# HUMAN CAPITAL AND DEVELOPMENT ACCOUNTING: NEW EVIDENCE FROM WAGE GAINS AT MIGRATION*

LUTZ HENDRICKS AND TODD SCHOELLMAN

October 16, 2017

We use new data on the pre- and post-migration wages of immigrants to the United States to measure wage gains at migration. The average immigrant from a middle income or poor country increases their wage by a factor of two to three upon migration. This wage gain is small relative to the underlying gap in GDP per worker. In a development accounting framework, this finding implies that switching countries accounts for 40 percent of cross-country income differences, while human capital accounts for 60 percent. Wage gains decline with education, consistent with imperfect substitution between skill types. We augment our analysis to allow for this possibility and bound the human capital share in development accounting to between one-half and two-thirds. We also provide results on the importance of pre-migration sector of employment, assimilation, and skill transfer. *JEL* Codes: O11, J31

# I.  INTRODUCTION

One of the central challenges for economists is to explain the large differences in gross domestic product (GDP) per worker across countries. Development accounting provides a useful first step toward this goal. It measures the relative contribution of physical capital, human capital, and total factor productivity (TFP) in accounting for cross-country income differences. These accounting results can help highlight the types of theories or mechanisms most likely to explain cross-country income differences. For example, a consensus in the literature that physical capital accounts for a small fraction of income differences has led researchers to de-emphasize theories that assign a prominent role to variation in physical capital per worker.[1]

The main unsettled question in this literature is the relative importance of TFP versus human capital in accounting for cross-country income differences. The literature has tried a number of approaches to measuring human capital and reached little consensus on the answer. Since TFP is measured as a residual explanatory factor, wide variation in measured human capital stocks implies wide variation in measured TFP and hence substantial disagreement about the relative contribution of the two. For example, the literature has found that human capital accounts for anywhere from one-fifth to four-fifths of cross-country income differences, with TFP in turn accounting for anywhere from three-fifths to none.[2]

Our contribution to this debate is to provide new evidence drawing on the experiences of immigrants to the United States. Intuitively, immigrants provide valuable information because they enter the United States with the human capital they acquired in their birth country, but not their birth country's physical capital or TFP. Hence, their labor market performance in the United States conveys information about their human capital separated from the other two country-specific factors. On the other hand, working with immigrants presents two well-known challenges. First, immigrants are selected: their human capital is not the same as the human capital of a randomly chosen person in their birth country. Second, their labor market performance may not accurately reflect their human capital if skills transfer imperfectly across countries.[3]

We address these challenges by bringing to bear new data on the pre- and post-migration labor market experiences of immigrants. Our main data source is the New Immigrant Survey (NIS), a sample of adult

---

[1]See, for example, Klenow and Rodríguez-Clare (1997), Hall and Jones (1999), Caselli (2005), or Hsieh and Klenow (2010) for classic references on development accounting and its interpretation.

[2]The former figure comes from Hall and Jones (1999); the latter comes from Jones (2014). The literature also includes a wide range of estimates in between. See, for example, Erosa, Koreshkova and Restuccia (2010), Hanushek and Woessmann (2012), Córdoba and Ripoll (2013), Weil (2007), or Cubas, Ravikumar and Ventura (2016).

[3]Previous papers that have investigated immigrants and cross-country differences in human capital include Hendricks (2002), Schoellman (2012), Schoellman (2016), and Lagakos et al. (forthcoming).

immigrants granted lawful permanent residence in the United States in 2003 (colloquially, green card recipients) (Jasso, Massey, Rosenzweig and Smith, 2007). We augment the NIS by using two additional data sources, the Mexican Migration Project and the Latin American Migration Project (jointly, the Migration Projects, or MPs), which collect similar information from immigrants who are not necessarily lawful permanent residents, who may have entered the United States illegally, and who are much less selected on observed characteristics.[4] We use these data in three ways. First, we construct a measure of the importance of human capital for development accounting based on immigrants' wage gains at migration. Second, we address the challenge of selection by comparing the pre-migration characteristics of immigrants to non-migrants. Third, we address the challenge of skill transferability by comparing the pre- to post-migration occupations of immigrants.

We start by revisiting the standard development accounting framework, focusing on the assumptions necessary to draw aggregate implications from the labor market experiences of immigrants. The most direct measure of the importance of physical capital and TFP is the wage gain at migration relative to the difference in GDP per worker. Intuitively, an immigrant has the same human capital but different physical capital and TFP before and after migrating. The wage gain at migration is thus an index of the relative importance of these country-specific factors, while the residual can be attributed to gaps in human capital per worker. In addition to simplicity, this measure also has the useful feature that it controls for selection in a straightforward manner by studying the wages of the exact same worker in two different countries.

Our empirical work thus relies heavily on a comparison of pre- to post-migration wages. The NIS offers carefully constructed and detailed wage data. It surveyed immigrants about up to two pre-migration jobs and up to three post-migration jobs. It also allowed for a great deal of flexibility in how workers report their earnings. They could report their pre-migration earnings from working in any country, denominated in any currency, from any reference year, at whatever pay frequency they preferred. We discuss in detail how we adjust these data for exchange rate, purchasing power parity (PPP), and differences in reporting year to arrive at estimates of their pre-migration and post-migration hourly wages, both denominated in real PPP-adjusted U.S. dollars. We also provide numerous robustness checks to address possible confounding issues such as episodes of inflation or currency revaluation.

We use these data to construct the wage change at migration relative to the gap in PPP GDP per worker. We focus on immigrants from poor countries, with GDP per worker less than one-quarter of the U.S. level.

---

[4]The Mexican Migration Project (MMP) is a collaborative research project based at Princeton University and the University of Guadalajara. We used version 161 of the database. It can be found online at `http://mmp.opr.princeton.edu`. The Latin American Migration Project is similar to the MMP but covers nine other countries. It can be found online at `http://lamp.opr.princeton.edu`.

The average wage gain at migration is 38 percent of the total gap in GDP per worker, implying that 38 percent of cross-country income differences are accounted for by physical capital and TFP, with the remaining 62 percent accounted for by human capital.

Jones (2014) emphasizes that development accounting results are sensitive to allowing for imperfect substitution between unskilled and skilled labor. We show that the wage gain at migration is larger for less educated immigrants. This finding is evidence of imperfect substitution: unskilled immigrants find their skills to be relatively scarcer in the U.S. labor market and hence experience larger wage gains compared to skilled immigrants. Our benchmark results bound the role of human capital in development accounting with imperfect substitutes; the plausible range is one-half to two-thirds. Under additional assumptions, we can provide a point estimate of the human capital share under imperfect substitutes, which we find to be 60 percent.

Our findings attribute a much higher share to human capital than earlier papers in the literature that used immigrant earnings (Hendricks, 2002; Schoellman, 2012). These earlier papers lacked data on pre-migration wages and so drew inferences based on a comparison of the post-migration wages of immigrants from poor and rich countries. The underlying assumption was that immigrants from poor countries and rich countries are similarly selected. Our data allow us to control for selection directly. We can also go a step further and back out the implied degree of selection by comparing the pre-migration characteristics of immigrants to those of non-migrants. We find that immigrants are highly selected on characteristics such as education or wages, and that immigrants from poor countries are much more selected on these characteristics than immigrants from rich countries. The correlation between selection and birth country development biased the inferences in the existing literature.

The data also allow us to measure the transferability of immigrants' skills. To investigate this issue, we compare the pre-migration and post-migration occupations of immigrants. Most immigrants switch occupations upon migration. Further, most immigrants experience occupational downgrading, meaning that their post-migration occupation is lower paying than their pre-migration occupation, as judged by the mean wage of natives in those occupations. To the extent that this occupational downgrading represents imperfect skill transfer, it implies that we may be understating post-migration wages and the wage gains at migration, which would lead us to understate the role of country and overstate the role of human capital. We investigate several ways to adjust for occupational downgrading and find that doing so lowers the human capital share to roughly one-half.

In addition to the work mentioned above, our paper is also closely related to two literatures that use

retrospective or panel data to investigate wage gains. The first literature specifically studies the wage gains for international immigrants, as we do, but typically for a very particular set of migrants (from just one country to another, or employed at a single firm). A particularly interesting set of these papers studies wage gains in special cases in which immigration slots are granted by lottery, allowing the authors to disentangle selection on gains to migration (see Clemens (2013), Gibson and McKenzie (2012), and especially the short-run and long-run gains in McKenzie, Stillman and Gibson (2010) and Gibson, McKenzie, Rohorua and Stillman (forthcoming)). It is comforting that these papers typically find wage gains that are in line with ours (when compared to the size of the GDP per worker gap).[5] The main difference from our work is that we have a broader sample (immigrants from many countries to the United States), and that we are focused on the aggregate implications for development accounting. In this sense we are closer to Jasso, Rosenzweig and Smith (2002) and Rosenzweig (2010), who also use the NIS data and the pre- and post-migration experiences of immigrants, but instead use this information to think about relative prices of different skills and factor price equalization. The second literature looks at the wage gains of workers who switch sectors or regions in a country and relates them to sectoral or regional productivity gaps (Alvarez, 2017; Hicks, Kleemans, Li and Miguel, 2017).

The rest of the paper proceeds as follows. Section 2 introduces the development accounting framework and the mapping from our micro evidence on immigrants to aggregate cross-country income differences. Section 3 discusses the data and how we construct comparable pre- and post-migration hourly wages. Section 4 provides the main results. Section 5 quantifies the importance of selection and Section 6 the importance of skill transferability. Section 7 concludes.

## II.   Development Accounting Framework

We begin by outlining the simplest development accounting framework, following the literature closely (see Caselli (2005) or Hsieh and Klenow (2010) for recent overviews). Our focus is on clarifying the assumptions needed to draw aggregate inferences from evidence on the wage gains at immigration.

---

[5]In addition to this work, our paper is also related to two other literatures that think about the gains to migration. First, Klein and Ventura (2009) and Kennan (2013) use models to quantify the gains from freer migration across countries. Second, a large literature estimates cross-country wage gaps between observably similar workers. The most similar work in this literature is Clemens, Montenegro and Pritchett (2008, forthcoming), who compare the wages of immigrants to the United States with the wages of observably similar non-migrants born in the same country, then use various approaches to bound the possible extent of immigrant selection on unobserved characteristics. See also the extensive reference lists in the last paper for further work in this area.

The aggregate production function is standard:

$$Y_c = K_c^\alpha (A_c H_c)^{1-\alpha},$$

where $Y_c$ is country $c$'s PPP-adjusted GDP, $K_c$ is its physical capital stock, $A_c$ is its total factor productivity, and $H_c \equiv h_c L_c$ is the total labor input, which in turn can be decomposed into human capital per worker $h_c$ and the number of workers $L_c$.

Following Klenow and Rodríguez-Clare (1997), we rewrite the production function in per worker terms:

$$(1) \qquad y_c = \left(\frac{K_c}{Y_c}\right)^{\alpha/(1-\alpha)} A_c h_c,$$

where $y_c$ denotes PPP GDP per worker. The goal of development accounting is to decompose the large cross-country differences in $y$ into three proximate sources, given on the right-hand side: capital-output ratios, total factor productivity, and average human capital. In this paper we focus primarily on distinguishing the share of human capital versus the other two factors jointly, so we define $z_c \equiv (K_c/Y_c)^{\alpha/(1-\alpha)} A_c$. We call this term the country component, because it is what changes when immigrants move to a new country, while their human capital remains the same.

We conduct our accounting exercises in log-levels. Doing so produces results that are additive and order-invariant. Our focus is on separating the relative contribution of human capital from the other two terms in accounting for the difference in PPP GDP per worker between $c$ and $c'$:

$$1 = \frac{\log(z_c) - \log(z_{c'})}{\log(y_c) - \log(y_{c'})} + \frac{\log(h_c) - \log(h_{c'})}{\log(y_c) - \log(y_{c'})}$$

$$(2) \qquad \equiv \text{share}_{\text{country}} + \text{share}_{\text{human capital}}.$$

## II.A.  Wage Gains of Immigrants and Development Accounting Implications

We use the wages of immigrants to inform us about the role of country and human capital for development accounting. Our approach builds on the insights of Bils and Klenow (2000), who showed that wages are informative about human capital under two assumptions. First, workers of different types are assumed to be perfect substitutes. In this case, workers may provide varying quantities of human capital, but the total labor supply is simply the total human capital of all workers. We relax this assumption in Section II.B.. Second, labor markets are assumed to be perfectly competitive, so that workers are paid their marginal

product. Given these assumptions, the representative firm hires a total quantity $H_c$ of human capital at the prevailing wage per unit of human capital $\omega_c$ to maximize profits:

$$\max_{H_c} K_c^{\alpha} \left(A_c H_c\right)^{1-\alpha} - \omega_c H_c.$$

The first-order condition of the firm implies that the wage per unit of human capital is $\omega_c = (1 - \alpha)z_c$, where $z_c$ is defined as in the previous subsection.

The observed hourly wage of worker $i$ in country $c$ $w_{i,c}$ is then the product of the wage per unit of human capital and the amount of human capital the worker possesses:

$$(3) \qquad\qquad \log(w_{i,c}) = \log\left[(1 - \alpha)z_c\right] + \log(h_i).$$

Given that we have data on both pre- and post-migration wages of immigrants, we can construct the log-wage gain to migration. If labor markets are competitive in both countries, then we can divide the log-wage gain at migration by the log-GDP per worker difference between $U.S.$ and $c$ to measure the share of cross-country income differences accounted for by the country component:

$$(4) \qquad\qquad \frac{\log(w_{i,U.S.}) - \log(w_{i,c})}{\log(y_{U.S.}) - \log(y_c)} = \frac{\log(z_{U.S.}) - \log(z_c)}{\log(y_{U.S.}) - \log(y_c)} = \text{share}_{\text{country}}.$$

We construct $\text{share}_{\text{human capital}} \equiv 1 - \text{share}_{\text{country}}$. Intuitively, a worker who migrates keeps the same human capital but switches physical capital and TFP levels. We study how much this changes the worker's wages relative to the total gap in GDP per worker. If the change in wages were as large as the gap in GDP per worker, then we would conclude that country accounts for all of the cross-country income differences, with no role for human capital. If there were no change in wages, then we would conclude that human capital accounts for all of the cross-country income differences, with no role for country. Our goal is to calculate where we stand between these two polar cases.

Note that this statistic controls for the usual selection concern, namely that immigrants may be more talented or harder working than non-migrants, because it uses wage observations from the same worker in two countries. In Section 5 we quantify the extent of selection by comparing the pre-migration wages of immigrants to the wages of non-migrants. If immigrants were instead selected on the gains to migration, as in McKenzie, Stillman and Gibson (2010), then our accounting metric would actually understate the share of human capital in development accounting.

## II.B.  Development Accounting with Imperfect Substitution

We also consider a framework with imperfect substitution between unskilled and skilled labor, motivated by the work of Jones (2014). In this case, the human capital aggregator is given by

$$H_c = \left( \theta_u H_{u,c}^{\frac{\sigma-1}{\sigma}} + \theta_s H_{s,c}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where $H_{u,c}$ and $H_{s,c}$ are the quantity of unskilled and skilled labor in country $c$, which are combined with weights $\theta_u$ and $\theta_s$ and an elasticity of substitution $\sigma$.

We continue to maintain the assumption that labor markets in both countries are competitive and workers are paid their marginal product. In this case, the wage gain at migration of any worker who provides type $j \in \{u, s\}$ labor is

(5) $$\log(w_{j,U.S.}) - \log(w_{j,c}) = \log(z_{U.S.}) - \log(z_c) + \frac{1}{\sigma} \left[ \log \left( \frac{H_{U.S.}}{H_{j,U.S.}} \right) - \log \left( \frac{H_c}{H_{j,c}} \right) \right].$$

As with the perfect substitutes case, the wage gain depends on the change in $z$. In the imperfect substitutes case there is a second term that captures the change in the relative price of type $j$ labor, which in turn depends on the change in the relative supply of type $j$ labor. Skilled immigrants' wage gains will be smaller than $\log(z_{U.S.}) - \log(z_c)$ because the United States is abundant in skilled labor, which pushes down the relative price of skilled labor (given the usual restriction $\sigma > 0$). By similar logic, unskilled immigrants' wage gains will be larger than $\log(z_{U.S.}) - \log(z_c)$.

Equation (5) can be interpreted as a simple test for imperfect substitution between skill types: if skilled and unskilled workers are imperfect substitutes, then unskilled workers should have larger wage gains at migration. We implement this test below and find support for imperfect substitution. In this case it also suggests a method to bound the importance of country effects in development accounting. Wage gains of unskilled workers overstate the importance of country-specific factors, because their wage gains capture in part the fact that unskilled labor is relatively scarce in the United States. Thus, their wage gains provide an upper bound on the role of country and a lower bound on the role of human capital. By a similar logic the wage gains of skilled workers provide a lower bound on the role of country and an upper bound on the role of human capital, which allows us to bound the contribution of human capital in development

accounting as

$$(6) \qquad 1 - \frac{\log(w_{u,U.S.}) - \log(w_{u,c})}{\log(y_{U.S.}) - \log(y_c)} \le \text{share}_{\text{human capital}} \le 1 - \frac{\log(w_{s,U.S.}) - \log(w_{s,c})}{\log(y_{U.S.}) - \log(y_c)}.$$

This bounding approach sidesteps a number of challenges in specifying $H_c$. It relies only on exploiting the large differences in the relative supplies of unskilled and skilled labor documented in Barro and Lee (2013). Now that we have outlined our approach, it is time to turn to the data.

## III. Data

Our main data source is the New Immigrant Survey (NIS), a representative sample of adult immigrants granted lawful permanent residence in the United States (colloquially, green card recipients) between May and November of 2003, drawn from government administrative records (Jasso, Massey, Rosenzweig and Smith, 2005, 2007). It includes both newly arrived immigrants granted lawful permanent residency from abroad and immigrants who adjusted to lawful permanent residency after previously entering the United States through other means. The survey consists of two rounds: round 1 was conducted in 2003–2004, shortly after the immigrants adjusted status. A follow-up round 2 was conducted in 2007–2009. The online appendix contains details on this and other data sources used in this paper, including sample restrictions, sample sizes, and so on.

The NIS includes four main types of information that we exploit. First, it surveys respondents about the usual set of demographic characteristics such as age and education, including detailed questions on where immigrants acquired their education. Second, it contains administrative data on the type of visa they used to enter the United States. Third, it surveys them about their labor market experiences in the United States. In round 1 they were asked about their first job after migration and their current (year 2003–2004) job. In round 2 they were again asked about their current (year 2007–2009) job. Fourth, it surveys them about their experiences before entering the United States, particularly their labor market experiences. Immigrants were asked in round 1 about up to two jobs before entry, their first (after age 16) and last (if different from the first). For all jobs, we know standard information such as earnings, hours and weeks worked, industry, and occupation.

Given our focus on the pre-migration wages of immigrants and the wage gains at migration, it is important that immigrants' reported wages be accurate. Fortunately, the NIS was careful to allow immigrants a

great deal of flexibility in reporting their pre-migration earnings. Immigrants reported both how much they earned and the frequency at which they were paid (hourly, daily, etc.). They also chose what year this report pertains to, what country they were working in, and what currency they were paid in. This flexibility is important because it allows immigrants to report earnings in the most natural way for them, rather than forcing them to do conversions. It also allows for unusual or non-obvious situations, such as the use of the U.S. dollar as a medium of payment even outside the United States, or the tendency for European migrants to remember their earnings denominated in both pre-euro currencies or euros.

The NIS provides a manual with the steps necessary to produce PPP-adjusted hourly wages in U.S. dollars. First, we use the reported earnings, payment frequency, and hours and weeks worked to construct the hourly wage for all immigrants. Second, we adjust the hourly wage to U.S. dollars by using the market exchange rate prevailing at the time. Third, we adjust wages for PPP. Note that in cases in which immigrants report the "natural" currency for their country (e.g., pesos in Mexico), these latter two adjustments are equivalent to simply dividing by the PPP exchange rate. Our exchange rates and PPP adjustments come from the Penn World Tables, mostly PWT 7.1, although we explored also using PWT 9.0. We exclude immigrants who report being paid in currencies that were subsequently devalued and flag immigrants who report unusual country-currency pairs (e.g., liras in Brazil) or who report being paid in currencies with high inflation for possible exclusion to minimize concerns about measurement error.

At this point, we have several estimates of both pre- and post-migration wages at different dates reported in U.S. dollars and adjusted for cost of living. Conceptually, the last step is to adjust these wages to a common date and construct the wage gains at migration. This step is complicated somewhat by immigrant assimilation: immigrants' occupational status, wages, and earnings are generally found to grow more quickly than those of comparable natives in the years after migration (Akresh, 2008; Duleep, 2015). This fact has three possible interpretations. First, it could be that initial wages are temporarily depressed by the absence of "search capital," meaning that immigrants have not yet found a job that suits them and values their talents. In this case, it would be preferable to focus on later post-migration jobs. Second, it could be that immigrants acquire human capital more rapidly than natives after migration, perhaps in response to the change in environment. Finally, it could be that immigrant wage patterns are driven by a composition effect through selective return migration based on wages (Lubotsky, 2007). In these latter cases, it would be preferable to focus on earlier post-migration jobs. There is no clear consensus in the literature about the relative importance of these three effects.[6]

---

[6]Lessem and Sanders (2014) use data from the NIS to quantify the role of labor market frictions; they find that frictions can account for some but not all of assimilation.

For our baseline results, we combine wage estimates from different jobs to maximize our sample size. We use the most recent valid pre-migration wage. For post-migration wages, we give preference to the 2003–2004 estimate, but use the first post-migration estimate or the estimate in the 2007–2009 follow-up if a valid estimate of the 2003–2004 wage is not available. We consider an estimate of the wage to be valid if we can construct the adjusted hourly wage; if it falls within the range of \$0.01 to \$1,000 per hour; for pre-migration wages, if the wage was from the year 1983 or later; and for post-migration jobs, if the immigrant had no education in the United States before working in that job. We convert all wages into year 2003 wages by adjusting for the wage growth of observably similar natives between year $t$ and 2003 in the Current Population Survey, where we use age, gender, and education as our observable characteristics. This adjustment corrects for inflation and life-cycle wage growth. Any excess wage growth due to assimilation is thus included in the measured wage gain at migration, which is the conservative choice in our approach. We further explore the importance of assimilation by studying how wages and the wage gain at migration evolve over time and across successive jobs in the online appendix. Our data support assimilation, but we find it plays a modest role in our calculations.

After these checks, the remaining immigrants from poor countries have straightforward immigration-job histories. For example, more than 80 percent of the resulting sample had never lived outside their birth country for more than six months before permanently immigrating to the United States. Again, more than 80 percent report working their first U.S. job within one year of their last pre-migration job; more than three-fourths of immigrants satisfy both restrictions. Our results are robust to focusing on this group. The final sample includes 2,006 immigrants with data on both pre- and post-migration wages that we use for our exercises. See the online appendix for details on the number of immigrants dropped by each of our sample restrictions. There we also compare the baseline sample to samples of immigrants who have only pre- or post-migration wages and show that they do not differ greatly on observed characteristics. We also compare the NIS to the sample of immigrants in the American Community Survey, a standard data set used in the literature.

Recall that our goal is to compare the log-wage change at migration to the log difference in GDP per worker in year 2005 from PWT 7.1. Confidentiality restrictions prevent us from reporting statistics by country of origin in all but a few cases. For this reason, our baseline approach is to report statistics for five income categories, constructed on the basis of PPP GDP per worker relative to the United States: less than 1/16, 1/16–1/8, 1/8–1/4, 1/4–1/2, and 1/2–1 (we exclude the few immigrants from countries richer than the United States). Panel A of table I lists the three countries with the most observations within each category.

TABLE I: Most Sampled Countries by Sample and Subsample

| Country Group | Most Sampled Countries | N |
|---|:---:|:---:|
| **Panel A: NIS Sample by GDP per worker category (relative to United States)** | | |
| $< 1/16$ | Ethiopia, Nigeria, Vietnam | 281 |
| $1/16 - 1/8$ | India, Philippines, China | 617 |
| $1/8 - 1/4$ | Dominican Republic, Ukraine, El Salvador | 436 |
| $1/4 - 1/2$ | Mexico, Poland, Russia | 263 |
| $1/2 - 1$ | Canada, United Kingdom, Korea | 409 |
| **Panel B: MP Sample by Subsample** | | |
| Mexican Migration Project | Mexico | 1,910 |
| Latin American Migration Project | Dominican Republic, El Salvador, Nicaragua | 224 |

*Notes.* Lists the three most common birth countries and sample size for immigrants from the respective subgroup of the NIS or MP samples.

## III.A. Migration Projects

Although the NIS data are ideal for our purposes in most respects, they do have one limitation: they are confined to lawful permanent residents. The vast majority of these immigrants entered the country through legal channels. As we document below, this sample turns out to be highly selected on a wide variety of dimensions, including pre-migration education, occupation, and wage. It is useful to be able to study the wage gains of less selected immigrants. We accomplish this goal by adding data from the Mexican and Latin American Migration Projects (jointly, the Migration Projects, or MPs) when appropriate.

The MPs are collections of surveys that share a common basic design, implemented in Mexico and nine other Latin American countries. In each survey year, the survey team identifies several communities where the interviewers expect some international migration activity. The communities are chosen to represent diverse sizes, but they are not representative of the country. In each community, a representative sample of households is interviewed. In addition, some surveys interview a small number of households that originate in the sampled communities but currently reside in the United States.

The surveys collect basic demographic information and individual job histories from household heads and their spouses. Job histories start with the first job ever held and record the start and end dates, location,

and occupation. Wages are recorded for each person's first and last home country job and first and last job held abroad (including the United States). These wages allow us to calculate the wage change at migration, albeit typically in the opposite fashion (e.g., the wage loss upon returning to the foreign country). We limit our attention to native-born household heads and spouses aged 18 to 75 with valid responses to key variables and who report being paid in their country's local currency (as defined in PWT 7.1). We adjust wages and impose the same sample selection criteria as for the NIS.
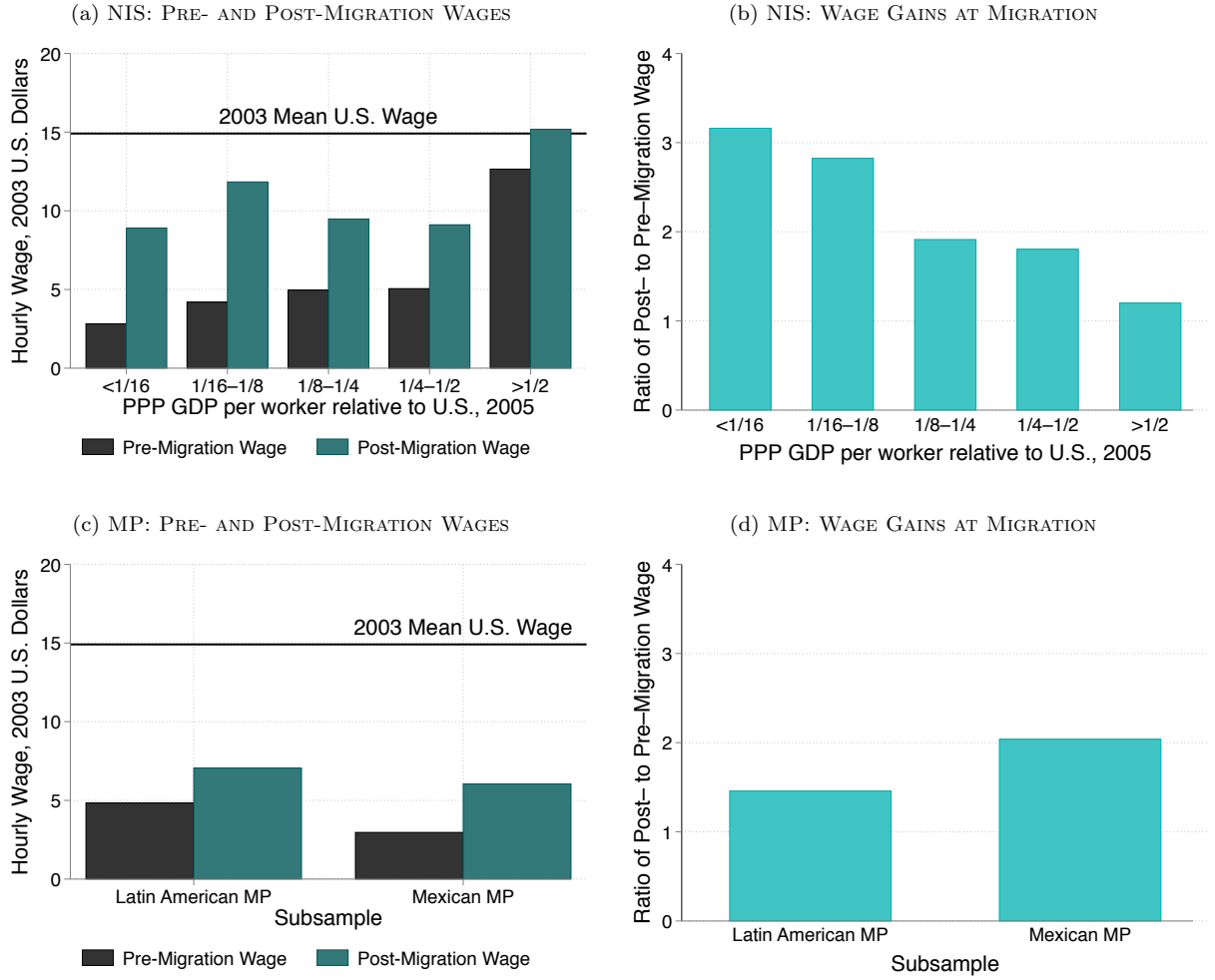
As with the NIS, we aggregate results from the MP data for reporting purposes. We report results separately for the Mexican and Latin American Migration Projects. The former is the bulk of the overall MP sample; the latter covers fewer migrants scattered across eight other poorer Latin American countries. Panel B of Table I gives the sample size and the most common source countries for the MP data.

# IV.  RESULTS

We now turn to our results. We begin by discussing the basic patterns of wages, reported in year 2003 U.S. dollars. We compute the mean pre- and post-migration log wage by PPP GDP per worker category in the NIS data. The exponentiated results are plotted in Figures I(a) and I(c) for the NIS and MP samples, with the exact figures given in Table II. Histograms of the underlying distributions of pre-migration wages, post-migration wages, and the wage gains at migration are available in the online appendix. Both pre- and post-migration wages are positively correlated with development, although the trend is not strong and Mexico stands as an obvious outlier. Most striking are the high levels of pre-migration wages for immigrants from poor countries: the PPP-adjusted hourly wage is $2.82 even for immigrants from the very poorest countries.

A key statistic for our approach is the wage gain at migration, which we compute for each individual as the log of the ratio of post-migration to pre-migration wages. We average this statistic by GDP per worker category and plot the exponentiated results in Figures I(b) and I(d) for the NIS and MP samples, with the exact figures given in Table II. The average immigrant has a substantial wage gain at migration. The wage gain is negatively correlated with development, as one would expect; immigrants from the poorest countries gain by a factor of 3.2, while immigrants from the richest gain by a factor of 1.3. Mexico is again a clear outlier with larger wage gains of 2.0. The gains for immigrants from poor countries are quite small relative to the gap in GDP per worker, suggesting that the country component plays a small role in development accounting. We formalize this idea in the next subsection.

FIGURE I: WAGES, WAGE GAINS, AND GDP PER WORKER

(a) NIS: PRE- AND POST-MIGRATION WAGES

(b) NIS: WAGE GAINS AT MIGRATION

(c) MP: PRE- AND POST-MIGRATION WAGES

(d) MP: WAGE GAINS AT MIGRATION

## IV.A.   Accounting Implications

Recall from equation (4) that our measure of the importance of human capital is one minus the log-wage change at migration relative to the log-GDP per worker gap. We construct the implied share for every immigrant in our sample. We then compute the mean of the share within each subsample for the NIS or the MP. The resulting estimates and 95 percent confidence intervals are given in Table II.[7]

Our primary focus is on poor countries because they are of greater interest for development accounting. Thus, in the NIS sample we focus for the remainder of the paper on immigrants from the three poorest

---

[7]We find very similar results if we use instead the median of the implied human capital shares, or if we first compute mean log-wage changes at migration and mean log-GDP per worker gaps and then construct the implied human capital share. Our confidence intervals are constructed using a normal approximation, but bootstrapped confidence intervals are very similar.

TABLE II: Implied Human Capital Share in Development Accounting

| Group | Hourly Wage | | Development Accounting | | | |
|---|---|---|---|---|---|---|
| | Pre-Mig. | Post-Mig. | Wage Gain | GDP Gap | $h$ share | 95% C.I. |
| **Panel A: NIS Sample by GDP per worker category** | | | | | | |
| $< 1/16$ | $2.82 | $8.91 | 3.2 | 31.8 | 0.66 | (0.60, 0.73) |
| $1/16 - 1/8$ | $4.19 | $11.83 | 2.8 | 11.9 | 0.58 | (0.54, 0.62) |
| $1/8 - 1/4$ | $4.95 | $9.48 | 1.9 | 5.6 | 0.63 | (0.55, 0.71) |
| $1/4 - 1/2$ | $5.05 | $9.11 | 1.8 | 3.0 | 0.48 | (0.34, 0.62) |
| $1/2 - 1$ | $12.64 | $15.18 | 1.2 | 1.3 | 0.48 | (-0.23, 1.19) |
| **Panel B: MP Sample by Subsample** | | | | | | |
| Latin American MP | $4.84 | $7.05 | 1.5 | 7.0 | 0.79 | (0.71, 0.87) |
| Mexican MP | $2.96 | $6.04 | 2.0 | 2.9 | 0.33 | (0.29, 0.37) |

*Notes.* Each row shows results for immigrants from the respective subgroup of the NIS or MP samples. Columns show the categories; the mean hourly pre- and post-migration wages, reported in 2003 U.S. dollars; the wage gain at migration; the average gap in GDP per worker, relative to United States; the implied human capital share; and the corresponding 95 percent confidence interval.

income groups, or those with GDP per worker less than one-quarter of the United States. The estimates from these three groups cover a narrow range of 0.58–0.66 with fairly tight confidence intervals. When pooled, the implied share of human capital in development accounting is 62 percent against a share of country-specific factors of only 38 percent. The 95 percent confidence interval is narrow, ranging from 58 to 65 percent, implying that we can rule out that human capital accounts for as little as even half of cross-country income differences.

We estimate the same statistics for the MP sample. The implied human capital share for the Latin American MP is 79 percent, as opposed to a much lower figure of 33 percent in the Mexican MP. When we pool the two, we find a combined figure of 38 percent. In the next section, we show that much of this difference can be explained by the composition of immigrants from Mexico.

The online appendix contains a lengthy exploration of these results and their robustness, focusing on the NIS sample where we know many more details and covariates of interest. We provide results by country (when possible) and visa status. We show how they are affected by the process of assimilation. And we show that they are robust to the details of how wages are constructed, currencies are converted, who is included in the sample, and so on. There is some variation across these robustness checks, but the implied human capital share is almost always greater than one-half. We now turn to extending the standard development accounting analysis to explore imperfect substitution between skill groups.

## IV.B.   Development Accounting and Imperfect Substitution

Our analysis of the case of imperfect substitution draws on the model laid out in Section II.B.. We begin by exploring whether the wage gains at migration vary systematically with education. To do so, we pool the NIS and the MP samples. As stated above, in the former we focus on immigrants from countries with GDP per worker less than one-quarter of the United States. We include Mexican immigrants in the MP sample even though Mexico has GDP per worker more than one-quarter of the United States because Mexican immigrants are the bulk of the MP sample and are much less educated on average, which is critical for our results in this section. We measure education using data on degree attainment or years spent in school. Workers are divided into five groups: those with no exposure to high school (less than 9 years of schooling); those with some high school but no degree (9–11 years); those with a high school degree (12 years); those with some college but not a bachelor's degree (13–15 years); and those with a bachelor's degree or more (16 or more years of schooling).

TABLE III: Wage Gains and Education

| | |
|---|---|
| No high school | 0.599*** |
| | (0.073) |
| Some high school | 0.463*** |
| | (0.076) |
| High school graduate | 0.264*** |
| | (0.073) |
| Some college | 0.132 |
| | (0.101) |
| Country fixed effects | x |
| Observations | 3,539 |

*Notes.* Estimated effects of education on wage gain at migration using the pooled sample of immigrants from poor countries in the NIS and the MP. Omitted category is college graduates. Standard errors are in parentheses. *** denotes estimates that are statistically different from zero at the 99 percent level.

We estimate wage gains at migration as a function of education level, controlling for country fixed effects. The results are given in Table III. The coefficients capture the log-wage gain relative to the omitted category, which is college graduates. The coefficients are all positive, indicating that less educated workers have larger wage gains. For those without any exposure to college, they are also large and statistically significant. For example, the coefficient on "no high school" indicates that immigrants who have never been to high school gain 82 percent more upon migration to the United States than immigrants with a college degree. These results help us begin to understand why Mexican immigrants in the MP sample have such large wage gains at migration: they are very poorly educated (62 percent have no exposure to high school). These results provide evidence that workers of different skill levels are imperfect substitutes.

We augment our development accounting results to allow for imperfect substitution between skill groups. We start with the bounding approach of equation (6). This approach requires us to partition our five education groups into two broad categories: unskilled and skilled. We explore three partitions, where the cutoff to be skilled ranges from some high school to some college. We focus on immigrants from countries with less than one-quarter of U.S. GDP per worker in the NIS sample so that figures will be comparable with the baseline figure reported above. For each possible partition, we construct the human capital share of development accounting separately for unskilled and skilled immigrants.

TABLE IV: Development Accounting with Imperfect Substitution: Bounding Approach

| Cutoff for Skilled Group | Lower Bound | Upper Bound |
|---|---|---|
| Any high school | 0.49 | 0.63 |
| High school graduate | 0.54 | 0.64 |
| Any college | 0.60 | 0.63 |

*Notes.* Development accounting results from the pooled sample of immigrants from poor countries in the NIS. Each row shows the implied results from a different division of the workforce into unskilled and skilled. The bounding approach produces lower and upper bounds as in equation (6).

The results of this procedure are given in Table IV. The plausible range for human capital is in line with other robustness checks, extending from a little less than one-half to a little less than two-thirds. The point estimates we derive in the perfect substitutes case are close to the upper bounds. This makes sense because most workers in our data are highly skilled. Since the perfect substitutes case takes the simple average across workers and most workers are skilled, it naturally produces results closer to the upper bound.

As a complementary approach we also construct human capital stocks directly, which requires us to impose further structure but allows us to produce point estimates of the human capital share. We group immigrants from poor countries in the NIS and the MP into a single composite country and compare them to the United States, in line with previous sections. We start by separating the total quantity of type $j$ labor into the product of the human capital per worker and the number of workers, $H_{j,c} \equiv h_{j,c} L_{j,c}$. We construct measures of $L_{j,c}$ by country using the data of Barro and Lee (2013). Their education categories map fairly neatly to ours. We assume that workers with different education levels within the unskilled or skilled group are perfect substitutes, allowing us to aggregate them using data on typical school duration and an assumed 10 percent rate of return per year of schooling (Banerjee and Duflo, 2005). See the online appendix for details and the resulting relative skilled labor supply by country.

We normalize $h_{u,U.S.} \equiv 1$, $z_{U.S.} \equiv 1$, and $\theta_u = \theta_s \equiv 1$. We then need to recover five parameters of interest: the three remaining unobserved human capital qualities $h_{j,c}$, the elasticity of substitution $\sigma$, and the country effect $z_c$. We do so using a procedure conceptually similar to Jones (2014): we solve for the five unknown parameters that satisfy five key equations from the CES model of Section II.B.: the wage gains at migration by skill type (equation (5)); the overall GDP per worker gap; and the skill premium by

TABLE V: Development Accounting with Imperfect Substitution: Direct
Calculation

| Cutoff for Skilled Group | $h_{u,p}/h_{u,U.S.}$ | $h_{s,p}/h_{s,U.S.}$ | $\sigma$ | $h$ share |
|---|---|---|---|---|
| Any high school | 0.49 | 0.30 | 8.03 | 0.63 |
| High school graduate | 0.45 | 0.29 | 4.84 | 0.59 |
| Any college | 0.39 | 0.39 | 5.46 | 0.60 |

*Notes.* Development accounting results from the pooled sample of immigrants from poor countries in the NIS. Each row shows the implied results from a different division of the workforce into unskilled and skilled. Columns give the gaps in human capital per unskilled and skilled worker between the poor country and the United States, the elasticity of substitution between unskilled and skilled labor, and the role of human capital in development accounting.

country, given by:

$$(7) \qquad \frac{w_{s,c}}{w_{u,c}} = \left( \frac{H_{s,c}}{H_{u,c}} \right)^{-1/\sigma} \frac{h_{s,c}}{h_{u,c}}.$$

The main difference between our approach and Jones (2014) is that we bring to bear new data on the wage gains at migration and use this to help us pin down $\sigma$.

Table V shows the results of this calculation. Columns (2) and (3) show that we find gaps in the human capital per worker for both unskilled and skilled workers. The gaps are generally larger for skilled workers, perhaps reflecting differences in education quality across countries.

The fourth column of Table V gives the implied elasticity of substitution, which ranges from roughly 5 to 8 depending on the division between unskilled and skilled labor. These values are larger than those typically estimated or used in the literature (Katz and Murphy, 1992; Ciccone and Peri, 2005; Jones, 2014). Our view is that we are estimating a very long run elasticity of substitution, which allows for additional, slow-moving margins of adjustment that may happen in response to the large differences in relative skill abundance between poor countries and the United States. For example, Acemoglu (2002) and Caselli and Coleman (2006) both provide theories where technology responds endogenously to factor endowments, generating differences between the short run and long run elasticity of substitution.

Finally, column (5) gives the implied human capital share in development accounting, which is consistently around 60 percent. The results vary little across different possible partitions between unskilled and skilled labor because $h_{u,c}$ and $h_{s,c}$ are calculated in each case to fit the wage gains of unskilled and skilled workers as we vary the partition.

One possible concern about both calculations in this section is that they rely on the wage gains of unskilled workers while our sample has few such workers. To explore this concern we perform similar calculations where we set $h_{u,p} = h_{u,U.S.} \equiv 1$ instead of matching the wage gains at migration of unskilled workers. This assumption implies that all unskilled workers in the world provide the same labor services; unskilled immigrants from poor countries then earn the same wages as unskilled Americans. The implied human capital share in development accounting is modestly lower: 59 percent when workers with any high school are skilled or 46 percent when high school graduates and above are skilled, in line with our earlier range of results. To push the human capital share much lower would require us to include workers with some college in the unskilled category; given the assumption $h_{u,c} \equiv 1$, this implies that the majority of the world's population, including all high school graduates, provides identical unskilled labor services. Even this extremely strong assumption would only push the human capital share in development accounting to 36 percent. These calculations all produce much larger wage gains for unskilled workers than we observe in our sample, a factor of 7.6 instead of 3.0–3.7 in the data.

Overall, the evidence supports imperfect substitution between unskilled and skilled workers. The human capital share in development accounting can be bounded between one-half and two-thirds; our best estimate from direct calculations is that it is around 60 percent. We now turn to quantifying selection, which is important for understanding why our results differ from those in the literature.

# V. Selection

We measure the importance of human capital for development accounting by comparing the wage gains at migration to the total gap in GDP per worker. As discussed in Section 2.1, this deals with the simplest form of immigrant selection. However, it is of interest to back out the implied degree of selection, which is the gap between immigrants' pre-migration characteristics and the characteristics of non-migrants born in the same country. The patterns and degree of selection are of interest in their own right. As we show below, they are also useful for understanding why our results differ so much from those in the literature.

## V.A. Selection and Wages

We start by measuring the implied extent of selection on wages. In principle, one would like to compare the pre-migration hourly wage of immigrant $i$ to the mean wage of non-migrants born in the same country, $w_{i,c}/\overline{w_c}$. Given the widespread prevalence of self-employment in poor countries, we substitute $\overline{w_c} = (1 -$

$\alpha_c)y_c/n_c$ to approximate the mean labor income per hour of all workers (instead of using only wages of wage workers.) Here, $n_c$ is hours worked per worker per year. Gollin (2002) documents that $\alpha_c$ does not vary systematically with average income, while Bick, Fuchs-Schundeln and Lagakos (forthcoming) document that hours worked per employed person do not differ much between the United States and poor countries. If we assume that these two factors are roughly constant, we arrive at a simple measure of selection for an individual:

$$(8) \qquad \rho_i = \frac{w_{i,c}/y_c}{w_{U.S.}/y_{U.S.}}.$$

In words, this equation says immigrants are highly selected if the ratio of their pre-migration wage to GDP per worker is high relative to the benchmark, which is the mean wage of Americans relative to U.S. GDP per worker.

We construct this measure of selection for all individuals in the NIS and MPs. For the NIS we average the results by GDP per worker category. For the MPs we differentiate between the large Mexican sample originating in the Mexican Migration Project and then pool the remaining poorer countries with much smaller samples from the Latin American Migration Project. The resulting measures of selection are plotted as "total selection" in Figure II. This exercise has two main takeaways. First, immigrants are substantially selected on pre-migration wages, with a mean selection of more than two for the entire sample. Second, the degree of selection varies systematically with PPP GDP per worker. Immigrants from the poorest countries are selected by a factor of six, whereas immigrants from the richest countries are nearly unselected by this measure. We also find that immigrants from Mexico are roughly unselected, in line with an existing literature that debates whether the selection is positive or negative (Morága, 2011).

A second question is whether this selection corresponds with observed characteristics of workers. To test this, we construct a measure of residual wages and selection along the lines of Hendricks (2002). The basic idea is to use a log-wage regression on a sample of natives to estimate the effect of observable characteristics, in this case age and education. We do so using the 2004 American Community Survey (ACS), which is a large representative sample that closely matches the time frame of the NIS. We construct a measure of selection on observable characteristics by valuing the difference in age and education of immigrants and non-migrants with the estimated coefficients. Our data on the characteristics of non-migrants come from Barro and Lee (2013), who give the educational attainment and age composition of the population for most countries worldwide.

FIGURE II: SELECTION OF IMMIGRANTS

(a) NIS SAMPLE                    (b) MP SAMPLE
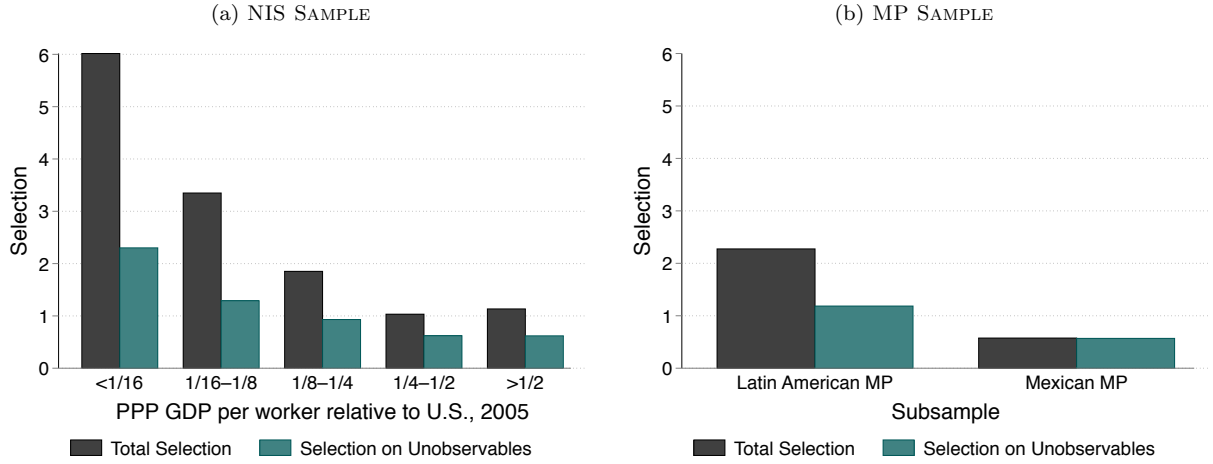


We then study selection on unobservables, which is the portion of selection on pre-migration wages that remains after netting out selection on observables as constructed above. The results are shown again in Figure II.[8] Immigrants from the poorest countries are much more selected on unobserved characteristics than those from the richest countries.

The degree and pattern of selection are interesting in their own right, but they also help to explain why our results differ so much from the previous literature, particularly the results in Hendricks (2002). Hendricks (2002) shows that residual wages are only modestly higher for immigrants from rich countries relative to those from poor countries. Under the assumption that these immigrants are equally selected on unobserved human capital, this finding implies relatively small differences in the human capital of non-migrants in rich and poor countries.[9] This logic is central to his result that human capital accounts for little of cross-country income differences.

Our data support the finding that residual (post-migration) wages are only modestly higher for immigrants from rich countries relative to those from poor countries. In the online appendix we show that the estimated relationship in the NIS is in line with the literature. However, Figure II suggests a very different interpretation of this finding. Immigrants from poorer countries are much more selected on unobserved characteristics

---

[8]Since the MP samples collect data on non-migrants in each country, we can also compute selection and residual selection directly using wages in these countries rather than using equation (8). The results are quite similar.

[9]He also argues that it is implausible that all of the wage gap between immigrants and non-migrants can be accounted for by selection. Our findings are consistent with this claim because we find that some but not all of the wage gap can be accounted for by selection. Focusing on the poorest GDP per worker group in the NIS, the total wage gap can be decomposed as follows: the true wage gain (factor of 3.2); selection on observed components (factor of 2.6); and selection on unobserved components (factor of 2.3).

than are immigrants from rich countries. The implied gap in human capital between non-migrants from rich and poor countries is thus found to be much larger than that in Hendricks (2002).

Our results are also larger than those in Schoellman (2012). That paper relies on a different identifying assumption, namely that selection on residual wages is uncorrelated with schooling for a given country. Although our sample size is too small to test this prediction, we show in the online appendix that selection on residual wages is not strongly correlated with schooling within a GDP per worker category. The more likely reason that our results are larger is that Schoellman (2012) has a more limited scope in trying to account for differences in quality-adjusted schooling, whereas our results include in principle all forms of human capital, including experience (as in Lagakos et al. (forthcoming)) or health.

## V.B.    *Selection on Other Characteristics*

Selection on residual characteristics plays an important role in explaining why our results differ from those in the previous literature. Given this role, we explore other non-wage attributes of immigrants from poor countries to see if they support strong selection. We start with the NIS sample, focusing particularly on the immigrants from the very poorest countries (less than 1/16 of U.S. GDP per worker). These immigrants are highly selected on education, with an average of 13 years of schooling. Thirty-two percent have a college degree, while only 18 percent have not graduated from high school. This finding is similar to what is reported in Schoellman (2012), namely that immigrants from poor countries are much more educated than non-migrants born in the same country.

Immigrants are also highly selected on non-wage occupational characteristics. For example, 79 percent of immigrants from the poorest countries were employed for wages in their pre-migration job, which stands at odds with the general prevalence of self-employment in poor countries. Selection on occupation is also strong. If we focus on 25 broad occupation categories, the most commonly reported are sales and related, office and administrative support, management, and education and training. Combined, they account for more than half of all pre-migration occupations. Only a single immigrant in the poorest group of countries reported having previously worked in agriculture, forestry, and fishing, even though this occupation group accounts for the majority of employment in most poor countries (Restuccia, Yang and Zhu, 2008).

Selection in the MPs is broadly similar except for Mexican immigrants, who are much less selected. They are much less educated, with only 7.1 years of schooling on average, and 60 percent have no exposure to high school. Further, they are actually over-representative of agriculture; 31 percent worked in agriculture,

as compared to 15 percent of non-migrants.

## V.C.    Selection and Sectoral Wage Gaps

Selection on pre-migration employment implies that our results intersect with the growing literature that documents sectoral and regional labor productivity gaps in poor countries (Restuccia, Yang and Zhu, 2008; Caselli, 2005; Herrendorf and Valentinyi, 2012). Two potential explanations account for these gaps. The first is selection by high human capital workers into non-agriculture and urban areas. In this case, the scarcity of former agricultural workers in our sample is simply another sign of strong selection on human capital. The second is gaps in the marginal value product of labor between sectors or regions combined with a "barrier" that prevents workers from reallocating to the sector or region with the higher marginal value product of labor. In this case, the NIS has oversampled immigrants from the most productive portions of poor countries. The extent to which selection or barriers account for sectoral productivity gaps is still an open question in the literature (Gollin, Lagakos and Waugh, 2014; Hicks, Kleemans, Li and Miguel, 2017; Herrendorf and Schoellman, forthcoming).

We can test these two hypotheses using our data. The barriers view implies that immigrants who previously lived in unproductive areas or worked in unproductive sectors had lower wages, which in turn implies a larger wage gain at migration (assuming, as is conventional, that there are no such gaps in the United States). Thus, we look for heterogeneity in the wage gains at migration by sector and region of pre-migration employment. For sector we focus on whether the immigrant was employed in agriculture or non-agriculture. For region we know only whether an immigrant grew up in a rural or an urban area, and only for the NIS.

We estimate wage gains as a function of country fixed effects and sector or region using the pooled NIS and MP samples of immigrants from countries with GDP per worker less than one-quarter of the United States, plus immigrants from Mexico. The results are given in columns (1) and (2) of Table VI. The effects of sector and region are large and statistically significant. Immigrants who previously worked in agriculture gain 71 percent more at migration than those who worked in non-agriculture; immigrants who grew up in rural areas gained 33 percent more than those who grew up in urban areas. One potential concern is that these results confound the effects of education. Columns (3) and (4) show the result of estimating the wage gain as a joint function of sector or region and education.[10] The results for sector are reduced only

---

[10]It would also be interesting to test the effect of sector versus the effect of region. Unfortunately, we cannot do so because we only know rural status in the NIS, whereas almost all observations for agricultural workers are in the MP sample.

TABLE VI: Wage Gains and Immigrant Characteristics

|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Agriculture | 0.536*** | | 0.476*** | |
| | (0.053) | | (0.054) | |
| Grew up rural | | 0.285*** | | 0.197** |
| | | (0.079) | | (0.081) |
| No high school | | | 0.495*** | 0.664*** |
| | | | (0.073) | (0.157) |
| Some high school | | | 0.431*** | 0.358*** |
| | | | (0.076) | (0.138) |
| High school graduate | | | 0.259*** | 0.175* |
| | | | (0.072) | (0.104) |
| Some college | | | 0.136 | 0.251* |
| | | | (0.100) | (0.144) |
| Country fixed effects | x | x | x | x |
| Observations | 3,539 | 1,400 | 3,539 | 1,400 |

*Notes.* Estimated effects of immigrant characteristics (education, sector of employment, region of childhood) on wage gain at migration. Columns (1) and (3) use the pooled NIS and MP samples, while columns (2) and (4) use only the NIS sample. Standard errors are in parentheses. ***, **, and ∗ denote estimates that are statistically different from college graduates at the 99, 95, and 90 percent level.

modestly, the results for region more so. These results are evidence in favor of gaps in the marginal value product of labor, especially between sectors. They also help us further to understand the high wage gains at migration for Mexican immigrants: Mexican immigrants are by far the most likely to have worked in agriculture before migrating.

These gaps imply that each country's aggregate $z$ and our average wage gains at migration are affected by the sectoral composition of employment. For logical consistency, the sectoral employment shares used to calculate each object should match, but the selection of immigrants implies that they do not. To correct for this mismatch, we construct the human capital share in development accounting separately for workers who previously worked in non-agriculture and in agriculture. We then reweight the two using the employment share in agriculture of the corresponding country group, taken from World Bank (2014).

We make this correction for the baseline NIS sample. Agricultural workers are undersampled: they are 1.1 percent of the sample, versus 33 percent for non-migrants. Correcting for this undersampling puts more weight on the large wage gains of agricultural immigrants, but the effect is modest: the implied human capital share is 55 percent instead of 62 percent in the baseline. This calculation puts a lot of weight on a small number of agricultural workers in the NIS. However, we get similar results if we pool the NIS with the MP with or without Mexico, which helps to expand the sample of agricultural workers used in the calculation.

A second question of interest is whether these results are more important for the very poorest countries where agriculture is more common. For example, countries in our poorest GDP per worker group have a 60 percent agricultural employment share. However, we know little about the wage gains at migration for agricultural workers from the poorest countries because our sample includes only one such worker. We can provide some preliminary calculations if we assume that agricultural workers would gain 0.536 more than non-agricultural workers, as implied by column (1) of Table VI.[11] In this case adjusting for composition effects reduces the human capital share from 68 to 57 percent. An effect twice as large would reduce the human capital share to 47 percent.

---

[11]We estimated wage gains as a function of sector and an interaction of sector and log GDP per worker. The coefficient on the interaction was positive and statistically insignificant. Thus, at least in our sample there is no systematic evidence that poorer countries have larger sectoral gaps in marginal value products.

# VI. Skill Transferability

Our baseline estimates measure the importance of country by comparing the pre- and post-migration wages of a fixed individual. If immigrants are able to use their human capital equally in the two countries, then the gap in wages is entirely determined by country-specific factors. However, a common concern with immigrants is that their skills may not transfer perfectly when they migrate. This could happen either if skills are heterogeneous and they have acquired skills that are not highly valued in the United States, or if barriers such as accreditation, licensure, or discrimination prevent them from fully utilizing their skills.

The first goal of this section is to provide evidence on skill transferability by studying proxies for skill transfer. Our main evidence comes from comparing immigrants' pre- and post-migration occupations. We focus on the NIS sample, which has detailed and consistent codes for each occupation. We document that occupational switching is widespread and that most immigrants move to lower-paying jobs, which is a possible sign of imperfect skill transfer. We then consider the importance of this finding for our development accounting results. If immigrants have skills but cannot use them in the United States, then this barrier depresses their post-migration wage and the wage gain at migration. It then follows that we understate the role of country and overstate the role of human capital in development accounting. Conservative corrections for skill transfer push our estimate of the human capital share down toward one-half.

## VI.A. Evidence on Skill Transferability

Our main measure for skill transfer comes from comparing immigrants' pre- and post-migration occupations.[12] Measuring skill transferability through occupational changes is subject to two biases that push in opposite directions and are not easy to quantify. On the one hand, we are assuming that immigrants who do not practice their pre-migration occupation do so because of a lack of skill transferability, ruling out a lack of skill altogether (i.e., they may simply have been unqualified). On the other hand, our measure does not capture within-occupation skill loss. For example, we capture doctors who are forced to work as taxi drivers, but not specialized doctors forced to work as family doctors. However, we note that the NIS uses the 2000 U.S. Census occupation codes, which include over 450 possible occupational choices. With these two caveats in mind, we now turn to analyzing occupational switches.

We begin by examining the frequency of occupation switches. Most immigrants switch jobs after migrating.

---

[12]The literature on the economics of immigration has explored several ways to measure skill transfer. Our approach and findings parallel those of Chiswick, Lee and Miller (2005) and especially Akresh (2008), who also uses the NIS. Chiswick and Miller (2009) employ an alternative strategy of comparing immigrants' education to that of natives in the same occupation, using "overeducation" as a proxy for imperfect skill transfer.

TABLE VII: Occupational Changes at Migration

| GDP category | Occupational Switch (%) | | | Mean Change (%) |
|---|---|---|---|---|
| | Lower-Paying | Same Occupation | Higher-Paying | |
| <1/16 | 68 | 9 | 23 | -17 |
| 1/16–1/8 | 61 | 16 | 22 | -15 |
| 1/8–1/4 | 67 | 6 | 26 | -16 |
| 1/4–1/2 | 60 | 10 | 30 | -13 |
| >1/2 | 49 | 25 | 26 | 0 |

*Notes.* Columns show the fraction of immigrants who switched to a lower-paying job, stayed at the same job, or switched to a higher-paying job at migration, as well as the average change in job pay at migration, where average pay is measured using the mean wage of natives. Rows show those results for different PPP GDP per worker groups. All results constructed from the NIS sample.

The fraction staying in the same occupation is shown in column 3 of Table VII and ranges from 6 to 25 percent depending on the level of development. This figure is driven mostly by changes to entirely new occupations; if we aggregate to broad occupation groups, still only 15–41 percent of immigrants work in the same broad occupation group after migrating.

A change in occupation does not indicate whether the new occupation is better or worse than the old occupation. As a proxy for the "quality" of an occupation, we construct the mean wage of natives employed in the occupation from the 2004 ACS. We merge this mean wage by occupation with both the pre- and post-migration occupations of immigrants in the NIS. This procedure provides us with a quantitative ranking of each immigrant's pre- and post-migration occupation and hence a measure of the extent to which an immigrant's new job is better or worse than his or her old one. For example, take an immigrant who worked as a physician in his or her birth country but works as a taxi driver in the United States. Based on the observation that the mean wage of taxi drivers in the United States is $9.58 while the mean wage of physicians is $37.11, we would infer that the immigrant's occupational switch involved a downgrade. The extent of the change in mean wages (74 percent) provides a metric to suggest that the occupational downgrading was significant.

The remaining columns of Table VII show a sense of the distribution and average change in occupation at arrival. Roughly two-thirds of immigrants move to a lower-paying job after migrating, while only one-quarter move to a higher-paying job, except for the highest GDP per worker group. The mean change

in occupation quality (again, judged by mean native wage) is a loss of 13–17 percent upon migration. Only immigrants from the richest countries report little occupational downgrading at migration. One interpretation of this finding is that most immigrants cannot perfectly transfer their skills to the United States.

Since occupations are only an imperfect measure of skill transfer, we also explore other proxies for ability to transfer skills, with a focus on two that we think are likely to be particularly relevant for immigrants: language and networks. For the former, we find that immigrants who speak English, and particularly those who use English at work, have larger wage gains and less occupational downgrading at migration. For the latter, we find that the extent of occupational downgrading declines over time, consistent with a theory in which immigrants need to build up networks: the first post-migration job is 18 percent worse, the round 1 job 14 percent worse, and the round 2 job 9 percent worse than the pre-migration job (wages also rise; see the online appendix for details). We also have two proxies for immigrants who may have had networks even before immigrating to the United States. Both immigrants who entered on employment visas and those who report having had a job offer in hand before immigrating to the United States, report larger wage gains and less occupational downgrading at migration. These proxies only add to the evidence that skill transfer is imperfect and the extent of skill transfer varies among immigrants. We now show how to correct our development accounting results for this imperfect skill transfer.

## VI.B.   Development Accounting with Imperfect Skill Transfer

If we interpret these findings as evidence of imperfect skill transfer, then they have important implications for our development accounting results. We explore this idea further in three ways, focusing throughout on the NIS sample of immigrants from countries with less than one-quarter of U.S. GDP per worker. First, since our index of occupational downgrading is smaller for later jobs, it may be more appropriate to use the wage gains and human capital share of later jobs. Using the wage gain from the last job leads to a human capital share of 0.53 instead of 0.62. Second, we check the robustness of our results to focusing on groups for whom skill transfer is likely to be less of a problem. The NIS includes four main groups: immigrants who entered the United States on employment visas; those who entered the United States with a job offer in hand; those who work the same detailed occupation before and after migrating; and those who speak English at work. The implied development accounting results for these subsamples are shown along with the baseline in Table VIII. While human capital accounts for 62 percent of cross-country income differences in the baseline, it accounts for 45–59 percent when focusing on these subsamples.

TABLE VIII: Development Accounting and Skill Transfer

| Robustness Check | Human Capital Share | 95% C.I. |
|---|---|---|
| Baseline | 0.62 | (0.58, 0.65) |
| Employment visa | 0.56 | (0.50, 0.62) |
| Job offer before migrating | 0.45 | (0.36, 0.55) |
| Same narrow occupation | 0.56 | (0.48, 0.64) |
| English at work | 0.59 | (0.54, 0.63) |
| Skill transfer: mean wage | 0.55 | (0.52, 0.59) |

*Notes.* Each column shows the implied human capital share in development accounting (one minus the wage gain at migration relative to the GDP per worker gap) and the 95 percent confidence interval. Each row shows the result from constructing these statistics for a different sample or using different measures of post-migration wages. All results constructed from the NIS sample.

As a second check, we consider imputing to immigrants a higher wage if they experienced occupational downgrading. This step is logical if the main reason for occupational downgrading is artificial barriers such as licensure rather than a lack of skills among immigrants. By increasing the post-migration wage of immigrants, we also increase the implied wage gains at migration and lower the implied human capital share for development accounting. We implement this idea by adding to each downgraded immigrant's wage the gap in mean native wages between his or her pre- and post-migration occupations. For example, take an immigrant who reports having been a doctor before arriving to the United States, but who is now a taxi driver earning $8 an hour. We would add to this wage the difference between the mean native wage of doctors and taxi drivers, which is $27.53, resulting in a total wage of $35.53. The resulting adjustment is substantial, increasing the mean post-migration wage of immigrants by 14 percent. We then recompute wage gains at migration and the human capital share in development accounting. The results are reported in the last row of Table VIII. We find that human capital in this case would still account for more than half of cross-country income differences.

This section offers two main takeaways. First, most immigrants switch to lower-paying occupations when they immigrate to the United States. If this fact is interpreted as the result of imperfect skill transfer, then our baseline results overstate the importance of human capital for development accounting. We conduct several checks that suggest that correcting for imperfect skill transfer could lower the human capital share to 45-59 percent, which is still much larger than the standard result in the literature. On the other hand,

if occupational downgrading indicates a lack of skills, then the baseline result of 62 percent is appropriate.

# VII. Conclusion

In this paper we use data on pre- and post-migration outcomes of immigrants along with an extended development accounting framework to infer the importance of human capital versus country in accounting for cross-country income differences. Our key finding is that immigrants' wage gains at migration are small relative to gaps in PPP GDP per worker. Using the standard development accounting framework in which workers of different types are perfect substitutes, these figures imply that human capital accounts for 62 percent of cross-country income differences. Wage gains are larger for less educated immigrants and those who previously worked in agriculture, so we also consider extending the development accounting results to allow for imperfect substitution between workers of different types and sectoral productivity gaps within poor countries. A plausible range of variation for the human capital share is from just under one-half to two-thirds.

We also provide novel evidence on two issues frequently raised in the literature. First, we find that immigrants are highly selected on observable and unobservable characteristics. Both forms of selection are negatively correlated with development. Second, we study skill transfer through immigrants' changes in occupation. We find evidence that immigrants move to lower-paying occupations upon arrival. We provide calculations to show that reasonable corrections for this possible imperfect skill transfer lower the human capital share in development accounting to roughly one-half.

University of North Carolina, Chapel Hill

Federal Reserve Bank of Minneapolis

# References

**Acemoglu, Daron**, "Directed Technical Change," *Review of Economic Studies*, 2002, *69* (4), 781–809.

**Akresh, Ilana Redstone**, "Occupational Trajectories of Legal US Immigrants: Downgrading and Recovery," *Population and Development Review*, 2008, *34* (3), 435–456.

**Alvarez, Jorge A.**, "The Agricultural Wage Gap: Evidence from Brazilian Micro-data," 2017. Mimeo, International Monetary Fund.

**Banerjee, Abhijit V. and Esther Duflo**, "Growth Theory through the Lens of Development Economics," in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 1A, Elsevier, 2005, chapter 7, pp. 473–554.

**Barro, Robert J. and Jong Wha Lee**, "A New Data Set of Educational Attainment in the World, 1950–2010," *Journal of Development Economics*, 2013, *104*, 184–198.

**Bick, Alex, Nicola Fuchs-Schundeln, and David Lagakos**, "How Do Hours Worked Vary With Income? Cross Country Evidence and Implications," *American Economic Review*, forthcoming.

**Bils, Mark and Peter J. Klenow**, "Does Schooling Cause Growth?," *American Economic Review*, 2000, *90* (5), 1160–1183.

**Caselli, Francesco**, "Accounting for Cross-Country Income Differences," in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 1A, Elsevier, 2005, chapter 9, pp. 679–741.

_ **and Wilbur John Coleman II**, "The World Technology Frontier," *American Economic Review*, 2006, *96* (3), 499–522.

**Chiswick, Barry R. and Paul W. Miller**, "The International Transferability of Immigrants' Human Capital," *Economics of Education Review*, 2009, *28* (2), 162–169.

_ , **Yew Liang Lee, and Paul W. Miller**, "A Longitudinal Analysis of Immigrant Occupational Mobility: A Test of the Immigrant Assimilation Hypothesis," *International Migration Review*, 2005, *39* (2), 332–353.

**Ciccone, Antonio and Giovanni Peri**, "Long-Run Substitutability Between More and Less Educated Workers: Evidence from US states, 1950–1990," *Review of Economics and Statistics*, 2005, *87* (4), 652–663.

**Clemens, Michael A.**, "Why do Programmers Earn More in Houston than Hyderabad? Evidence from Randomized Processing of US Visas," *American Economic Review*, 2013, *103* (3), 198–202.

_ , **Claudio E. Montenegro, and Lant Pritchett**, "The Place Premium: Wage Differences for Identical Workers across the US Border," 2008.
World Bank Policy Research Working Paper No. 4671.

_ , _ , **and** _ , "Bounding the Price Equivalent of Migration Barriers," *Review of Economics and Statistics*, forthcoming.

**Córdoba, Juan Carlos and Marla Ripoll**, "What Explains Schooling Differences Across Countries?," *Journal of Monetary Economics*, 2013, *60* (2), 184–202.

**Cubas, German, B. Ravikumar, and Gustavo Ventura**, "Talent, Labor Quality, and Economic Development," *Review of Economic Dynamics*, 2016, *21*, 160–181.

**Duleep, Harriet Orcutt**, "The Adjustment of Immigrants in the Labor Market," in Barry R. Chiswick and Paul W. Miller, eds., *Handbook of the Economics of International Migration*, Elsevier, 2015, chapter 3, pp. 105–182.

**Erosa, Andrés, Tatyana Koreshkova, and Diego Restuccia**, "How Important is Human Capital? A Quantitative Theory Assessment of World Income Inequality," *Review of Economic Studies*, 2010, *77* (4), 1421–1449.

**Gibson, John and David McKenzie**, "The Economic Consequences of 'Brain Drain' of the Best and Brightest: Microeconomic Evidence from Five Countries," *Economic Journal*, 2012, *122* (560), 339–375.

_ , _ , **Halahingano Rohorua, and Steven Stillman**, "The Long-Term Impacts of International Migration: Evidence from a Lottery," *World Bank Economic Review*, forthcoming.

**Gollin, Douglas**, "Getting Income Shares Right," *Journal of Political Economy*, 2002, *110* (2), 458–474.

_ , **David Lagakos, and Michael E. Waugh**, "The Agricultural Productivity Gap," *Quarterly Journal of Economics*, 2014, *129* (2), 939–993.

**Hall, Robert E. and Charles I. Jones**, "Why Do Some Countries Produce So Much More Output Per Worker Than Others?," *Quarterly Journal of Economics*, 1999, *114* (1), 83–116.

**Hanushek, Eric A. and Ludger Woessmann**, "Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation," *Journal of Economic Growth*, 2012, *17* (4), 267–321.

**Hendricks, Lutz**, "How Important Is Human Capital for Development? Evidence from Immigrant Earnings," *American Economic Review*, 2002, *92* (1), 198–219.

**Herrendorf, Berthold and Ákos Valentinyi**, "Which Sectors Make Poor Countries So Unproductive?," *Journal of the European Economic Association*, 2012, *10* (2), 323–341.

_ **and Todd Schoellman**, "Wages, Human Capital, and Barriers to Structural Transformation," *American Economic Journal: Macroeconomics*, forthcoming.

**Hicks, Joan Hamory, Marieke Kleemans, Nicholas Y. Li, and Edward Miguel**, "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata," January 2017.
Mimeo, UC Berkeley.

**Hsieh, Chang-Tai and Peter J. Klenow**, "Development Accounting," *American Economic Journal: Macroeconomics*, 2010, *2* (1), 207–223.

**Jasso, Guillermina, Douglas S. Massey, Mark R. Rosenzweig, and James P. Smith**, "The U.S. New Immigrant Survey: Overview and Preliminary Results Based on the New-Immigrant Cohorts of 1996 and 2003," in Beverley Morgan and Ben Nicholson, eds., *Immigration Research and Statistics Service Workshop on Longitudinal Surveys and Cross-Cultural Survey Design: Workshop Proceedings.*, London: Crown Publishing, 2005.

_ , _ , _ , **and** _ , "The New Immigrant Survey Restricted Use Data, Versions 1 and 2," 2007.
A research project funded by NIH HD33843, NSF, USCIS, ASPE & Pew. Retrieved February 2014 and December 2016. Persons interested in obtaining NIS Restricted Use Data should see `http://nis.princeton.edu/data_restricted.html` for further information.

_ , **Mark R. Rosenzweig, and James P. Smith**, "The Earnings of U.S. Immigrants: Work Skill Prices, Skill Transferability, and Selectivity," March 2002.
Mimeo, New York University.

**Jones, Benjamin F.**, "The Human Capital Stock: A Generalized Approach," *American Economic Review*, 2014, *104* (11), 3752–3777.

**Katz, Lawrence F. and Kevin M. Murphy**, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, February 1992, *107* (1), 35–78.

**Kennan, John**, "Open Borders," *Review of Economic Dynamics*, 2013, *16* (2), L1–L13.

**Klein, Paul and Gustavo Ventura**, "Productivity Differences and the Dynamic Effects of Labor Movements," *Journal of Monetary Economics*, 2009, *56* (8), 1059–1073.

**Klenow, Peter J. and Andrés Rodríguez-Clare**, "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?," in Ben S. Bernanke and Julio J. Rotemberg, eds., *NBER Macroeconomics Annual 1997*, MIT Press, 1997, pp. 73–103.

**Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman**, "Life-Cycle Human Capital Accumulation Across Countries: Lessons from U.S. Immigrants," *Journal of Human Capital*, forthcoming.

**Lessem, Rebecca and Carl Sanders**, "Immigrant Wage Assimilation in the United States: The Role of Occupational Upgrading," 2014.
Mimeo, Carnegie Mellon University.

**Lubotsky, Darren**, "Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings," *Journal of Political Economy*, 2007, *115* (5), 820–867.

**McKenzie, David, Steven Stillman, and John Gibson**, "How Important is Selection? Experimental vs. Non-Experimental Measures of the Income Gains from Migration," *Journal of the European Economic Association*, 2010, *8* (4), 913–945.

**Morága, Jesús Fernandez-Huertas**, "New Evidence on Emigrant Selection," *Review of Economics and Statistics*, 2011, *93* (1), 72–96.

**Restuccia, Diego, Dennis T. Yang, and Xiaodong Zhu**, "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis," *Journal of Monetary Economics*, 2008, *55* (2), 234–250.

**Rosenzweig, Mark R.**, "Global Wage Inequality and the International Flow of Migrants," January 2010.
Yale University Economic Growth Center Discussion Paper No. 983.

**Schoellman, Todd**, "Education Quality and Development Accounting," *Review of Economic Studies*, 2012, *79* (1), 388–417.

_ , "Early Childhood Human Capital and Development," *American Economic Journal: Macroeconomics*, 2016, *8* (3), 145–174.

**Weil, David N.**, "Accounting for the Effect of Health on Economic Growth," *Quarterly Journal of Economics*, 2007, *122* (3), 1265–1306.

**World Bank**, *World Development Indicators*, Washington D.C.: World Bank, 2014.