	25%**	27%**	27%**
	movers	24%	34%	25%	30%	23%	28%	32%	36%
11. % wlling to move internally for a job	nonmovers	27%	24%**	18.80%	17%**	31%	30%	32%**	32%**
	movers	27%	41%	18.80%	26%	31%	41%	43%	52%
12. % willing to move abroad for a job	nonmovers	25%**	21%**	20.10%	19%**	35%	32%	24%**	25%**
	movers	22%	35%	18%	24%	33%	44%	34%	42%

As evident from Table 2.1 though just seeing positive coefficients based on higher earnings of those who moved might not be a clear sign of positive gains to mobility as those who do and who do not move differ. This is particular so if we look at recent mobility. We try to control for this by matching mobile and immobile on observable characteristics.

Lastly it is likely that there is a problem of self-selection into mobility. Given the history of the region it is unclear if this is necessarily a story of positive self-selection. For example, during the times of the Soviet Union many people were relocated involuntarily and often these were the groups that were likely to not be accepted at the place of new location. Additionally relocation was an option to earn money fast for those who were not registered with a local labor market (not due to their skills but due to their birthplace) or could not be offered employment otherwise. A positive self-selection story is the one that is more likely to happen under normal conditions of unrestrained mobility with those who move being the ones who gain the most by moving.

There is evidence in the literature that duration of stay might influence gains from relocation. This can be partially explained by process of assimilation in the destination (Borjas et al 1992). The rate of assimilation might also differ depending on the level of education (Yamauchi 2004). To account for this we include the number of years in a given location (which for non-movers is automatically collinear with age), but is a more relevant variable for those who moved.

2.3.1 Empirical Specification.

Given the nature of the data, the estimation needs to be done at the household level. This is quite different from other studies where the analysis is done at the individual level. Since we are working with household level data we have to account for different types of households. In particular this is important since we are using expenditure data to approximate for income and one can hypothesize that different types of households will have different spending behavior. For example, households with children are likely to have higher expenditures on non-durable goods such as education than childless households. Thus we create nine different types of households based on their size and composition in terms of number of working age adults, seniors and children. Additionally we account for the total number of the people in the households as with an increase in number of people it is very possible that disposable income measured by expenditures on durable and non-durable goods combined with savings will be higher.

We perform analysis predominantly at the regional level.

$$ln(Income)_h = \beta_0 + \beta_1 * (typeM)_h + \beta_2 * X_h + \delta_h + \gamma_c + \beta_3 * log(localexp)_h + \gamma_c * (typeM)_h + \gamma * soviet + \gamma * female + \epsilon_{hc}$$

where $typeM_h$ denotes one of the seven mover types identified earlier (with rural non-mover being the reference category), X_h represents individual characteristics of the head of household such as educational level (primary, low secondary, upper secondary, post secondary, college degree and more), gender, marital status, age (logarithm); δ_h denotes the type of a household out of nine possible types, which take in account both size of the household and composition in terms of number of working adults, seniors, and children; $log(localexp)_h$ stands for logarithm of a number of years spent in a current location; $soviet_h$ is a dummy variable indicating if a person entered labor force prior to collapse of Soviet Union. Furthermore, we also add an interaction between having at least college level education and dummy variable for soviet, to capture possible difference in returns to education obtained during Soviet era and the one obtained later. Lastly γ_c denotes country fixed effects. This variable is interacted with each type of relocation to account for different returns to different types of mobility in different countries. Additionally it is interacted with individual characteristics of the head of the household such as entering labor market during Soviet era and being female as it is likely that income changes associated with those are country specific. Standard errors are clustered at the country level.

There are two types of dependent variable that are used: (i)logarithm of income denominated in USD PPP, and (ii) logarithm of income denominated in USD PPP adjusted for cost of living. Two types of mobility are used as well: standard and recent (past 20 years classification).

Recent Movers. Additionally in light of differences in migration behavior of people in the area prior to the fall of Soviet Union (with a lot of relocation then being only vaguely voluntary) and in the past 20 years we introduce an additional classification into recent movers. Only those who were mobile in the past 20 years are considered movers under that classification and the rest are automatically assigned a nonmover status.

Cost of living adjustment. All regional regressions use USD PPP as a unit of measure for income. As an additional check inspired by Moretti (2011) I introduce income measured in USD PPP adjusted for the cost of living. However, in light of unavailability of location specific CPI measure, I create the following proxy. For each country I estimate a median household expenditure (durable and nondurable consumption), then for each locality I create a median household expenditure. I use the ratio of location specific median household expenditure to the median expenditure at the country level as a deflator.

2.3.2 Instruments.

There is a very likely possibility of selection bias. Those who choose to move might be the ones who are more likely to gain from relocation compared to the ones who choose to stay. In this case a negative coefficient or not a statistically significant one have more weight as it is likely that we are predicting the lower bound on potential gains from migration. The realized gains can be lower due to congestion, change in relative wages due to increase in migration, etc.

We use an IV labeled "real estate based IV" that builds on a combination of nascent real estate market in the region and a sporadic nature of real estate privatization that has been implemented in many transition countries. First of all there is variation in exposure to privatization even in the same country. Privatization of real estate in some countries has been implemented in some but not in all country's regions with sometimes little systematic approach. Second of all due to rather ad hoc nature of implementation and having to build on the previously command economy, privatization is likely to not be strongly correlated with household's income. In some places it was mixed in with ad hoc grants of land (in particular in rural areas) or had to build on the bureaucratic assignment of real estate to individuals. Lastly some part of privatization has been done through collective ownership decision, which minimizes the risk of endogeneity of privatization and mobility decisions.

This IV does not work for every region meaning it does not always pass the test for not being a weak instruments (Bound, Jaeger, and Baker (1993; 1995); Stock and Yogo (2005)) for CIS extended region and Yugoslavia.

While we have seven types of mobility behavior our IVs are binary. Thus for instrumented regressions the sample of households in the region is split into those initially rural (rural location prior to the move and rural non-movers) and initially urban (urban location prior to the move and urban/metro non-movers). Additionally two types of mobility are considered: any relocation and move to a different type of location (i.e. rural to urban relocation for initially rural households, and urban to rural relocation for initially urban households).

Country and mobility interactions are not included in the instrumented regressions.

IV results allow us to see if we are likely to under or overestimate gains to mobility in our OLS regressions depending on the region.

2.3.3 Simulations.

Movers and non-movers differ significantly in the individual characteristics of the head of household (such as age, gender, education) and in terms of household types. Thus in addition to selection bias on unobservable characteristics it is likely that those who do not move are the ones who are less likely to gain by doing so just based on their observable characteristics. To identify those we create the following counterfactual.

The sample again is split into initially urban and initially rural households. We start with a very detailed regional level regression as specified above but additionally include interaction of different types of relocation with household type and with household level characteristics. For this regression we use recent type of mobility as gains/losses captured by those who have relocated no longer than 20 years ago are likely to be more informative of the potential gains given current labor market conditions.

We generate predicted incomes for those who are non-movers using *haty* from the regression above (accounting for the fact that regression was run in logs.) Then for these households we create predicted incomes from various possible relocation options using coefficients from the regressions above and taking in account their characteristics.

Results from this procedure allow us to note that relocation is not necessarily associated with a gain in income even for the median household in a given region or country.

Due to estimated changes in income being most likely the upper bounds on gains from mobility we identify the proportion of those who are currently immobile who rationally remain immobile given status quo of the economy.

2.4 Data

We use data from Life in Transition Survey (LITS) II, conducted jointly by the European Bank for Reconstruction and Development and the World Bank in late

2010. It surveyed almost 39,000 households in 34 countries to assess public attitudes, well-being and the impacts of economic and political change.

LITS provides very useful data on various indicators that both influence and are impacted by labor mobility. In addition, having a uniform survey conducted across a large number of countries enables us to conduct comparative exercises. This is rarely possible with other data sources that are almost always country specific.

The advantage of using LITS data is that it allows us to assess income not based on wage but based on a combination of both spending and saving without omitting income from potentially black labor market activities. Additionally it also allows to identify the proportion of those in the pool of immobile population who tend to rely on informal sources of income.

Such income will tend to reduce emigration from high unemployment (low wage) regions, if the share of unmeasured income components is higher in these regions than what could be obtained elsewhere (see for instance Abdulloev et al. (2011) for evidence that persons with good access to black market activities are less likely to emigrate in Tajikistan). In this case actual income disparities will be smaller than measured income and unemployment disparities. This may induce labor market searchers to stay at home rather than move elsewhere in the country. Furthermore, to the degree that such unmeasured income components are earned in kind, rather than in cash, this may make it difficult for persons to move if cash payments are needed to pay for migration costs. Thus for instance Friebel and Guriev (2000) show that in kind payments of firms to Russian workers reduces their willingness to move, a similar role could also be played by in kind transfers within the family.

LITS, naturally has its several drawbacks which need to be taken into account when determinants and implications of labor mobility are analyzed. For example, many of the variables on occupation, education, income and mobility are only collected for the head of the household. Thus we might be unable to differentiate between households with two or more wage earners and the one's that rely solely on the earnings of the household's head. Additionally, due to mobility questions being answered at the household level it is not possible to control for scenarios where, for example, one of the spouses moved at some point but the family did not move as a unit so they answered the question as mobility as "no."

We are also unable to control for the number and frequency of relocation as we have data only on the last move. Thus those who are labeled movers in our sample can be much more heterogenous in their mobility behavior than those who have never moved.

2.4.1 Mobility variables.

Seven different mobility groups are created based on the answers to the following questions:

- Question 705: "How long have you lived in this city/town/village?" Response to this question is numerical in terms of number of years, with a code of 98 corresponding to a person who has never moved in her/his life. People who have never moved are classified as *non-movers* for the purposes of this paper, the rest are classified as movers. For additional checks we create an alternative categorization of movers, labeled *recent movers* to which only those who have relocated in the past 10 years are assigned with everyone else being categorized as a non-mover.

- To differentiate between different type of non-movers we use the answer to the type of location, which has three categories for the current location: rural, urban and metropolitan. One has to note that not all countries have locations that are specified to be metropolitan. Additionally it looks like the threshold for number of people living in a given city to be labeled metropolitan is rather high. For example, in Russia, only Moscow is labeled to be a metropolitan area.

- For those who are movers we also need to classify their initial/previous location. Thus we use Question 706: "Where did you move from?", which classifies previous locations into two types: urban and rural. Unfortunately there is a few limitations to this variable. First of all we do not know the exact location of previous residence and thus are not able to differentiate between internal and international migration. [8] Second of all the previous location categorization does not include metropolitan area as an option. Thus category of urban to urban movers includes: those who moved from urban area (that could have been metropolitan) to current metropolitan area, those who moved between two urban areas, and those who moved from urban area (that could have been metropolitan) to urban area, those who moved from clearly urban area to metropolitan area. Analogously the category of those who are labeled to be urban to rural area movers includes those who could have resided in a metropolitan area before.

Logarithm of the number of years indicated in question 7.05 is used in some of the regressions as well to control for the role of local experience in terms of earnings.

2.4.2 Household characteristics

To create nine household classifications the following procedure is used. Based on the description of characteristics of each of the household members each one of them is categorized as either: a child (16 years old or younger), working age adult (age is between 16 and 64), or as a senior (older than 64). Then based on all possible

[8]We can possibly use a proxy of mother tongue being different from the local language to identify those who are likely to be international immigrants.

combinations in terms of number of those in a household 52 unique groups are created. These 52 groups are later assigned to one of the following broader 9 categories:

1. Single working adult
2. Single senior widower
3. Workding age couple
4. Senior couple
5. Nuclear family
6. Senior parents supported by adult children
7. Multiple working adults household
8. Seniors plus children (likely grandparents and grand children)
9. All other big households

To create the education profile for the head of the household the answer to Question 5.15 “What is the highest level of education you already completed?” is used and people are assigned to one of the following categories:

- Primary (equivalent to high school drop outs)
- Low secondary (high school graduates)
- Upper secondary (some college but less than Bachelors degree)
- Bachelor degree and more

Additionally to account for potentially different styles of education and varying quality of education we create an interaction between having a Bachelor's degree and being at least 19 years of age in 1989. 1989 is chosen to be a break point year due to the fact that it was the first year that was marked by clear change of attitudes manifested in a change in behavior with people exercising their democratic rights and also joining demonstrations and protests in Poland, Azerbaijan, Armenia, Georgia, Moldova, Belarus, Uzbekistan, Kazakhstan, Estonia, Lithuania and Latvia.

2.4.3 Income

To create a variable to approximate for the total monthly income of a household we use the answers to the following questions that capture expenditures on non-durable and durable consumption goods and also information on the savings. The questions are:

- Question 2.22 "Approximately how much does your household spend on each of these items per month?". Items in the list include non-durable goods such as: food, beverages, and tobacco; utilities and transportation (both public transportation and money for the fuel for the car.)

- Question 2.24"Approximately how much does your household spend on each of these items during past 12 months?" Items in the list include non-durable spending such as: education (including tuition, books, kindergarten expenses); health (including medicines and health insurance); clothing and footwear; durable goods (furniture, household appliances, TV, car, etc).

- Question 2.23"At the end of a typical month, does your household have anything left over to put into savings? Approximately how much does your household save in a typical month?"

The answers from all of the questions are converted into monthly values. Since they are reported in local currencies they all are converted into USD as well as into values adjusting for purchasing power parity (PPP). The latter might be more useful for regional level regressions.

2.4.4 Regions

We focus on the following four regions among which almost every country in the sample is covered:

- *EU10*, which includes Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia;
- *Former Yugoslavia*, which includes Bosnia, Croatia, Macedonia, Serbia, Slovenia, Kosovo, Montenegro;
- *Western European Comparator countries*, which include France, Germany, Great Britain, Italy, and Sweden;
- *Extended Commonwealth of Independent States* (CIS), which includes all official members: Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan and Uzbekistan, – and is expanded to include unofficial and former states: Ukraine and Georgia.

2.5 Results

2.6 Ordinary Least Squares Results

Tables with results can be found in Appndix B. Thus I just refer to them by number for the rest of the section. We start with running a set of OLS regressions for the following regions: CIS (that includes Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan, and Uzberkistan); extended CIS that in addition to other members includes Ukraine and Georgia; EU 10, set of comparator countries from Western Europe (France, Germany, Italy, United Kingdom and Sweden), Baltic states, and former Yugoslavian countries. We also run supplementary regressions for Low Income CIS, Middle Income CIS and Central Asia to see if patterns differ for these particular regions.

Table 1 present results for CIS countries. Overall controlling for length of local experience, individual and household characteristics, and country fixed effects and interaction of country fixed effects and various relocation options there is evidence of mobility being associated with gains in income for all the countries in the region with exception of Armenia and Kyrgyzstan. Additionally, one can notice that consistently with results derived using US data by Borjas local experience is associated with higher income. It is in particular so for urban to urban movers.

If not controlling for interaction with country fixed effects signs on the variables are as predicted. On average in the region being in a non-mover in an urban or metropolitan area is correlated with higher income than being a rural non-mover. However, for the case of metropolitan residents these result seems to be driven by countries like Russia, Azerbaijan, Belarus, while the opposite would be true for Armenia, Kazakhstan. On average in the area relocation from rural to urban area is associated with about 0.4 percent gain in income even controlling for the length of local experience. However, as with being a metropolitan non-mover gains here vary depending on the country and while being positive for some like Moldova (where they are associated with about 94 percent increase in income) they can be negative for the others. Urban to urban relocation is associate with about 0.12 percent gain in income. However this is not robust to controlling for local experience and is likely to be driven by those who have made this move long time ago.

Table 2 presents results for EU10 economies, which include Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. Similarly to CIS mobility on average is associated with gains in income for individuals in this region. For example, a relocation from urban to urban area is correlated with a 0.3 percent gain in income. Relocation from rural to urban is associated with 0.92 percent and rural to rural relocation with 0.32 percent gain in income. This however, is again driven by some countries and can be even negative for the others, such as Czech Republic, Hungary, and Latvia.

Table 3 presents results for former Yugoslavian countries. In this region changes in income associated with mobility vary a bit more than in the previous two. This also might be due to consequences of a conflict associated with involuntary mobility. It seems that mobility between similar types of areas such as urban to urban or rural to rural is associated overall with bigger gains in income than relocation between different types of areas regardless of the direction.

Lastly Table 4 present results from OLS regressions for the set of the so-called comparator countries, which contain France Germany, Great Britain, Italy and Sweden. Surprisingly there seem to be a lot less positive or negative changes in income associated with relocation in these countries. It can be so due to generally more equal distribution of incomes within the countries, even though they do differ between the countries.

However, it is possible that difference in the cost of living between urban and rural areas is what drives the positive correlation between relocation and income. We are trying to control for it by using the cost of living adjustment described in the methodology section.

Table 5 presents results for OLS regression run on the extended CIS region but adjusting for the difference in cost of living for each locality. First of all what stands out is that local experience consistently with OLS on unadjusted income is strongly positively correlated with income post urban to urban relocation. Interestingly enough overall rural to rural relocation is associate with increase in income even adjusting for the cost of living and thus controlling for moving to possibly more expensive locations. In the overall this move is associated with about 11 percent increase in income. However, this result is not uniform across countries. Overall positive sign on this relocation might be driven by observations from large countries where rural to rural relocation is associated with high income even controlling for the cost of living. These countries are: Kazakhstan with 13 percent increase in income, Russia with about 27 percent increase in income, Tajikistan with about 7 percent increase and Uzbekistan with about 7 percent. This relocation is associated with negative changes in income in countries such as Kyrgyzstan and Ukraine. In case of Kyrgyzstan majority of relocation seems to be associated with negative changes in income which can be driven by relocation due to conflict, which was not motivated by economic gains/incentives.

Adjusting for the cost of living rural to urban relocation might be associated more with moving to a more expensive area than necessarily with moving to a place where one has higher income. On the other hand moving in between of urban areas is correlated with an increase in income but it is not robust to controlling for local experience which suggests that real benefits of this relocation might be reaped when more experience is accumulated, while initially one might be able to afford less compared to the ones who did not relocate.

Table 6 presents results for the EU 10 region when income is adjusted by the cost of living. As opposed to extended CIS local experience is statistically significant only for the urban to rural relocation. Negative sign on metro non-mover stand out but it is likely capturing that overall in the sample of EU countries life in metropolitan area is more costly. There is, however, a robust positive association between relocation between rural areas and income even controlling for cost of living. Additionally urban to rural relocation seems to be correlated with gains in terms of real income. However, while there are positive gains associated with relocation to urban area or in between urban areas they are not robust to the inclusion of local experience. This might indicate that gains are not immediate.

Similar with the sample of extended CIS changes in income associated with various relocation options are not uniformly distributed across countries. For example, when looking at the changes in income associated with relocation between rural areas while positive for the overall sample they are associated with negative changes in terms of real income. For example: a change of negative 15 percent in Czech Republic, negative 10 percent in Estonia, negative 35 percent in Latvia, and negative 46 percent in Romania. While positive significant gains to this relocation are observed in Poland, Slovakia and Slovenia.

Table 7 presents results for former Yugoslavian countries. Results differ significantly from the other two regions. There is only one relocation that is associated with gains in the overall sample, which is relocation between two urban areas. However, this might be driven by the fact that there is a lot of variation in the results are the country level thus in the overall sample they are cancelled out.

Table 8 presents results for a sample of comparator countries. The only type of relocation that is correlated with positive changes in income is rural to rural relocation. Negative sign on metropolitan non-movers income reflects high cost of living in metropolitan areas. In UK a urban to urban relocation is associated with positive changes in income but it is not robust to the exclusion of local experience. Same with rural to rural relocation in Italy.

Additionally we assess results for the sample of recent movers. As described in the methodology section we define recent movers to be people who have relocated in the past 20 years. One of the rationales for this is that these are people who are more likely to have moved voluntarily as opposed to the movers during the Soviet times where relocation has not always been a matter of choice.

Table 9 presents results for a sample of recent movers in the extended CIS region. Similarly as for the standard definition of movers local experience does come out statistically significant and positive both for the urban to rural and urban to urban relocation. Urban to urban relocation seems to be associated with the gains in income for overall sample. However, it looks like these gains might be just masking relocation to areas that are more expensive to live in. Additionally the positive sign in the overall sample is driven by a few big countries that provide lots of observations and also for which this relocation is associated with increase in nominal income such as Kazakhstan and Russia. The only country for which this relocation is associated with positive gains even adjusting for the cost of living is Tajikistan.

Table 10 presents results for the sample of EU10 countries. First of all local experience associated with all types of relocations (with exception of rural to urban) comes out as positive and statistically significant. Overall rural to rural relocation is positively correlated with income and in particular for Bulgaria it stays so even when the differences in the cost of living are accounted for. The same is true for urban to rural and urban to urban moves. The result that stands out in particular in Table 11 is that urban to urban relocation is associated with positive changes in income even after controlling for differences in the cost of living. Table 12 where results for select comparator Western European countries are presented highlights that there is quite a bit of variation in changes in income associated with relocation even in the Western European countries. For example in Germany relocation is associated with negative changes in income for almost all the options. The opposite is true for UK and Italy though even adjusting for the differences in the cost of living.

2.6.1 IV results

Before moving on the IV results we run a linear probability regressions to identify the relationship between various household characteristics and its propensity to relocate. Results are represented in Tables 14-16. While the results indicate that there is clearly a lot of differences in mobility behavior between the regions, privatization is consistently negatively correlated with mobility for both CIS extended and former Yugoslavia urban populations. These are the two regions where real estate privatization has happened in the least organized manner.

Tables 16 and 17 present results from regressions that employ two stage least squares instrumental variables. In light of differences in social behavior and real estate market structure identified instrument does not pass the weak instrument test for some of the regions. Thus we present results only for the cases when using Stock and Yogo (2005) statistics we can be sure that used instrument is not weak. This leaves us with two regions for analysis: extended CIS and Yugoslavia.

Judging by results from the instrumental variable regressions the selection process into migration is opposite in these two regions. There is likely to be a negative selection into migration in the CIS extended region, which could be a result of the legacy of a big part of this migration happening during Soviet Union. On the other hand the direction of the selection bias is unclear in the former Yugoslavia.

Table 16 presents results for recent movers only from households that were initially urban in CIS region. For income measured in USD PPP for any type of relocation the coefficient stays negative. However, its magnitude decreases making it less negative still suggesting the possibility of some sort of negative selection mechanism for migration of urban population. On the other hand when urban to rural relocation is isolated we do have a clear sign of positive selection among recent non-movers in the overall regional sample as the sign on the coefficient stays negative but the effect becomes more negative.

On the other hand Table 17 presents results for recent movers among initially urban households in former Yugoslavia with real estate ownership based IV. The coefficients become more positive but not more statistically significant. Thus the direction of the selection is unclear.

2.6.2 Predicted Income Changes

Table 18 presents predicted changes in income from relocation associated with various relocation options for the sample of those who are currently immobile controlling for their characteristics. Given characteristics of recent non-movers a median non-mover household will not necessarily benefit from relocation. Yugoslavia stands out as the place where almost more than 50 percent of immobility can be explained by lack of monetary gains, while in EU10 region the opposite is true with only 1 percent of rural non-movers not gaining by relocating to another rural area. CIS countries are somewhere in between. These numbers are quite impressive keeping in mind that we are estimating upper bounds and those for whom negative gains are predicted are very likely to see negative gains.

In the region of former Yugoslavia about 30 percent of rural non-movers do not gain from a rural to urban move and a whole 82 percent will not see any monetary gains from relocating to another rural area. Any relocation for a person with characteristics of a median urban non-mover household will result in decline in income. About 53 percent of urban non-movers will not see any gains from urban to rural relocation and a surprising 92 percent of urban non-movers do not gain by urban to urban relocation.

The story in EU10 is the opposite a household with characteristics of a median urban or rural non-mover household might see gains associated with relocation. Only 1 percent of rural non-movers do not gain from rural to rural relocation, but 20 percent will not gain from rural to urban move. Among urban non-movers 31 percent do not gain from moving to rural area, and 42 from relocation to another urban.

In CIS region 17 percent of rural non-movers do not have monetary gains to a rural to rural relocation and therefore remain immobile rationally. The proportion of rational immobility is higher among urban non-movers with 33 percent not seeing any gains to relocation. However, there are countries like Tajikistan, where relocation seems to almost always generate gains< especially for urban non-movers. Even though there are indications that there might be a negative-self selection into relocation it is still likely that our estimates are an upper bound to potential gains given assumptions of wage rigidity and no destination market congestion.

2.7 Conclusions.

While numerically there might be too little mobility in transition economies compared to Western Europe and the United States, it is unclear to what extent it consists of people who would have gained by moving given their characteristics and current labor market conditions but due to institutional and social impediments choose not to and which proportion represents people who do not move because they do not gain anything by moving. Using data from LITS we try to uncover answer to this question.

We find that in some regions mobility seems to be clearly beneficial from the point of view of gains in individual income even when controlling for the differences in the cost of living, but people remain immobile. One of the regions where this is the case is CIS that seems to also feature negative self-selection into mobility. On the other hand there are regions where not all types of mobility are beneficial and some proportion of mobility is explained by the lack of individual level economic incentives.

There are unfortunately a few draw backs to our analysis that include the lack of data on the distance of relocation, which could allow us to control for the option of commuting, lack of household's history of mobility and information at the individual level. All of these could be important in terms of making sure that we are not under-estimating gains to mobility by counting those who commute as non-movers or by not differentiating between those who moved multiple times and one time movers.

Additionally a more thorough answer to the question of individual rationality of mobility decisions would have been possible if data on unemployment rates or vacancies for people with job market characteristics of those currently immobile would have been available.

Appendix A

Tables for Chapter 1

Table A.1: Effects of immigrants on native enrollment of unskilled native-born ages 18 to 34 controlling for exogenous income

	Year fixed effects only				Year and state Fixed effects				Year, state, race, gender and age fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	0.775***	0.27	1.321***	2.036***	0.860***	0.304	1.756***	1.932***	0.606***	0.222	1.218***	1.313***
	(0.197)	(0.222)	(0.296)	(0.425)	(0.204)	(0.230)	(0.357)	(0.354)	(0.155)	(0.166)	(0.268)	(0.278)
Δ ln (median income)	0.0229*	0.009	0.0361**	0.0499***	0.0241**	0.009	0.0432***	0.0567***	0.0170**	0.007	0.0295***	0.0395***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.011)	(0.012)	(0.014)	(0.016)	(0.008)	(0.008)	(0.011)	(0.011)
Δ (ln(median income)*ln(unskilled/ skilled)imm)	-0.0816***	-0.0275	-0.139***	-0.189***	-0.0861***	-0.030	-0.164***	-0.214***	-0.0608***	-0.022	-0.113***	-0.150***
	(0.020)	(0.022)	(0.029)	(0.031)	(0.021)	(0.023)	(0.032)	(0.035)	(0.016)	(0.017)	(0.024)	(0.025)
Δ ln(immigrants, students)	0.0248*	-0.0423**	0.102	-0.0402	-0.00925	-0.0261**	-0.0511	0.0233	-0.00476	-0.0209**	-0.0239	0.0392
	(0.014)	(0.019)	(0.079)	(0.136)	(0.009)	(0.010)	(0.054)	(0.082)	(0.008)	(0.009)	(0.042)	(0.065)
Constant	0.304***	0.339***	0.264***	0.278***	0.300***	0.325***	0.250***	0.331***	0.257***	0.274***	0.217***	0.287***
	(0.010)	(0.011)	(0.033)	(0.027)	(0.012)	(0.012)	(0.065)	(0.056)	(0.014)	(0.014)	(0.056)	(0.044)
Observations	8,302	8,302	8,302	8,302	8,302	8,302	8,302	8,302	8,302	8,302	8,302	8,302
R-squared	0.042	0.013	0.017		0.064	0.035	0.03		0.261	0.246	0.244	0.214

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for native-born individuals ages 18-34. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Table A.2: Effects of immigrants on native enrollment of unskilled native-born ages 18 to 22 controlling for exogenous income.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	0.535***	0.267*	0.925***	1.382***	0.562***	0.259**	0.959***	1.352***	0.396***	0.214***	0.552***	0.640***
	(0.135)	(0.139)	(0.263)	(0.399)	(0.120)	(0.126)	(0.244)	(0.336)	(0.079)	(0.080)	(0.153)	(0.227)
Δ ln (median income)	0.0190**	0.012	0.0267***	0.0348***	0.0176***	0.0102*	0.0279***	0.0339***	0.0122***	0.00758**	0.0166***	0.0198***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.006)	(0.006)	(0.010)	(0.009)	(0.004)	(0.004)	(0.006)	(0.006)
Δ (ln(median income)*ln(unskilled/	-0.0561***	-0.0281**	-0.0904***	-0.122***	-0.0525***	-0.0242*	-0.0949***	-0.121***	-0.0374***	-0.0209***	-0.0558***	-0.0698***
	(0.013)	(0.014)	(0.021)	(0.024)	(0.012)	(0.013)	(0.022)	(0.024)	(0.008)	(0.008)	(0.014)	(0.014)
Δ ln(immigrants, students)	0.0105	-0.0550**	0.0201	-0.0906	-0.0143	-0.0253**	-0.046	-0.0854	-0.0132	-0.0165	-0.0128	0.00681
	(0.021)	(0.026)	(0.084)	(0.136)	(0.012)	(0.011)	(0.070)	(0.082)	(0.010)	(0.010)	(0.046)	(0.058)
Constant	0.576***	0.615***	0.556***	0.572***	0.598***	0.618***	0.614***	0.576***	0.590***	0.602***	0.599***	0.611***
	(0.015)	(0.015)	(0.032)	(0.032)	(0.032)	(0.031)	(0.072)	(0.067)	(0.033)	(0.033)	(0.045)	(0.045)
Observations	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078	3,078
R-squared	0.076	0.052	0.06		0.138	0.116	0.116	0.086	0.368	0.359	0.364	0.353

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for ages 18 to 22. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Table A.3: Effects of immigrants on native enrollment of unskilled native-born ages 23 to 27 controlling for exogenous income.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	-0.129	-0.245*	-0.164	-0.0638	0.0448	-0.064	0.337	0.412*	0.0455	-0.0098	0.318	0.362**
	(0.134)	(0.133)	(0.260)	(0.248)	(0.142)	(0.154)	(0.279)	(0.215)	(0.116)	(0.124)	(0.233)	(0.184)
Δ ln (median income)	0.00832	0.007	-0.000637	0.000513	0.00793	0.006	0.00599	0.0153	0.00184	0.001	0.0000525	0.00681
	(0.009)	(0.008)	(0.012)	(0.013)	(0.009)	(0.008)	(0.012)	(0.012)	(0.007)	(0.007)	(0.011)	(0.010)
Δ (ln(median income)*ln(unskilled/skilled)imm)	0.0116	0.0247*	0.0158	0.0349	-0.00709	0.004	-0.0203	-0.0476*	-0.0071	-0.00135	-0.0209	-0.0378*
	(0.014)	(0.014)	(0.029)	(0.046)	(0.015)	(0.016)	(0.027)	(0.025)	(0.012)	(0.013)	(0.024)	(0.021)
Δ ln(immigrants, students)	0.00611	-0.0254	0.143	-0.0829	-0.00589	-0.021	0.0274	0.0288	-0.00211	-0.0177	0.0334	0.0181
	(0.015)	(0.019)	(0.100)	(0.175)	(0.008)	(0.013)	(0.061)	(0.045)	(0.008)	(0.013)	(0.053)	(0.042)
Constant	0.217***	0.185***	0.150***	0.196***	0.203***	0.161***	0.134*	0.193***	0.184***	0.152***	0.123*	0.165***
	(0.011)	(0.015)	(0.040)	(0.034)	(0.006)	(0.010)	(0.078)	(0.026)	(0.007)	(0.011)	(0.070)	(0.026)
Observations	2,359	2,359	2,359	2,359	2,359	2,359	2,359	2,359	2,359	2,359	2,359	2,359
R-squared	0.015	0.02			0.103	0.104	0.03	0.093	0.29	0.29	0.232	0.281

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for ages 23 to 27. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Table A.4: Effects of immigrants on native enrollment of unskilled native-born ages 28 to 32 controlling for exogenous income.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	-0.0465	-0.089	-0.219	-0.117	0.0402	0.0329	0.00733	-0.0846	-0.057	-0.0384	-0.14	-0.231
	(0.066)	(0.062)	(0.155)	(0.133)	(0.067)	(0.064)	(0.185)	(0.178)	(0.059)	(0.057)	(0.165)	(0.152)
Δ ln (median income)	-0.00932*	-0.00927**	-0.0145***	-0.0121**	-0.00977**	-0.00981**	-0.0139**	-0.0106**	-0.00177	-0.001	-0.00669	-0.00366
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Δ (ln(median income)*ln(unskilled/skilled)imm)	0.00386	0.00945	0.0208	0.0206	-0.005	-0.004	0.00808	-0.00241	0.00531	0.00341	0.0230*	0.0146
	(0.007)	(0.006)	(0.016)	(0.020)	(0.007)	(0.007)	(0.016)	(0.016)	(0.006)	(0.006)	(0.014)	(0.013)
Δ ln(immigrants, students)	0.0158**	-0.00835	0.0719*	0.00272	0.000536	-0.00996**	0.014	0.0482	0.00113	-0.0137***	0.0185	0.0447
	(0.008)	(0.010)	(0.044)	(0.076)	(0.006)	(0.005)	(0.038)	(0.036)	(0.006)	(0.005)	(0.036)	(0.032)
Constant	0.115***	0.124***	0.0903***	0.101***	0.0992***	0.106***	0.0628	0.120***	0.0657***	0.0739***	0.031	0.0834***
	(0.006)	(0.007)	(0.020)	(0.012)	(0.009)	(0.010)	(0.049)	(0.031)	(0.008)	(0.009)	(0.049)	(0.026)
Observations	2,083	2,083	2,083	2,083	2,083	2,083	2,083	2,083	2,083	2,083	2,083	2,083
R-squared	0.007	0.006			0.089	0.09	0.026	0.057	0.251	0.252	0.187	0.226

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for ages 28 to 32. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Table A.5: Effects of immigrants on enrollment of Caucasian unskilled native-born ages 18 to 34.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reporte	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	0.862**	0.244	1.577***	2.336***	1.046***	0.335	2.224***	2.684***	1.051***	0.326	2.298***	2.810***
	(0.381)	(0.386)	(0.482)	(0.448)	(0.384)	(0.427)	(0.553)	(0.434)	(0.389)	(0.425)	(0.552)	(0.422)
Δ ln (median income)	-0.0182	-0.027	-0.0085	0.00169	-0.0148	-0.025	0.00144	0.00288	-0.0154	-0.023	-0.0011	-0.00182
	(0.046)	(0.045)	(0.048)	(0.049)	(0.032)	(0.031)	(0.039)	(0.044)	(0.033)	(0.033)	(0.040)	(0.046)
Δ (ln(median income)*ln(unskilled/skilled)imm)	-0.0877**	-0.0246	-0.155***	-0.230***	-0.107***	-0.035	-0.213***	-0.282***	-0.108***	-0.0341	-0.220***	-0.295***
	(0.038)	(0.039)	(0.047)	(0.047)	(0.038)	(0.042)	(0.047)	(0.038)	(0.039)	(0.042)	(0.048)	(0.038)
Δ ln(immigrants, students)	0.0112	-0.00858	0.0368	0.0334	0.00675	-0.00014	-0.0251	0.0296	0.00687	-0.0001	-0.0274	0.0321
	(0.018)	(0.014)	(0.061)	(0.093)	(0.007)	(0.010)	(0.037)	(0.063)	(0.007)	(0.010)	(0.038)	(0.066)
Constant	0.261***	0.273***	0.233***	0.226***	0.251***	0.268***	0.195***	0.243***	0.252***	0.264***	0.203***	0.258***
	(0.016)	(0.013)	(0.025)	(0.029)	(0.022)	(0.018)	(0.067)	(0.044)	(0.025)	(0.022)	(0.070)	(0.050)
Observations	3,450	3,450	3,450	3,450	3,450	3,450	3,450	3,450	3,450	3,450	3,450	3,450
R-squared	0.035	0.014	0.014		0.071	0.047	0.034		0.071	0.047	0.031	

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for Caucasian native-born individuals ages 18-34. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are

Table A.6: Effects of immigrants on enrollment of African-American unskilled native-born ages 18 to 34.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in labor force	0.514***	0.224	0.715***	1.039***	0.441***	0.152	0.905**	0.847***	0.456***	0.157	0.933**	0.864***
	(0.152)	(0.171)	(0.242)	(0.274)	(0.129)	(0.154)	(0.406)	(0.263)	(0.128)	(0.156)	(0.416)	(0.266)
Δ ln (median income)	0.00344	-0.007	0.01	0.0208	0.00715	-0.002	0.00625	0.0295**	0.0103	0.001	0.00876	0.0337**
	(0.011)	(0.012)	(0.012)	(0.014)	(0.009)	(0.010)	(0.022)	(0.013)	(0.009)	(0.010)	(0.023)	(0.014)
Δ (ln(median income)*ln(unskilled/skilled) imm)	-0.0571***	-0.0231	-0.0851**	-0.119***	-0.0473***	-0.016	-0.0639*	-0.115***	-0.0491***	-0.0163	-0.0651*	-0.119***
	(0.015)	(0.018)	(0.026)	(0.033)	(0.014)	(0.016)	(0.036)	(0.032)	(0.014)	(0.017)	(0.037)	(0.032)
Δ ln(immigrants, students)	0.00816	-0.0526**	0.116	0.0857	-0.00185	-0.0530***	-0.0696	0.0904	-0.0013	-0.0547***	-0.0737	0.0954
	(0.016)	(0.026)	(0.121)	(0.176)	(0.012)	(0.016)	(0.162)	(0.075)	(0.012)	(0.016)	(0.169)	(0.079)
Constant	0.274***	0.296***	0.233***	0.246***	0.233***	0.260***	0.14	0.284***	0.216***	0.245***	0.118	0.267***
	(0.012)	(0.015)	(0.058)	(0.041)	(0.006)	(0.009)	(0.190)	(0.043)	(0.007)	(0.010)	(0.197)	(0.044)
Observations	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506
R-squared	0.038	0.021	0.008		0.161	0.149	0.116	0.113	0.168	0.155	0.117	0.117

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for African-American native-born individuals ages 18-34. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Table A.7: Effects of immigrants on enrollment of Asian-American unskilled native-born ages 18 to 34.

	Year fixed effects only				Year and state Fixed effects				Year, state, race, and gender fixed effects			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV	As Reported	Imputed	Osborne IV	Standard IV
Δ ln(unskilled/skilled) imm in	0.838***	0.326	0.0526	0.91	0.363*	0.0376	4.118	0.617	0.362*	0.037	4.112	0.604
labor force	(0.206)	(0.215)	(1.163)	(0.660)	(0.210)	(0.191)	(11.210)	(0.856)	(0.210)	(0.192)	(11.260)	(0.855)
Δ ln (median income)	0.0301***	0.0195**	0.0407	0.0468***	0.0228***	0.0161***	0.00994	0.0506***	0.0227***	0.0161***	0.00934	0.0506***
	(0.008)	(0.009)	(0.039)	(0.015)	(0.007)	(0.006)	(0.130)	(0.019)	(0.007)	(0.006)	(0.131)	(0.019)
Δ (ln(median income)*ln(unskilled/ skilled)	-0.0662***	-0.0188	-0.0892*	-0.138***	-0.0352*	-0.001	-0.062	-0.122***	-0.0350*	-0.000562	-0.0608	-0.122***
imm)	(0.017)	(0.018)	(0.048)	(0.043)	(0.019)	(0.018)	(0.140)	(0.047)	(0.019)	(0.018)	(0.141)	(0.047)
Δ ln(immigrants, students)	-0.105	-0.350***	0.222	0.172	-0.0318	-0.225***	-1.403	0.00719	-0.032	-0.226***	-1.399	0.0107
	(0.094)	(0.116)	(1.264)	(0.353)	(0.045)	(0.069)	(4.041)	(0.412)	(0.045)	(0.069)	(4.057)	(0.412)
Constant	0.580***	0.695***	0.622	0.570***	0.853***	0.955***	-0.121	1.102***	0.843***	0.944***	-0.138	1.096***
	(0.061)	(0.062)	(0.429)	(0.098)	(0.059)	(0.070)	(3.652)	(0.323)	(0.060)	(0.071)	(3.681)	(0.328)
Observations	964	964	964	964	964	964	964	964	964	964	964	964
R-squared	0.057	0.069			0.34	0.338		0.219	0.341	0.338		0.218

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

Notes: Results with inclusion of median total household pre-tax income net of personal pre-tax income for Asian/Asian-Pacific native-born individuals ages 18-34. Unit of observation is gender*race*age*state*year cell. Explanatory variable, however, varies only at the state/year level. Data extracted from Census 1970-2000 (1 percent sample) and 1 percent Census sample from 1960 is used for imputation and creation of weights for the instrumental variable. Standard errors are clustered at state-year level.

Appendix B

Tables for Chapter 2

Table B.1: Ordinary Least Squares results for CIS region using USD PPP denominated income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD
soviet	0.0217	0.0148	0.00913	0.0160
	(0.0203)	(0.0209)	(0.0199)	(0.0200)
female	-0.0806*	-0.0782*	-0.0807*	-0.0814*
	(0.0370)	(0.0384)	(0.0396)	(0.0381)
married	-0.0211***	-0.0254***	-0.0243***	-0.0199***
	(0.00558)	(0.00521)	(0.00458)	(0.00500)
low_sec	0.144	0.146	0.132	0.131
	(0.0930)	(0.0897)	(0.0852)	(0.0886)
up_sec	0.215**	0.217**	0.193**	0.191**
	(0.0703)	(0.0682)	(0.0603)	(0.0622)
post_sec	0.292**	0.290**	0.268***	0.272***
	(0.0886)	(0.0869)	(0.0779)	(0.0797)
BAmore	0.494***	0.495***	0.469***	0.468***
	(0.0428)	(0.0422)	(0.0338)	(0.0341)
BA_soviet	-0.171**	-0.177**	-0.183**	-0.177**
	(0.0617)	(0.0623)	(0.0602)	(0.0601)
log_age	-0.0534	-0.0882**	-0.0835**	-0.0472
	(0.0308)	(0.0324)	(0.0313)	(0.0294)
Local experience for rural to rural mover		0.187*	0.216*	
		(0.0965)	(0.101)	
Local experience for urban to rural mover		0.0745**	0.0723**	
		(0.0288)	(0.0295)	
Local experience for rural to urban mover		-0.00502	0.00103	
		(0.0206)	(0.0232)	
Local experience for urban to urban mover		0.156***	0.158***	
		(0.0206)	(0.0249)	
Urban nonmover	0.344**	0.350**	0.135***	0.136***
	(0.118)	(0.119)	(0.00207)	(0.00210)
Metropolitan nonmover	0.756**	0.760**	-0.237***	-0.240***
	(0.243)	(0.243)	(0.0173)	(0.0189)
Rural to rural mover	0.126	-0.443	-0.856**	-0.217***
	(0.0948)	(0.241)	(0.293)	(0.00756)
Rural to urban move	0.361***	0.388***	-0.222***	-0.220***
	(0.0719)	(0.108)	(0.0616)	(0.00400)
Urban to urban move	0.462***	0.0333	-0.459***	-0.0239*
	(0.0996)	(0.112)	(0.0739)	(0.0109)
Urban to rural move	0.285**	0.102	-0.137	0.0648***
	(0.108)	(0.0712)	(0.0767)	(0.00927)
Household size	0.100**	0.100**	0.0975***	0.0969**
	(0.0309)	(0.0300)	(0.0288)	(0.0299)
Constant	5.232***	5.388***	5.837***	5.668***
	(0.163)	(0.137)	(0.107)	(0.110)
Observations	9,944	9,940	9,940	9,944
R-squared	0.099	0.102	0.113	0.111
N	9944	9940	9940	9944
df_m	7	7	7	7
F	.	.	.	.
rss	14647	14613	14422	14458
rmse	1.216	1.215	1.210	1.211

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.2: Ordinary Least Squares results for EU 10 region using USD PPP denominated income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD
female	0.0212	0.0179	0.0118	0.0141
	(0.0206)	(0.0201)	(0.0226)	(0.0237)
married	0.00769	0.00703	0.00896	0.00848
	(0.0201)	(0.0214)	(0.0211)	(0.0195)
low_sec	0.0809	0.0739	0.0356	0.0394
	(0.112)	(0.122)	(0.125)	(0.116)
up_sec	0.184*	0.180	0.140	0.142
	(0.0912)	(0.0999)	(0.102)	(0.0945)
post_sec	0.413***	0.409***	0.347***	0.349***
	(0.0409)	(0.0409)	(0.0634)	(0.0631)
BAmore	0.585***	0.584***	0.522***	0.520***
	(0.0363)	(0.0374)	(0.0447)	(0.0422)
BA_soviet	-0.0814	-0.0886	-0.101*	-0.0954*
	(0.0507)	(0.0500)	(0.0446)	(0.0440)
log_age	-0.213	-0.224	-0.221	-0.221
	(0.141)	(0.136)	(0.135)	(0.140)
Log local experience for rural to rural move		0.0290	0.0318	
		(0.0200)	(0.0202)	
Log local experience for urban to rural move		0.205***	0.0786*	
		(0.0418)	(0.0391)	
Log local experience for rural to urban move		-0.0774	-0.0930	
		(0.125)	(0.136)	
Log local experience for urban to urban move		0.0407	0.0295	
		(0.0574)	(0.0602)	
urban nonmover	0.156**	0.147*	-0.151***	-0.152***
	(0.0658)	(0.0661)	(0.0227)	(0.0243)
Metro nonmover	0.0884	0.0955	-0.0615	-0.0615
	(0.0802)	(0.0795)	(0.0344)	(0.0362)
Urban to rural move	0.751**	0.171	0.174	0.375***
	(0.248)	(0.295)	(0.0987)	(0.00601)
Urban to urban move	0.423***	0.300*	0.0699	0.158***
	(0.102)	(0.141)	(0.192)	(0.0180)
rural to rural	0.649**	0.558**	0.122	0.232***
	(0.257)	(0.201)	(0.0746)	(0.0118)
rural to urban	0.257***	0.500	0.406	0.0920***
	(0.0515)	(0.378)	(0.445)	(0.0158)
soviet	0.171	0.169	0.170	0.169
	(0.154)	(0.158)	(0.153)	(0.150)
Household size	0.107***	0.105***	0.111***	0.111***
	(0.0218)	(0.0220)	(0.0231)	(0.0229)
Constant	5.868***	5.936***	6.159***	6.160***
	(0.384)	(0.366)	(0.413)	(0.432)
Observations	10,730	10,719	10,719	10,730
R-squared	0.097	0.099	0.110	0.110
N	10730	10719	10719	10730
df_m	8	8	8	8
F	.	.	.	.
rss	30597	30540	30145	30169
rmse	1.691	1.691	1.684	1.684

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.3: Ordinary Least Squares results for the region of former Yugoslavia using USD PPP denominated income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD	Log (income) in PPP USD
soviet	0.258***	0.258***	0.244***	0.280***
	(0.0517)	(0.0524)	(0.0445)	(0.0396)
female	-1.45e-06	-0.000580	0.000980	-0.0556***
	(0.0212)	(0.0214)	(0.0218)	(0.00687)
married	-0.0383	-0.0391	-0.0417	-0.0446
	(0.0221)	(0.0228)	(0.0238)	(0.0239)
low_sec	0.136***	0.135***	0.145***	0.143***
	(0.0188)	(0.0187)	(0.0155)	(0.0143)
up_sec	0.307***	0.308***	0.318***	0.320***
	(0.0534)	(0.0537)	(0.0505)	(0.0492)
post_sec	0.433***	0.431***	0.419***	0.419***
	(0.107)	(0.106)	(0.108)	(0.108)
BAmore	0.549**	0.551**	0.559**	0.548**
	(0.156)	(0.157)	(0.170)	(0.161)
BA_soviet	0.0452	0.0422	0.0439	0.0572
	(0.163)	(0.164)	(0.180)	(0.170)
log_age	-0.181*	-0.187*	-0.153	-0.146
	(0.0840)	(0.0824)	(0.0821)	(0.0780)
Log of ocal experience for rural to rural move		0.00589	0.0313	
		(0.0337)	(0.0227)	
Log of loccal experience for urban to rural move		0.0492	0.0480	
		(0.0551)	(0.0558)	
Log of local experience for rural to urban move		0.0181	-0.00181	
		(0.0549)	(0.0570)	
Log of local experience for urban to urban move		0.0189	0.0270*	
		(0.0180)	(0.0120)	
Urban nonmover	0.287**	0.287**	0.0125	0.0155
	(0.0879)	(0.0879)	(0.0157)	(0.0141)
Rural ro urban move	0.389***	0.333	-0.00616	-0.00696
	(0.0804)	(0.204)	(0.164)	(0.0275)
Urban to urban move	0.461***	0.407***	0.345***	0.415***
	(0.0650)	(0.0535)	(0.0523)	(0.0268)
rural to rural move	0.157*	0.140	0.351***	0.449***
	(0.0794)	(0.148)	(0.0613)	(0.0148)
urban to rural	0.363***	0.233	0.133	0.245***
	(0.0388)	(0.130)	(0.125)	(0.00907)
total_HH	0.0834	0.0833	0.0826*	0.0815
	(0.0444)	(0.0445)	(0.0422)	(0.0430)
Constant	6.044***	6.073***	6.076***	6.062***
	(0.399)	(0.402)	(0.378)	(0.344)
Observations	7,773	7,773	7,773	7,773
R-squared	0.131	0.131	0.139	0.140
N	7773	7773	7773	7773
df_m	5	5	5	5
F	.	.	.	.
rss	12087	12086	11983	11963
rmse	1.249	1.250	1.247	1.246

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.4: Ordinary Least Squares results for the sample of comparator Western European countries using USD PPP denominated income (lifetime mobility).

	(1) Log (Income) in USD PPP	(4) Log (Income) in USD PPP	(5) Log (Income) in USD PPP	(9) Log (Income) in USD PPP
female	-0.0442	-0.0432	-0.0478	-0.0491*
	(0.0366)	(0.0370)	(0.0353)	(0.0259)
married	-0.00335	-0.00392	-0.00459	-0.00365
	(0.0136)	(0.0137)	(0.0148)	(0.0150)
low_sec	0.153	0.151	0.147	0.150***
	(0.0753)	(0.0737)	(0.0743)	(0.0537)
up_sec	0.269***	0.264***	0.259***	0.265***
	(0.0482)	(0.0478)	(0.0474)	(0.0531)
post_sec	0.376***	0.375***	0.368***	0.371***
	(0.0742)	(0.0762)	(0.0739)	(0.0589)
BAmore	0.529***	0.530***	0.522***	0.522***
	(0.0888)	(0.0908)	(0.0891)	(0.0504)
log_age	0.0865	0.0488	0.0575	0.0956*
	(0.0483)	(0.0650)	(0.0543)	(0.0544)
Log of local experience rural to rural relocation		-0.0540	-0.0815	
		(0.0430)	(0.0420)	
Log of local experience urban to rural move		0.00337	0.0206	
		(0.0529)	(0.0552)	
Logr of local experience rural to urban move		0.0810	0.0912	
		(0.0636)	(0.0609)	
Log of local experience urban to urban move		0.0247	0.0231	
		(0.0211)	(0.0221)	
Urban nonmover	-0.0566	-0.0552	0.140***	0.148
	(0.123)	(0.125)	(0.0113)	(0.207)
Metro nonmover	-0.0894	-0.0908	-0.171	-0.138
	(0.0483)	(0.0479)	(0.120)	(0.185)
rural to urban move	-0.00546	-0.235	-0.102	0.135
	(0.113)	(0.267)	(0.171)	(0.181)
urban to urban move	0.0502	-0.0173	0.0210	0.0855
	(0.0925)	(0.0602)	(0.0572)	(0.180)
Rural to rural move	0.138**	0.288*	0.331**	0.133
	(0.0405)	(0.119)	(0.101)	(0.183)
Urban to rural move	0.119	0.105	0.119	0.170
	(0.0839)	(0.205)	(0.102)	(0.181)
Household size	0.157***	0.159***	0.159***	0.158***
	(0.0151)	(0.0157)	(0.0149)	(0.0370)
Constant	5.864***	6.021***	5.947***	5.786***
	(0.176)	(0.223)	(0.241)	(0.276)
Observations	5,487	5,456	5,456	5,487
R-squared	0.196	0.198	0.211	0.208
N	5487	5456	5456	5487
df_m	3	3	3	49
F	.	.	.	.
rss	3761	3736	3676	3704
rmse	0.830	0.830	0.825	0.826

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.5: Ordinary Least Squares results for CIS region using cost of living adjusted income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log income in USD PPP (Adjusted) (without experience or country fixed effects)	Log income in USD PPP (Adjusted) (experience+country fixed effects)	Log income in USD PPP (Adjusted) (experience +country fixed effect+interactions)	Log income in USD PPP (Adjusted) (country fixed effects+interactions)
soviet	0.0979***	0.0987***	0.0966***	0.0942**
	(0.0294)	(0.0285)	(0.0292)	(0.0302)
female	-0.0424	-0.0403	-0.0392	-0.0413
	(0.0280)	(0.0258)	(0.0268)	(0.0293)
married	-0.0307***	-0.0341***	-0.0349***	-0.0314***
	(0.00832)	(0.00759)	(0.00890)	(0.00939)
low_sec	-0.0643	-0.0702	-0.0678	-0.0605
	(0.0996)	(0.101)	(0.104)	(0.102)
up_sec	-0.0135	-0.0181	-0.0142	-0.00912
	(0.0652)	(0.0658)	(0.0681)	(0.0674)
post_sec	0.0515	0.0406	0.0457	0.0577
	(0.0819)	(0.0849)	(0.0871)	(0.0843)
BAmore	0.234***	0.229***	0.236***	0.241***
	(0.0291)	(0.0303)	(0.0314)	(0.0297)
BA_soviet	-0.124	-0.128	-0.130	-0.125
	(0.0960)	(0.0975)	(0.0975)	(0.0961)
log_age	-0.202***	-0.230***	-0.229***	-0.197***
	(0.0414)	(0.0460)	(0.0445)	(0.0417)
Log of local experience after rural to rural relocaiton		0.000589	-0.0257	
		(0.0263)	(0.0268)	
Log of local experience after urban to rural relocation		-0.00387	-0.00873	
		(0.0182)	(0.0192)	
Log of local experience after rural to urban relocation		0.00233	0.0138	
		(0.0345)	(0.0419)	
Log of local experience after urban to urban relocation		0.169***	0.176***	
		(0.0442)	(0.0418)	
Urban nonmover	0.0185	0.0177	-0.121***	-0.121***
	(0.0312)	(0.0316)	(0.00530)	(0.00512)
Metro nonmover	-0.0150	-0.0173	-0.0850***	-0.0870***
	(0.0764)	(0.0771)	(0.0114)	(0.0120)
Rural to rural relocation	0.110	0.107**	0.0471	-0.0287***
	(0.0677)	(0.0477)	(0.0799)	(0.00315)
Rural to urban relocation	0.0387	0.0347	-0.163	-0.126***
	(0.0330)	(0.137)	(0.113)	(0.00330)
Urban to rural relocation	0.138**	0.152*	0.0719	0.0388***
	(0.0551)	(0.0733)	(0.0548)	(0.00418)
Urban to urban relocation	0.0645	-0.412***	-0.448***	0.0374***
	(0.0447)	(0.0850)	(0.109)	(0.00831)
total_HH	0.0763***	0.0769***	0.0775***	0.0770***
	(0.0170)	(0.0167)	(0.0174)	(0.0176)
Constant	6.421***	6.551***	6.620***	6.479***
	(0.154)	(0.173)	(0.200)	(0.187)
Observations	12,441	12,436	12,436	12,441
R-squared	0.094	0.097	0.102	0.100
N	12441	12436	12436	12441
df_m	9	9	9	9
F	.	.	.	.
rss	12520	12490	12415	12447
rmse	1.005	1.004	1.003	1.004

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.6: Ordinary Least Squares results for EU 10 region using cost of living adjusted income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log income in USD PPP (Adjusted) (without experience or country fixed effects)	Log income in USD PPP (Adjusted) (experience+country fixed effects)	Log income in USD PPP (Adjusted) (experience +country fixed effect+interactions)	Log income in USD PPP (Adjusted) (country fixed effects+interactions)
soviet	0.0777	0.0769	0.0880	0.0874
	(0.116)	(0.119)	(0.113)	(0.111)
female	0.0371	0.0357	0.0311	0.0324
	(0.0397)	(0.0387)	(0.0382)	(0.0396)
married	0.0373	0.0372	0.0377	0.0373
	(0.0334)	(0.0341)	(0.0345)	(0.0335)
low_sec	0.0702	0.0662	0.0627	0.0656
	(0.0494)	(0.0570)	(0.0697)	(0.0636)
up_sec	0.143**	0.142*	0.143*	0.144*
	(0.0593)	(0.0647)	(0.0761)	(0.0708)
post_sec	0.301***	0.299***	0.294***	0.295***
	(0.0658)	(0.0645)	(0.0801)	(0.0806)
BAmore	0.457***	0.459***	0.472***	0.469***
	(0.0737)	(0.0750)	(0.0689)	(0.0675)
BA_soviet	-0.0391	-0.0449	-0.0625	-0.0576
	(0.0510)	(0.0522)	(0.0448)	(0.0440)
log_age	-0.0876	-0.0842	-0.103	-0.109
	(0.120)	(0.119)	(0.109)	(0.112)
Log of local experience after rural to rural move		-0.0143	-0.00948	
		(0.0176)	(0.0148)	
Log of local experience after urban to rural relocation		0.103***	0.0577**	
		(0.0251)	(0.0210)	
Log of local experience after rural to urban move		-0.0756	-0.0786	
		(0.0907)	(0.1000)	
Log of local experience after urban to urban move		0.0196	0.0214	
		(0.0531)	(0.0563)	
Urban nonmover	-0.0666	-0.0699	-0.0207	-0.0219
	(0.0910)	(0.0903)	(0.0246)	(0.0261)
Metro nonmover	-0.0366	-0.0323	-0.390***	-0.392***
	(0.0587)	(0.0570)	(0.0381)	(0.0396)
Rural to rural relocation	0.292**	0.337***	0.232***	0.199***
	(0.112)	(0.0772)	(0.0557)	(0.0108)
Urban to rural relocation	0.363**	0.0723	0.230***	0.378***
	(0.122)	(0.142)	(0.0560)	(0.00476)
Rural to urban relocation	0.00517	0.244	0.459	0.195***
	(0.0834)	(0.279)	(0.319)	(0.0188)
Urban to urban	0.134*	0.0752	0.104	0.167***
	(0.0732)	(0.119)	(0.183)	(0.0205)
Household size	0.0924***	0.0906***	0.0943***	0.0950***
	(0.0242)	(0.0241)	(0.0242)	(0.0241)
Constant	5.839***	5.836***	5.876***	5.899***
	(0.290)	(0.279)	(0.280)	(0.288)
Observations	10,550	10,539	10,539	10,550
R-squared	0.071	0.071	0.077	0.077
N	10550	10539	10539	10550
df_m	8	8	8	8
F	.	.	.	.
rss	24700	24675	24518	24535
rmse	1.533	1.533	1.532	1.531

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.7: Ordinary Least Squares results for the region of former Yugoslavia using cost of living adjusted income (lifetime mobility).

	(1) Log income in USD PPP (Adjusted) (without experience or country fixed effects)	(2) Log income in USD PPP (Adjusted) (experience+country fixed effects)	(3) Log income in USD PPP (Adjusted) (experience +country fixed effect+interactions)	(4) Log income in USD PPP (Adjusted) (country fixed effects+interactions
soviet	0.235*	0.234*	0.221*	0.222*
	(0.103)	(0.103)	(0.0999)	(0.101)
female	-0.00775	-0.00779	-0.00481	-0.00434
	(0.0188)	(0.0189)	(0.0203)	(0.0202)
married	-0.0441	-0.0449	-0.0465*	-0.0452*
	(0.0232)	(0.0239)	(0.0238)	(0.0231)
low_sec	0.132***	0.133***	0.132***	0.132***
	(0.0182)	(0.0185)	(0.0161)	(0.0156)
up_sec	0.255***	0.258***	0.264***	0.261***
	(0.0488)	(0.0500)	(0.0516)	(0.0500)
post_sec	0.324***	0.324***	0.312***	0.313***
	(0.0677)	(0.0680)	(0.0719)	(0.0713)
BAmore	0.415*	0.416*	0.411*	0.408*
	(0.188)	(0.191)	(0.195)	(0.193)
BA_soviet	0.0654	0.0646	0.0776	0.0813
	(0.207)	(0.208)	(0.215)	(0.215)
log_age	-0.238***	-0.243***	-0.221***	-0.211***
	(0.0426)	(0.0413)	(0.0485)	(0.0494)
Log of local experience after rural to rural relocation		0.0639	0.0690	
		(0.0334)	(0.0366)	
Log of local experience after urban to rural relocation		0.0159	0.0420	
		(0.0613)	(0.0592)	
Log of local experience after rural to urban relocation		-0.00984	-0.0104	
		(0.0586)	(0.0636)	
Log of local experience after urban to urban relocation		0.0210	0.0465***	
		(0.0136)	(0.0111)	
Urban nonmover	0.104	0.103	-0.0992***	-0.0983***
	(0.0644)	(0.0645)	(0.0156)	(0.0149)
Urban to rural relocation	0.365**	0.322	0.0651	0.153***
	(0.144)	(0.261)	(0.132)	(0.0231)
Rural to urban relocation	0.132**	0.164	0.0228	-0.00229
	(0.0427)	(0.195)	(0.181)	(0.0246)
Urban to urban relocation	0.182***	0.122**	0.218***	0.321***
	(0.0426)	(0.0380)	(0.0541)	(0.0313)
Rural to rural relocation	0.151	-0.0404	0.0356	0.222***
	(0.0905)	(0.169)	(0.0964)	(0.0132)
total_HH	0.0543	0.0542	0.0560	0.0559
	(0.0384)	(0.0384)	(0.0363)	(0.0364)
Constant	6.512***	6.535***	6.538***	6.496***
	(0.133)	(0.153)	(0.163)	(0.139)
Observations	7,724	7,724	7,724	7,724
R-squared	0.113	0.113	0.121	0.120
N	7724	7724	7724	7724
df_m	5	5	5	5
F	.	.	.	.
rss	10021	10019	9931	9935
rmse	1.141	1.141	1.139	1.139

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.8: Ordinary Least Squares results for the set of comparator Western European countries using cost of living adjusted income (lifetime mobility).

	(1)	(2)	(3)	(4)
	Log income in USD PPP (Adjusted) (without experience or country fixed effects)	Log income in USD PPP (Adjusted) (experience+country fixed effects)	Log income in USD PPP (Adjusted) (experience +country fixed effect+interactions)	Log income in USD PPP (Adjusted) (country fixed effects+interactions)
female	-0.0483*	-0.0481*	-0.0510*	-0.0515**
	(0.0212)	(0.0224)	(0.0214)	(0.0253)
married	-0.00759	-0.00817	-0.00982	-0.00892
	(0.0116)	(0.0119)	(0.0123)	(0.0147)
low_sec	0.0897	0.0854	0.0849	0.0902*
	(0.0568)	(0.0563)	(0.0567)	(0.0529)
up_sec	0.205**	0.197**	0.199**	0.207***
	(0.0548)	(0.0556)	(0.0551)	(0.0520)
post_sec	0.306**	0.301**	0.297**	0.304***
	(0.0727)	(0.0760)	(0.0749)	(0.0576)
BAmore	0.412**	0.412**	0.411**	0.412***
	(0.0903)	(0.0924)	(0.0907)	(0.0489)
log_age	0.0460	0.00767	0.0230	0.0620
	(0.0679)	(0.0896)	(0.0798)	(0.0527)
Log of local experience after rural to rural relocation		-0.0716*	-0.0954**	
		(0.0296)	(0.0333)	
Log of local experience after urban to rural relocation		0.0196	0.0425	
		(0.0246)	(0.0337)	
Log of local experience after rural to urban relocation		0.0746	0.0838	
		(0.0569)	(0.0532)	
Log of local experience after urban to urban relocation		0.0325	0.0293	
		(0.0244)	(0.0252)	
Urban nonmover	-0.0111	-0.00990	0.179***	0.188
	(0.103)	(0.103)	(0.0113)	(0.191)
Metro nonmover	-0.0149	-0.0162	-0.694***	-0.658***
	(0.0372)	(0.0345)	(0.128)	(0.169)
Rural to urban	-0.0206	-0.235	-0.0312	0.188
	(0.0746)	(0.205)	(0.145)	(0.164)
Urban to urban	0.0209	-0.0699*	0.0304	0.111
	(0.0549)	(0.0263)	(0.0708)	(0.163)
Rural to rural relocation	0.0137	0.212***	0.407***	0.174
	(0.0593)	(0.0347)	(0.0736)	(0.168)
Urban to rural relocation	0.103	0.0454	0.170**	0.267
	(0.0781)	(0.133)	(0.0544)	(0.164)
total_HH	0.126***	0.127***	0.126***	0.125***
	(0.0174)	(0.0182)	(0.0174)	(0.0359)
Constant	6.234***	6.397***	6.212***	6.047***
	(0.290)	(0.360)	(0.380)	(0.260)
Observations	5,484	5,453	5,453	5,484
R-squared	0.167	0.169	0.181	0.177
N	5484	5453	5453	5484
df_m	3	3	3	49
F	.	.	.	.
rss	3556	3532	3484	3511
rmse	0.807	0.807	0.803	0.804

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

Notes: Column 1 shows results without country level interaction effects or controlling for local experience. In column 2 local experience is controlled for. Specification in Column 3 controls for both. Specification in Column 4 accounts only for country interaction effects. Standard errors are clustered at country level.

Table B.9: Ordinary Least Squares results for CIS region using both income denominated in USD PPP and cost of living adjusted income (recent movers).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of income (USD PPP) (no experience, no interactions)	Log of income (USD PPP) (local experience but no interactions)	Log of income (USD PPP) (local experience +interactions)	Log of income (USD PPP) (only interactions)	Log of income (USD PPP), adjusted for cost of living (no local experience, no interactions)	Log of income (USD PPP), adjusted for cost of living (local experience only)	Log of income (USD PPP), adjusted for cost of living (local experience+interactions)	Log of income (USD PPP), adjusted for cost of living (interactions only)
soviet	0.0416*	0.0367	0.0348	0.0410*	0.102**	0.0973***	0.0954***	0.100**
	(0.0203)	(0.0218)	(0.0204)	(0.0188)	(0.0322)	(0.0299)	(0.0301)	(0.0325)
female	-0.0501	-0.0550	-0.0559	-0.0496	-0.0412	-0.0418	-0.0426	-0.0418
	(0.0441)	(0.0470)	(0.0473)	(0.0438)	(0.0285)	(0.0281)	(0.0281)	(0.0285)
married	-0.0317**	-0.0344**	-0.0332**	-0.0307**	-0.0301***	-0.0340***	-0.0341***	-0.0303**
	(0.0133)	(0.0135)	(0.0133)	(0.0128)	(0.00927)	(0.00804)	(0.00862)	(0.00976)
low_sec	0.117*	0.116*	0.103	0.104	-0.0715	-0.0755	-0.0756	-0.0713
	(0.0643)	(0.0623)	(0.0590)	(0.0603)	(0.104)	(0.103)	(0.105)	(0.105)
up_sec	0.169**	0.170**	0.152**	0.152**	-0.0197	-0.0206	-0.0181	-0.0161
	(0.0537)	(0.0542)	(0.0510)	(0.0499)	(0.0681)	(0.0674)	(0.0701)	(0.0699)
post_sec	0.249***	0.246***	0.226***	0.229***	0.0428	0.0385	0.0397	0.0446
	(0.0607)	(0.0599)	(0.0546)	(0.0548)	(0.0864)	(0.0855)	(0.0876)	(0.0879)
BAmore	0.492***	0.487***	0.466***	0.471***	0.237***	0.229***	0.234***	0.242***
	(0.0300)	(0.0304)	(0.0259)	(0.0254)	(0.0284)	(0.0299)	(0.0327)	(0.0303)
BA_soviet	-0.143*	-0.144*	-0.151*	-0.148*	-0.131	-0.130	-0.135	-0.135
	(0.0725)	(0.0753)	(0.0764)	(0.0725)	(0.0986)	(0.0974)	(0.0959)	(0.0967)
log_age	-0.119*	-0.140**	-0.133**	-0.112*	-0.210***	-0.230***	-0.228***	-0.209***
	(0.0556)	(0.0552)	(0.0542)	(0.0549)	(0.0472)	(0.0457)	(0.0449)	(0.0456)
total_HH	0.111***	0.111***	0.110***	0.111***	0.0764***	0.0766***	0.0776***	0.0778***
	(0.0288)	(0.0283)	(0.0274)	(0.0286)	(0.0171)	(0.0166)	(0.0170)	(0.0177)
Log of local experience after rural to rural moved		0.0553	0.0809**			0.0340	0.0366	
		(0.0356)	(0.0344)			(0.0233)	(0.0258)	
Log of local experience after urban to rural moved		0.0898**	0.115***			0.0330*	0.0363*	
		(0.0303)	(0.0283)			(0.0165)	(0.0181)	
Log of local experience after rural to urban move		-9.44e-05	-0.00512			0.0104	0.00907	
		(0.0238)	(0.0218)			(0.0113)	(0.00996)	
Log of local experience after urban to urban move		0.0373**	0.0333**			0.0538***	0.0528***	
		(0.0144)	(0.0133)			(0.0147)	(0.0142)	
Urban nonmover	0.329***	0.387***	0.168***	0.106***	0.0332*	0.0438	-0.135***	-0.139***
	(0.0493)	(0.116)	(0.0283)	(0.00468)	(0.0167)	(0.0445)	(0.0167)	(0.00261)
Metro nonmover	0.651***	0.708***	-0.226***	-0.292***	-0.0912**	-0.0763	-0.120***	-0.128***
	(0.124)	(0.183)	(0.0231)	(0.0125)	(0.0301)	(0.0434)	(0.0137)	(0.0119)
Rural to rural	-0.00519	-0.0739	-0.515***	-0.382***	0.0829**	0.0256	-0.141**	-0.0732***
	(0.0366)	(0.0630)	(0.0626)	(0.00992)	(0.0334)	(0.0146)	(0.0587)	(0.00952)
Urban to rural	0.250***	0.149**	-0.162***	0.00114	0.141**	0.114*	-0.0583***	-0.0108
	(0.0626)	(0.0642)	(0.0184)	(0.0219)	(0.0449)	(0.0524)	(0.0165)	(0.0113)
Rural to urban	0.247**	0.308	-0.134	-0.218***	-0.0355	-0.0306	-0.0506	-0.0543***
	(0.0911)	(0.180)	(0.0802)	(0.0116)	(0.0620)	(0.0914)	(0.0413)	(0.00806)
Urban to urban	0.320***	0.306**	-0.00890	-0.00688	-0.0704***	-0.154***	0.00624	0.0992***
	(0.0548)	(0.107)	(0.0401)	(0.0198)	(0.0167)	(0.0267)	(0.0238)	(0.0134)
Constant	5.530***	5.563***	5.961***	5.933***	6.502***	6.569***	6.619***	6.551***
	(0.259)	(0.296)	(0.224)	(0.217)	(0.207)	(0.181)	(0.193)	(0.204)
Observations	12,500	12,495	12,495	12,500	12,441	12,436	12,436	12,441
R-squared	0.118	0.120	0.129	0.125	0.095	0.097	0.100	0.098
N	12500	12495	12495	12500	12441	12436	12436	12441
df_m	9	9	9	9	9	9	9	9
F	.	.	.	.	.	.	.	.
rss	16187	16144	15979	16049	12511	12484	12438	12465
rmse	1.140	1.138	1.135	1.137	1.004	1.004	1.004	1.005

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

Notes: Columns (1)-(4) use dependent variable denominated in USD PPP, (5)-(8) use dependent variable denominated in USD PP but additionaly adjusted for the variation in cost of living. Standard errors are clustered at the country level.

Table B.10: Ordinary Least Squares results for CIS region using both income denominated in USD PPP and cost of living adjusted income (recent movers).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of income (USD PPP) (no experience, no interactions)	Log of income (USD PPP) (local experience but no interactions)	Log of income (USD PPP) (local experience +interactions)	Log of income (USD PPP) (only interactions)	Log of income (USD PPP), adjusted for cost of living (no local experience, no interactions)	Log of income (USD PPP), adjusted for cost of living (local experience only)	Log of income (USD PPP), adjusted for cost of living (local experience+interactions)	Log of income (USD PPP), adjusted for cost of living (interactions only)
soviet	0.0416*	0.0367	0.0348	0.0410*	0.102**	0.0973***	0.0954***	0.100**
	(0.0203)	(0.0218)	(0.0204)	(0.0188)	(0.0322)	(0.0299)	(0.0301)	(0.0325)
female	-0.0501	-0.0550	-0.0559	-0.0496	-0.0412	-0.0418	-0.0426	-0.0418
	(0.0441)	(0.0470)	(0.0473)	(0.0438)	(0.0285)	(0.0281)	(0.0281)	(0.0285)
married	-0.0317**	-0.0344**	-0.0332**	-0.0307**	-0.0301***	-0.0340***	-0.0341***	-0.0303**
	(0.0133)	(0.0135)	(0.0133)	(0.0128)	(0.00927)	(0.00804)	(0.00862)	(0.00976)
low_sec	0.117*	0.116*	0.103	0.104	-0.0715	-0.0755	-0.0756	-0.0713
	(0.0643)	(0.0623)	(0.0590)	(0.0603)	(0.104)	(0.103)	(0.105)	(0.105)
up_sec	0.169**	0.170**	0.152**	0.152**	-0.0197	-0.0206	-0.0181	-0.0161
	(0.0537)	(0.0542)	(0.0510)	(0.0499)	(0.0681)	(0.0674)	(0.0701)	(0.0699)
post_sec	0.249***	0.246***	0.226***	0.229***	0.0428	0.0385	0.0397	0.0446
	(0.0607)	(0.0599)	(0.0546)	(0.0548)	(0.0864)	(0.0855)	(0.0876)	(0.0879)
BAmore	0.492***	0.487***	0.466***	0.471***	0.237***	0.229***	0.234***	0.242***
	(0.0300)	(0.0304)	(0.0259)	(0.0254)	(0.0284)	(0.0299)	(0.0327)	(0.0303)
BA_soviet	-0.143*	-0.144*	-0.151*	-0.148*	-0.131	-0.130	-0.135	-0.135
	(0.0725)	(0.0753)	(0.0764)	(0.0725)	(0.0986)	(0.0974)	(0.0959)	(0.0967)
log_age	-0.119*	-0.140**	-0.133**	-0.112*	-0.210***	-0.230***	-0.228***	-0.209***
	(0.0556)	(0.0552)	(0.0542)	(0.0549)	(0.0472)	(0.0457)	(0.0449)	(0.0456)
total_HH	0.111***	0.111***	0.110***	0.111***	0.0764***	0.0766***	0.0776***	0.0778***
	(0.0288)	(0.0283)	(0.0274)	(0.0286)	(0.0171)	(0.0166)	(0.0170)	(0.0177)
Log of local experience after rural to rural moved		0.0553	0.0809**			0.0340	0.0366	
		(0.0356)	(0.0344)			(0.0233)	(0.0258)	
Log of local experience after urban to rural moved		0.0898**	0.115***			0.0330*	0.0363*	
		(0.0303)	(0.0283)			(0.0165)	(0.0181)	
Log of local experience after rural to urban move		-9.44e-05	-0.00512			0.0104	0.00907	
		(0.0238)	(0.0218)			(0.0113)	(0.00996)	
Log of local experience after urban to urban move		0.0373**	0.0333**			0.0538***	0.0528***	
		(0.0144)	(0.0133)			(0.0147)	(0.0142)	
Urban nonmover	0.329***	0.387***	0.168***	0.106***	0.0332*	0.0438	-0.135***	-0.139***
	(0.0493)	(0.116)	(0.0283)	(0.00468)	(0.0167)	(0.0445)	(0.0167)	(0.00261)
Metro nonmover	0.651***	0.708***	-0.226***	-0.292***	-0.0912**	-0.0763	-0.120***	-0.128***
	(0.124)	(0.183)	(0.0231)	(0.0125)	(0.0301)	(0.0434)	(0.0137)	(0.0119)
Rural to rural	-0.00519	-0.0739	-0.515***	-0.382***	0.0829**	0.0256	-0.141**	-0.0732***
	(0.0366)	(0.0630)	(0.0626)	(0.00992)	(0.0334)	(0.0146)	(0.0587)	(0.00952)
Urban to rural	0.250***	0.149**	-0.162***	0.00114	0.141**	0.114*	-0.0583***	-0.0108
	(0.0626)	(0.0642)	(0.0184)	(0.0219)	(0.0449)	(0.0524)	(0.0165)	(0.0113)
Rural to urban	0.247**	0.308	-0.134	-0.218***	-0.0355	-0.0306	-0.0506	-0.0543***
	(0.0911)	(0.180)	(0.0802)	(0.0116)	(0.0620)	(0.0914)	(0.0413)	(0.00806)
Urban to urban	0.320***	0.306**	-0.00890	-0.00688	-0.0704***	-0.154***	0.00624	0.0992***
	(0.0548)	(0.107)	(0.0401)	(0.0198)	(0.0167)	(0.0267)	(0.0238)	(0.0134)
Constant	5.530***	5.563***	5.961***	5.933***	6.502***	6.569***	6.619***	6.551***
	(0.259)	(0.296)	(0.224)	(0.217)	(0.207)	(0.181)	(0.193)	(0.204)
Observations	12,500	12,495	12,495	12,500	12,441	12,436	12,436	12,441
R-squared	0.118	0.120	0.129	0.125	0.095	0.097	0.100	0.098
N	12500	12495	12495	12500	12441	12436	12436	12441
df_m	9	9	9	9	9	9	9	9
F	.	.	.	.	.	.	.	.
rss	16187	16144	15979	16049	12511	12484	12438	12465
rmse	1.140	1.138	1.135	1.137	1.004	1.004	1.004	1.005

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

Notes: Columns (1)-(4) use dependent variable denominated in USD PPP, (5)-(8) use dependent variable denominated in USD PP but additionaly adjusted for the variation in cost of living. Standard errors are clustered at the country level.

Table B.11: Ordinary Least Squares results for EU 10 region using both income denominated in USD PPP and cost of living adjusted income (recent movers).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of income (USD PPP) (no experience, no interactions)	Log of income (USD PPP) (local experience but no interactions)	Log of income (USD PPP) (local experience+interactions)	Log of income (USD PPP) (only interactions)	Log of income (USD PPP), adjusted for cost of living (no local experience, no interactions)	Log of income (USD PPP), adjusted for cost of living (local experience only)	Log of income (USD PPP), adjusted for cost of living (local experience+interactions)	Log of income (USD PPP), adjusted for cost of living (interactions only)
soviet	0.192	0.172	0.169	0.190	0.0863	0.0810	0.0848	0.0902
	(0.169)	(0.162)	(0.162)	(0.169)	(0.121)	(0.121)	(0.121)	(0.120)
female	0.0448	0.0200	0.0180	0.0409	0.0484	0.0373	0.0354	0.0455
	(0.0246)	(0.0203)	(0.0246)	(0.0293)	(0.0411)	(0.0395)	(0.0428)	(0.0441)
married	0.0125	0.00582	0.00460	0.0116	0.0394	0.0362	0.0353	0.0391
	(0.0223)	(0.0209)	(0.0202)	(0.0215)	(0.0336)	(0.0336)	(0.0334)	(0.0334)
low_sec	0.115	0.0686	0.0314	0.0692	0.0894*	0.0637	0.0616	0.0836
	(0.106)	(0.125)	(0.124)	(0.104)	(0.0470)	(0.0584)	(0.0675)	(0.0576)
up_sec	0.208*	0.174	0.125	0.145	0.159**	0.138*	0.138	0.152*
	(0.0953)	(0.104)	(0.102)	(0.0918)	(0.0599)	(0.0674)	(0.0756)	(0.0685)
post_sec	0.447***	0.402***	0.340***	0.373***	0.319***	0.294***	0.288***	0.307***
	(0.0439)	(0.0401)	(0.0690)	(0.0762)	(0.0650)	(0.0608)	(0.0811)	(0.0852)
BAmore	0.615***	0.577***	0.493***	0.517***	0.471***	0.452***	0.448***	0.460***
	(0.0347)	(0.0347)	(0.0447)	(0.0416)	(0.0757)	(0.0698)	(0.0711)	(0.0750)
BA_soviet	-0.0608	-0.0872	-0.0833	-0.0619	-0.0223	-0.0426	-0.0438	-0.0257
	(0.0458)	(0.0503)	(0.0520)	(0.0463)	(0.0451)	(0.0526)	(0.0532)	(0.0469)
log_age	-0.165	-0.255	-0.253	-0.164	-0.0620	-0.110	-0.128	-0.0775
	(0.130)	(0.145)	(0.145)	(0.131)	(0.116)	(0.125)	(0.119)	(0.112)
total_HH	0.102***	0.105***	0.111***	0.111***	0.0914***	0.0928***	0.0935***	0.0938***
	(0.0230)	(0.0218)	(0.0231)	(0.0245)	(0.0258)	(0.0249)	(0.0250)	(0.0261)
Log of local experience after rural to rural relocation		0.176**	0.180**			0.0759**	0.0781**	
		(0.0685)	(0.0682)			(0.0313)	(0.0307)	
Log of local experience after urban to rural relocation		0.252***	0.250***			0.120***	0.125***	
		(0.0441)	(0.0464)			(0.0256)	(0.0220)	
Log of local experience after rural to urban relocation		0.0262	0.0281			0.00804	0.0137	
		(0.0273)	(0.0299)			(0.0282)	(0.0298)	
Log of local experience after urban to urban relocation		0.0896**	0.0752**			0.0596**	0.0554**	
		(0.0318)	(0.0264)			(0.0252)	(0.0237)	
Urban nonmover	0.0127	0.161*	0.0232	-0.160***	-0.111	-0.0471	0.0437	-0.0247
	(0.0482)	(0.0815)	(0.0883)	(0.0204)	(0.0695)	(0.103)	(0.0469)	(0.0234)
Metro nonmover	-0.0902	0.0967	0.291***	0.0906***	-0.147**	-0.0626	-0.126***	-0.206***
	(0.158)	(0.0796)	(0.0715)	(0.0243)	(0.0559)	(0.0533)	(0.0364)	(0.0288)
Rural to rural relocation	0.453*	0.289*	0.0667	0.260***	0.198*	0.136	0.0712	0.151***
	(0.216)	(0.145)	(0.104)	(0.0271)	(0.0977)	(0.0766)	(0.0650)	(0.0344)
Urban to rural relocation	0.368**	0.0539	0.200***	0.421***	0.191**	0.0400	0.297***	0.418***
	(0.151)	(0.129)	(0.0166)	(0.00534)	(0.0721)	(0.0612)	(0.0105)	(0.00656)
Rural to urban relocation	0.0564	0.182	0.160	-4.66e-05	-0.0791	-0.0110	0.198**	0.128***
	(0.0647)	(0.182)	(0.135)	(0.0274)	(0.0920)	(0.169)	(0.0807)	(0.0241)
Urban to urban relocation	0.145	0.150	0.555***	0.488***	-0.0244	-0.0582	0.226***	0.242***
	(0.138)	(0.117)	(0.0592)	(0.0262)	(0.0929)	(0.0859)	(0.0550)	(0.0249)
Constant	5.835***	6.058***	6.105***	5.920***	5.809***	5.939***	5.933***	5.803***
	(0.360)	(0.385)	(0.390)	(0.369)	(0.280)	(0.290)	(0.282)	(0.270)
Observations	10,730	10,719	10,719	10,730	10,550	10,539	10,539	10,550
R-squared	0.083	0.098	0.106	0.092	0.066	0.071	0.076	0.071
N	10730	10719	10719	10730	10550	10539	10539	10550
df_m	8	8	8	8	8	8	8	8
F	.	.	.	.	.	.	.	.
rss	31082	30552	30281	30789	24814	24688	24563	24691
rmse	1.705	1.691	1.688	1.701	1.536	1.533	1.533	1.536

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

Notes: Columns (1)-(4) use dependent variable denominated in USD PPP, (5)-(8) use dependent variable denominated in USD PP but additionaly adjusted for the variation in cost of living. Standard errors are clustered at the country level.

Table B.12: Ordinary Least Squares results for the region of former Yugoslavia using both income denominated in USD PPP and cost of living adjusted income (recent movers).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of income (USD PPP) (no experience, no interactions)	Log of income (USD PPP) (local experience but no interactions)	Log of income (USD PPP) (local experience+interactions)	Log of income (USD PPP) (only interactions)	Log of income (USD PPP), adjusted for cost of living (no local experience, no interactions)	Log of income (USD PPP), adjusted for cost of living (local experience only)	Log of income (USD PPP), adjusted for cost of living (local experience+interactions)	Log of income (USD PPP), adjusted for cost of living (interactions only)
soviet	0.262***	0.258***	0.243***	0.248***	0.237*	0.233*	0.222*	0.227*
	(0.0515)	(0.0533)	(0.0475)	(0.0465)	(0.0984)	(0.100)	(0.0962)	(0.0944)
female	0.00984	-0.00601	-0.00842	0.00806	0.00337	-0.00932	-0.00888	0.00417
	(0.0197)	(0.0216)	(0.0221)	(0.0196)	(0.0193)	(0.0185)	(0.0189)	(0.0195)
married	-0.0373	-0.0430*	-0.0469*	-0.0418*	-0.0434*	-0.0469*	-0.0476*	-0.0442*
	(0.0192)	(0.0208)	(0.0217)	(0.0206)	(0.0214)	(0.0230)	(0.0232)	(0.0220)
low_sec	0.124***	0.126***	0.134***	0.130***	0.126***	0.130***	0.131***	0.126***
	(0.0191)	(0.0181)	(0.0155)	(0.0180)	(0.0164)	(0.0175)	(0.0175)	(0.0165)
up_sec	0.284***	0.290***	0.295***	0.287***	0.243***	0.251***	0.252***	0.244***
	(0.0451)	(0.0467)	(0.0441)	(0.0429)	(0.0491)	(0.0491)	(0.0526)	(0.0532)
post_sec	0.405***	0.406***	0.385***	0.383***	0.311***	0.314***	0.302***	0.299***
	(0.0880)	(0.0894)	(0.0869)	(0.0867)	(0.0645)	(0.0645)	(0.0677)	(0.0684)
BAmore	0.520**	0.527**	0.543**	0.535**	0.403*	0.408*	0.412*	0.405*
	(0.150)	(0.153)	(0.160)	(0.156)	(0.186)	(0.188)	(0.189)	(0.187)
BA_soviet	0.0448	0.0374	0.0194	0.0260	0.0634	0.0593	0.0580	0.0624
	(0.169)	(0.165)	(0.171)	(0.174)	(0.203)	(0.203)	(0.203)	(0.202)
log_age	-0.180*	-0.209**	-0.166*	-0.141	-0.236***	-0.253***	-0.221***	-0.207***
	(0.0862)	(0.0847)	(0.0852)	(0.0883)	(0.0421)	(0.0379)	(0.0430)	(0.0454)
total_HH	0.0840	0.0858	0.0842*	0.0826	0.0532	0.0550	0.0562	0.0549
	(0.0455)	(0.0450)	(0.0433)	(0.0435)	(0.0388)	(0.0385)	(0.0361)	(0.0362)
Log of local experience after rural to rural relocation		0.0647**	0.0769***			0.0664**	0.0726**	
		(0.0191)	(0.0205)			(0.0189)	(0.0208)	
Log of local experience after urban to rural relocation		0.138***	0.141***			0.105***	0.108***	
		(0.0182)	(0.0129)			(0.0253)	(0.0271)	
Log of local experience after rural to urban relocation		0.0285	0.0187			0.00453	0.000397	
		(0.0225)	(0.0229)			(0.0161)	(0.0137)	
Log of local experience after urban to urban relocation		0.0509*	0.0431			0.0293	0.0252	
		(0.0221)	(0.0229)			(0.0209)	(0.0193)	
Urban nonmover	0.325**	0.343**	0.0354*	0.0252	0.0971	0.126	-0.0821***	-0.0935***
	(0.0947)	(0.102)	(0.0161)	(0.0152)	(0.0511)	(0.0666)	(0.0171)	(0.0160)
Rural to rural relocation	0.0412	-0.0594	0.201***	0.345***	-0.00739	-0.114	0.0198	0.156***
	(0.131)	(0.135)	(0.0362)	(0.0247)	(0.171)	(0.166)	(0.0338)	(0.0167)
Urban to rural relocation	0.257***	0.00996	-0.105**	0.142***	0.323	0.140	-0.110	0.0765**
	(0.0326)	(0.0250)	(0.0314)	(0.0167)	(0.188)	(0.160)	(0.0693)	(0.0289)
Rural to urban relocation	0.349**	0.327*	-0.0265	0.00664	0.122*	0.150	0.0373	0.0301
	(0.108)	(0.139)	(0.0799)	(0.0386)	(0.0587)	(0.0935)	(0.0575)	(0.0322)
Urban to urban relocation	0.418***	0.353***	0.348***	0.423***	0.109*	0.0858***	0.254**	0.293***
	(0.0889)	(0.0849)	(0.0730)	(0.0365)	(0.0469)	(0.0178)	(0.0751)	(0.0382)
Constant	6.035***	6.148***	6.153***	6.052***	6.514***	6.570***	6.549***	6.493***
	(0.394)	(0.400)	(0.363)	(0.362)	(0.114)	(0.144)	(0.145)	(0.113)
Observations	7,773	7,773	7,773	7,773	7,724	7,724	7,724	7,724
R-squared	0.130	0.134	0.142	0.138	0.110	0.114	0.122	0.119
N	7773	7773	7773	7773	7724	7724	7724	7724
df_m	5	5	5	5	5	5	5	5
F	.	.	.	.	.	.	.	.
rss	12096	12040	11930	11988	10046	10011	9915	9953
rmse	1.250	1.247	1.244	1.247	1.143	1.141	1.138	1.140

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

Notes: Columns (1)-(4) use dependent variable denominated in USD PPP, (5)-(8) use dependent variable denominated in USD PP but additionaly adjusted for the variation in cost of living. Standard errors are clustered at the country level.

Table B.13: Ordinary Least Squares results for the comparator Western European countries using both income denominated in USD PPP and cost of living adjusted income (recent movers).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of income (USD PPP) (no experience, no interactions)	Log of income (USD PPP) (local experience but no interactions)	Log of income (USD PPP) (local experience+interactions)	Log of income (USD PPP) (only interactions)	Log of income (USD PPP), adjusted for cost of living (no local experience, no interactions)	Log of income (USD PPP), adjusted for cost of living (local experience only)	Log of income (USD PPP), adjusted for cost of living (local experience+interactions)	Log of income (USD PPP), adjusted for cost of living (interactions only)
female	-0.0408	-0.0411	-0.0557	-0.0534	-0.0461	-0.0467*	-0.0579**	-0.0557*
	(0.0375)	(0.0358)	(0.0333)	(0.0346)	(0.0218)	(0.0215)	(0.0207)	(0.0204)
married	-0.00230	-0.00415	-0.000317	0.00194	-0.00741	-0.00869	-0.00599	-0.00448
	(0.0133)	(0.0141)	(0.0136)	(0.0131)	(0.0109)	(0.0121)	(0.0116)	(0.0106)
low_sec	0.155	0.151	0.147	0.157	0.0914	0.0861	0.0859	0.0951
	(0.0757)	(0.0731)	(0.0708)	(0.0751)	(0.0563)	(0.0565)	(0.0564)	(0.0572)
up_sec	0.270***	0.267***	0.253***	0.260***	0.209**	0.204**	0.197**	0.206**
	(0.0492)	(0.0475)	(0.0461)	(0.0477)	(0.0545)	(0.0543)	(0.0558)	(0.0552)
post_sec	0.379***	0.378***	0.365***	0.372***	0.310**	0.306**	0.295**	0.304**
	(0.0773)	(0.0784)	(0.0780)	(0.0767)	(0.0749)	(0.0774)	(0.0792)	(0.0765)
BAmore	0.537***	0.529***	0.518***	0.510***	0.421***	0.412**	0.411***	0.437**
	(0.0920)	(0.0899)	(0.0893)	(0.0943)	(0.0900)	(0.0900)	(0.0888)	(0.102)
log_age	0.111*	0.0592	-0.272	-0.197	0.0511	0.0258	-0.234	-0.186
	(0.0484)	(0.0645)	(0.130)	(0.102)	(0.0690)	(0.0837)	(0.142)	(0.120)
total_HH	0.158***	0.157***	0.152***	0.155***	0.125***	0.126***	0.122***	0.123***
	(0.0159)	(0.0156)	(0.0181)	(0.0182)	(0.0179)	(0.0187)	(0.0214)	(0.0206)
Log of local experience after rural to rural relocation		0.0152	0.0183			-0.0184	-0.00901	
		(0.0231)	(0.0149)			(0.0244)	(0.0154)	
Log of local experience after urban to rural relocation		0.0218*	0.0406			0.0245	0.0437	
		(0.00987)	(0.0203)			(0.0137)	(0.0213)	
Log of local experience after rural to urban relocation		0.0403*	0.0589**			0.0197	0.0366	
		(0.0171)	(0.0156)			(0.0181)	(0.0176)	
Log of local experience after urban to urban relocation		0.0376*	0.0478**			0.0196	0.0311	
		(0.0154)	(0.0150)			(0.0179)	(0.0171)	
Urban nonmover	-0.0709	-0.109	-0.190**	-0.0973***	-0.0200	-0.0482	-0.137*	-0.0559**
	(0.133)	(0.132)	(0.0522)	(0.0201)	(0.107)	(0.111)	(0.0572)	(0.0177)
Metro nonmover	-0.120	-0.147	-0.154*	-0.0615*	-0.0727**	-0.0948	-0.294**	-0.209***
	(0.0619)	(0.0853)	(0.0645)	(0.0279)	(0.0236)	(0.0537)	(0.0694)	(0.0273)
Rural to rural	0.0922	0.0982	-0.00825	-0.0374	0.00989	0.0540	0.0245	-0.00630
	(0.0582)	(0.0570)	(0.0403)	(0.0409)	(0.0344)	(0.0424)	(0.0335)	(0.0394)
Urban to rural	0.0678	0.0452	-0.00833	0.00193	0.0689	0.0211	0.00276	0.0597
	(0.118)	(0.1000)	(0.0724)	(0.0439)	(0.110)	(0.0801)	(0.0823)	(0.0400)
Rural to urban	-0.125	-0.168	-0.0244	0.0128	-0.0867	-0.120	-0.0167	0.0255
	(0.133)	(0.161)	(0.0739)	(0.0393)	(0.0869)	(0.114)	(0.0798)	(0.0410)
Urban to urban	-0.00179	-0.0404	-0.0828	-0.0558	-0.00188	-0.0323	-0.110	-0.0711
	(0.0959)	(0.101)	(0.0816)	(0.0465)	(0.0560)	(0.0664)	(0.0813)	(0.0428)
Constant	5.842***	6.008***	7.119***	6.877***	6.241***	6.337***	7.216***	7.032***
	(0.171)	(0.246)	(0.489)	(0.398)	(0.275)	(0.340)	(0.593)	(0.495)
Observations	5,487	5,456	5,456	5,487	5,484	5,453	5,453	5,484
R-squared	0.195	0.198	0.218	0.213	0.167	0.169	0.186	0.183
N	5487	5456	5456	5487	5484	5453	5453	5484
df_m	3	3	3	3	3	3	3	3
F	.	.	.	.	.	.	.	.
rss	3764	3734	3641	3679	3555	3535	3461	3488
rmse	0.830	0.830	0.821	0.823	0.807	0.807	0.801	0.801

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

Notes: Columns (1)-(4) use dependent variable denominated in USD PPP, (5)-(8) use dependent variable denominated in USD PP but additionaly adjusted for the variation in cost of living. Standard errors are clustered at the country level.

Table B.14: Determinants of mobility in CIS region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of relocation at least once in life (urban)	Probability of relocation at least once in life (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation at least once in life (rural)	Probability of relocation at least once in life (rural)	Probability of relocation in past 20 years (rural)	Probability of relocation in past 20 years (rural)
soviet	0.0490*	0.0808**	0.0246	0.0583	-0.0383	-0.0432	-0.0609**	-0.0535
	(0.0221)	(0.0354)	(0.0238)	(0.0342)	(0.0269)	(0.0337)	(0.0242)	(0.0343)
female	0.000211	5.58e-05	0.0115	0.0123	0.127***	0.115***	0.0628***	0.0525**
	(0.0140)	(0.0155)	(0.0118)	(0.0102)	(0.0157)	(0.0175)	(0.0163)	(0.0209)
married	0.0671***	0.0748***	0.0298**	0.0401***	0.0715**	0.0844***	0.0495**	0.0608***
	(0.00538)	(0.00747)	(0.00987)	(0.0114)	(0.0253)	(0.0259)	(0.0169)	(0.0173)
low_sec	0.0434	0.0495	0.0659**	0.0667**	0.0624**	0.0661**	-0.0146**	-0.0145**
	(0.0277)	(0.0422)	(0.0214)	(0.0239)	(0.0246)	(0.0281)	(0.00593)	(0.00554)
up_sec	0.0581*	0.0420	0.108***	0.0969***	0.0138	0.0255	-0.0187	-0.0152
	(0.0276)	(0.0282)	(0.0235)	(0.0225)	(0.0352)	(0.0391)	(0.0126)	(0.0180)
post_sec	0.0328	0.0210	0.0561**	0.0498*	0.0218	0.0272	-0.0416*	-0.0474*
	(0.0225)	(0.0317)	(0.0251)	(0.0242)	(0.0542)	(0.0523)	(0.0225)	(0.0231)
BAmore	0.0904**	0.0871**	0.113***	0.106***	0.0306	0.0249	0.0971***	0.104*
	(0.0369)	(0.0334)	(0.0216)	(0.0225)	(0.0612)	(0.0529)	(0.0262)	(0.0514)
BA_soviet	-0.0571**	-0.0602	-0.0383*	-0.0470**	0.0105	0.0293	-0.134***	-0.145**
	(0.0255)	(0.0339)	(0.0203)	(0.0207)	(0.0320)	(0.0258)	(0.0326)	(0.0650)
log_age	0.0249	-0.00501	-0.128**	-0.157**	0.0241	-0.00988	-0.241***	-0.256***
	(0.0483)	(0.0596)	(0.0509)	(0.0620)	(0.0439)	(0.0444)	(0.0528)	(0.0639)
total_HH	-0.0129	-0.0257	0.000536	-0.000243	0.0154	0.0189	0.0101	0.00877
	(0.0143)	(0.0206)	(0.00986)	(0.00952)	(0.0128)	(0.0153)	(0.00566)	(0.00592)
private	-0.0905***	-0.101***	-0.106***	-0.0998***	0.177**	0.181**	-0.00411	-0.00652
	(0.0193)	(0.0229)	(0.0238)	(0.0235)	(0.0766)	(0.0712)	(0.0250)	(0.0211)
jobB	-0.0400**	-0.0408***	0.00702	0.00107	0.0392*	0.0265**	0.0544***	0.0396***
	(0.0162)	(0.00826)	(0.00843)	(0.00818)	(0.0215)	(0.0116)	(0.0130)	(0.00913)
friend	0.0318	0.0241	0.0120	0.00242	-0.0903**	-0.0794***	-0.0185*	-0.0192*
	(0.0329)	(0.0298)	(0.0125)	(0.00949)	(0.0297)	(0.0201)	(0.00949)	(0.00940)
willing_internally		0.132***		0.0834***		-0.0165		0.0370
		(0.0238)		(0.00245)		(0.0181)		(0.0260)
willing_internationally		-0.0955*		-0.0317		0.00973		0.000133
Constant	0.107	0.230	0.578**	0.674**	0.384*	0.501**	1.239***	1.286***
	(0.207)	(0.287)	(0.214)	(0.273)	(0.186)	(0.207)	(0.218)	(0.256)
Observations	6,033	5,510	6,033	5,510	6,372	6,036	6,372	6,036
R-squared	0.033	0.046	0.050	0.056	0.210	0.225	0.131	0.138
N	6033	5510	6033	5510	6372	6036	6372	6036
df_m	9	9	9	9	9	9	9	9
F	.	.	.	.	.	.	.	.
rss	1230	1110	783.3	696.0	1258	1169	815.8	769.1

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

Table B.15: Determinants of mobility in EU10 region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of relocation at least once in life (urban)	Probability of relocation at least once in life (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation at least once in life (rural)	Probability of relocation at least once in life (rural)	Probability of relocation in past 20 years (rural)	Probability of relocation in past 20 years (rural)
soviet	-0.0198	-0.0356	-0.00873	-0.0169	0.105**	0.120**	-0.0285	-0.0143
	(0.0324)	(0.0244)	(0.0182)	(0.0173)	(0.0457)	(0.0412)	(0.0357)	(0.0380)
female	0.0523**	0.0594***	0.0183	0.0208	0.0737	0.0647	0.0185	0.0108
	(0.0174)	(0.0182)	(0.0115)	(0.0126)	(0.0481)	(0.0488)	(0.0147)	(0.0138)
married	0.0374*	0.0561***	0.0106	0.0187	0.0608*	0.0529	-0.0150	-0.0111
	(0.0175)	(0.0141)	(0.0114)	(0.0106)	(0.0322)	(0.0362)	(0.0214)	(0.0189)
low_sec	0.0805***	0.0858***	-0.00679	-0.00209	0.0633	0.0685	0.0169	0.0140
	(0.0195)	(0.0179)	(0.0121)	(0.0129)	(0.0687)	(0.0661)	(0.0159)	(0.0195)
up_sec	0.0869**	0.0837**	0.0114	0.00819	0.0415	0.0556	-0.0135	-0.0123
	(0.0341)	(0.0312)	(0.0123)	(0.00953)	(0.112)	(0.104)	(0.0208)	(0.0215)
post_sec	0.0839	0.0790	-0.0114	-0.0224	0.0415	0.0454	-0.0265	-0.0343
	(0.0532)	(0.0563)	(0.0170)	(0.0229)	(0.132)	(0.130)	(0.0476)	(0.0506)
BAmore	0.0798	0.0641	-0.00166	-0.0180	0.0616	0.0831	-0.00793	0.00732
	(0.0872)	(0.0715)	(0.0482)	(0.0414)	(0.127)	(0.133)	(0.0674)	(0.0780)
BA_soviet	0.0935**	0.102**	0.0234	0.0291	-0.0286	-0.0599*	0.0329	0.00295
	(0.0392)	(0.0325)	(0.0271)	(0.0251)	(0.0325)	(0.0279)	(0.0473)	(0.0566)
log_age	0.0853*	0.129***	-0.139***	-0.124***	-0.0504	-0.0722	-0.283***	-0.282***
	(0.0404)	(0.0322)	(0.0286)	(0.0354)	(0.0712)	(0.0681)	(0.0405)	(0.0377)
total_HH	-0.0358*	-0.0396*	-0.0237	-0.0274**	0.0172	0.0172	0.0255	0.0239
	(0.0162)	(0.0191)	(0.0130)	(0.0112)	(0.0409)	(0.0430)	(0.0160)	(0.0162)
private	0.0289	0.0280	-0.0759	-0.0738	-0.0438	-0.0386	-0.0502***	-0.0492***
	(0.0431)	(0.0424)	(0.0429)	(0.0463)	(0.0990)	(0.0995)	(0.0106)	(0.0120)
jobB	0.0174	-0.000377	0.0109	0.00101	-0.0371	-0.0371	0.00339	-0.00395
	(0.0280)	(0.0225)	(0.0210)	(0.0179)	(0.0247)	(0.0256)	(0.0165)	(0.0206)
friend	-0.0327	-0.0379*	-0.000839	-0.00451	-0.0161	-0.0132	-0.0236	-0.0261
	(0.0193)	(0.0174)	(0.0163)	(0.0165)	(0.0512)	(0.0498)	(0.0244)	(0.0242)
willing_internally		0.149***		0.0843***		0.0567*		0.0682***
		(0.0231)		(0.0105)		(0.0272)		(0.0135)
willing_internationally		-0.00982		-0.00921		-0.0813		-0.0193
		(0.0337)		(0.0185)		(0.0579)		(0.0236)
Constant	-0.0291	-0.222***	0.734***	0.667***	0.626**	0.695**	1.288***	1.268***
	(0.0900)	(0.0642)	(0.0751)	(0.0967)	(0.211)	(0.218)	(0.136)	(0.124)
Observations	6,141	5,577	6,141	5,577	4,390	4,076	4,390	4,076
R-squared	0.050	0.068	0.059	0.070	0.068	0.066	0.126	0.130
N	6141	5577	6141	5577	4390	4076	4390	4076
df_m	8	8	8	8	8	8	8	8
F	.	.	.	.	.	.	.	.
rss	1302	1176	777.2	693.9	1014	947.2	467.9	426.4

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

Table B.16: Determinants of mobility in former Yugoslavia region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of relocation at least once in life (urban)	Probability of relocation at least once in life (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation at least once in life (rural)	Probability of relocation at least once in life (rural)	Probability of relocation in past 20 years (rural)	Probability of relocation in past 20 years (rural)
soviet	0.0426	0.0407	0.0324	0.0335	0.0108	0.0117	-0.0222	-0.0126
	(0.0282)	(0.0313)	(0.0401)	(0.0432)	(0.0186)	(0.0173)	(0.0184)	(0.0139)
female	0.0643***	0.0663***	0.0299**	0.0318**	0.163***	0.168***	0.0522***	0.0537***
	(0.00822)	(0.0111)	(0.00926)	(0.0108)	(0.0339)	(0.0360)	(0.00748)	(0.00843)
married	0.103***	0.110***	0.0328	0.0400*	0.0924**	0.0951**	0.0464***	0.0551***
	(0.0199)	(0.0205)	(0.0203)	(0.0190)	(0.0275)	(0.0277)	(0.00589)	(0.00836)
low_sec	-0.0386	-0.0423	-0.0189	-0.0156	-0.0307**	-0.0212	-0.00370	-0.00309
	(0.0630)	(0.0546)	(0.0431)	(0.0399)	(0.00934)	(0.0113)	(0.0124)	(0.0134)
up_sec	-0.0361	-0.0459**	-0.0161	-0.0222*	0.0164	0.00941	0.0145	0.00202
	(0.0210)	(0.0175)	(0.0100)	(0.0103)	(0.0133)	(0.0134)	(0.0286)	(0.0276)
post_sec	-0.0368	-0.0497	-0.0482	-0.0516	-0.0375	-0.0354	-0.0437***	-0.0504***
	(0.0555)	(0.0508)	(0.0286)	(0.0280)	(0.0303)	(0.0365)	(0.00857)	(0.0107)
BAmore	0.0205	0.0264	0.0483	0.0575	0.0686	0.0532	0.132	0.105
	(0.0306)	(0.0276)	(0.0305)	(0.0317)	(0.0899)	(0.0970)	(0.0914)	(0.0953)
BA_soviet	-0.0203	-0.0302	-0.0724***	-0.0864**	-0.0351	-0.0252	-0.132	-0.119
	(0.0701)	(0.0603)	(0.0168)	(0.0237)	(0.0995)	(0.108)	(0.0819)	(0.0854)
log_age	-0.0318	-0.00938	-0.182**	-0.161*	0.00705	0.0206	-0.126	-0.124
	(0.0396)	(0.0559)	(0.0688)	(0.0764)	(0.0417)	(0.0369)	(0.0764)	(0.0786)
total_HH	-0.000326	0.00132	0.00976	0.0118*	-0.0267***	-0.0291***	-0.0189***	-0.0213***
	(0.0172)	(0.0171)	(0.00635)	(0.00588)	(0.00641)	(0.00689)	(0.00353)	(0.00434)
private	-0.108***	-0.106**	-0.0804***	-0.0777***	0.201*	0.194*	0.0109	0.0118
	(0.0270)	(0.0291)	(0.0130)	(0.0149)	(0.0880)	(0.0893)	(0.0245)	(0.0190)
jobB	0.00239	-0.00339	0.0322*	0.0254	-0.0491***	-0.0568***	-0.0125	-0.0183**
	(0.0239)	(0.0265)	(0.0160)	(0.0151)	(0.0115)	(0.0115)	(0.00895)	(0.00563)
friend	-0.0399***	-0.0449***	-0.00700	-0.00860	-0.108**	-0.112**	-0.0304*	-0.0321*
	(0.0105)	(0.0106)	(0.0107)	(0.0158)	(0.0329)	(0.0326)	(0.0144)	(0.0162)
willing_internally		0.0307		0.0405		0.0415*		0.0839***
		(0.0267)		(0.0236)		(0.0208)		(0.0124)
willing_internationally		0.0230		0.0283*		0.0210		-0.00346
		(0.0127)		(0.0130)		(0.0176)		(0.0127)
Constant	0.276*	0.176	0.786**	0.679**	0.178	0.110	0.631*	0.595*
	(0.140)	(0.204)	(0.243)	(0.270)	(0.166)	(0.150)	(0.277)	(0.283)
Observations	3,976	3,753	3,976	3,753	3,309	3,119	3,309	3,119
R-squared	0.093	0.100	0.052	0.060	0.142	0.146	0.098	0.106
N	3976	3753	3976	3753	3309	3119	3309	3119
df_m	5	5	5	5	5	5	5	5
F	.	.	.	.	.	.	.	.
rss	752.0	707.4	498.1	463.3	615.1	583.7	320.2	304.4

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

Table B.17: Determinants of mobility in the set of comparator Western European countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of relocation at least once in life (urban)	Probability of relocation at least once in life (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation in past 20 years (urban)	Probability of relocation at least once in life (rural)	Probability of relocation at least once in life (rural)	Probability of relocation in past 20 years (rural)	Probability of relocation in past 20 years (rural)
soviet	0.0156	0.0116	0.0949*	0.0961**	-0.0543	-0.0465	0.0270	0.0324
	(0.0291)	(0.0247)	(0.0393)	(0.0319)	(0.0694)	(0.0740)	(0.0330)	(0.0296)
female	-0.00388	-0.00180	-0.0208	-0.0147	0.0174	0.0242	0.0155	0.0190
	(0.00688)	(0.00846)	(0.0161)	(0.0152)	(0.0170)	(0.0171)	(0.0184)	(0.0186)
married	0.0971**	0.0979*	0.0267	0.0336	0.0140	0.0217	-0.0519	-0.0460
	(0.0309)	(0.0355)	(0.0345)	(0.0399)	(0.0173)	(0.0223)	(0.0313)	(0.0305)
low_sec	0.0499	0.0507	0.0223	0.0157	-0.00531	-0.00934	-0.000608	-0.00942
	(0.0525)	(0.0494)	(0.0344)	(0.0297)	(0.0355)	(0.0383)	(0.0526)	(0.0525)
up_sec	0.0239	0.0230	0.0106	0.00370	-0.0403	-0.0391	-0.0415	-0.0413
	(0.0299)	(0.0301)	(0.0337)	(0.0301)	(0.0317)	(0.0333)	(0.0600)	(0.0618)
post_sec	0.0588*	0.0567*	0.0498	0.0333	0.0160	0.00692	0.0162	0.00302
	(0.0262)	(0.0252)	(0.0584)	(0.0516)	(0.0267)	(0.0327)	(0.0699)	(0.0726)
BAmore	0.217*	0.206*	0.260***	0.239***	0.0481	0.0315	0.0928	0.0693
	(0.0908)	(0.0861)	(0.0285)	(0.0301)	(0.0392)	(0.0499)	(0.0938)	(0.0896)
BA_soviet	-0.0716	-0.0631	-0.160***	-0.159***	-0.0554**	-0.0595**	-0.0854	-0.0771
	(0.0528)	(0.0491)	(0.0198)	(0.0153)	(0.0179)	(0.0186)	(0.0656)	(0.0608)
log_age	0.0610	0.0860*	-0.422***	-0.393***	0.0468	0.0579	-0.490**	-0.476***
	(0.0433)	(0.0346)	(0.0878)	(0.0750)	(0.0760)	(0.0887)	(0.113)	(0.102)
total_HH	0.0307	0.0267	0.0524	0.0510	0.00678	0.00153	0.0168*	0.0121
	(0.0166)	(0.0168)	(0.0260)	(0.0294)	(0.00703)	(0.00771)	(0.00725)	(0.00744)
private	-0.0841**	-0.0873**	-0.0364	-0.0377	-0.0245	-0.0222	0.00121	0.000534
	(0.0290)	(0.0274)	(0.0568)	(0.0578)	(0.0432)	(0.0428)	(0.0476)	(0.0476)
jobB	-0.00959	-0.0243	-0.00758	-0.0294	-0.0177*	-0.0312**	0.0537	0.0339
	(0.0246)	(0.0281)	(0.0271)	(0.0264)	(0.00657)	(0.00841)	(0.0258)	(0.0197)
friend	-0.000284	0.000235	-0.0277	-0.0300	-0.0345	-0.0363	-0.0147	-0.0187
	(0.00784)	(0.00840)	(0.0242)	(0.0271)	(0.0342)	(0.0343)	(0.0256)	(0.0276)
willing_internally		0.0725		0.0886**		0.0713		0.0662***
		(0.0371)		(0.0242)		(0.0454)		(0.0140)
willing_internationally		0.0119		0.0429**		0.0259		0.0359
		(0.0148)		(0.00949)		(0.0395)		(0.0463)
Constant	0.605**	0.469*	2.087***	1.920***	0.754**	0.664*	2.399***	2.310***
	(0.184)	(0.175)	(0.336)	(0.301)	(0.242)	(0.286)	(0.430)	(0.399)
Observations	3,636	3,506	3,636	3,506	1,766	1,711	1,766	1,711
R-squared	0.199	0.204	0.225	0.236	0.491	0.492	0.293	0.302
N	3636	3506	3636	3506	1766	1711	1766	1711
df_m	3	3	3	3	3	3	3	3
F	.	.	.	.	.	.	.	.
rss	643.4	617.5	647.1	616.6	212.7	206.4	260.9	249.6

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

Table B.18: Instrumented regression for initially urban dwellers in CIS region.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS (no experience, no interactions) Log (income) USD PPP	OLS (no experience, no interactions) Log (income) USD PPP	IV (no exp, no interactions) Log (income) USD PPP	IV (no exp, no interaction) Log (income) USD PPP	OLS (no experience, no interactions) Log (income) USD PPP COLA	OLS (no experience, no interactions) Log (income) USD PPP COLA	IV (no exp, no interactions) Log (income) USD PPP COLA	IV (no exp, no interactions) Log (income) USD PPP COLA
Anyt type of relocation in the past 20 years	**-0.100*** **		**-0.659*** **		**-0.0180**		**-0.741*** **	
	(0.0252)		**(0.0732)**		**(0.0218)**		**(0.129)**	
soviet	-0.0447	-0.0444	-0.0359*	-0.0328**	-0.0318**	-0.0329**	-0.0227	-0.0205
	(0.0259)	(0.0257)	(0.0191)	(0.0159)	(0.0131)	(0.0118)	(0.0268)	(0.0291)
female	-0.00929	-0.00733	-0.00582	0.00820	-0.0263	-0.0284	-0.0188	-0.00235
	(0.0241)	(0.0233)	(0.0193)	(0.0127)	(0.0161)	(0.0165)	(0.0145)	(0.0238)
married	-0.0570***	-0.0572***	-0.0554***	-0.0567***	-0.0354***	-0.0353***	-0.0344***	-0.0371***
	(0.0132)	(0.0123)	(0.0156)	(0.00973)	(0.00832)	(0.00856)	(0.0115)	(0.00504)
low_sec	-0.129	-0.139	-0.0890	-0.157	-0.0860	-0.0855	-0.0333	-0.110
	(0.177)	(0.180)	(0.171)	(0.183)	(0.185)	(0.183)	(0.173)	(0.199)
up_sec	0.0263	0.0157	0.0885	0.0193	0.0639	0.0613	0.145	0.0692
	(0.0971)	(0.101)	(0.0878)	(0.0955)	(0.117)	(0.117)	(0.0961)	(0.119)
post_sec	0.0444	0.0385	0.0783	0.0400	0.0930	0.0918	0.138	0.0924
	(0.131)	(0.132)	(0.123)	(0.123)	(0.133)	(0.134)	(0.122)	(0.129)
BAmore	0.258**	0.240*	0.326***	0.201*	0.219**	0.221**	0.305***	0.165
	(0.104)	(0.109)	(0.0970)	(0.119)	(0.0849)	(0.0861)	(0.0734)	(0.100)
BA_soviet	-0.0188	-0.0136	-0.0412	-0.00694	-0.0476	-0.0475	-0.0765	-0.0392
	(0.0419)	(0.0397)	(0.0475)	(0.0338)	(0.0844)	(0.0848)	(0.0948)	(0.0766)
log_age	-0.0886	-0.0693	-0.177***	-0.0485	-0.0979**	-0.0983**	-0.208**	-0.0561
	(0.0650)	(0.0670)	(0.0531)	(0.0705)	(0.0385)	(0.0365)	(0.0835)	(0.0401)
total_HH	0.134**	0.134**	0.138***	0.138***	0.105**	0.104**	0.110***	0.110***
	(0.0495)	(0.0497)	(0.0460)	(0.0482)	(0.0361)	(0.0361)	(0.0333)	(0.0356)
Urban to rural relocation		**-0.161*** **		**-1.130*** **		0.105***		**-1.283** **
		(0.0233)		**(0.420)**		(0.0253)		**(0.646)**
loc_expmR								
Constant	5.980***	5.908***	6.350***	5.871***	6.038***	6.034***	6.500***	5.936***
	(0.301)	(0.305)	(0.241)	(0.292)	(0.216)	(0.207)	(0.367)	(0.210)
Observations	6,033	6,033	6,033	6,033	6,027	6,027	6,027	6,027
R-squared	0.115	0.116	0.085	0.057	0.100	0.101	0.041	
N	6033	6033	6033	6033	6027	6027	6027	6027
df_m	9	9	29	29	9	9	29	29
F	.	.	.	.	.	.	.	.
rss	7267	7261	7516	7749	6342	6337	6759	7313
First stage F			18.77	28.29			18.47	27.95

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

Table B.19: Instrumented regression for initially urban dwellers in the region of former Yugoslavia.

	(1)	(2)	(3)	(3)	(5)	(6)	(7)	(8)
	OLS (no experience, no interactions) Log (income) USD PPP	OLS (no experience, no interactions) Log (income) USD PPP	IV (no exp, no interactions) Log (income) USD PPP	IV (no exp, no interaction) Log (income) USD PPP	OLS (no experience, no interactions) Log (income) USD PPP COLA	OLS (no experience, no interactions) Log (income) USD PPP COLA	IV (no exp, no interactions) Log (income) USD PPP COLA	IV (no exp, no interactions) Log (income) USD PPP COLA
Any type of relocation	**0.0511**		**0.0685**		0.0866		-0.128	
	(0.0757)		**(0.882)**		(0.0551)		(0.742)	
soviet	0.301**	0.303**	0.300**	0.303***	0.204	0.210	0.211	0.206
	(0.114)	(0.116)	(0.128)	(0.101)	(0.164)	(0.168)	(0.165)	(0.142)
female	0.0406	0.0420	0.0400	0.0414	0.0345	0.0340	0.0421	0.0393
	(0.0509)	(0.0495)	(0.0573)	(0.0480)	(0.0489)	(0.0481)	(0.0568)	(0.0472)
married	-0.0560*	-0.0573*	-0.0556*	-0.0573**	-0.0590**	-0.0614**	-0.0642*	-0.0610***
	(0.0235)	(0.0249)	(0.0318)	(0.0230)	(0.0236)	(0.0244)	(0.0347)	(0.0220)
low_sec	0.0635	0.0626	0.0639	0.0627*	0.0426	0.0413	0.0388	0.0410
	(0.0413)	(0.0403)	(0.0393)	(0.0376)	(0.0481)	(0.0481)	(0.0475)	(0.0461)
up_sec	0.297***	0.297***	0.297***	0.298***	0.237***	0.245***	0.233***	0.231***
	(0.0681)	(0.0672)	(0.0508)	(0.0457)	(0.0532)	(0.0510)	(0.0383)	(0.0294)
post_sec	0.392***	0.390***	0.393***	0.393***	0.332***	0.343***	0.320***	0.319***
	(0.0514)	(0.0475)	(0.0211)	(0.0226)	(0.0452)	(0.0405)	(0.0293)	(0.0306)
BAmore	0.503*	0.507*	0.502**	0.510***	0.303	0.326	0.313	0.298
	(0.243)	(0.248)	(0.255)	(0.189)	(0.278)	(0.271)	(0.294)	(0.214)
BA_soviet	0.0628	0.0592	0.0641	0.0594	0.143	0.138	0.127	0.136
	(0.242)	(0.246)	(0.274)	(0.231)	(0.300)	(0.303)	(0.326)	(0.280)
log_age	-0.166***	-0.176***	-0.163	-0.177***	-0.156***	-0.177***	-0.192	-0.167***
	(0.0203)	(0.0224)	(0.151)	(0.0304)	(0.0391)	(0.0352)	(0.122)	(0.0363)
total_HH	0.110**	0.110**	0.110**	0.110**	0.0872**	0.0854**	0.0886**	0.0890**
	(0.0436)	(0.0442)	(0.0436)	(0.0454)	(0.0343)	(0.0345)	(0.0347)	(0.0354)
Urban to rural relocation		0.0203		0.0599		0.231*		-0.112
		(0.0657)		(0.772)		(0.116)		(0.649)
loc_expmR								
Constant	6.194***	6.237***	6.180***	6.240***	6.278***	6.365***	6.450***	6.339***
	(0.228)	(0.240)	(0.570)	(0.261)	(0.170)	(0.146)	(0.496)	(0.199)
Observations	3,976	3,976	3,976	3,976	3,965	3,965	3,965	3,965
R-squared	0.146	0.146	0.146	0.146	0.137	0.140	0.132	0.131
N	3976	3976	3976	3976	3965	3965	3965	3965
df_m	5	5	25	25	5	5	25	25
F	.	.	.	.	.	.	.	.
rss	4220	4221	4220	4221	4015	4001	4038	4040
First stage F			44.13	31.02			41.65	30.74

Robust standard errors in parentheses

Table B.20: Predicted gains to mobility for currently immobile by country and region.

	Rural Nonmovers						Urban Nonmovers					
	Median predicted change in income associated with **rural to rural** relocation for those who are currently rural nonmovers (USD PPP)	Median predicted change in income associated with **rural to urban** relocation for those who are currently rural nonmovers (USD PPP)	Median predicted % change in income associated with **rural to rural** relocation for those who are currently rural nonmovers (%)	Median predicted % change in income associated with **rural to urban** relocation for those who are currently rural nonmovers (%)	**% not gaining from rural to rural move**	**%not gaining from rural to urban**	Median predicted change in income associated with **urban to rural** relocation for those who are currently urban nonmovers (USD PPP)	Median predicted change in income associated with **urban to urban** relocation for those who are currently urban nonmovers (USD PPP)	Median predicted % change in income associated with **urban to rural** relocation for those who are currently urban nonmovers (%)	Median predicted % in income associated with **urban to urban** relocation for those who are currently urban nonmovers (%)	**% not gaining from urban to rural move**	**% not gaining from urban to urban move**
CIS extended region	**$309.12**	**$349.02**	**38%**	**43%**	**17%**	**19%**	**($86.49)**	**$122.18**	**-9%**	**19%**	**56%**	**33%**
Armenia	$126.09	$208.51	10%	21%	27%	20%	($90.42)	($80.27)	-7%	-8%	77%	51%
Azerbaijan	$710.11	$564.58	45%	41%	1%	21%	($381.77)	$238.68	-29%	14%	100%	27%
Belarus	$103.90	$34.04	23%	7%	24%	31%	$54.81	$294.40	14%	79%	27%	8%
Georgia	$62.49	$75.29	19%	17%	32%	31%	($63.82)	$316.21	-9%	78%	84%	8%
Kazakhstan	$346.34	$409.07	57%	70%	6%	7%	($105.21)	($0.59)	-19%	0%	56%	50%
Kyrgyzstan	$207.71	$287.05	21%	42%	15%	12%	($101.43)	$350.23	-16%	54%	55%	13%
Moldova	$397.88	$311.22	77%	60%	11%	20%	($326.05)	$168.32	-47%	35%	100%	26%
Russia	$239.35	$627.82	38%	79%	26%	14%	($105.49)	$159.43	-12%	23%	55%	32%
Tajikistan	$384.03	$273.87	51%	36%	1%	20%	$470.13	$1,286.08	165%	361%	0%	0%
Ukraine	$276.70	$276.37	31%	31%	11%	25%	($74.61)	$54.78	-9%	7%	54%	37%
Uzbekistan	$329.72	$85.58	35%	7%	13%	28%	($26.54)	$121.90	-3%	18%	74%	46%
Former Yugoslavia region	**($435.01)**	**$307.59**	**-23%**	**19%**	**82%**	**30%**	**($18.54)**	**($455.18)**	**-1%**	**-30%**	**53%**	**92%**
Bosnia	$21.01	$606.63	1%	32%	45%	0%	$147.44	($84.25)	16%	-11%	14%	86%
Croatia	($282.23)	$2.55	-16%	0%	91%	50%	$7.53	($668.29)	1%	-41%	49%	98%
Kosovo	($857.35)	$702.00	-35%	33%	100%	5%	$89.97	($777.47)	5%	-40%	42%	99%
Macedonia	($1,414.15)	($577.22)	-33%	-16%	100%	86%	$407.87	($630.28)	22%	-31%	22%	96%
Montenegro	($715.19)	$735.08	-34%	35%	100%	0%	$230.12	($284.99)	16%	-15%	12%	95%
Serbia	($475.03)	$137.63	-32%	8%	100%	43%	($228.86)	($484.61)	-15%	-32%	100%	93%
Slovenia	$323.25	$1,450.54	14%	57%	36%	0%	$186.40	($342.02)	13%	-20%	12%	81%
EU10 Region	**$1,652.58**	**$1,409.43**	**105%**	**86%**	**1%**	**20%**	**$209.09**	**$67.37**	**15%**	**5%**	**31%**	**42%**
Bulgaria	$1,326.60	$875.63	61%	49%	0%	40%	$1,070.82	$102.86	76%	9%	0%	27%
Czech Republic	$1,671.36	$1,043.64	38%	26%	9%	33%	($34.85)	($176.25)	-2%	-8%	57%	75%
Estonia	$745.44	$1,197.38	19%	41%	4%	25%	$789.66	$330.97	63%	25%	3%	0%
Hungary	$908.91	$1,052.91	47%	97%	0%	28%	($153.94)	$53.17	-9%	4%	88%	40%
Latvia	$459.48	$1,017.36	14%	37%	6%	27%	$59.16	$174.99	6%	11%	33%	18%
Lithuania	$1,860.38	$1,762.00	77%	102%	0%	26%	$443.99	$262.03	31%	19%	13%	1%
Poland	$2,667.54	$2,111.22	243%	198%	0%	10%	$1,074.89	($126.73)	117%	-16%	0%	90%
Romania	$1,012.90	$577.00	67%	52%	0%	33%	$328.69	$303.75	23%	23%	16%	1%
Slovakia	$3,023.22	$2,221.26	113%	113%	0%	21%	$129.04	($679.16)	6%	-36%	23%	100%
Slovenia	$5,341.82	$3,278.25	159%	130%	0%	14%	$599.18	$183.74	22%	8%	16%	34%

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