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ESSAYS ON MIGRATION AND DEVELOPMENT

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Abstract

US-educated Indian engineers played a major role in the establishment of the "Silicon Valley of Asia" in Bangalore. The experience of India and other countries shows that returning well-educated emigrants, despite their small numbers, can make a difference. The first part of this dissertation builds a model of "local" knowledge spillovers, in which migration of a small number of highly skilled individuals greatly affects country-level human capital accumulation. All economic activity occurs in pairs of individuals randomly matched to each other. Each pair produces the consumption good; the skills of the two partners are complementary. At the same time, the less skilled partner increases human capital by learning from the more skilled colleague. With poor institutions at home, highly skilled individuals leave the country seeking better opportunities abroad. On the contrary, improved institutions foster return migration of emigrants who have acquired more knowledge while abroad. These return migrants greatly amplify the positive effect of better institutions.

In the second part of the dissertation, I empirically analyze the propensity of US immigrants to return. Today, little is known about the returnees: who are they and how do they compare to those who did not return? How does their decision to return depend on economic situation at home? To identify return migration, I use the method adopted from Van Hook *et.al.* (2006). The method is based the U.S. Current Population Survey (CPS) which interviews households for two consecutive years. About a quarter of foreign-born individuals drop out of the sample between the first and the second years, due to various causes including return migration. After eliminating all other causes of dropout, I estimate the propensity of immigrants to return, depending on personal and home country characteristics. I find that the difference between recent immigrants and other immigrants is greater than the difference between men and women, or skilled and unskilled migrants. Thus, assimilation differentiates immigrants more in their decision to return than education or gender. In particular, distance to home country negatively affects return propensity of those who arrived over 10 years ago, and has no effect on recent immigrants.

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1 Introduction

The volume of international migration has exploded in the past few decades. In the United States, the number of immigrants is increasing by one million each year, and has already surpassed thirty five million[2] – more than the entire population of a country like Canada. The number of immigrants in the European Union is rising at a somewhat slower rate – "only " half-million persons per year – and is currently exceeding twenty million people.

At the same time, not all of the immigrants stay at their new destination for good – many of them return home after a while. The magnitude of return migration, according to various estimates, is from one fifth to one third of all immigrants. This dissertation is an attempt to provide better understanding of the phenomenon of return migration.

In the existing literature on the topic, several major questions have been debated. First, how to quantify return migration? Unlike first-move immigration which is always well-documented by the receiving country, return most of the time remains unnoticed by statistical agencies – simply because no special permit is needed to return. Various indirect methods have been developed; they are all based on measuring the *decrease* in the number of a certain cohort of immigrants, and attributing this decrease to return migration. The third chapter of this dissertation contributes to this strand of literature by developing an explicit econometric model of discrete choices made by an immigrant, and estimating the model using matched American Current Population Survey datasets.

Second, why do migrants return? Several theories have been developed on this issue. The neoclassical theory of international movement of production factors, currently taught in any undergraduate course of international economics, postulates that labor migration is always one-way – from a country with low marginal productivity of labor, to the one with high productivity.

[2] not counting the US-born children of immigrants

In this light, return migration can be viewed either as a mistake, or as an attempt to correct a past mistake of leaving home in the first place.

In the early 1990s, alternative theories emerged. In particular, Oded Stark (1991) argued that return migration may be part of a planned life cycle – workers travel abroad to enjoy higher wages and to accumulate wealth; once enough is saved, they return to enjoy lower prices and better social networks at home. In particular, return of retiring Turkish workers from Germany is a well-known phenomenon.

In the mid-2000s, it became apparent that migrants sometimes return not only to spend money, but also to make money and to apply skills earned abroad. A book by Anna Lee Saxenian (2006) describes stories of several developing countries to which highly skilled US-trained IT specialists returned. Thus, people may travel back and forth not only to gain financial capital, but also to gain human capital that can be applied at home once the environment there becomes sufficiently favorable.

Third, what is the effect of return migration on the home country? There are several well-documented examples of rapid economic growth correlated with return migration – the most stark are Bangalore in India and Taiwan, to which highly skilled US-educated entrepreneurs returned shortly prior to the emergence of a period of rapid economic growth. However, it is still unclear whether this return migration was the *cause* or the *consequence* of developments at home. Empirical analysis of the relationship between return migration and development remains a challenge; so far, this relationship is debated only on the theoretical level. The second chapter of this dissertation contributes to this debate by introducing a new mechanism of *local* technology spillovers: the knowledge is initially brought to the home country by return migrants, and then spread from one person to another much like a virus.

This theory also explains why the empirical analysis of causality is so difficult. The initial macroeconomic effect of return migration is negligible because of a small number of returnees. The long-run path of development, according to the proposed theory, may be significantly altered as more and more people get infected by the knowledge introduced by the returnees. However, since the initial impact (the return migration) and the observed effect (economic growth) may take place years and even decades apart, the relationship between them is also extremely difficult to quantify.

Another empirical problem is that returnees are very unequal in their capability to generate knowledge spillovers. Those who return home after retirement at the age of 70 are less likely to change the environment at home. Even those at productive age may be very heterogenous, even after controlling for education and all other kinds of observable characteristics. The amount of entrepreneurial talent is not easy to measure; moreover, it may be distributed very unequally not only within, but also across different cohorts of return migrants.

Finally, one can ask how is return migration related to international trade? Gould (1994) and Rauch (1999) argue that foreign diasporas and international social networks matter for bilateral trade flows. Return migration may, in turn, serve as a way to maintain those networks active and thus be related to trade. To my knowledge, this question was not investigated in the literature, nor it was studied within this dissertation. The problem remains open for future research.

2 Migration, Learning, and Development

2.1 Motivation

High-skilled emigrants returning home can make a difference. Saxenian (2006) describes how the rapid growth of the information technology industry in Israel, India, Taiwan, and later mainland China was tightly related to return migration of Israeli, Indian, and Chinese high-skilled engineers living in the US, mainly in the Silicon Valley. These engineers used their US experience to start new businesses at home, train local employees, and enter the global market with their new products.

Recent economic models of growth and development can do little to explain such rapid productivity growth on such a large scale. There exist models of brain drain (for example, Haque and Kim 1995) and return migration (such as Dos Santos and Postel-Vinay 2003) which are based on the assumption that average human capital of the previous generation has a positive effect on human capital acquisition by the new generation. Emigration of the highly-skilled reduces average human capital in the country, thus reducing human capital of future generations. Likewise, return of the highly-skilled increases average human capital, which has a positive externality on the young people.

Empirically, however, the number of returning high-skilled emigrants is usually too small to have any significant effect on average human capital. Few hundreds of Indian talented engineers cannot change the average human capital of the Indian labor force with its half-billion people; they can only change the 99th percentile of the human capital distribution. There has to be another mechanism, in which people at the top of human capital distribution play a much greater role than those at the bottom.

Another problem is to explain the incentives of return migrants. It is relatively easy to create a model of one-way migration, but it proved more difficult to explain why a person who migrated from one country to another decides to reverse his decision after a while. The existing literature tends to explain return by "homesickness": although they are more productive abroad, some emigrants choose to return home after accumulating enough knowledge or wealth.[3]

One more problem is to explain why emigrants do return to some home countries, and don't return to others. Borjas and Bratsberg (1996) in their empirical cross-country study conclude that the probability of a US immigrant returning home positively depends on GDP per capita at home, which is easy to explain: wealthier countries typically have lower crime and provide better public goods, and therefore more attractive for living. Yet, the above mentioned countries (India, Taiwan, mainland China, Israel) did not have high income levels and good infrastructure from the start, but still experienced significant high-skilled return migration. An explanation of this fact may come from another finding of Borjas and Bratsberg (1996): they show that the "communist country" dummy is highly negatively significant,[4] which suggests that home country institutions may be an important factor affecting migration decisions.

In this paper, I propose a model of "local" knowledge spillovers. Instead of assuming that a high-skilled individual has a *small* positive externality on *all* young individuals by increasing average human capital, I assume that such an individual has a *large* positive externality on *someone*, and no immediate effect on the rest of population. For example, Amartya Sen returning to India would have a far greater influence on his immediate colleagues and students than on illiterate people living in remote villages.

After a while, those who learn from high-skilled returnees become high-skilled themselves, which enables them to train more unskilled individuals.

[3]Alternatively, some papers assume that individual productivity is exogenously lower if he works abroad, which creates return incentives

[4]Their data was collected in the 1970's, at the peak of the cold war

Thus, the number of individuals with high human capital increases exponentially. With this "bootstrap" training technology, a small number of new high-skilled individuals may lead to a major shift of the human capital distribution over time.

Both production and learning occur in partnerships which consist of two individuals, randomly matched to each other. The amount of output they produce is a complementary function of their human capitals; they divide their joint output according to a bargaining rule. At the same time, the less skilled individual (the "apprentice") learns from the more skilled partner (the "master").[5] Due to skill complementarities of the two partners in production, the opportunity cost of such education is wasted talent of the master, in terms of current production. Obviously, in order to learn, the apprentice should compensate this wasted talent by accepting a lower, or even negative, share of their joint output. The two partners may choose to split anytime; then, they are randomly matched to new partners after a waiting period.

The time needed to find a new partner may exogenously differ across countries, and it serves as a proxy for institutional quality in the model. In countries with high corruption and bureaucracy, starting a new business typically requires much more time and money; it is widely believed that these entry costs have a significant impact on country development. For example, the startup cost is one of the components of business environment indicators constructed by the World Bank and by the World Economic Forum. I this paper, I show that such entry cost differences alone may lead to major differences in income levels. The higher entry barriers affect bargaining over output: highly skilled people get a lower reward for training their low-skilled partners. Also, individuals of different skills match to each other less

[5]The terms "master" and "apprentice" are used here because learning occurs simultaneously with production. However, the "apprenticeship" here is somewhat different from its original meaning – medieval apprentices were bonded to their masters until they pay off their debt, while in my model they typically consume out of their own savings and have no financial obligations

optimally, which results in a lower distribution of human capital. When emigration is allowed, some people with high skill emigrate from countries with poor institutions, which further lowers the human capital distribution at home; nobody wants to return.

When the home country improves its institutions, its migration patterns are drastically changed: people with average human capital emigrate to acquire knowledge abroad, and return once their human capital becomes high enough. As a result, the home country grows three times faster than it would grow without return migration, despite the fact that the number of returnees per year is only about 0.1% of home country population.

In my model, return migration is a perfectly rational choice even without "homesickness"or exogenous productivity differences. When enough human capital is acquired, it may become optimal to return, because high skill is endogenously rewarded better in countries with scarce skill but good institutions.

2.2 The model of closed economy

2.2.1 Individuals

This is a one-sector dynamic model set up in discrete time. The economy is populated by a continuum of individuals of a finite mass. Each individual i at each point in time t is endowed with human capital $h_{i,t} \in [0, \infty)$ which evolves endogenously.

For each individual, there exists a small probability δ of death at each moment of time; for simplicity, death rate does not depend on individual's age. The same number of new people is born; their (initial) human capital is zero. As a result, the country population remains constant.

All individuals have identical risk-neutral preferences over the only consumption good:

$$U_i = \sum_{t=t_{0,i}}^{\infty} \beta^{t-t_{0,i}} c_{i,t}$$

where β is the discount factor, $c_{i,t}$ is consumption, and $t_{0,i}$ is the birth date of individual i. The date of death is uncertain; the probability of death is built into the discount factor β.

Due to complete credit markets, people can borrow and save. Assuming the interest rate equals the discount rate, people are indifferent between having more consumption today and more consumption tomorrow due to their linear preferences; they simply maximize their discounted stream of earnings. As a result, there is no need to model savings explicitly.

2.2.2 Production and learning

The production of the good occurs in partnerships; each partnership consists of two individuals. The only inputs in production are the human capitals of the two partners. When individuals i and j work together, they produce

$$y(h_i, h_j) = \min\{h_i, h_j\} \tag{1}$$

Note there exists a complementarity between human capitals of the two partners.[6]

The evolution of an individual's human capital depends on her partner's human capital. Suppose an apprentice with human capital h_1 works with a master with human capital h_2 (which implies $h_1 \leq h_2$). Then, the next period human capitals are

$$\begin{aligned} h_1' &= h_1 + g(h_2 - h_1) + \lambda_0 \\ h_2' &= h_2 + \lambda_0 \end{aligned} \tag{2}$$

[6] Generally, any production function with complementary inputs can be used – for example, O-ring production function used by Kremer (1991).

The master's knowledge increases at a small rate λ_0 which reflects "learning from experience". Apprentice's knowledge increment is much higher and depends on master's knowledge. If an individual does not have a partner, he also increases his human capital at rate λ_0.

I assume the following properties of the learning function $g(\cdot)$:

- $g(0) = 0$ — no learning from an equal partner
- $g'(0) = \lambda$ with $\lambda \in (0, 1)$ — if the master is just slightly smarter than the apprentice, the latter reduces the knowledge gap by fraction λ each period
- $g''(x) < 0$ for all $x \geq 0$ — marginal returns from a smarter master are diminishing

Throughout the paper, I use the following learning function:

$$g(x) = \log(1 + \lambda x) \tag{3}$$

It satisfies all the properties mentioned above.

Note that in the absence of learning from a partner ($\lambda \equiv 0$) the Pareto-optimal allocation is to match individuals of as close as possible skill because of the production complementarity.

2.2.3 Matching

At the beginning of each period, most individuals are matched to a partner, but some are unmatched. A randomly chosen fraction θ of the unmatched individuals are randomly matched to each other; the remaining fraction $1 - \theta$ stays unemployed this period. The parameter θ serves as a proxy for institutional quality in a country. With higher θ, the unmatched individuals have more frequent opportunities to form a new partnership.

Individuals coupled to each other (both previously matched and newly matched) can decide whether to work together or split and remain unemployed this period. Those who work need to decide how they divide their joint revenue — this decision is made according to Nash bargaining rule (see below). The apprentice's share may be even negative in equilibrium, which implies some sort of tuition for education.

If the two partners decide to stay together, most likely they will be matched to each other again. For most couples, this is beneficial: it enables them to form long-term relationships, the apprentice can acquire most of master's knowledge. Some couples, however, are worse off from being matched to each other again: they would prefer to be matched to new randomly chosen partners. By assumption, changing a partner requires at least one period of unemployment; as a result, partnerships last longer than they would in the absence of search frictions. With poor country institutions (low θ), establishing a new partnership takes more time, which makes people reluctant to shut down existing partnerships, and therefore making them less efficient.

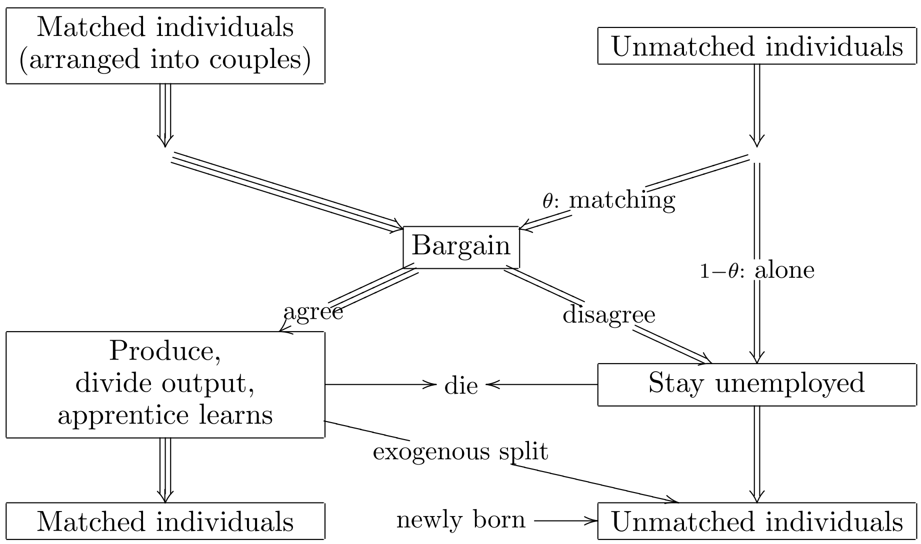
Although working partners are usually matched to each other again and again, there exists a small probability that they are forced to join the pool of unmatched people. This happens than one of the partners dies; I also assume that a small fraction of couples are forced to split exogenously, even when both partners survive.[7]

2.2.4 Bargaining

A couple of partners divides their joint output according to Nash bargaining rule. Each potential partner i calculates his reservation wage $\underline{w}_t(h_i, h_j)$, which makes him indifferent between staying with current partner j, and

[7]The reason for introducing the exogenous split is technical: when some individuals are forced to enter the job market, the distribution of skill on the job market becomes more stable, which greatly improves the numerical algorithm

Figure 1: Timing in closed economy



Arrow thickness indicates fraction of population following this path in a typical steady state

remaining unemployed this period and meeting a new partner tomorrow:

$$\underline{w}_t(h_i, h_j) + \beta[(1-\gamma)V^m_{t+1}(h'_i, h'_j) + \gamma V^u_{t+1}(h'_i)] \equiv \beta V^u_{t+1}(h_i + \lambda_0)$$

where $V^m_t(h_i, h_j)$ is the value of i being matched with j at time t, V^u_t is the value of being unmatched, γ is the probability of exogenous split, h'_i and h'_j are future human capitals of i and j if they work together.

Then, the surplus created by the match is the difference between the joint output of i and j, and the sum of their reservation wages:

$$y(h_i, h_j) - (\underline{w}_t(h_i, h_j) + \underline{w}_t(h_j, h_i))$$

If the surplus is non-negative, i and j stay together; otherwise they split. Since the possibility frontier is linear, Nash bargaining implies that each partner earns his reservation wage plus half of the surplus, hence i's wage when working with j is

$$w_t(h_i, h_j) = \underline{w}_t(h_i, h_j) + \frac{1}{2}\left(y(h_i, h_j) - (\underline{w}_t(h_i, h_j) + \underline{w}_t(h_j, h_i))\right)$$

Since the individuals divide the surplus equally, their accept-reject decisions (whether to stay together or split) are always synchronized: either both partners choose to be together, or both of them choose to split.

2.2.5 Equilibrium and steady state

The equilibrium in this model consists of the following:

- Distributions of individuals across types, at every moment of time: $f_1, f_2, ..., f_t, ...$ with

  $$f_t = \{f_t^m(h_i, h_j), f_t^u(h_i)\}$$

  where f_t^m describes the density of individuals of type i matched with those of type j, and f_t^u describes the density of unmatched individuals

- Path of wages, or bargaining outcomes, for every potential couple of partners: $w_1, w_2, ..., w_t, ...$

- Values associated with each state, at every moment of time: $V_1, V_2, ..., V_t, ...$ where

  $$V_t = \{V_t^m(h_i, h_j), V_t^u(h_i)\}$$

  These values are defined as follows. Define $V_t^{in}(h_i, h_j)$ as the value of i working with j, and $V_t^{out}(h_i)$ as the value of being unemployed:

  $$V_t^{in}(h_i, h_j) = w_t(h_i, h_j) + \beta[(1-\gamma)V_{t+1}^m(h_i', h_j') + \gamma V_{t+1}^u(h_i')]$$
  $$V_t^{out}(h_i) = \beta V_{t+1}^u(h_i + \lambda_0)$$

Then, the values of being matched and unmatched are

$$V_t^m(h_i, h_j) = \max\{V_t^{in}(h_i, h_j), V_t^{out}(h_i)\} \tag{4}$$

$$V_t^u(h_i) = \theta \frac{\int V_t^m(h_i, h_j) f^u(h_j) dh_j}{\int f^u(h_j) dh_j} + (1-\theta) V_t^{out}(h_i) \tag{5}$$

In a steady state, all objects mentioned above are time-invariant. The rest of this paper, except the last section, deals with computing and analyzing steady states.

2.2.6 Results

As many models with heterogenous agents, this model is too complex for analytical analysis. I solve the model numerically, using parameter values described below. I consider two scenarios: the "North" (a closed economy with good institutions) and the "South" (an economy with poor institutions). Note that the value of the speed of learning λ is chosen such that in the Northern steady state the national educational expenses, measured as the sum of all negative incomes of apprentices, were roughly equal to 7.5% of GDP – the US level of educational spending.

The computational procedure of finding steady states is described in appendix A.1.

Due to higher entry barriers, it is harder to start a partnership in the South. As a result, Southern individuals are less careful when choosing a partner, and more reluctant to terminate inefficient partnerships, which results in a lower distribution of human capital in the long run. Figure 2 shows the steady-state distribution of human capital in the North and in the South. In both countries, the distribution peaks at zero — there is a mass point of newly born individuals; then, the distribution peaks again near the highest available human capital — because it is relatively easy to reach the frontier of knowledge by learning from others, but very hard to go beyond that frontier.

Table 1: Parameters of the model

Variable	Notation	Value	Comment
Model period, frequency of matching		1 month	
Discount factor	β	0.995	people discount future at about 6% per year
Death rate	δ	$1/720$	Active (on average) for 60 yrs
Probability of exogenous split	γ	0.005	minimal for good convergence
Speed of learning by experience	λ_0	$1/720$	without learning from others, human capital increases by 1 during average lifetime
Speed of learning from others	λ	0.015	Education expenses are 7.5% of GDP in Northern steady state
Probability of being matched with new partner	θ	$1(\frac{1}{6})$	Wait 1(6) month(s) for a match

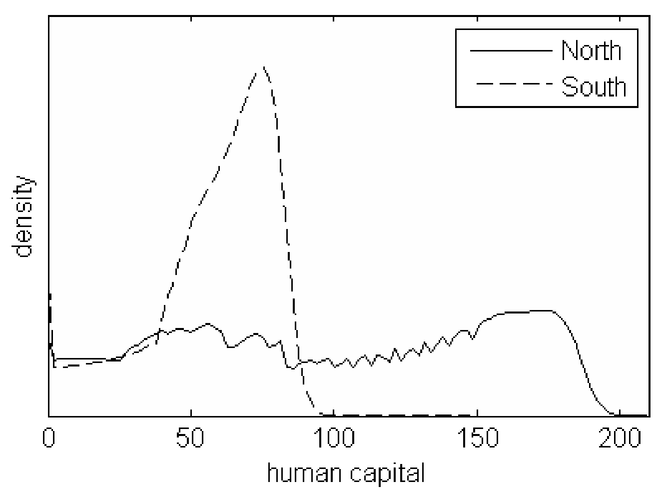


Figure 2: Steady-state distribution of human capital

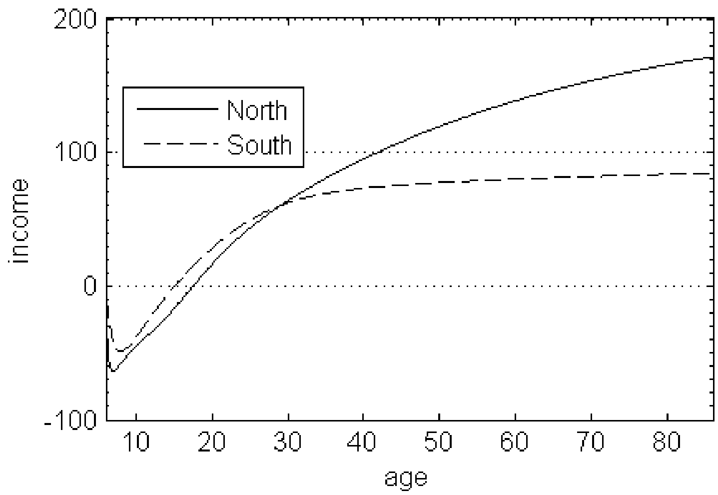


Figure 3: Expected lifetime income path

I have no formal proof that the steady state is unique; however, in all my experiments with different initial distributions, the system has converged to the same steady state.

Individual wage $w(h_i, h_j)$, obviously, increases with own human capital:

$$\frac{dw(h_i, h_j)}{dh_i} > 0$$

The dependence of wage on partner's human capital h_j is less trivial. It is always true that the two equal partners ($h_j = h_i$) would divide their joint output equally. Otherwise, the wage depends on model parameters, but some common patterns can be traced. I consider two distinct cases: less skilled partner ($h_j < h_i$) and more skilled partner ($h_j > h_i$).

When j is more skilled, today's output $y(h_i, h_j) = \min\{h_i, h_j\}$ does not depend on h_j, so the amount of wealth to be divided does not change as h_j increases. A higher h_j, however, implies that i would learn faster and be able to earn more tomorrow, therefore i agrees to accept lower wages today. This results in a negatively sloped wage function:

$$\frac{dw(h_i, h_j)}{dh_j} < 0 \qquad \text{when} \qquad h_j > h_i$$

This property, combined with the fact that $w(0,0) = 0$, implies that an individual with zero human capital earns a negative income as long as partner's skill is positive.[8]

When j is less skilled than i, there are two effects of increased h_j. First, since now the output is determined by j's skill, the amount of wealth to be divided increases as h_j increases; both partners, i and j, benefit from it. Second, increased h_j means a smaller knowledge gap between i and j, and therefore less learning occurs, which lowers the reward of the master i. The first effect, increasing i's wage, dominates when h_j is small; the second effect, decreasing i's wage, dominates when h_j gets close to h_i. As a result, for every master with human capital h_i there exists an "optimal" apprentice who provides the highest income for i.

The effect of poor institutions (lower θ) is worse outside opportunities of both bargaining parties. Since the low-skilled individuals have low outside opportunities anyway, they have a relatively stronger bargaining position, and get a higher fraction of output. As a result, learning from a higher partner is cheaper in the South, where institutions are poor; conversely, teaching lower-skilled individuals is rewarded better in the North. This discrepancy creates a basis for South-North high-skilled emigration, when migration becomes available. Figure 5 compares wages in the North and in the South. The scale of human capital is such that Northern average equals 100; wage differences are measured as percentage points of Northern GDP per capita.

[8] I have considered a version of the model with borrowing constraints, when young individuals can only learn if they have enough initial wealth. In this setting individuals are characterized by two state variables: knowledge and wealth, thus the matches of individuals are defined in four-dimensional state space. This model was abandoned due to excessive numerical complexity

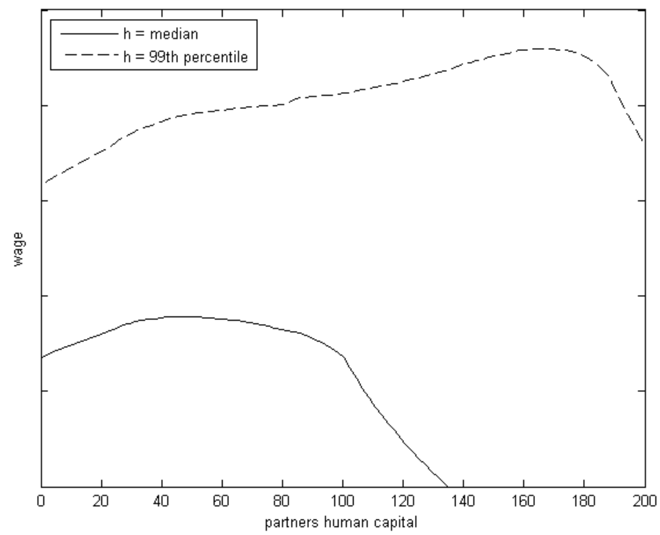


Figure 4: Wage in the North, as a function of partner's human capital

The figure shows that highly skilled individuals are better rewarded in the North. Persons of low skill get a higher income in the South, but that doesn't mean they are better off – their expected utility may be still lower than that of their Northern counterparts, because they expect to learn more slowly.

Figure 6 shows optimal accept-reject decisions in the steady state, in the North. Individuals do not work together if their human capitals are equally low – because no learning occurs when the partners have equal human capital. Individuals with low human capitals also do not match with those who have very high human capital – because the learning function is concave, it is better to match low-h apprentices with average-h masters. In the South, the opportunity cost of a match is much higher; this means a wider white area on a similar Southern graph.

In the South, the autarky GDP per capita is about 57% of the Northern value.

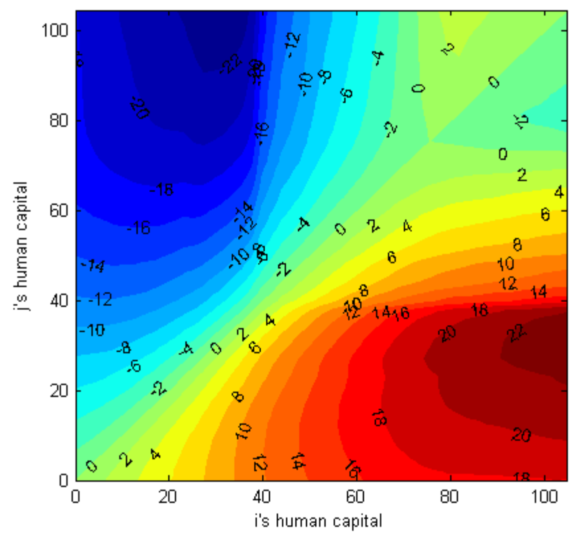


Figure 5: North-South wage difference in autarky

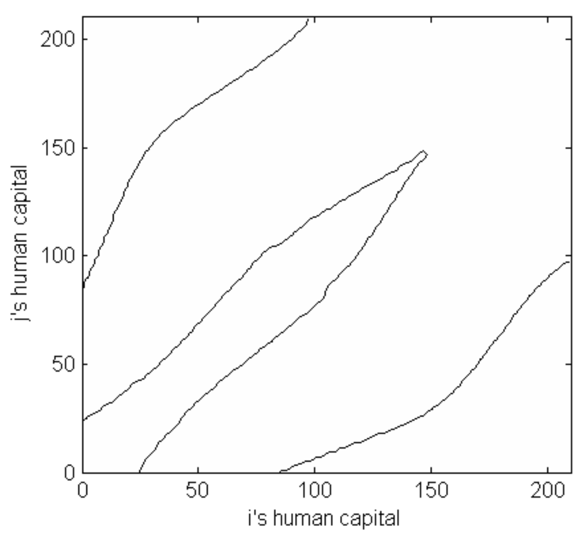


Figure 6: Accept-reject decisions of Northern randomly matched partners
Matches are accepted if skills are neither too similar nor too different

2.3 One-way migration and brain drain

When modeling migration between North and South, a number of additional assumptions is made.

- The North is a large country: migration has no effect on its steady state
- The Northerners always live in their home country; only Southerners migrate. With this assumption, the South is not flooded with Northerners once the value of living in the South gets high
- Migration is available at the end of each period, and only for unmatched individuals
- Migration is instantaneous; the migrants join the unmatched pool at the new location
- The number of people born each period in the South is constant; it does not depend on migration patterns. This assumption allows to define a steady state with migration
- The North restricts immigration: the number of Southerners living in the North cannot exceed 5% of Southern population at any time. The Northern government imposes an emigration fee, which makes this restriction incentive compatible

This last assumption is needed to prevent too much South-North migration. In practice, developed countries do restrict immigration, and only a small fraction of the developing world population is able to emigrate.[9]

Assuming that South retains its poor institutions, I show below that migration occurs only in one direction: South to North. Emigrants never

[9] According to the study of Docquier and Marfouk (2004), the number of immigrants in the OECD countries does not exceed 60 million people (this number includes migrants from one OECD country to another), which is only about 1% of the world population

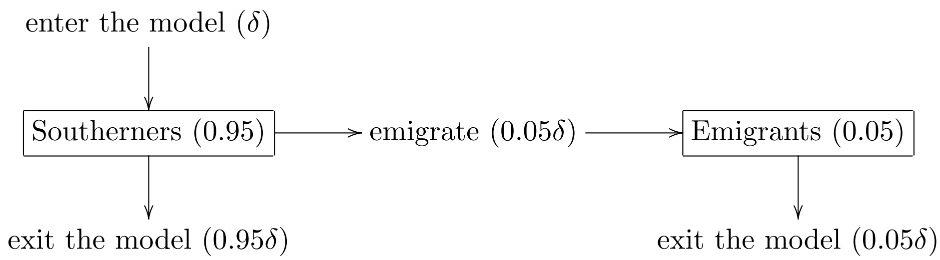


Figure 7: Steady state with emigration

return, and the emigration quota is fully exhausted. This makes Southerners living in the North identical to Northerners themselves; their value of living in the North is identical to that of Northern-born population. This allows us to introduce migration into the model in a cheap way: emigration simply becomes an outside opportunity; to find the steady state, there is no need to track the history of emigrants.

Given that the number of people born each period in the South does not depend on migration patterns, there exists a permanent flow of migrants from the South to the North. Each period, a mass δ Southerners are born in the South. Since 5% of Southerners live in the North, a mass 0.05δ of them die abroad each period, giving way to the same mass of new Southerners to enter the North. Figure 7 shows a graphical representation of the argument.

In the new steady state, all Southerners benefit from emigration. Due to Northern immigration restrictions, only a few of them, those with the highest incentives, emigrate. Surprisingly, the emigrants have high, but not the highest skill; figure 8 shows that emigration incentive peaks around $h = 60$ (78th percentile of Southern human capital), and declines between 60 and 80 (Southern highest human capital). As a result, individuals with human capital around 60 offer the highest emigration fee, and only they actually emigrate. Their emigration causes a depression of human capital distribution at 60; in the long run, because the emigrants do not pass their knowledge onto

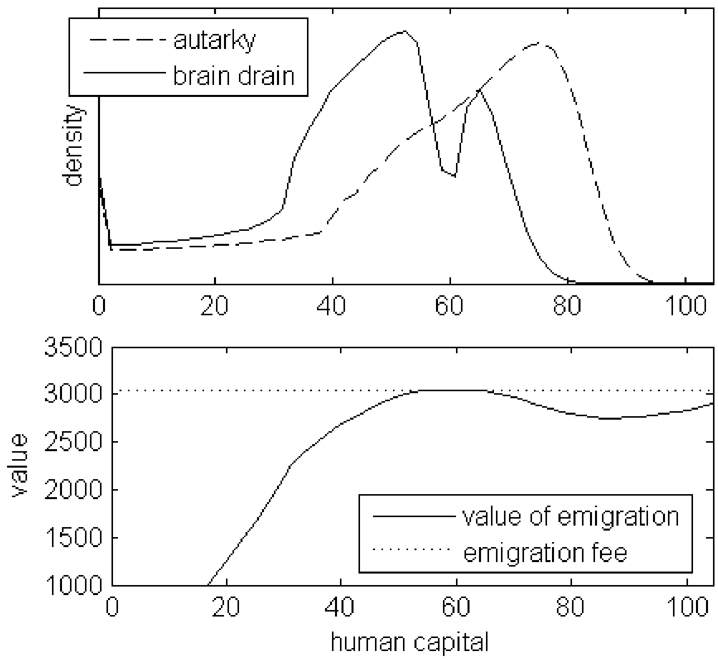


Figure 8: Characteristics of Southern steady state with one-way emigration
Upper graph: human capital distribution; lower graph: benefits of emigration

young Southerners, the human capital distribution deteriorates compared to the autarky scenario. Figure 8 also confirms that no emigrant wants to return: everyone's emigration benefit is far above zero.

Why is emigration benefit non-monotonic? There are several factors that affect migration incentives. One factor is the difference in bargaining solutions, $w(h_i, h_j)$, between North and South. In the South, everyone has bad outside opportunities, which makes bargaining less dependent on human capitals. High-skilled Southerners generally earn a lower reward for their skill, which makes them more willing to migrate — emigration benefit is generally upward sloping. On the other hand, it pays off to be the "king of the hill" in a country — having slightly more human capital than anybody else in the economy slightly increases the reward because such an individual is basically a monopolist possessing a scarce resource. Consequently, Southerners with a very high (by Southern standards) skill are slightly less willing to emigrate and make a slightly lower bid to purchase the right to do so.

A natural question arises: if individuals of modest skill emigrate, and no one lives forever, then who are the people at the top of human capital distribution and where did they come from? The explanation comes from the fact that people face idiosyncratic shocks: if an individual from the "emigration range" of skills was suddenly left without a partner, he emigrates; if such an individual was learning from a top-skilled master, the former does not emigrate and jumps over the emigration range. Once individual's skill rises above the emigration range of skills, he stays in the South for good.

What happens to Southern emigrants abroad? Because they work with more educated Northerners, the emigrants learn a lot while they live in the North; their skills grow far beyond the Southern knowledge frontier. Their return would have a great effect on the Southern human capital distribution; however, they have no interest in returning.

Due to emigration of the highly skilled, the GDP per capita among Southerners decreases down to 45% of the Southern autarky level. Obviously, the joint income of Southerners at home and Southerners abroad is higher, but still only 50% of its autarky level. Thus, we may conclude that the brain drain hurts the Southern economy. This result confronts Mountford's (1997) idea that emigration possibility increases learning incentives and thus may be beneficial for home country.

I have tested the one-way migration steady state with different values of θ (institutional quality). As long as the Southern institutions are worse than that of the North, one-way emigration is incentive-compatible in the steady state: nobody wants to return.[10] With improved institutions, the "king of the hill" effect gets stronger: the bargaining position of the highly-skilled individuals improves, and they get a better reward for training those below

[10]Return migration only may exist during the transition from one steady state to another

Table 2: Effect of brain drain on Southern economy

Northern institutions	$\theta_N = 1$	$\theta_N = 1$
Southern institutions	$\theta_S = \frac{1}{6}$	$\theta_S = \frac{1}{12}$
Northern income	100.00	100.00
Southern income: autarky	57.50	47.23
Southern income: migration	45.08	27.86
Income of emigrants	138.21	126.39
Income of all Southern-born	49.74	32.82
Emigration fee	3040	3340
Emigrants' skill selection rate	1.31	1.46
Emigrants' skill percentile	78	88

them. Conversely, with worse institutions the "king of the hill" effect weakens until it totally disappears: when institutions are bad enough, the very best people emigrate. I have computed the *selection rate* defined as the ratio of the emigrant's average skill to average skill of all Southerners.[11] In experiments, it is inversely related to the quality of institutions: as the institutional quality improves from $\theta = 1/12$ to $1/6$ (benchmark), the selection rate decreases from 1.46 to 1.31. The summary statistics of the effect of brain drain on the Southern economy is given in table 2

This negative relationship is supported by the data. Docquier and Marfouk (2004) provide data on the stock of migrants from most world countries to the OECD countries, disaggregated by three levels of skill (low, medium, high). Based on this data, I calculate the selection rate, by country of migrants' origin, as the fraction of the highly-skilled among emigrants, divided by the fraction of the highly-skilled among all workforce at home. As a proxy for institutional quality, I use the "government effectiveness" from the cross-country dataset constructed by Kaufmann, Kraay and Mastruzzi (2006). They define the government effectiveness as

> the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality

[11] Emigrant's skill is measured at the moment of migration

Table 3: Effect of brain drain on Southern economy

Dependent variable: selection rate			
Explanatory variables	Value	Std.err.	t-stat.
Constant	6.1685	0.9115	6.7677
Govt. effectiveness	-3.5315	0.7823	-4.5145
Workforce at home (mln)	0.0132	0.0117	1.1306
Landlocked country dummy	6.3973	1.9167	3.3377

of policy formulation and implementation, and the credibility of the governments commitment to such policies

I regress the selection rate on the government effectiveness and a couple of control variables; the results are shown in table 3.

The effect of the government quality on the selection rate is negative and significant, which supports the predictions of the model.

2.4 Improved institutions and return migration

2.4.1 The story

What happens if the South improves its institutions to the Northern level? In the rest of the paper, I study the effects of unexpected institutional improvement on the Southern economy. To isolate the effect of return migration, I compare two scenarios: return migration is allowed and free; return migration is prohibited. In both scenarios, I assume that the Northern government preserves its 5% quota on immigrants at any moment of time.

The long-run effect of the institutional improvement is trivial: under both scenarios, the Southern economy converges to the Northern steady state.[12] The interesting question here is the *speed* of adjustment, which appears to

[12] At least, no "poverty traps" have been discovered

be drastically different. Approximating the speed of adjustment, however, requires to calculate the equilibrium transition path. Appendix A.2 describes the computational strategy.

2.4.2 Results

No return migration The institutional improvement has instantaneous effect on bargaining. Now, changing partners becomes easy; high-skilled individuals ask a higher reward for teaching. The benefit of emigration drastically decreases; for people with very high human capital it becomes negative, which means that highly-skilled emigrants would return if they could (figure 9 demonstrates new migration incentives). The emigration pattern changes; the emigrants have lower skill than before: about 45 (the Southern median skill), compared to 60 (about 78th percentile) before the reform. The new emigration pattern doesn't hurt the Southern economy as much. The 5% emigration quota is still fully used; the flow of emigrants each period does not change.

Return migration possible With poor Southern institutions, emigrants left for good; while living in the North, they acquired a lot of human capital. Figure 9 shows that highly-skilled emigrants are better off from returning home, when institutions improve. Intuitively, high skill is scarce in the South; with efficient institutions, highly (by Northern standards) skilled emigrants can earn more by returning and training highly (by Southern standards) skilled locals.

As a result, in the first year following the reform, about 10% of emigrants, the most skilled ones, return, greatly expanding the frontier of available human capital. In subsequent periods, the following migration pattern arises: some individuals with medium (around 40) human capital emigrate; once they acquire a sufficient amount of knowledge in the North, they return. The average human capital of return migrants is about 120, far above locals'

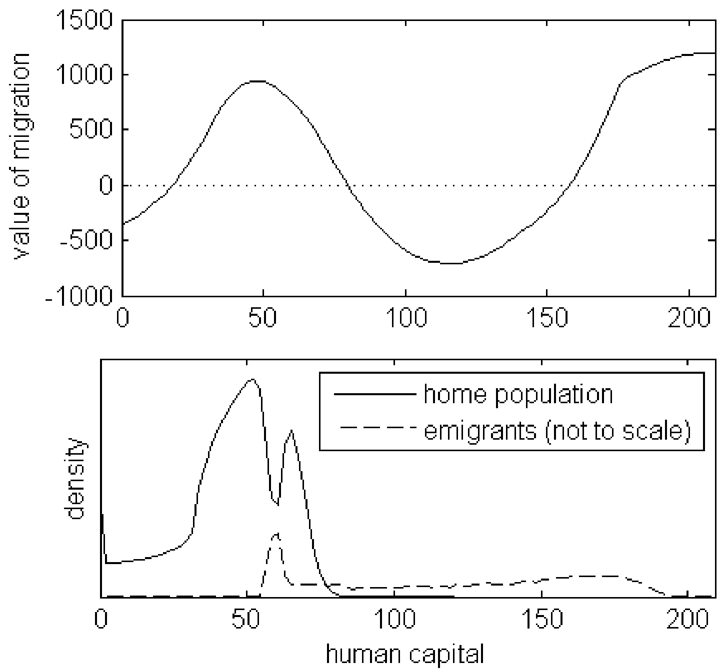


Figure 9: Benefits of emigration from the South, depending on human capital, immediately after the reform
Negative benefit implies willingness to return. Lower figure shows Southern human capital distributions at the moment of reform

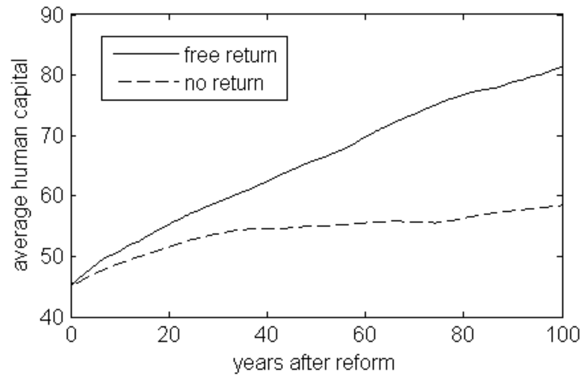


Figure 10: Evolution of economy aggregates under the two scenarios

human capital. Overall, about 55% of all emigrants return. Due to high return migration, the North admits more immigrants every period of time which causes higher migration flows.

Still, the flow of return migrants is very small: on an average year, the number of return migrants is about 0.1% of total Southern population. Nevertheless, the effect of return migration is tremendous: the returnees bring home knowledge that was previously unavailable; this knowledge is disseminated onto other Southerners. Figure 10 compares the average Southern human capital growth with and without return migration. With return migration, the growth is approximately three times faster. Figure 10 also demonstrates the evolution of per capita GDP under the two scenarios. In the first five years following the reform, both scenarios produce similar results. Immediately after the reform, GDP drops by about 40%: with better institutions, many existing partnerships are terminated, and skills are reallocated in a new, more efficient way. By the end of the second year, GDP is restored to its original level and then continues its growth. After the fifth year, the difference between the two scenarios becomes apparent; the economy grows faster with return migration. Again, GDP growth is about three times faster when return migration is available.

Figure 11 disaggregates the transition path: it shows human capital dis-

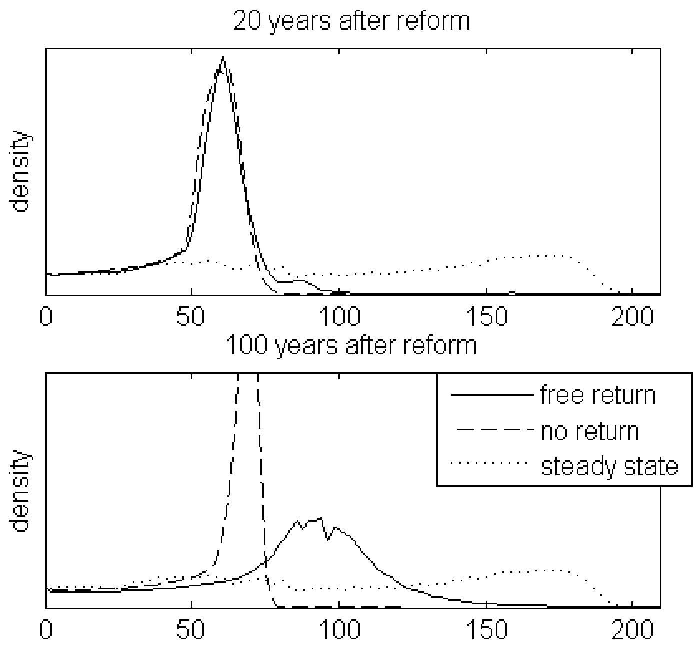


Figure 11: Distribution of human capital before and after the reform

tributions under the two scenarios, twenty and one hundred years after the reform. After twenty years, the difference between the two scenarios seems small, but return migration brings a long thin tail of highly skilled individuals. Their skill gradually disseminates onto locals through the matching process, and by the year 100 the difference between the two scenarios becomes obvious. Without return migration, most people get close to Southern knowledge frontier (around 70), but expansion of that frontier is a very slow process; without knowledge spillovers from the North, it may take thousands of years to catch up. With return migration, the highest available knowledge in the South (around 150) is just slightly below that of the North; it will probably take another hundred years to get close to Northern human capital distribution.

2.5 Conclusion

This paper constructs a model of "local" knowledge spillovers, in which less skilled individuals learn from more skilled partners; the matching of partners is random. The quality of country institutions, modeled as the degree of matching frictions, greatly affects the accept-reject decisions in the matching process and thus affects the long-run distribution of human capital available on the job market.

When migration becomes available between countries with good (North) and bad (South) institutions, highly-skilled Southerners emigrate for good, leading to a permanent deterioration of the Southern human capital distribution.

When the South improves its institutions to the Northern level, the most highly-skilled emigrants return, because the payoff of being the "king of the hill" in the South now outweighs the payoff of having smarter partners in the North. The return migrants bring home previously unavailable knowledge; local population learns from the return migrants which leads to a rapid human capital growth. Along the equilibrium transition path, the average number of return migrants per year is only about 0.1% of local population; despite their small number, they triple the economy growth after the institutional improvement, compared to no-return-migration scenario.

3 Return Migration: an Empirical Investigation

3.1 Introduction

Many emigrants eventually return home. Yet, little is known about the returnees. Are they more or less successful than those who stayed abroad? Does the return propensity increase or decrease with age? Are family ties significant for decisions to return? How do the return patterns depend on their home country culture and economic performance?

In this paper, I analyze empirically the factors affecting return migration. I use Current Population Survey (CPS) data collected by the U.S. Census. This database has three features that make it particularly useful for a study of return migration. First, its size: there are hundreds of thousands person observations available each year. Second, its information on nativity of respondents: the survey identifies immigrants from over 90 world countries and territories, which enables a cross-country analysis. Third, the sample design: each address is questioned several times during two consecutive years, which makes observations longitudinal. By observing respondents prematurely leaving the sample, we can estimate the fraction of immigrants leaving the US, as a function of individual and home country characteristics.

Indeed, an individual may drop out of the sample not only due to emigration, but also due to death, due to moving to another address in the US, and simply due to refusal to continue participation in the survey. All these outcomes cannot be directly identified in the data; in this paper, I develop a methodology for accounting for these causes when the propensity to return home is estimated.

Another problem is that the decision to return is not always voluntary; it is often the case that the US government requires immigrants to leave.

This requirement is very likely to depend on personal characteristics, such as education and family ties, as well as the nativity of the immigrant: one might expect that extending their stay in the US is much easier for a person from the UK than for a person from Afghanistan, all other things being equal. Given these considerations, one might think of a supply-demand model: the US government provides the supply of visas or green cards, depending on immigrants' characteristics, and foreign-born individuals demand these visas depending on the same characteristics. Separating supply from demand, however, remains a methodological problem, which was not solved in this paper. I only estimate the dependence of observed outcomes on observed immigrant characteristics.

3.1.1 Existing methodology

Overall, return migration is a scarcely studied topic due to lack of data. Data is usually collected within one country, and therefore migrants are not tracked as they move across borders.[13] Given this data limitation, the common approach to approximate return migration is to estimate the number of people which "disappear" from the host country over time. Historically, two methods have been used.

Repeated cross sections With two repeated cross-section nationwide databases (such as decennial US Census), one can use the method developed by Warren and Peck (1980). In economic literature, a version of this method has been used by Borjas and Bratsberg (1996). According to this

[13] The only known exception is the dataset constructed by German *Institut fur Arbeitsmarks und Berufsforschung* (IAB) which contains information on Turkish migrants returning home from Germany, both before and after their return migration. The study, however, focused only on individuals intending to return, and therefore cannot be used to compare returnees and non-returnees. Since it includes only one home and one host country, it cannot be used for cross-country analysis. Dustmann and Kirchkamp (2002) provide a study based on this dataset

approach, the entire sample is divided into non-overlapping groups (e.g., immigrants by country of birth). The decrease in the number of migrants within a certain group can be attributed to return migration. Indeed, the researcher should exclude all new migrants, arriving between the two dates (and therefore must observe everyone's year of entry). One observation is thus not an individual, but a subsample of individuals (e.g. all immigrants from Kenya). This method is suitable for studying macroeconomic factors affecting return decisions, but not particularly useful for studying demographic characteristics of return migrants. Indeed, we can disaggregate immigrants by exogenous characteristics (gender, age, year of entry into the host country.[14]) But variable characteristics such as education cannot be controlled for, because individuals can make unobservable transitions from one educational group to another. For example, the number of low-skilled immigrants may decrease not only due to emigration or death, but also because some of them have acquired more skill.

One more problem with using repeated Census data is incomplete coverage of the population. In theory, the Census should interview *all* residents of the country. In reality, a small share of population, especially foreign-born population, is not covered. Moreover, the coverage is improving over time, causing a strong downward bias in return migration estimates. For example, the number of people born in country X who entered the US before 1990 must decrease between years 1990 and 2000, due to death and emigration. But due to improved coverage between dates 1990 and 2000, the estimated number of these people may actually increase, resulting in low or even negative return migration estimates.

Panel data With longitudinal/panel data, dropping out of the sample may be attributed to return migration (of course, one has to eliminate other causes of dropping out such as death). The popular sample is German Socio-

[14]the year of entry is exogenous in the sense that it cannot be changed after the person has immigrated

Economic Panel (GSOEP) which has been used, among others, by Kirdar (2004), Bellemare (2004), Constant and Massey (2003). The strength of GSOEP is that it follows individuals when they migrate within Germany,[15] thus greatly reducing the dropout rate and allowing to identify return migrants more accurately. A shortcoming of GSOEP is that it covers immigrants from relatively few countries (mainly, Southern Europe) and therefore does not allow to study the effect of home country characteristics on the decision to return.

In contrast with Germany, the United States has a large population of immigrants from most world countries, making it the best object of study when cross-(home)country differences in migration patterns are in question. And the largest longitudinal source of data about the US immigrants is the Current Population Survey, making it a natural choice of a researcher interested in return migration patterns: it allows to study the effects of both personal characteristics, and home-country macroeconomic characteristics, on the decision to return. None of other known datasets allows to study the effect of both of these groups simultaneously.

A methodology for estimating return migration using the CPS data was developed in the demographic literature (Van Hook *et.al.* 2006) and, to my knowledge, has not been used in the field of economics. Demographers, however, are mostly interested in estimating the total number of returnees, as it allows to estimate the population remaining in the US more accurately. In contrast, the main goal of this paper is to estimate not the amounts of return migration, but the factors affecting the decision to return. Hence, the estimation methodology proposed in this paper is considerably different from Van Hook *et.al.* (2006), although the same data source was used.

[15]which is not the case in the American CPS

3.1.2 Existing hypotheses and findings about return migration

Historically, two disjoint sets of hypotheses about return migrants have been discussed: how return migration patterns differ by country of origin, and how they differ by personal characteristics such as age, gender, human capital or job market performance.

The studies of return migration depending on home country characteristics usually find that immigrants are more likely to return to wealthier and to geographically closer countries (e.g. Jasso and Rosenzweig 1982, Borjas and Bratsberg 1996). In this paper, home country GDP is found insignificant for return migration decisions, while distance to home does matter, but not for all groups of immigrants. Borjas and Bratsberg (1996) also find that migrants from Communist countries[16] are far less likely to return than others. This finding hints that large institutional differences between country X and the US makes immigrants from X much less likely to return home from the US. A similar pattern is observed in this paper: immigrants from muslim countries, which have vast institutional and ideological differences from the US, rarely leave the US. At the same time, institutional differences between the US and ex-Soviet countries have diminished, and immigrants from those countries are not much different from other immigrants.

The effect of personal characteristics also received attention in the literature. In this literature, there exist undisputable findings such as: family ties at home increase the likelihood of return; family ties in the host country reduce the likelihood of return; recent immigrants are more likely to return than others. In this paper, these finings are confirmed. At the same time, it is unclear whether more successful or less successful immigrants are more likely to return; Constant and Massey (2003) report a dozen of different studies, with widely ranging results. I find that unskilled migrants return more often;

[16] they use data on US immigrants in the 1970's

also, personal and home-country characteristics affect skilled and unskilled migrants somewhat differently.

The interaction of macroeconomic and personal characteristics, to my knowledge, has never been discussed, due to data limitations. For example, does the difference between male and female immigrants depend on the country of origin? It is quite likely that gender differences for immigrants from OECD countries are not the same as gender differences among those born in muslim countries. Similarly, it may (or may not) be the case that unskilled immigrants from different countries have much higher heterogeneity in return migration decisions than their skilled counterparts. The methodology offered in this paper allows, possibly for the first time, to test such hypotheses.

3.1.3 Return migration vs. emigration to third countries

When estimating the fraction of immigrants leaving the US, we cannot claim that they necessarily return home: part of them could go to third countries. Given limited data availability, it is not possible to estimate accurately how many foreign-born emigrants choose to return home, and how many migrate to third countries. However, a partial inference can be made using Integrated Public Use Microdata Series (IPUMS) which provides large (up to 10% of population) samples collected in several countries of the world. The IPUMS database has a particularly good coverage of the Latin countries: it has data from Mexico, Costa Rica, Colombia, Brazil, Argentina, and Chile, covering most of the Latin world.[17] Information from another likely destinations of Latin foreign-born leaving the US – Spain and Portugal – is also available. Using this information, we can estimate the number of, say, Mexican-born individuals who migrated to the US and then either returned to Mexico (re-

[17]Samples from Ecuador and Venezuela are also available, but they lack data on previous migration experience which is vital for identification of return- and third-country migrants

Table 4: Return migration vs. third-country emigration

Home country	Living in US	returned home from US in past 5 yrs	moved to 3rd country from US in past 5 yrs
Mexico	9.3M	267,000	386
Costa-Rica	76,000	4,820	146
Colombia	526,000	22,370	555
Brazil	223,000	12,600	209
Argentina	131,000	4,310	424
Chile	84,000	5,550	204

Note: possible "third countries" are countries listed in first column (excluding home country), Spain, Portugal.

turn migrants) or migrated to all other countries listed above (third-country migrants). The same exercise can be done for all other Latin countries listed above. The results are listed in table 4. Mexicans leaving the US rarely travel to third countries; among other countries, about 97% of those leaving the US return home and 3% go to other destinations (Argentina is a notable exception with 90/10 ratio). Given these results, we may conclude that migration to third countries is a rare phenomenon compared to return migration. Throughout the rest of the paper, I ignore migration to third countries and assume that all immigrants leaving the US return home, and the terms "emigration of the foreign-born" and "return migration" are used interchangeably.

3.2 The method

3.2.1 The main model

Consider an immigrant i living in the US at date t and making choices that affect his/her status at year $t+1$. Generally, the following outcomes are possible:

- stay in the same house – in this case, the immigrant would be observed twice if a survey visits his/her house in years t and $t+1$;

- move to another address in the US;

- emigrate from the US;

- die – of course, this is not the choice of an immigrant but rather an exogenous random process.

I assume that these outcomes are produced by the following discrete choice model. First, the "nature" chooses whether the individual i dies or lives, depending on his/her personal characteristics and an exogenous random process. The following "mortality" function (by analogy with utility function) is computed:

$$U_{di} = X_i \theta_d + \epsilon_{di}$$

where X_i is a vector of observed personal and home country characteristics, θ_d is a vector of parameters labeled as the "propensity to die", while ϵ_{di} is the unobserved component affecting death incidence. The latter is assumed to be drawn from a known distribution and i.i.d. across individuals.

I assume that the individual dies if $U_{di} > 0$ and lives otherwise. Assuming logistic distribution of ϵ_{di}, the probability that the individual dies is

$$P_{di} = \frac{e^{X_i \theta_d}}{1 + e^{X_i \theta_d}}$$

where θ_d reflects the propensity to die, depending on personal characteristics.[18]

[18] The choice of logistic distribution for ϵ_{di} was motivated by the fact that θ_d was borrowed from another research which used the logit model for estimation, see section 3.2.2 for details.

If the individual i lives, he chooses whether to stay in the US or return home. The utility from return is

$$U_{ei} = X_i\theta_e + \epsilon_{ei}$$

where θ_e is the propensity to emigrate, and ϵ_{ei} is unobserved i.i.d. random shock drawn from a normal distribution. The utility from non-return is normalized to zero; thus the individual emigrates if $U_{ei} > 0$ and stays in the US otherwise. Assuming independence of ϵ_{ei} from ϵ_{di},the probability of emigration, conditional on not dying, is

$$P_{ei} = 1 - \Phi(-X_i\theta_e) = \Phi(X_i\theta_e)$$

where Φ is the standard normal cumulative distribution function.

Finally, if i does not emigrate, he/she chooses whether to move to another address in the US or stay in the same residence. The model of moving/not moving choice is analogous to the model of emigration. The propensity to move is labeled θ_m; the unobserved component ϵ_{mi} is normally distributed and independent across individuals. ϵ_{mi} may or may not be independent from $\epsilon_e i$. If independent, the probability of moving, conditional on not emigrating and not dying, is

$$P_{mi} = \Phi(X_i\theta_m)$$

The implications of ϵ_{mi} dependent on $\epsilon_e i$ are discussed in section 3.2.3.

To estimate the model, I use the data provided by the Current Population Survey. Due to the nature of the data, the econometrician only observes whether the person has stayed in the same house one year later (about 73% of all foreign-born) or moved out for whatever reason. In the latter case, the econometrician does not observe what happened to the person: death, or return migration, or moving to another address. Therefore, we have to use some additional sources of information to estimate the chances of death and moving to another address, to figure out the propensity to emigrate θ_e which

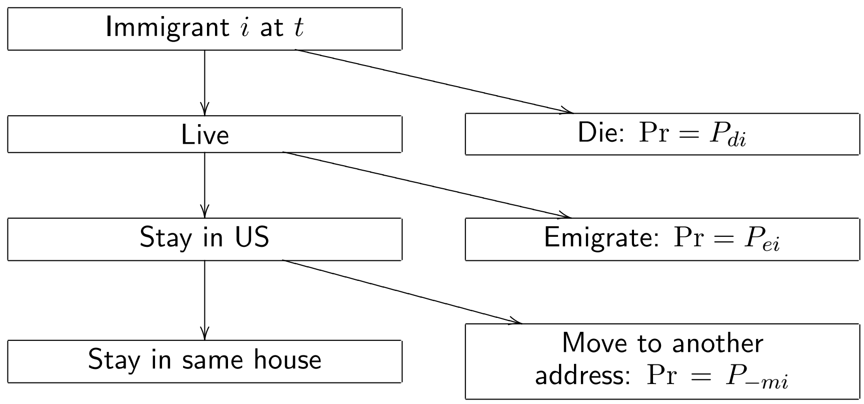


Figure 12: The discrete choice model

is out estimation target.

3.2.2 Additional data and model

Death rates The propensity to die, θ_d, was taken from Van Hook *et.al.* (2006) who use data from National Health Interview Surveys and National Health Index to estimate the death rate coefficients shown in table 5.

Mobility within the US To estimate the propensity to move within the US θ_m, we can use the information about recent migration experience of CPS respondents: they report where they lived one year ago. Since the CPS is a representative sample of the US population, the fraction of recent movers among the CPS respondents approximately equals the true fraction of movers within the US. It is true not only about the *entire* population but also about some groups of population such as foreign-born. Therefore, using recent mobility as a dependent variable in a binary logit model, with personal characteristics X serving as independent variables, should produce a good estimate of θ_m.

One problem related to estimating θ_m arises from the timing of mea-

Table 5: Death rates of immigrants, depending on personal characteristics

Variable	Logit model coefficient
Intercept	-2.017
Male	0.517
Race/Ethnicity (other = 0)	
Mexican	0.336
Other Hispanic	0.067
Non-Hispanic white	0.230
Black	0.176
Age (75 and over = 0)	
18-24	-3.984
25-34	-3.722
35-44	-3.324
45-54	-2.756
55-64	-1.818
65-74	-0.994
Health (poor = 0)	
Excellent	-1.181
Very good	-1.135
Good	-0.937
Fair	-0.586

surements. The model described in section 3.2.1 estimates probabilities of various events within one year, as a function of person characteristics at the *beginning* of the year. The proposed method of θ_m estimation, however, relies on information collected at the *end* of the period. Clearly, some person characteristics might change during the year: age obviously increases by one, educational attainment might improve, citizenship status and employment status might change. All these changes, except age, are not observed and hence cannot be controlled for, creating a possible bias in the estimation of θ_m.

The employment status is the most likely cause of bias because it changes more frequently than educational attainment or marital status or citizenship status, and because it is unclear whether unemployment causes mobility or vice versa. When estimating θ_m, we observe the employment status *after* moving to a new address; the observed positive correlation between mobility and unemployment implies that unemployment may be a *consequence* of recent mobility. However, when estimating the main model described in section 3.2.1, we assume that unemployment is the *cause* of mobility, whether internal or international. Therefore, applying the estimates of θ_m to the main model may produce spurious results. To prevent the problem, I do not use employment status, income, and other volatile characteristics in the regression.

3.2.3 The system of equations: correlated errors

As follows from the above discussion, fitting the model parameters involves estimation of the following system of equations:

$$\begin{aligned} y_i &= I(X_{di}\theta_d + \epsilon_{di} < 0) \times I(X_{ei}\theta_e + \epsilon_{ei} < 0) \times I(X_{mi}\theta_m + \epsilon_{mi} < 0) \quad i \in S_y \\ z_i &= I(X_{mi}\theta_m + \nu_i < 0) \quad i \in S_z \end{aligned}$$

Here y_i is the indicator that the individual i was followed up in year $t+1$, after being first interviewed in year t; I is the indicator function; S_y is the subset of all immigrants of ages 18-70;[19] z_i is the indicator that the person interviewed at t lived in the same house at $t-1$; and $S_z \subset S_y$ includes immigrants of ages 18-70 who lived in the US, either in the same house or at different address, in year $t-1$.

It is generally possible that errors ϵ_{di}, ϵ_{ei}, ϵ_{mi} and ν_i are correlated between each other. The correlation between death error ϵ_{di} and other errors is the least likely and not discussed in this paper; the remaining three errors are more likely to be mutually correlated.

Since the dependent variable in the first equation, y_i, does not depend on ν_i, while the second dependent variable z_i does not depend on $\{\epsilon_{ei}, \epsilon_{mi}\}$,

[19] younger immigrants were excluded because they are unlikely to make individual decisions, and older immigrants were excluded because the probability of death, as well as the error in estimating that probability, is too high

accounting for possible correlation between ν_i and $\{\epsilon_{ei}, \epsilon_{mi}\}$ is not necessary for obtaining consistent estimates of model parameters. But possible correlation between ϵ_{ei} and ϵ_{mi} cannot be ignored, as it may bias the estimate of θ_e. Identifying the correlation between ϵ_{ei} and ϵ_{mi}, however, remains a methodological problem: there are four unobserved errors and only two observed dependent variables, hence the errors cannot be identified.

The problem can be partially solved by accounting for correlation between ν_i and $\{\epsilon_{ei}, \epsilon_{mi}\}$. The following error structure can be specified:

$$\begin{aligned} \epsilon_{ei} &= \phi_e \nu_i + \zeta_{ei} \\ \epsilon_{mi} &= \phi_m \nu_i + \zeta_{mi} \end{aligned}$$

where ζ_{ei} and ζ_{mi} are normal i.i.d. residuals. However, even this assumption does not fully identify the model: we still cannot separate ϵ_{ei} from ϵ_{mi} in the data. For identification of the unknowns, I use the data on another group of the CPS respondents: second-generation Americans (children of immigrants). The following assumptions are made about this group:

- The parameter ϕ_m specified above is the same for the foreign-born and the second-generation Americans. In other words, correlation between past and future mobility within the US is the same for these two groups of respondents. Since second-generation Americans are closer (or, at least, not more distant) to immigrants than any other comparison group, their mobility patterns are the closest to that of immigrants. Indeed, they might still be unequal, but there is no information to identify the difference.

- Second-generation Americans never emigrate. Docquier and Marfouk (2004) report that only 0.4% of US-born working-age population live in other OECD countries. Indeed, some US-born also live in countries other than OECD, but their number is probably even smaller, hence the total number of emigrants should be far below 1% of US adult population. Even if second-generation Americans have a somewhat higher propensity to live outside of the US,[20] these numbers are still incompatible with the estimate of 30% of first-generation immigrants eventually leaving the US (Warren and Peck 1980). With this assumption, we have enough data to identify ϕ_m for the second generation Americans.

3.2.4 The estimation algorithm

The following algorithm estimates the propensity to emigrate, given all above considerations.

First, I estimate ϕ_m, the correlation between past and future internal mobility, using the data on second-generation Americans. I estimate their propensity to move internally, θ_m, by regressing the follow-up indicator y_i on observed characteristics X_i and past mobility indicator z_i.[21] The coefficient for this last regressor, past mobility, is a proxy for ϕ_m, correlation between past and future mobility.

Second, I estimate internal migration propensity θ_m of foreign-born by regressing past mobility z_i on personal characteristics X_i. A simple probit model is used.

Third, I compute the probability P_{mi} that a person moves within the US after the first interview, as a function of observed characteristics X_i and past mobility data z_i. For the former, I use coefficients θ_m estimated in the second step, while for the latter I apply ϕ_m from the first step.

Fourth, I compute the propensity to emigrate θ_e, as a function of personal characteristics and past mobility, after adjusting for the probability of respondent's death and moving within the US.

All estimates are made using the Maximum Likelihood method.

[20] from table 9, their likelihood of living abroad is twice as high

[21] The probability of death was also accounted for

3.2.5 Independent variables: age-period-cohort problem

Among factors that might affect return migration probability, the econometrician may be interested in the following:

- the age of the immigrant. Predicted effect on return migration – uncertain;

- immigrant's duration of stay in the host country: expected to have a negative effect on return probability;

- immigrant's age at entry: should have a positive effect, because younger people assimilate more easily.

These three regressors cannot be directly and simultaneously used in the model because of the collinearity: age equals age at entry plus duration of stay. In the sociological literature this problem, named the age-period-cohort problem,[22] has been discussed since early 1970s, and a number of methods have been developed; see Mason and Wolfinger (2002) for a review. The easiest solution is, indeed, simply to exclude one of these variables from the model. In this paper, I exclude the age of the immigrant and keep duration of stay and age at entry. However, where second-generation Americans are involved, I use their age only because the other two characteristics are not applicable for non-immigrants.

3.2.6 Shortcomings of the method

One disadvantage of this method is that the return migration estimate is not guaranteed to be positive for *all* subsamples of the data. Suppose that some group of people drop out of sample with probability 10%. It may happen that

[22]In classical literature on this problem, the three variables are age, year of observation (period) and year of birth (cohort)

the estimated probability of dropping out for reasons other than migration (that is, moving internally or death) is actually higher than 10%, forcing the emigration probability to be negative. In the logit model, negative probability is impossible; in such cases, the estimation algorithm tries to reduce θ_e down to negative infinity (making emigration probability equal to zero). As a result, computational time greatly increases, and estimates become less accurate. To avoid the problem, I set lower bounds on θ_e parameters.

Another problem is assumed independence of residuals ζ_{ei} and ζ_{mi}. It is generally possible that unexplained willingness to emigrate ζ_{ei} is positively correlated with unexplained willingness to move within the US ζ_{mi}. Accounting for this correlation, however, is impossible, because we do not observe whether the person has died or emigrated or moved if he/she was not followed up.

One more problem is assumed independence across observations: we assume that observations i and j are completely independent from each other. It is most likely not the case if two individuals are members of the same household: their propensity to move or emigrate may be correlated. Since the information on family relationships is available in the CPS data, it is theoretically possible to account for inter-person residual correlations. However, doing so considerably complicates the model; solving this problem is a subject of future research.

3.3 Data

This paper uses data which can be divided into two major categories: person-level and country-level data. The former is information about immigrants in the US, the latter is about their home countries. All data covers years 1998-2007.

3.3.1 Person Data: Current Population Survey

The Current Population Survey is a project administered by the US Census Bureau since early 1940s. Its main goal is to collect data on the US labor force characteristics. Currently, the CPS visits about 100,000 (65,000 before 2002) addresses across all of the US every month. Each month, one-eighth of all addresses are replaced by new randomly chosen addresses, thus each address is visited and interviewed exactly eight times.[23] The visiting pattern is as follows: every address is visited four consecutive months, then left out for eight months, and then visited for four more months. In the dataset, the interviews are numbered by the *month in sample* variable. For example, a household could be visited monthly from February to May 2004 (months in sample 1-4), and then again February to May 2005 (months in sample 5-8). The list of questions asked varies from month to month, but generally consistent across years.

In this study, I use the data collected in March of years 1998-2007. The March survey is the most commonly used by economists and demographers, because it contains the most comprehensive list of socioeconomic questions. Since the interviews are conducted for two consecutive years, each address that was visited in March of year t, must have been also visited either in year $t-1$ or in year $t+1$ (but not both). Consider an example given above: an address visited from February to May 2004, and then again February to May 2005. Since we use March samples only, we observe this household twice: March 2004 (when it was visited for the second time, month in sample = 2) and in March 2005 (month in sample = 6). By observing people living at this address at both dates, we can identify those who have left during the year for whatever reason.

To match person records across years, we have to conduct three steps:

[23] except a small number of addresses which became non-residential between visits

Table 6: Number of duplicate address ID's

year	unique ID	2 duplicate ID's	3+ duplicate ID's
1998	64,656	0	3
1999	65,327	38	12
2000	64,857	78	9
2001	64,246	102	14
2002	61,283	33,930	3,635
2003	93,390	6,320	276
2004	93,324	5,372	283
2005	98,664	0	0
2006	97,352	0	0
2007	98,015	0	0

first, match addresses across years; second, identify whether an address is occupied by the same household; third, match person records for the same household across years.

Matching addresses Each address is identified by *household identification number*, which is supposed to be unique for a given combination of sample year and month-in-sample. In practice, however, there are many occasions of duplicate ID's before the year 2005 when the identification methodology was improved. The number of duplicate ID's peaked in year 2002, when only about 60% of ID's were unique. To prevent potential erroneous matches, I dropped all addresses with non-unique ID's. Since the ID's were assigned by the CPS staff, most likely they were not correlated with household characteristics, and therefore dropping ambiguous records should not bias the estimation results. After removing ambiguous records, addresses were matched across years; records without a match were dropped.

Matching households To identify whether the same household lives at an address one year later, the CPS dataset contains the *household number*. In theory, the household number is equal to one during the first interview; in subsequent interviews, it remains the same if the address is occupied by the same household, and increments by one otherwise. In practice, the household number sometimes *decreases* over time (about 0.2% of all addresses), which implies it could be recorded with an error. An erroneous household number could result in both erroneous match (two different households are treated as one) and erroneous mismatch (two records one the same household are treated as different households), causing noise in observations. To account for these errors, I conduct additional checks as described below.

Matching individuals Usually there are several people living in a household; these people are differentiated by the *line number*. The line number is constant over time for the same person. When a person moves out, the line number is left blank in subsequent interviews. When a new person moves in, he/she is assigned a new (unique) line number. However, when the entire household moves out and is replaced by another household, the line number count starts over. Thus, if two different households were erroneously treated as the same household, the line numbers of two different people could match. To estimate the likelihood of a possible mismatch, I check for consistency of other information supplied by individuals at different dates.

Quality of matching To check whether person records were matched correctly, I check the consistency across years of the following three additional characteristics:

- gender
- age: generally should increase by one. Since the interviews were conducted not *exactly* one year apart, age remaining the same and increasing by two were also accepted
- migration status: "place of residence one year ago" reported in the second year. Respondents should report that they lived in the same place at the time of the first-year interview

Table 7: Person record matching outcomes, respondents of age 18-70
Percentage points in parentheses

number of matching additional characteristics	same household number	other household number
All three	248,236 (92.85)	555 (1.43)
Two	12,614 (4.72)	3,066 (7.92)
One	4,612 (1.73)	8,820 (22.78)
None	1,887 (0.71)	26,281 (67.87)
Total	267,349 (100.00)	38,722 (100.00)

The results are presented in table 7.

Overall, 267,349 (78.11%) of all person records could be matched across years according to *household number* parameter.[24] Of them, 92.85% have consistent sex, age, and migration status; 4.72% have a mismatch in one of those characteristics; remaining records have a mismatch in two or all three characteristics.

These results could be produced by erroneously recorded personal characteristics. To approximate the probability of an error in a certain characteristic, I calculate the frequency of a mismatch in this characteristic, conditional on all other characteristics matching. For example, there are 464 observations in which gender doesn't match, while household number, age, and migration status do. Similarly, there are 7,945 (4,205) observations in which age (migration status) is the only mismatching characteristic. Table 7 indicates that there are 555 records with a similar mismatch in the household number: while age, gender, and migration status match (meaning that this is most likely the same person), the household number is different.

Apparently, the household number and gender are much higher quality observations – they are ten times less likely to be recorded with an error. Possibly, there are fewer errors because these characteristics are identified by

[24]In theory, we should check the consistency of the household number for all household members simultaneously. But for computational speed, all persons were treated independently

Figure 13: Distribution of reported age

the interviewer, while age and migration status are reported by the respondent. It is quite likely that the respondent does not remember the exact date of moving to the current residence, or misunderstood the question. It is also possible that the respondent has rounded up his/her age. Figure 13 reports the distribution of respondents' age; there are clearly visible spikes at years 25, 30, 35, etc., which implies that a good number of people are rounding up. It is quite likely that people with certain characteristics (e.g. low education, or foreign-born) are more likely to round up age than others. For example, among natives, 1.98% of all respondents have a mismatch in age (while other characteristics match), while among foreign-born individuals, this figure is 4.43% – more than twice as high! Thus, using age as one of the matching criteria may lead to biased results in the analysis of return migration.

Throughout the paper, I match person records using the household number only. To check for robustness of results, I use an alternative matching rule: person records are matched if at least three out of four characteristics (household number, gender, age, migration status) match. See section 3.4.3 for the results of robustness checks.

Table 8: Observed year $t+1$ outcomes, for respondents of age 18-70
Percentage points

Year-2 observed outcome	natives	second generation	foreign-born
(1) Person followed up	78.91	77.67	73.14
(2) Person absent, same household	5.09	6.02	6.48
(3) Address occupied by other household	5.64	5.87	8.44
(4) No second interview	5.47	5.75	5.82
(5) Vacant address	4.89	4.68	6.11
Number of observations	272,294	22,521	47,450

Description of observed year $t+1$ outcomes For a person observed in year t, the following outcomes can be observed in year $t+1$: (1) person observed again (followed up); (2) person absent, the address is occupied by the same household; (3) the address is occupied by a new household; (4) the second interview could not be conducted (e.g., no one was at home, or the respondents refused to continue participation); (5) the address was vacant in year $t+1$. Outcomes (2), (3), and (5) imply that the person is no longer living in that residence (for whatever reason – death, emigration, or moving to a new address). The fourth outcome is the most problematic: it does not give any information whether the person is still living there or not. The frequencies of these outcome are reported in table 8, for three groups of respondents: natives (US-born respondents with US-born parents), second-generation Americans (US-born with at least one foreign-born parent), foreign-born.

For comparison, table 9 summarizes information on self-reported recent mobility experience of respondents.

The first group of respondents, natives, are the least likely to emigrate: only 0.15% of them returned to the US from abroad within the last year, with probably the same fraction of them moving abroad from the US. Therefore, most of non-followup outcomes (table 8) should be attributed to mobility

Table 9: Reported migration experience in the past year
For respondents of age 18-70. Percentage points. Based on year-1 interview

Migration status, 1 yr ago	natives	second generation	foreign born
Lived in same house	85.94	86.38	82.21
Other house in US	13.90	13.33	14.98
Abroad	0.15	0.29	2.81

within the US, and non-followup rates, after some adjustments, should match up with self-reported mobility (table 9). Below, I verify whether the two sources of information about mobility of respondents match up.

Among natives, about 21% drop out of sample before year $t + 1$. Of course, people not responding to the second interview (the fourth outcome in table 8) do not necessarily leave their residence. Assuming that non-response is independent from mobility decisions, I drop those who did not respond; among the remaining population, only 16.5% were not followed up. Of them, some people could die rather than move. Assuming that the death rate for individuals of ages 18-70 is about 0.5%, we end up with about 16% of natives moving from one address to another. On the other hand, table 9 indicates that only about 14% of respondents lived at another address one year ago. The discrepancy in different estimates is about 2%. Given available information, this discrepancy cannot be eliminated.

Birthplace of CPS respondents The CPS asks respondents about their place of birth, which allows to identify immigrants, and about their parents' place of birth, allowing to identify second-generation immigrants. Overall, about 100 distinct home countries can be identified with that data.

Before use, several adjustments had to be made to the birthplace data. First, I exclude observations with too vague birthplace categories such as "other Central America" or "other Africa".

Second, I correct information on birth countries which no longer exist. For example, there are people who describe their birthplace as "Czechoslovakia"

Table 10: Immigrant count, ex-USSR and ex-Czechoslovakia

reported country of birth	immigrated in 1991 or before	immigrated after 1991
USSR	51	87
Latvia	22	9
Lithuania	24	36
Armenia	61	61
Russia	318	484
Ukraine	120	227
Czechoslovakia	68	8
Czech Republic	27	16
Slovakia	22	23

and those who were born in "Czech Republic". The criteria of choosing between the two options are not clear; the CPS does not provide any instructions regarding this issue. Table 10 reports the number of immigrants from such countries, disaggregated by the year of immigration.

A problem with dissolved countries of birth is that recently collected home country characteristics (e.g., recent GDP per capita) are not applicable to those countries, and therefore cannot be used as regressors. To handle this problem, I merge immigrants from dissolved countries with immigrants from the most likely successor countries. People born in Czechoslovakia were attributed to Czech Republic, those from Soviet Union were attributed to Russia. The resulting bias is expected to be small, because the number of immigrants with ambiguous birthplace is relatively small, and because successor countries (Czech Rep. and Slovakia, Russia and Ukraine) have similar institutions and similar economic performance.

3.3.2 Home country data

To study the effect of home country characteristics on return migration, I use several sources of country-level data. Most characteristics are disaggregated not only by country but also by year: this allows to study the effects of not only *levels*, but also *changes* in home country characteristics. Also, with only about 100 home countries observed, one cannot include more than 8-10 country characteristics (some of which are highly correlated) because of regressor collinearity problem. Disaggregation of country data by year greatly increases the number of macro-level observations, allowing to include all observed characteristics into the regression.

The distance between the US and the home country was calculated using the EuGene software (Bennett Stam 2000); it is measured as the shortest distance between national capitals. The missing data was filled manually using Google Earth software.

The economic data was taken from World Economic Outlook database compiled by the International Monetary Fund (IMF data henceforth). Years 1998-2007 were used. The two statistics used were GDP per capita (based on Purchasing Power Parity (PPP), in current prices), and the "exchange rate" defined as the ratio of PPP-based GDP over nominal GDP.[25] This variable was created to verify the hypothesis that the decision to return may be related to a higher purchasing power of the US dollar at home.

Some countries and territories present in the CPS sample are missing in the IMF data (Bermuda, Cuba, Iraq, Puerto-Rico). Information on these countries was taken from PennWorld tables (PWT, Heston Summers Aten 2006). Since this data is available only until 2004, I extrapolated GDP per capita using information on GDP and population growth for these countries; to fill missing exchange rates, I simply extrapolated the last available observation.

Statistics on one more country – Myanmar – was taken from the CIA World Factbook, because neither IMF data nor PWT had reliable information on this country.

The data on the quality of institutions was taken from "Governance" dataset compiled by Kaufmann, Kraay, and Mastruzzi (2006), which pro-

[25]an alternative definition is nominal over PPP exchange rate

vides the following measures: “Voice and Accountability”, “Political Stability”, “Government Effectiveness”, “Regulatory Quality”, “Rule of Law”, and “Control of Corruption”. The data is measured biannually between 1996 and 2002, and annually between 2003 and 2007. The observations for 1997, 1999, and 2001 were imputed by interpolating the 1996, 1998, 2000, and 2002 data.

In the Governance database, each country-year observation is made by interviewing a small number of experts that are familiar with the country. The observations are thus made with errors which are estimated by the dataset designers. Typically, the errors are higher in smaller and more remote countries, because fewer experts on these countries could be found. In theory, one has to account for these errors in regression analysis by giving a smaller weight to observations with higher error. For the purpose of this research, however, these measurement errors were ignored: in the CPS data, there are usually fewer immigrants observed from smaller countries; therefore these smaller countries will receive a lower weight in the regression anyway.

Another problem in the Governance data is a very high correlation between some measures. For example, the “rule of law” and “control of corruption” measures have a correlation of almost 97%. Therefore, these measures cannot be used all at once. Throughout the paper, I use the sum of all six characteristics as a measure of institutions.

Besides economic and political measures mentioned above, I include the following country dummies: English-speaking country (a measure of cultural similarity), an OECD country, a transition economy, a muslim country, and a small island country. The list of English-speaking countries was taken from EuGene database, all others were borrowed from Docquier and Marfouk (2005) data. Members of each group are listed in appendix B.

3.4 Results

3.4.1 Benchmark model

The results of the model estimation are given in table 11. Both emigration propensity θ_e and propensity to move internally θ_m are reported.

The propensity to move within the US θ_m has generally predictable patterns. Women, married people, those living in own house are less mobile. Higher education increases mobility within the US. Immigrants become less mobile as they spend more time in the US. The effect of age (age = age at entry + years in the US) is highly negatively significant: the probability that a person moves decreases by about 4% with each extra year of age.

Our main estimation target, the propensity to emigrate θ_e, is presented in the first column of table 11. Since this parameter was basically computed as residual non-followup, many coefficients have a considerably higher standard error than those of θ_m; nevertheless, most of them are significant.

The dependence of θ_e on personal characteristics has a pattern similar to that of θ_m. Women and married people return less often; recent immigrants and those without citizenship status are more likely to leave the US. Higher age at entry increases the likelihood of return, but the effect of current age (-0.029+0.005=-0.024) is negative: older people return less often. It turns out that less educated immigrants are more likely to leave the US. It could be not their own choice but the policy of the US government, which has more restrictive immigration and visa extension rules for those of low skill.

People living in muslim countries have very low rates of emigration to the West, including the United States (see Docquier and Marfouk 2005). From table 11, it follows that they are also far less likely to return – muslim immigrants appear to have made a firm choice not to go back, probably because of institutional differences. Borjas and Bratsberg (1996) made a similar finding about immigrants from Communist countries.[26] Home country institutions

[26] they used data collected in the 1970s, at the peak of the cold war

Table 11: Benchmark model

regressor	emigration	moving within US
notation	θ_e	θ_m
constant	0.059	-0.337
	(1.488)	(0.461)
person characteristics		
female	-0.167***	-0.061***
	(0.041)	(0.016)
married	-0.437***	-0.073***
	(0.042)	(0.017)
higher education	-0.172***	0.089***
	(0.058)	(0.018)
own house	-0.315***	-0.446***
	(0.045)	(0.017)
health	0.000	-0.017**
	(0.021)	(0.008)
age at entry	0.005**	-0.017***
	(0.002)	(0.001)
years in USA	-0.029***	-0.024***
	(0.003)	(0.001)
non-citizen	0.257***	-0.016
	(0.067)	(0.020)
home country characteristics		
Mexico	0.358***	-0.031
	(0.077)	(0.027)
English-speaking country	-0.136	0.032
	(0.103)	(0.026)
OECD country	0.063	0.070*
	(0.157)	(0.037)
transition economy	-0.283*	-0.083*
	(0.168)	(0.045)
muslim country	-1.030*	0.028
	(0.569)	(0.039)
small island country	0.080	-0.098***
	(0.098)	(0.035)
log(distance to US)	-0.133**	0.003
	(0.061)	(0.016)
log(GDP per capita)	-0.026	0.205
	(0.572)	(0.182)
exchange rate	0.067	0.016
	(0.075)	(0.022)
institutions	-0.018	0.003
	(0.018)	(0.005)
time trend (base=1998)	-0.020**	-0.025***
	(0.009)	(0.003)
past mobility error	0.010	0.323***
	(0.059)	(0.030)
# of observations	41974	40791

* – significant at 90%, ** – at 95%, *** – at 99% level. Standard errors reported in parentheses

do matter in making a decision to return. Not surprisingly, modern immigrants from ex-communist countries (transition economy dummy) do show only a modest difference from the rest of the sample – with changed institutions, migration patterns have also changed and became more "normal".

It is well known that residents of small island countries are far more likely to emigrate than others (Docquier and Marfouk 2005): one fifth of population living abroad, mainly in the US and Europe, is not uncommon for these countries. One might expect that such high emigration rates lead to shortages in the labor market at home, and eventually to higher return migration rates. According to table 11, this hypothesis is not confirmed: immigrants from small island countries are not any more likely to return than others. However, immigrants from these countries are still different from others; the difference is shown in table 14 and discussed in section 3.4.2.

Immigrants from geographically closer countries are found to me more mobile than others; this is especially true for those from Mexico. Apparently, people from closer countries are more likely to travel back-and-forth than others. People who travel back and forth, obviously, stay in the US for shorter periods and thus more likely to fall in the "recent immigrant" category. If there are more back-and-forth migrants from Mexico, we might expect that the difference in θ_e between recently immigrated Mexicans and other Mexicans is greater than such difference among non-Mexicans. This hypothesis is verified below.

The negative effect of distance to home on return migration was pointed out by Borjas and Bratsberg (1996). However, their other finding, the positive effect of GDP on return migration, could not be confirmed. The exchange rate (the purchasing power of the US dollar in the home country) is also not significant. The effect of institutions, measured as the sum of all six Governance parameters, is of the "wrong" (negative) sign. The insignificance of institutional measures may be due to the fact that there were no major institutional changes in 1998-2004, when the data was collected, and also due to measurement error of the institutional quality.

Overall, we may conclude that economic and Governance institutional characteristics of home countries cannot be used as powerful predictors of migration patterns. Country group dummies providing information about their geography and culture are more powerful determinants of migration patterns.

3.4.2 Emigration by gender, education, length of stay in US

In demographic literature, it is common to treat males and females (especially immigrants) separately, because they are believed to follow very different patterns. My research, however, did not find vast differences between genders in their return migration pattern; table 12 reports the results.

We can point out the large difference between muslim men and women: the coefficient for muslim women is -3 (the lower bound for this parameter, see section 3.2.6 for explanation). This basically means that they never return; in such cases, the estimates have large standard errors which prevent us from making judgements about significance of these estimates.

Table 13 reports migration differences by educational level. Immigrants from OECD countries stand out against others. Skilled immigrants from OECD are *more* likely to return than other skilled immigrants, which indicates that OECD-US skilled migration is a brain circulation rather than a brain drain. On the other hand, unskilled immigrants from OECD are *less* likely to return than other unskilled emigrants – possibly because of more favorable attitude of the US immigration authorities.

Also, Mexican skilled emigrants stand out against their non-Mexican counterparts much more than unskilled Mexicans do – this finding indicates

Table 12: Emigration by gender

regressor	female	male	difference
constant	-0.105	0.115	-0.219
	(2.138)	(2.003)	(2.929)
person characteristics			
married	-0.436***	-0.428***	-0.007
	(0.063)	(0.057)	(0.085)
higher education	-0.114	-0.189**	0.075
	(0.084)	(0.078)	(0.114)
own house	-0.290***	-0.339***	0.050
	(0.066)	(0.060)	(0.089)
health	0.058*	-0.052*	0.110***
	(0.031)	(0.028)	(0.042)
age at entry	0.008***	0.003	0.005
	(0.003)	(0.003)	(0.004)
years in USA	-0.018***	-0.036***	0.018***
	(0.004)	(0.004)	(0.006)
non-citizen	0.344***	0.164*	0.179
	(0.100)	(0.086)	(0.132)
home country characteristics			
Mexico	0.281**	0.422***	-0.141
	(0.114)	(0.102)	(0.153)
English-speaking country	-0.074	-0.185	0.111
	(0.140)	(0.145)	(0.201)
OECD country	0.123	-0.008	0.131
	(0.210)	(0.229)	(0.311)
transition economy	-0.197	-0.345	0.148
	(0.243)	(0.223)	(0.330)
muslim country	-3.000	-0.578*	-2.422
	(327.219)	(0.318)	(327.220)
small island country	0.016	0.128	-0.111
	(0.135)	(0.138)	(0.193)
log(distance to US)	-0.141*	-0.116	-0.025
	(0.081)	(0.088)	(0.119)
log(GDP per capita)	-0.128	0.004	-0.132
	(0.831)	(0.760)	(1.126)
exchange rate	-0.020	0.118	-0.138
	(0.115)	(0.097)	(0.150)
institutions	-0.030	-0.010	-0.020
	(0.025)	(0.025)	(0.035)
time trend (base=1998)	-0.028**	-0.016	-0.013
	(0.013)	(0.012)	(0.018)
past mobility error	-0.008	0.040	-0.048
	(0.097)	(0.074)	(0.122)
# of observations	21529	20445	

* – significant at 90%, ** – at 95%, *** – at 99% level

Table 13: Emigration by educational level

regressor	skilled	unskilled	difference
constant	0.066	0.193	-0.127
	(2.921)	(1.787)	(3.424)
female	-0.046	-0.183***	0.137
	(0.102)	(0.044)	(0.111)
married	-0.584***	-0.358***	-0.226*
	(0.107)	(0.044)	(0.116)
own house	-0.404***	-0.287***	-0.116
	(0.117)	(0.047)	(0.126)
health	0.037	0.010	0.027
	(0.057)	(0.022)	(0.061)
age at entry	0.010**	0.000	0.010*
	(0.005)	(0.002)	(0.005)
years in USA	-0.169***	-0.019***	-0.151***
	(0.026)	(0.003)	(0.026)
non-citizen	0.502*	0.187***	0.315
	(0.268)	(0.065)	(0.276)
Mexico	0.673***	0.190**	0.484**
	(0.190)	(0.080)	(0.206)
English-speaking country	-0.075	-0.185	0.110
	(0.184)	(0.126)	(0.223)
OECD country	0.564*	-0.394*	0.958***
	(0.296)	(0.216)	(0.367)
transition economy	-0.312	0.109	-0.421
	(0.245)	(0.176)	(0.302)
muslim country	-1.721	-1.401	-0.319
	(1.119)	(2.329)	(2.584)
small island country	-0.053	0.071	-0.124
	(0.242)	(0.103)	(0.262)
log(distance to US)	-0.138	-0.149*	0.011
	(0.099)	(0.080)	(0.127)
log(GDP per capita)	0.088	0.065	0.024
	(1.129)	(0.676)	(1.317)
exchange rate	0.011	0.014	-0.003
	(0.130)	(0.091)	(0.159)
institutions	-0.081**	0.000	-0.081*
	(0.037)	(0.020)	(0.042)
time trend (base=1998)	-0.032	-0.021**	-0.010
	(0.022)	(0.010)	(0.024)
past mobility error	-0.213	0.065	-0.277
	(0.158)	(0.062)	(0.170)
# of observations	17636	24338	

* – significant at 90%, ** – at 95%, *** – at 99% level

that returning Mexicans, as well as migrants returning to OECD countries,[27] are subject to positive selection by skill.

Table 14 reports differences between recent immigrants, who spend ten or less years in the US, and those who arrived over ten years ago. The differences between these two groups are far greater than the differences by skill or by gender. In particular, virtually all characteristics indicating the degree of assimilation and sedentariness, such as marital status, house ownership, and citizenship, affect recent immigrants much more than their non-recent counterparts. For example, receiving the US citizenship within the first ten years since immigration greatly reduces the probability of return migration; for those who arrived over ten years ago and still in the US, citizenship plays a smaller role.

The distance to home country differentiates only those who came to the US more than ten years ago; it has no effect on recent immigrants. This finding suggests that distance to home country does not matter *per se*: the decision to return does not directly depend on the cost of return ticket, or on the flight duration. Distance to home may affect migrants in an indirect way: those from more distant countries maintain fewer contacts with home and meet their relatives less frequently; over time, links to home country vanish, which reduces the incentive to return. In the first few years, however, the ties to home are still strong regardless of distance to home, which makes the distance insignificant factor for recent immigrants.

Table 14 also indicates that duration of stay in the US affects immigrants from small island economies (labeled "islanders" for short) very differently from other immigrants. Recently arrived islanders return *more* often than other recent immigrants. At the same time, non-recent islanders return *less* often than other non-recent immigrants. This finding means that there two very different groups of islanders: those who come to the US for a short

[27] In this research, Mexico was not included into the list of OECD countries, because it has very different migration patterns

Table 14: Emigration by length of stay

regressor	0-10 yrs in USA	over 10 yrs in USA	
constant	-0.370	0.748	-1.119
	(1.930)	(2.178)	(2.910)
female	-0.213***	-0.108*	-0.104
	(0.055)	(0.056)	(0.079)
married	-0.550***	-0.315***	-0.236***
	(0.057)	(0.058)	(0.081)
higher education	-0.064	-0.425***	0.362***
	(0.073)	(0.098)	(0.122)
own house	-0.474***	-0.247***	-0.227**
	(0.069)	(0.058)	(0.090)
health	0.001	0.027	-0.026
	(0.029)	(0.027)	(0.039)
age at entry	0.003	0.003	-0.000
	(0.002)	(0.003)	(0.004)
non-citizen	0.555***	0.129**	0.426***
	(0.152)	(0.062)	(0.165)
Mexico	0.435***	0.157	0.278*
	(0.106)	(0.097)	(0.143)
English-speaking country	-0.244**	-0.003	-0.241
	(0.121)	(0.157)	(0.199)
OECD country	0.152	-0.359	0.511*
	(0.171)	(0.246)	(0.299)
transition economy	-0.320	0.151	-0.471
	(0.206)	(0.219)	(0.301)
muslim country	-1.032*	-0.396	-0.636
	(0.599)	(0.368)	(0.703)
small island country	0.322**	-0.251*	0.574***
	(0.133)	(0.129)	(0.186)
log(distance to US)	0.058	-0.408***	0.465***
	(0.078)	(0.106)	(0.131)
log(GDP per capita)	-0.571	0.273	-0.844
	(0.748)	(0.800)	(1.095)
exchange rate	-0.054	0.203**	-0.258*
	(0.105)	(0.093)	(0.140)
institutions	0.003	-0.022	0.025
	(0.022)	(0.025)	(0.033)
time trend (base=1998)	-0.014	-0.011	-0.002
	(0.012)	(0.012)	(0.017)
past mobility error	-0.082	0.333***	-0.414***
	(0.076)	(0.076)	(0.107)
# of observations	13593	28381	

* – significant at 90%, ** – at 95%, *** – at 99% level

period of time, and those who come for good.

It is likely that some immigrants go to the US for a temporary work, and return after they earn enough. One might expect that higher purchasing power of the US dollar at home (labeled as the exchange rate in the regression), makes potential migrants more willing to do so. One might also expect that earning the desired amount of money takes several years of time, and therefore recent immigrants are less affected by the exchange rate. These considerations are confirmed by table 14: a better exchange rate has an insignificant effect on recent immigrants, while it makes non-recent immigrants return more often.

A major methodological problem related to duration of stay in the US is possible selection bias: those who leave are not the same as those who stay, and thus those immigrants who are still in the US after ten years have different characteristics, both observed and unobserved. The latter may become a source of an estimation bias.

The unobserved characteristics are partly captured by recent mobility experience of a respondent. Table 14 indicates that recent mobility within the US affects recent and non-recent immigrants differently: it has no significant effect on former, and a positive effect on the latter. This finding has a plausible explanation: recent immigrants are all mobile by definition, simply because they changed their country of residence in the past few years. Recent mobility within the US does not reveal any new information about them. At the same time, immigrants who arrived over ten years ago may be very heterogenous in their ability to move. Recent mobility experience reveals they are still on the move, and thus more likely to return.

3.4.3 Robustness

As mentioned in the data description, matching person records across years is not straightforward and several algorithms can be used. Table 15 reports

Table 15: Model with alternative matching of person records

regressor	emigration	moving within US
notation	θ_e	θ_m
constant	0.355	-0.337
	(1.041)	(0.461)
person characteristics		
age	0.000	0.000
	(0.000)	(0.000)
female	-0.130***	-0.061***
	(0.029)	(0.016)
married	-0.314***	-0.073***
	(0.030)	(0.017)
higher education	-0.133***	0.089***
	(0.038)	(0.018)
own house	-0.406***	-0.446***
	(0.031)	(0.017)
health	-0.016	-0.017**
	(0.015)	(0.008)
age at entry	0.001	-0.017***
	(0.001)	(0.001)
years in USA	-0.010***	-0.024***
	(0.002)	(0.001)
non-citizen	0.139***	-0.016
	(0.039)	(0.020)
home country characteristics		
Mexico	0.150***	-0.031
	(0.049)	(0.027)
English-speaking country	-0.145**	0.032
	(0.067)	(0.026)
OECD country	-0.268***	0.070*
	(0.099)	(0.037)
transition economy	-0.358***	-0.083*
	(0.136)	(0.045)
muslim country	-0.429***	0.028
	(0.147)	(0.039)
small island country	-0.107*	-0.098***
	(0.064)	(0.035)
log(distance to US)	-0.232***	0.003
	(0.039)	(0.016)
log(GDP per capita)	0.449	0.205
	(0.406)	(0.182)
exchange rate	0.015	0.016
	(0.054)	(0.022)
institutions	-0.016	0.003
	(0.012)	(0.005)
time trend (base=1998)	-0.031***	-0.025***
	(0.006)	(0.003)
past migration error	0.070*	0.293***
	(0.042)	(0.030)
# of observations	41974	40791

* – significant at 90%, ** – at 95%, *** – at 99% level

results of a model with alternative method of matching person records: the two records are considered to be records on the same person, if at least three out of four person characteristics match. Generally, coefficients do not change dramatically compared to the benchmark model described in table 11, but some coefficient signs (e.g., OECD country dummy) are reversed. Thus, a more accurate method of matching person records is needed, which is a subject for future work. It is possible to create a model of CPS data collection with explicitly defined error probabilities. These error probabilities can be estimated using the maximum likelihood method; given these estimates, it would be possible to estimate the probability of a match or mismatch of a given person record. The probability of mismatch in each observation could be subsequently used in the estimation of the main model parameters.

3.5 Discussion and future work

This essay utilizes the American Current Population Survey (CPS) to estimate the return migration patterns of US foreign-born. The key feature of the CPS is that each household is interviewed eight times within two years. By using two of these eight interviews, made exactly one year apart, I infer which of the respondents have departed during this year. After adjusting for the probability of death and migration within the US, I estimate what factors affect immigrants' decision to return.

I find that the heterogeneity across recent and non-recent immigrants is greater than the heterogeneity across men and women, or skilled and unskilled migrants. Thus, assimilation differentiates immigrants more in their decision to return than education or gender. In particular, distance to home country negatively affects return propensity of those who arrived over 10 years ago, and has no effect on recent immigrants. This finding implies that distance has no direct immediate effect on foreign-born, but corrodes links to home country, making immigrants from distant countries less willing to return over time. Also, I find that a higher purchasing power of the US dollar in the home country has a positive effect on the return decision, but only for those who have spent a relatively long time in the US.

To improve the estimation methodology, the following things can be done. First, since the CPS data is collected with errors, the algorithm of matching person records across years could be improved by creating a model of CPS data collection with explicitly defined error probabilities.

Another way to improve the results is to use not only March surveys, but also data collected in all other months. It would allow to increase the number of observations, since many households are visited in months other than March. It would also allow to use eight records on each household instead of two. The latter increases the quality of matching of person records across time: one could identify recording errors more accurately by comparing data from several consecutive months. This strategy would, however, require a more sophisticated matching methodology.

Although a considerable attention was paid to possible correlation of errors in the model, there may still exist unaccounted correlation which may bias the results. Available data does not allow to test or estimate the degree of such correlation. However, it is possible to create a model with a more sophisticated error structure; by making *ad hoc* assumptions about the correlation of errors, I could test whether the model estimates are robust to changing such assumptions.

Finally, it is also possible to include family-level estimation errors into the model, to account for possible correlation of observation errors within the same family.

A Migration, Learning, and Development

A.1 Computing steady states

As mentioned above, the concept of the steady state includes the following time-invariant objects:

- Distribution of individuals across types $f = \{f^m(h_i, h_j), f^u(h_i)\}$
- Wages $w(h_i, h_j)$
- Values $V = \{V^m(h_i, h_j), V^u(h_i)\}$

To solve the model, I approximate the continuous distribution across types by 201 discrete types of human capital, ranging from 0 to 200. Theoretically, individual human capital does not have an upper bound because each period individuals increment their knowledge by at least λ_0, a finite positive value, and because individual duration of life is not bounded from above. The calculations, however, show that the probability of reaching beyond some finite threshold of human capital becomes negligibly small, hence a finite grid is a good approximation of human capital distribution.

The total number of individual states is then $201^2 + 201 = 40602$, which renders impossible the precise computation of values and densities at each state. I calculate the unknowns approximately using an iterative algorithm described below. One problem I faced during the computation was discreteness of decisions: individuals accept or reject matches by comparing the two values; they randomize if the values are equal. Since the number of individual types is finite and the mass of individuals of most types is strictly positive, it is highly likely that in a steady state one of the types will be randomizing between the two options. However, because I compute the values approximately using an iterative procedure, the values of accepting or rejecting the

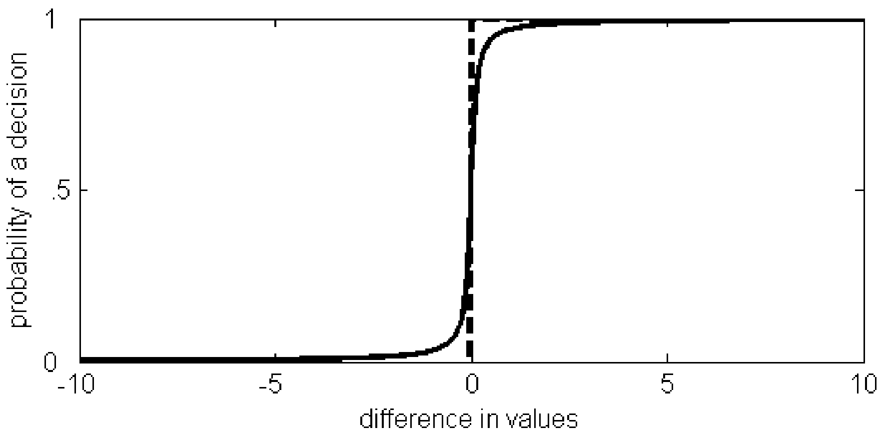


Figure 14: Accept-reject decision randomization
Dashed line represents outcomes in the theoretical model; solid line represents randomizing individuals

matches will never be identical, and no individual will ever randomize. Because of this problem, the system may never fully converge to a steady state: some types of matches will be "blinking", staying together in one iteration but splitting in the next. To override this problem, I force individuals to randomize between the two options: when the values of accepting and rejecting are close, individuals choose the outcome randomly, with probability of accepting sharply increasing as the difference in values increases. This approach is illustrated on figure 14. This randomization was ignored when calculating the values.

Another problem is that future states (human capitals after learning) lie off the grid. I use the standard solution for this problem: when tomorrow human capital falls off the grid, individuals are randomly assigned to one of the nearest grid points. For example, future human capital of 5.2 implies that human capital will be 5 with probability 80%, and 6 with probability 20%.

Below, I describe in detail the steps that I made to find steady states.

Step 0: Initialization Define an initial distribution of individuals across states, values of each state, and wages at each matched state.

Step 1: Update wages and values The values are computed using the Bellman equation. First, I compute the wages $w(h_i, h_j)$ as described in section 2.2.4, using values V^m and V^u taken from the previous iteration. Then, I compute the values V^m and V^u using the newly computed wage w and the distribution of potential partners f^u. I run multiple iterations to update wages and values, given the same distribution f^u, until the change in values becomes small enough.

Step 2: Distribution update Given wages and values, I simulate individual decisions and compute the resulting distribution across states. The distribution update is performed a fixed number of times.[28]

After that, I return to step 1; the whole procedure is repeated until the change in distribution becomes small enough.

A.2 Computing transition dynamics

Because convergence to the steady state takes an infinite number of periods, and because each period in transition is different from the other, the precise transition path cannot be computed; some kind of approximation is required. I use the parametric path approach inspired by Judd (1999). This method exploits the fact that the distribution of individuals across states evolves smoothly over time, and therefore can be approximated by a smooth function of time:

$$f_t^u(h) = \left(\frac{\sum_{k=0}^{K} \phi_k(h) a_k t^k}{\sum_{k=0}^{K} a_k t^k} \right) e^{-\alpha t} + f_\infty^u(h) \left(1 - e^{-\alpha t}\right) \tag{6}$$

[28]more than once – otherwise the algorithm would be too slow, because the distribution is changing slowly

where f^u_∞ is the steady state distribution of potential partners, α is the speed of convergence to the steady state, $\phi_k(h)$ are ex-ante chosen density functions which resemble f^u_t at different moments of time (notably, $\phi_0(h)$ is the initial distribution), and a_k are the unknown parameters to be estimated. Judd (1999) assumes that α is known ex-ante when solving the model, which is not true in our case: the speed of convergence depends greatly on migration patterns, which in turn depend greatly on individual expectations. Therefore, I estimate the α along with other parameters.

A.2.1 Computing transition path, given beliefs about future

Values and wages: backward induction If emigrants are allowed to return, they are no longer identical to Northerners: when bargaining, they have more outside opportunities than Northerners do. Therefore, we need to calculate not only the values of living in the South, but also the values of emigrants living in the North.

Using the bargaining rules described in section 2.2.4, the Bellman equation, and individual beliefs about the evolution of potential Southern partners[29], I compute the path of values $V_0, V_1, ..., V_t, ...$

The backward induction procedure implies that we start from some final date T and from some ex-ante chosen value V_T. This terminal value is likely to be incorrect, but the error should decrease as we move from one iteration to another. My goal was to compute transition dynamics between years 0 and 100; to have accurate values between these dates, I started my backward induction from the terminal year 150.

Distributions: forward induction Given the path of values, I simulate individual accept-reject decisions in bargaining, and migration decisions. To

[29] The distribution of Northern partners does not change over time and is known precisely

increase the accuracy of results, I exploit the following property: with good institutions ($\theta = 1$), the value of being unmatched tomorrow is

$$V_{t+1}^{u}(h_i) = \frac{\int V_{t+1}^{m}(h_i, h_j) f_{t+1}^{u}(h_j) dh_j}{\int f_{t+1}^{u}(h_j) dh_j} \tag{7}$$

As mentioned above, it is impossible to calculate a perfectly accurate V^m because it depends on entire stream of unknown future distributions; however, it is possible to compute rational beliefs about f_{t+1}^{u} and therefore compute more accurate V^u using (7).

The transition is computed as follows. At the beginning of period t, people have beliefs about V_{t+1}^{m} and f_{t+1}^{u}; using (7), they compute the V_{t+1}^{u}. Then, everybody makes decisions (bargaining, migration), which result in new tomorrow distribution f_{t+1}^{u}. Using this new distribution and the same V_{t+1}^{m}, I compute the new V_{t+1}^{u}, and so on, until beliefs about f_{t+1}^{u} become perfectly rational. Then, I proceed to the next period.

A.2.2 Computing beliefs

To use Judd's method described by (6), we need to specify the speed of convergence α, distributions ϕ_k, and weight parameters a_k. I do this in two stages: first, I find α and suggest ϕ_k by computing a crude transition path; then, I search for a for more accurate approximation.

Crude approximation At this stage, I use the simplest version of (6) to model beliefs:

$$f_t^u(h) = f_0^u(h) e^{-\alpha t} + f_\infty^u(h) \left(1 - e^{-\alpha t}\right)$$

I pick up a parameter α and use these beliefs to compute the values, and then the transition path as described in section A.2.1. Given the transition path, I estimate a new α, and so on, until the change in α becomes small enough.

With this crude approximation, the actual distribution along the path differs quite drastically from individual beliefs about that distribution. I define $\phi_1(h)$ as the "average" distribution over time[30]

$$\phi_1(h) = \frac{1}{T}\sum_{t=1}^{T} f_t^u(h)$$

More accurate approximation Since we add only one function $\phi_1(h)$ to Judd's formula (6), there is only one unknown parameter a_1.[31] I choose the a_1 to minimize the discrepancy between the actual transition path and individual beliefs about that transition. Given a_1 and new beliefs, I compute the new transition path, then estimate new a_1, and so on, until the change in a_1 becomes small enough. Figure 15 demonstrates actual distributions of potential partners, and beliefs about those distributions, at different points in time.

A.3 If there were no matching frictions

Without matching frictions, when each individual can directly match with the optimal partner, the model simplifies in a number of ways. First, because there is a large number of potential partners of each type, everyone's reservation wage exactly equals their actual income. Second, since another partner can be found instantaneously, the state of an individual is described only by his own human capital and does not depend on partner's h:

$$V(h_i) = \max_{h_j} w(h_i, h_j) + \beta V(h_i')$$

where h_i' is the future human capital described by (2). This problem can be split into two subproblems: when i is the master ($h_i \geq h_j$), and when i is

[30]We could also pick ϕ_2 and ϕ_3 and so on, but apparently only one extra degree of freedom does a good job in approximation

[31]The a_0 can be normalized to unity

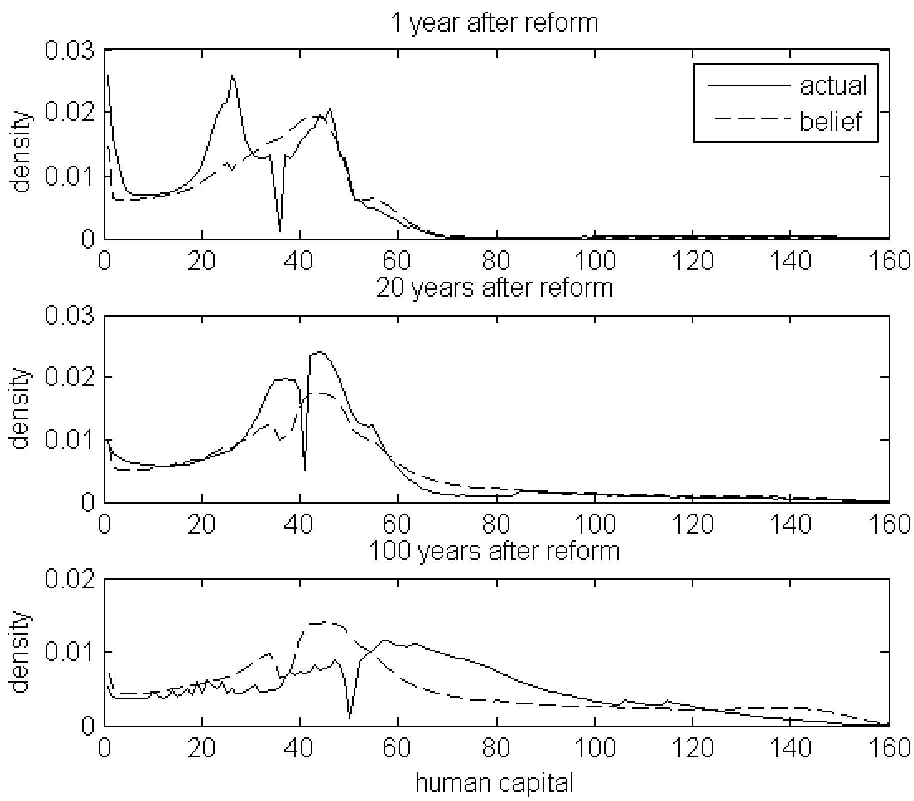


Figure 15: Distribution of potential partners in the South at different points in time

the apprentice ($h_i < h_j$). Since master's future state does not depend on apprentice's knowledge, he simply maximizes current income. Therefore, we can define master's reservation wage as

$$\underline{w}^M(h_i) = \max_{h_j \le h_i} w(h_i, h_j)$$

On the other hand, if i wants to learn from a higher partner j, he realizes that j should earn his reservation wage and i will earn the residual; i's problem is

$$\max_{h_j > h_i} y(h_i, h_j) - \underline{w}^M(h_j) + \beta V(h_i + g(h_j - h_i) + \lambda_0) \tag{8}$$

Since the production function is Leontief, current output does not depend on master's knowledge which simplifies the above optimization problem.[32]

Generally, this problem appears to have no analytical solution; but it can be solved with the following

Assumption Individuals are always indifferent between being masters and apprentices.

Then, the individual value function takes the form

$$V(h_i) = \frac{1}{2}\frac{h_i}{1-\beta} + C \tag{9}$$

where C is a positive constant. With this value, it can be shown that when i is the master, his reservation wage is $\underline{w}^M(h_i) = \frac{1}{2}h_i + C_w$, where C_w is another positive constant.

The apprentice's problem is to solve (8); the first-order condition is

$$-\frac{1}{2} + \frac{1}{2}\frac{\beta}{1-\beta}\frac{\lambda}{1+\lambda(h_j^* - h_i)} = 0$$

[32]That is exactly why the Leontief production function was chosen

As a result, the optimal master-apprentice knowledge gap is

$$h_j^* - h_i = \frac{\beta}{1-\beta} - \frac{1}{\lambda}$$

It is positive as long as $\lambda > \frac{1-\beta}{\beta}$, and it does not depend on apprentice's current state. By calculating apprentice's value, we can confirm that the latter equals (9).

One big problem of frictionless matching is incentive compatibility: the number of individuals with human capital h_1 willing to learn from those with human capital h_2 must be exactly equal to those with h_2 willing to teach h_1. Generally, it cannot be achieved under the assumption made above; finding an equilibrium in such environment might become an arduous task. With random matching, this problem dissolves, at the cost of adding more dimensions to the state space.

B Return Migration: an Empirical Investigation

List of English-speaking countries Australia, Bahamas, Barbados, Belize, Canada, Dominica, Fiji, Ghana, Grenada, Guyana, Hong Kong, India, Ireland, Jamaica, New Zealand, Nigeria, Philippines, Puerto Rico, Singapore, South Africa, Trinidad and Tobago, United Kingdom

List of OECD countries Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom

List of transition economies Armenia, Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania, Russia, Serbia, Slovakia, Ukraine

List of muslim countries Afghanistan, Bangladesh, Egypt, Guyana, Indonesia, Iran, Iraq, Jordan, Lebanon, Malaysia, Morocco, Nigeria, Pakistan, Saudi Arabia, Syria, Turkey

List of small island economies developing economies Bahamas, Barbados, Belize, Bermuda, Cuba, Dominica, Dominican Republic, Fiji, Grenada, Guyana, Haiti, Jamaica, Singapore, Trinidad and Tobago

Table 16: List of countries

country	records	country	records	country	records
Afghanistan	78	France	252	New Zealand	38
Argentina	166	Germany	1480	Nicaragua	299
Armenia	97	Ghana	115	Nigeria	155
Australia	83	Greece	223	Norway	38
Austria	81	Grenada	37	Pakistan	269
Bahamas, The	21	Guatemala	671	Panama	115
Bangladesh	113	Guyana	271	Peru	421
Barbados	68	Haiti	539	Philippines	2174
Belgium	63	Honduras	446	Poland	591
Belize	64	Hong Kong	234	Portugal	440
Bermuda	19	Hungary	116	Puerto Rico	1799
Bolivia	70	India	1498	Romania	138
Brazil	318	Indonesia	96	Russia	649
Burma	41	Iran	407	Saudi Arabia	30
Cambodia	178	Iraq	135	Serbia	187
Canada	1330	Ireland	227	Singapore	29
Chile	124	Israel	185	Slovakia	30
China	1233	Italy	589	South Africa	104
Colombia	735	Jamaica	618	Spain	151
Costa Rica	86	Japan	626	Sweden	71
Cuba	1288	Jordan	70	Switzerland	53
Czech Republic	87	Kenya	53	Syria	66
Denmark	43	Korea, South	996	Taiwan	392
Dominica	32	Laos	218	Thailand	239
Dominican Republic	1018	Latvia	19	Trinidad and Tobago	253
Ecuador	475	Lebanon	175	Turkey	133
Egypt	147	Lithuania	44	Ukraine	212
El Salvador	1443	Malaysia	61	United Kingdom	1004
Ethiopia	121	Mexico	12886	Uruguay	64
Fiji	17	Morocco	45	Venezuela	165
Finland	20	Netherlands	125	Vietnam	1112

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