Human Capital and Development Accounting: New Evidence from Immigrant Earnings

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Abstract

We reconsider the role for human capital in accounting for cross-country differences. Our contribution is to bring to bear new data on the pre- and post-migration labor market experiences of immigrants. Immigrants from poorer countries experience log-wage gains that are only roughly one-third as large as the log-GDP per worker gap. This fact implies human capital accounts for two-thirds of cross-country income differences. We also use the data to provide direct measures of selection of immigrants and the extent to which they can transfer their skills to the US and find both to be important features of the data. Finally, we provide evidence on the elasticity of substitution between skilled and unskilled labor.

JEL Classification: O11, J31

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1 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 towards 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, the consensus in the literature is that physical capital accounts for a small fraction of income differences, which has suggested to researchers to de-emphasize theories that rely on large cross-country variation in physical capital.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, with widely different answers. 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 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 from the experiences of immigrants to the United States. Intuitively, immigrants provide valuable information because they enter the U.S. with the human capital they acquired in their former country, but not the physical capital or TFP. Hence, their labor market performance in the U.S. can be used to learn about the relative importance of human capital versus 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


²The former figure comes from Hall and Jones (1999); the latter comes from Manuelli and Seshadri (2014) or Jones (2014). The literature also includes a wide range of estimates in between. See, for example, Erosa et al. (2010), Hanushek and Woessmann (2012), Cordoba and Ripoll (2013), or Cubas et al. (2015).

³Previous papers that have investigated immigrants and cross-country differences in human capital include Hendricks (2002), Schoellman (2012), Schoellman (2013), and Lagakos et al. (2014).
We address these challenges by utilizing new data from the New Immigrant Survey, a sample of new legal residents in the United States in 2003 (Jasso et al., 2006). The unique advantage of this dataset is that it asked immigrants detailed questions about both their pre- and post-migration education and labor market experiences. We use this data in three ways. First, we construct a simple measure of the relative importance of human capital versus country by comparing the pre- to post-migration wages of immigrants. Second, we address the challenge of selection directly 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 labor market characteristics of immigrants, such as occupation and hours worked.

We start by revisiting the standard development accounting framework. We describe the assumptions that are necessary to draw aggregate implications from the labor market experiences of immigrants. We show that the most direct statistic is a comparison of the log-wage gain to migration and the gap in log GDP per worker. Intuitively, this captures the fraction of the total GDP per worker gap that is closed when a worker changes physical capital and TFP (by moving) but holds their human capital fixed. Hence, it captures the relative importance of physical capital and TFP, with the remainder of the gap in GDP per worker attributable to human capital.

Our empirical work thus relies heavily on a comparison of pre- to post-migration wages. A desirable feature of the New Immigrant Survey is that it allows for a great deal of flexibility in how workers report their earnings. In particular, they can report their pre-migration earnings from working in any country, paid in any currency, in any year, at many different frequencies. We discuss in detail how we adjust these data for exchange rate, purchasing power parity, and wage growth to arrive at an estimate of their pre-migration hourly wage in PPP-adjusted U.S. dollars in 2003 and their post-migration hourly wage in the U.S. in 2003. We also provide detailed information on sensitivity and robustness checks to possible confounding issues such as episodes of inflation or currency revaluation, migrants who report working in their non-birth country, and so on.

As discussed above, our preferred statistic is the log wage change at migration relative to the median gap in log GDP per worker. We focus on immigrants from poor countries, with PPP GDP per worker less than one-fourth the U.S. level. We find that for the median immigrant in this group the statistic is 0.37, implying that a little more than one-third of cross-country income differences are accounted for by physical capital and TFP variation, and a little less than two-thirds to human capital variation. Our standard error for this
statistic is 0.039, indicating that it is reasonably precise. We show that this figure is robust to many of the details of sample selection and wage construction. For example, we show that similar results hold for immigrants who entered the U.S. with very different education levels and visa categories.

This finding attributes a much higher share to human capital than what is typical even in the literature on immigrants and development accounting (Hendricks, 2002; Schoellman, 2012). These earlier papers relied on assumptions about immigrant selection being uncorrelated with birth country GDP per worker. We find that selection is systematically related to PPP GDP per worker, with immigrants from poorer countries much more strongly selected on education, occupation, formal employment, and pre-migration wages than are immigrants from richer countries. This selection on attributes that were previously unobservable attenuated the estimated importance of human capital in previous studies.

Our data also allow us to speak directly to two other important issues. The first is how to aggregate labor provided by workers with different skill levels. Although the development accounting literature usually assumes that they are perfect substitutes, Jones (2014) has recently shown that even moderate degrees of imperfect substitution would dramatically raise the importance of human capital in development accounting. We extend our framework and show that a natural measure of the elasticity of substitution is the relative wage gain of workers with different skill levels. Imperfect substitution implies that skilled workers from poorer countries should gain less than unskilled ones, because while both experience the same change in physical capital and TFP, unskilled workers also experience a favorable change in relative labor supply, while skilled workers experience an unfavorable one. Empirically, we find that wage gains are very similar across education groups, with no systematic trend between less educated and more educated immigrants. We conclude that a model with perfect substitution across skill types fits the data well.

The second issue is the transferability of skills of immigrants. To investigate this issue, we compare the non-wage characteristics of their pre- and post-migration jobs. Our most important evidence draws on their occupations. We find that it is common for immigrants to switch occupations, even across broad occupation groups. Further, there is some evidence of skill loss: immigrants’ post-migration occupations are generally lower-paying, as measured by the mean wage among natives. To investigate whether this is important for our conclusions, we assign downgraded immigrants the mean native wage of their pre-migration occupation, implicitly assuming that their downgrading was due to skill loss and that they would have earned the same as natives in the absence of that skill loss. We then repeat
our development accounting exercise. We find that this correction for occupational downgrading lowers the share of human capital in development accounting from two-thirds to one-half, which is appreciably lower but still larger than is typically found in the literature.

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 results. Section 5 investigates the elasticity of substitution between workers with different skill levels and Section 6 investigates skill transferability. Section 7 concludes.

2 Development Accounting Framework

We begin by outlining our accounting framework, which follows the literature closely (see Caselli (2005) or Hsieh and Klenow (2010) for recent overviews). Our particular focus here is on clarifying the assumptions needed to draw aggregate inferences from evidence on the wages of immigrants, and how our assumptions differ from the existing literature. We start with the standard aggregate production function,

\[ Y_c = K_c^\alpha (A_c h_c L_c)^{1-\alpha} \]

where \( Y_c \) is country c’s PPP-adjusted GDP, \( K_c \) is its physical capital stock, \( L_c \) is the number of workers, \( h_c \) is average human capital of the workforce, and \( A_c \) is total factor productivity.

Following Klenow and Rodriguez-Clare (1997), we re-write the production function in per worker terms:

\[ y_c = \left( \frac{K_c}{Y_c} \right)^{\alpha/(1-\alpha)} A_c h_c \]  

where \( y_c \) denotes PPP-adjusted GDP per worker. It is well-known that there is large variation in this object across countries. The goal of development accounting is to decompose variation in \( y \) into variation in three components, given on the right-hand side: capital-output ratios; total factor productivity; and average human capital.

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 \( c' \):

\[
1 = \frac{\alpha}{1-\alpha} \left[ \log\left(\frac{K_c}{Y_c}\right) - \log\left(\frac{K_{c'}}{Y_{c'}}\right) \right] + \log(A_c) - \log(A_{c'}) + \frac{\log(h_c) - \log(h_{c'})}{\log(y_c) - \log(y_{c'})} \\
\equiv share_{country} + share_{human capital}
\]

(2)

We refer to the other two factors as the effect of country, as distinct from the human capital of its labor force. This description is apt given that we work with immigrants, or workers who take their human capital to a new country.\(^4\)

Implementation of equation (2) requires us to measure each country’s stocks of physical capital and human capital. Given these, TFP is inferred as a residual in the standard way. The literature has settled on the use of the perpetual inventory method to construct each country’s physical capital stock. What is less settled and less clear is how to measure human capital stocks. We turn to this issue now.

### 2.1 Development Accounting, Wages, and Immigrants

Bils and Klenow (2000) provide a major conceptual advance in the construction of human capital stocks. Their insight was to use microeconometric evidence on wage patterns to discipline the construction of human capital stocks. Their analysis uses two assumptions. First, workers of different types are assumed to be perfect substitutes. In this case, workers may provide more or less human capital, but the total labor input is simply the sum of all human capital. This assumption is already implicit in most accounting papers when one talks about an average level of human capital. Second, labor markets are assumed to be perfectly competitive, so that workers are paid their marginal product.

Given these assumptions, we can write the labor demand problem of the representative firm as

\[
\max_{L_{i,c}} K_c^\alpha \left( A_c \sum_i h_{i,c} L_{i,c} \right)^{1-\alpha} - \sum_i w_{i,c} L_{i,c}.
\]

Here we think of labor as coming in \( i \) discrete types differentiated by their human capital;

\(^4\)The literature has also considered an alternative accounting equation that features the capital-labor ratio rather than the capital-output ratio. The two equations differ in how they attribute the “credit” for high capital-labor ratios in countries with high TFP; see Caselli (2005) for a clear discussion. Since we focus only on differentiating between human capital and the sum of the other two factors, our results would be the same if we used that alternative equation.
the firm chooses how much of each type to hire given the prevailing wages. We use the first assumption above to write the production function in terms of the sum of labor inputs across types. The second allows one to use the first-order condition to characterize the resulting equilibrium wages. In log terms, they are given by:

\[
\log(w_{i,c}) = \log \left[ (1 - \alpha) \left( \frac{K_c}{Y_c} \right)^{\alpha/(1-\alpha)} A_c \right] + \log(h_{i,c}) \\
\equiv \ z_c + \log(h_{i,c})
\]

(4)

\( z_c \) captures the aggregate factors common to all workers in country \( c \); it corresponds to what we labeled the effect of country above. \( h_{i,c} \) captures the human capital of the worker, which varies by group.

The basic insight from this equation is that under the two assumptions made above, wages are proportional to human capital. Hence, wage patterns can be used to discipline the construction of human capital stocks. Immigrants are particularly useful in this analysis because they carry all of their human capital – both observed and unobserved – from their birth country \( b \) to a new country \( c \). At the same time, they experience a change in physical capital and TFP as captured by \( z_b \). If we think about a worker’s country of birth \( b \) as representing their human capital type \( i \), it follows immediately that their log-wage is given by:

\[
\log(w_{b,c}) = z_c + \log(h_{b,c}).
\]

Studying immigrants in a single country has the advantage of holding fixed all the country-specific factors in \( z_c \) and capturing all their human capital, even the portion associated with unobservable characteristics. However, the human capital of an immigrant is not the same as the human capital of the average person born in \( b \). To capture this idea, we denote the wage of an immigrant from \( b \) in \( c \) as \( \log(h_{b,c}) \equiv \log(h_b) + \log(\alpha_{b,c}) \), where \( \alpha_{b,c} \) captures the selection of workers who move from \( b \) to \( c \), with the normalization \( \log(\alpha_{b,b}) \equiv 0 \). The existing literature on immigrants and human capital only has data on the post-migration wages of immigrants to a single country, typically the United States. The typical thought experiment is then to compare the wages of workers from poor versus rich countries to try to measure how much their human capital varies. Intuitively, this can be thought of as
measuring:

$$\frac{\partial \log(w_{b,c})}{\partial \log(y_b)} = \frac{\partial \log(h_b) + \log(\alpha_{b,c})}{\log(y_b)}.$$ 

The identifying assumption is that immigrants are either unselected ($\log(\alpha_{b,c}) = 0$) or that immigrants from different countries are selected the same ($\frac{\partial \log(\alpha_{b,c})}{\partial \log(y_b)} = 0$). In this case, data on post-migration wages of immigrants can be used to infer the importance of human capital in accounting for cross-country income differences.\(^5\)

Given that we have data on both pre- and post-migration wages of immigrants, we can construct an alternative, simpler statistic, which is the log-wage gain to migration. If we divide this by the log-GDP per worker difference between $b$ and $c$, we find a direct measure of the importance of countries:

$$\frac{\log(w_{b,c}) - \log(w_{b,b})}{\log(y_c) - \log(y_b)} = \frac{\log(z_c) - \log(z_b)}{\log(y_c) - \log(y_b)} = \text{share}_{\text{country}}$$

We construct the importance of human capital simply as $1 - \text{share}_{\text{country}}$.

Note that we do not need to make assumptions about how the process of immigrant selection correlates with birth-country GDP per worker. By comparing the wage of a given worker across locations we can “control” for any amount of selection. Alternatively, we can test assumptions about selection by constructing a measure of selection which compares pre-migration wages of immigrants to average pre-migration wages in their former country. In practice, we accomplish this by assuming that the hourly wage gap between non-migrants in $b$ and the US should be proportional to the gap in PPP GDP per worker. In this case, we can measure the selection of immigrants from $b$ as:

$$\text{selection}_{b,c} = \frac{w_{US,US}}{w_{b,c}} \frac{y_b}{y_{US}}.$$  

We compute hourly wage of US natives separately from the 2003 Current Population Survey and find a value of $14. Of course, changes to this value only rescale the level of our measure of selection.

\(^5\)The actual identifying assumptions can be more complicated. For example, Borjas (1987) and Hendricks (2002) control for observable differences between immigrants and non-migrants. The identifying assumption in this case is that workers from different countries are not selected differently on unobserved characteristics. Schoellman (2012) compares the return to schooling across immigrants from different countries. The identifying assumption in this case is that workers with different education levels are not selected differently across countries. Each empirical strategy requires an assumption about the constancy of selection between rich and poor country immigrants.
Now that we have a unified theory that maps micro-evidence on immigrants to the aggregate implications, we turn to the data.

3 New Immigrant Survey

The New Immigrant Survey is a nationally representative sample of adult immigrants admitted to legal permanent residence between May and November of 2013 (Jasso et al., 2005, 2006). The sampling frame for the study was the government’s administrative records on new legal immigrants during this time frame. It includes both newly-arrived immigrants granted legal permanent status from abroad and immigrants who adjust to legal permanent resident status after previously entering the United States on a temporary visa (or, in some cases, illegally).

The sample consisted of 12,500 potential adult interviewees. The New Immigrant Survey sought to directly interview all of them between June 2003 and June 2004; they were able to do so in 68.6 percent of cases. The survey also collected detailed data on the spouse of the interviewee. In many cases the spouse was also an immigrant; in such cases, we include the spouse in our sample, although we show below that this is not important for our main results. We utilize the restricted version of the data, which allows us to identify the exact country of birth and work, rather than broad geographic regions.

The New Immigrant Survey includes four main sets of information that we exploit. First, it surveys respondents about the usual set of demographic characteristics, such as age and education. Importantly, it asks immigrants about any education acquired since arrival in the U.S.; we exclude immigrants with positive responses from our sample. Second, it contains administrative data on the type of visa they obtained. We exploit this information for some of our results. Third, it surveys them about their labor market experiences in the United States. We know information such as occupation, industry, labor income (reported at different frequencies) and hours and weeks worked. We use this information to construct hourly wage in the U.S. for those who work. Note that while interviewees were contacted shortly after obtaining legal permanent residency, many had jobs because they had previously lived in the U.S. and adjusted to legal permanent residency. Further, workers who entered the U.S. on employment visas would also naturally be working at this time.

The final set of information we exploit covers immigrants’ pre-migration experiences, particularly their labor market experiences. Immigrants were surveyed about up to two jobs before entry, their first (after age 16) and last (if different than the first). For each they were
asked to report the same information as for their U.S. job, as well as when they held the job, the country where the job was held and the currency they were paid in. Throughout, we focus on the most recent job.

Our goal is to study the pre- and post-migration wages of immigrants, but especially their wage gains at migration. It is important for our analysis that immigrants’ reported wages be accurate. Fortunately, the New Immigrant Survey was careful to allow immigrants a great deal of flexibility in reporting their pre-migration wages. Immigrants reported both how much they earned and the frequency at which they were paid (hourly, daily, weekly, monthly, annual, 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 wages 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 widespread use of the U.S. dollar as a medium of payment even outside of the U.S., or the tendency for European migrants to remember their payment denominated in both pre- and post-euro currencies.

Of course, this flexibility necessitates a great deal of adjustment on our part. First, we use reported earnings and payment frequency to construct hourly wage for all immigrants. Denote this wage by $w_{d,b,t}$: hourly wage denominated in currency $d$ from working in country $b$ at time $t$. We then make three further adjustments. First, we translate the currency to U.S. dollars by using the market exchange rate between currency $d$ and the dollar $\$\,$ prevailing at time $t$, taken from the Penn World Tables.\footnote{We use PWT 7.1 for most countries. Our pre-euro European exchange rates come from PWT 6.2; our pre-dollarization Ecuadorian exchange rate from PWT 6.1; and our exchange rate for the Soviet bloc economies of USSR, Czechoslovakia, and Yugoslavia come from PWT 5.6 (Heston et al., 2012, 2006, 2002, n.d.).} We use these exchange rates to convert the wage to the dollar equivalent, $w_{\$,b,t}$. We then adjust wages for the purchasing power parity prevailing in country $b$ at time $t$, again taken from the Penn World Tables.\footnote{This object was provided directly and called price level ($P$) in some editions of the Penn World Table; in others it is constructed as the ratio of purchasing power parity to nominal exchange rates ($PPP/XRAT$).} This yields an estimate of $w_{\$,US,t}$, the purchasing power parity-adjusted dollar wage at time $t$. Note that in cases where workers report the “natural” currency for their country (e.g., pesos in Mexico) these first two adjustments are equivalent to simply dividing by the PPP exchange rate.

Finally, we adjust for wage growth between year $t$ and 2003, the year of observation for post-migration wages. We perform this adjustment using U.S. wage growth for similar workers. We use Current Population Survey data to compute mean wage by age, gender, education,
and year. We then inflate each worker’s reported year $t$ wage by using the observed wage growth for workers of the same age, gender, and education between year $t$ and year 2003. This yields an estimate of $w_{t,US,2003}$. Some of the reports of the last job worked are quite dated. In our baseline sample we exclude all reports of a last job before 1983 (twenty years before the sample) to help alleviate concerns about measurement error in reporting. We explore using only the most recent immigrants in our robustness section below.

These adjustments are important for our results, so we are concerned especially about two groups whose adjustments are more complicated. The first group consists of immigrants who report being paid in currencies that have experienced large changes in value or revaluations. This raises the concern that immigrants may report wages in the wrong year, which would then substantially affect the implied value, or that they may report their wage in the wrong currency, such as Brazilian cruzeiros instead of reals. The New Immigrant Survey documentation show that countries who have experienced revaluations have unusual patterns in the wage data. For this reason, we exclude from the sample all workers who report wages in a currency that has subsequently had a revaluation; the NIS documentation list the relevant currency-years. We also flag workers who report wages denominated in currencies that have ever had a revaluation or ever had high inflation but not revaluation and consider our robustness to excluding these workers. The second group consists of workers who report unusual country-currency pairs. As noted above, our adjustment is simple for workers who report the “natural” country-currency pair, but more complicated for those who do not. Further, there are some cases of country-currency pairs that lack a natural explanation. We again flag these observations and consider the robustness of our results to their exclusion.

Recall that our goal is to compare the log-wage change at migration to the log difference in GDP per worker. Our baseline measure of this difference is the log-difference in GDP per worker between the U.S. and country $b$ in 2005 from PWT 7.1. We also explore the robustness of our results to using instead the log-difference in GDP per worker in year $t$. Confidentiality restrictions prevent us from reporting statistics by country of origin. Instead, we report the statistics for each of five PPP GDP per worker categories: less than 1/16th U.S. income; 1/16–1/8; 1/8–1/4; 1/4–1/2; and more than half. Table 1 lists the

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8We previously adjusted only for aggregate changes in nominal U.S. GDP per worker between $t$ and 2003 and found roughly similar results.

9Inflation data comes from the World Bank (2014).

10 Data on currency-country pairs come mostly from the Penn World Tables and the CIA Factbook; we have also allowed some pairs where a currency is not the official currency of a country but has been in common use, such as the U.S. dollar in former Soviet economies in the 1990s.
### Table 1: Most Sampled Countries by GDP per Worker Category

<table>
<thead>
<tr>
<th>GDP Category</th>
<th>Most Sampled</th>
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<tbody>
<tr>
<td>&lt; 1/16</td>
<td>Ethiopia, Nepal, Nigeria</td>
</tr>
<tr>
<td>1/16 − 1/8</td>
<td>India, Philippines, China</td>
</tr>
<tr>
<td>1/8 − 1/4</td>
<td>Dominican Republic, Ukraine, Bulgaria</td>
</tr>
<tr>
<td>1/4 − 1/2</td>
<td>Mexico, Poland, Russia</td>
</tr>
<tr>
<td>&gt; 1/2</td>
<td>Canada, United Kingdom, Korea</td>
</tr>
</tbody>
</table>

three countries with the most observations within each category.

### 4 Results

We now turn to our results. We begin by discussing the basic patterns of wages. Recall that our adjustments are designed to produce pre- and post-migration wages in 2003 US dollars, adjusted for purchasing power parity. We compute the median of each wage by PPP GDP per worker category and plot the results in Figure 1a. There are two main features to notice here. The first is general trend: both pre- and post-migration wages are generally increasing in PPP GDP per worker. The second is the levels, especially for poorer countries. Pre-migration wages were already strikingly high, on the order of $2.50-$5 per hour. Post-migration wages are also fairly high.

![Figure 1: Wages and GDP per worker](image-url)
A key statistic for our approach is the wage gain at migration, which we compute as the ratio of post- to pre-migration hourly wage. We show the results for the same groups of countries in Figure 1b. Again, the two main results concern the trends and the levels. Immigrants from richer countries gain less at migration; even immigrants from the poorest countries, with more than a factor of sixteen income difference, experience a wage gain of less than a factor of three at migration. This fact hints at a relatively low importance for place. We turn to this point in the next section.

4.1 Accounting Implications

Recall from equation (5) that our measure of the importance of country is the log-wage change at migration relative to the log-GDP per worker gap, with the importance of human capital constructed as one minus the importance of country. We implement this idea by constructing these statistics for every immigrant in our sample. We then compute the median within each PPP GDP per worker category. Treating each immigrant as an observation also allows us to compute the standard error of this estimate and thus the 95 percent confidence interval for the importance of country and human capital.\footnote{The implied shares are roughly log-normal, which implies that we can use the simple formula that the standard error of the median is approximately 1.253 times the standard error of the mean.}

![Figure 2: Implied Accounting Share of Human Capital](image)

The resulting estimates and 95 percent confidence intervals are plotted against GDP per
worker category in Figure 2. The estimates from the three poorest income groups agree closely on an estimate in the range of 0.55–0.75 with fairly tight confidence intervals. By contrast estimates from richer countries are lower and have much wider confidence intervals. This is attributable to two factors. First, wage gains at migration are much more variable for immigrants from rich countries, with a non-trivial number of immigrants experience wage losses. Second, sample sizes are smaller especially for immigrants from the richest group of countries.

Our preferred view is that the experience of immigrants from rich countries is not informative about the experiment at hand. Hence, we focus on the immigrants from the three poorest groups of countries, and we often pool immigrants from these three groups. For our baseline sample, the pooled statistic is a share of human capital of 63 percent against a share of country-specific factors of only 37 percent. The 95 percent confidence interval in this case ranges from 55 to 71 percent.

These figures are substantially larger than what is typically found in the development accounting literature, including in previous papers that have used the experience of immigrants. For example, we calculate the equivalent figure to be 21 percent in Hall and Jones (1999), 20 percent in Caselli (2005), 30 percent in Hendricks (2002), and 42 percent in Schoellman (2012). There are two main reasons for the difference. First, the results in Hall and Jones (1999) and Caselli (2005) refer explicitly to the value of human capital acquired through years spent in schooling. One advantage of using immigrants is that they bring all their human capital with them, including other forms that may be less directly observable (education quality, experience and training, and so on). Second, our results differ from Hendricks (2002) and Schoellman (2012) in how they address the topic of selection. Recall that both Hendricks (2002) and Schoellman (2012) relied on assumptions that immigrants from poor and rich countries were selected similarly. We can test these assumptions directly in our data, which we do now.

4.2 Selection

We construct selection on average hourly wages as in equation (6). The results are plotted against PPP GDP per worker in Figure 3. There are two main takeaways. First, immigrants are substantially selected on pre-migration earnings, 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 more than a factor
of four, whereas immigrants from the richest countries are hardly selected at all by this measure.

Figure 3: Implied Selection of Immigrants by GDP per worker

Selection plays a central role in our development accounting results. We find small wage gains at migration in part because we find large pre-migration wages, which suggests strong selection for immigrants from poor countries. Given this, we also examine the other pre-migration attributes of immigrants from the poorest countries, to see if they are consistent with the large degree of selection suggested by Figure 3. We find that they are. For example, immigrants from the poorest group have on average 13.8 years of schooling, with 43 percent having a college degree versus only 13 percent who have not graduated 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.

We also study the characteristics of workers’ pre-migration jobs. We again find that they are consistent with strong selection. First, 81 percent of immigrants from the poorest countries were employed for wages in their pre-migration job. This fact stands at odds with the general prevalence of self-employment in poor countries. Second, we study occupation as reported in 25 broad groupings. Of these 25, the four most commonly reported are office and administrative support; sales and related; education, training, and literacy; and management. They account for more than half of all the pre-migration occupations. On the other hand, not a single immigrant in the poorest group reports having previously worked in agriculture, despite the fact that this occupation accounts for the majority of employment.
in most poor countries. We conclude that there is ample evidence that immigrants from the poorest countries are extremely selected on their occupation.

### 4.3 Robustness

We have now covered our main results, which are strong selection of immigrants and relatively small wage gains at migration, suggesting a large role for human capital in development accounting. The goal of this section is to investigate the robustness of these conclusions.

For each robustness check we vary the data construction or focus on a particular subsample of interest. We focus throughout on immigrants from countries with GDP per worker less than one-fourth the U.S. level. To compare the results using a common metric, we report the estimated share of human capital in development accounting for each exercise. We also report the corresponding 95 percent confidence interval and number of immigrants in the subsample. The results are reported in Table 2.

The first row reports the baseline results discussed above, for comparison. The next four

<table>
<thead>
<tr>
<th>Robustness Check</th>
<th>Human Capital Share</th>
<th>95% Confidence Interval</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.63</td>
<td>(0.55, 0.71)</td>
<td>974</td>
</tr>
<tr>
<td>Currency-Country Match</td>
<td>0.62</td>
<td>(0.54, 0.70)</td>
<td>931</td>
</tr>
<tr>
<td>No Revaluations</td>
<td>0.64</td>
<td>(0.55, 0.73)</td>
<td>725</td>
</tr>
<tr>
<td>No High Inflation</td>
<td>0.63</td>
<td>(0.55, 0.70)</td>
<td>951</td>
</tr>
<tr>
<td>No High Inflation Ever</td>
<td>0.66</td>
<td>(0.60, 0.72)</td>
<td>589</td>
</tr>
<tr>
<td>Sampled Interviewees Only</td>
<td>0.61</td>
<td>(0.52, 0.69)</td>
<td>671</td>
</tr>
<tr>
<td>No Secondary Migration</td>
<td>0.64</td>
<td>(0.56, 0.72)</td>
<td>927</td>
</tr>
<tr>
<td>Wage Workers</td>
<td>0.61</td>
<td>(0.52, 0.69)</td>
<td>853</td>
</tr>
<tr>
<td>Recent Arrivals</td>
<td>0.60</td>
<td>(0.49, 0.70)</td>
<td>555</td>
</tr>
<tr>
<td>Employment Visa</td>
<td>0.52</td>
<td>(0.41, 0.63)</td>
<td>211</td>
</tr>
<tr>
<td>Family Visa</td>
<td>0.62</td>
<td>(0.45, 0.78)</td>
<td>146</td>
</tr>
<tr>
<td>Diversity Visa</td>
<td>0.70</td>
<td>(0.51, 0.89)</td>
<td>210</td>
</tr>
<tr>
<td>Refugee/Asylee Visa</td>
<td>0.46</td>
<td>(-0.15, 1.06)</td>
<td>27</td>
</tr>
<tr>
<td>Other Visa</td>
<td>0.69</td>
<td>(0.48, 0.91)</td>
<td>98</td>
</tr>
<tr>
<td>Spouse of Sample</td>
<td>0.66</td>
<td>(0.50, 0.82)</td>
<td>282</td>
</tr>
</tbody>
</table>
rows discuss robustness to exclusion of immigrants whose pre-migration wage is more complicated to construct. The second row excludes immigrants whose currency and country do not match, as discussed above. The third row excludes immigrants whose payment currency has ever been devalued; recall that we exclude those who have had a devaluation since their last job in the baseline sample already. The fourth and fifth rows exclude immigrants from countries who have had a period of high inflation since their last job or at any time, where high inflation is defined as greater than fifty percent in a year. We find largely similar results across all of these checks.

The next several rows check the robustness to inclusion of immigrants who may present difficulties in our wage regressions. The sixth row focuses only on immigrants who were directly sampled in the New Immigrant Survey, excluding the spouses that were questioned and that we have included elsewhere. The seventh row excludes immigrants who had secondary migration, measured as reporting a last job worked in a country other than their birth country. The eighth row focuses on workers who worked for wages both before and after immigration. Finally, the ninth row focuses on the subsample of workers whose last job worked was during or after 1998, narrowing the window between last job worked and current job in the U.S. In all cases we find we find very similar estimates of the human capital share in development accounting.

Finally, we exploit the information we have on each immigrant’s visa status. This check is useful for thinking again about selection, because the selection process works very differently for, say, immigrants on employment visas and immigrants on refugee visas. We aggregate categories slightly, grouping the family visas together and refugees and asylees together, so that we have five categories: employment; family; diversity; refugee/asylee; and other. We also explicitly break out a sixth category, which is spouses of the main sample. The NIS does not contain their visa status but we find it worthwhile to present their results separately here.

We start with the raw data on wages and wage gains, given in Figure 4. As in the rest of this section we pool all immigrants with GDP per worker less than one-fourth the U.S. level. We then break out the results by visa category. In terms of wage levels, immigrants on employment visas are clearly selected on pre- and post-migration wages, while the other groups are fairly similar. There is even less variation in terms of wage gains, which range from a factor of two to a factor of four. Returning to Table 2, we can see that the implied accounting shares are in line with the previous results, although somewhat more variable. If we exclude the case of refugees/asylees, which has very few observations, then we find
that the implied share of human capital in development accounting ranges from 0.52 to 0.70.

In sum, we have examined the robustness of our results along a number of dimensions. Throughout, we find a consistent pattern: human capital accounts for a larger share of cross-country income differences than was previously thought. Our baseline estimate is 63 percent; across the many checks here we find that a plausible range is one-half to two-thirds.

5 Elasticity of Substitution Across Skill Types

Our estimates so far have all followed the precedent of the accounting literature by assuming that workers of different skill levels are perfect substitutes in the aggregate production function. Jones (2014) has recently called this assumption into question, noting that there is little direct evidence for it, and further that development accounting results are very sensitive to it. Even modest reductions of the elasticity of substitution (from infinity) can substantially increase the role for human capital in accounting for cross-country income differences.

Immigrants present a natural laboratory to investigate the elasticity of substitution. To see why, it is helpful to extend the standard development accounting setup to allow for two
types of labor, skilled and unskilled. In this case the production function is:

\[ Y_c = K_c^\alpha \left\{ A_c \left[ \theta_u \left( \sum b h_{b,c,u} L_{b,c,u} \right)^{\frac{\sigma-1}{\sigma}} + \theta_s \left( \sum_i h_{b,c,s} L_{b,c,s} \right)^{\frac{\sigma-1}{\sigma}} \right] \right\}^{1-\alpha} \]

where \( \theta_u + \theta_s = 1 \). Here we allow for the possibility that workers come in two distinct types that are imperfect substitutes. As in Jones (2014), we also allow for the possibility of heterogeneity within the categories of skilled and unskilled, but assume that different types of skilled workers are perfectly substitutable.

We continue to maintain the assumption that labor markets are competitive and workers are paid their marginal product. In this case, the wages of workers born in country \( b \), working in country \( c \), with skill level \( i \in \{u, s\} \) are given by:

\[
\log(w_{b,c,i}) = \log \left( K_c^\alpha A_c^{1-\alpha} \left[ \theta_u \left( \sum b h_{b,c,u} L_{b,c,u} \right)^{\frac{\sigma-1}{\sigma}} + \theta_s \left( \sum_i h_{b,c,s} L_{b,c,s} \right)^{\frac{\sigma-1}{\sigma}} \right] \right) - \log(h_{b,c,i}) + \log(z_c) + \log(p_{c,i})
\]

In this case, the marginal product depends on three terms. The first is the country-specific effect common to all workers, which we collapse into \( z_c \). The second is a country-skill type specific price shared by all skilled or unskilled workers in \( c \), which we denote by \( p_{c,u} \) and \( p_{c,s} \). These terms are decreasing in the aggregate supply of unskilled or skilled labor. Finally, the last term captures the worker’s human capital.

Our approach is to construct a simple double-difference: we compare the wage gains at migration for skilled versus workers. Following the above, this is given by:

\[
[\log(w_{b,c,s}) - \log(w_{b,b,s})] - [\log(w_{b,c,u}) - \log(w_{b,b,u})] = (p_{c,s} - p_{b,s}) - (p_{c,u} - p_{b,u}).
\]
labor supply in each country with native labor supply to find:

$$(p_{c,s} - p_{b,s}) - (p_{c,u} - p_{b,u}) = -\frac{1}{\sigma} \log \left[ \frac{h_{c,c,s} L_{c,s} h_{b,b,u} L_{b,u}}{h_{c,c,u} L_{c,u} h_{b,b,s} L_{b,s}} \right].$$  \hspace{1cm} (10)$$

Note that the term in brackets on the right hand side is simply the relative supply of skilled labor in \(c\) versus \(b\). For immigrants from poor countries this is easy to sign: the relative supply of skilled labor in \(c\) will be higher than in their birth country \(b\), implying that the right-hand side of this expression can be signed to be negative. Further, its magnitude is increasing in the gap in skilled labor supply and in the elasticity of substitution \(\sigma\).

Intuitively, we can compare wage gains of skilled and unskilled immigrants to infer the elasticity of substitution. To implement this idea, we focus again on immigrants from countries with PPP GDP per worker less than one-quarter the U.S. level. We measure education by combining data on degree attainment and years of schooling, giving preference to the former where available. We then break workers into four groups: those with less than a high school degree (or less than twelve years of schooling); those with exactly a high school degree (or twelve years of schooling); those with some college but not bachelor’s degree (or 13–15 years of schooling); and those with a bachelor’s degree or more (or 16 or more years of schooling).

Figure 5 shows the pre-migration wage, post-migration wage, and wage gain at migration by education group. We find little variation in pre- or post-migration wages among the first three groups, whereas college graduates earn more both before and after migration. In terms of wage gains, however, we find very similar results for each of the groups of immigrants.

In principle this figure could be biased by composition effects: perhaps college graduates come from richer countries. To control for this, we compute the implied human capital share in development accounting for each education category. Recall that this statistic is simply (one minus) the log wage change at migration divided by the log GDP per worker gap. Hence, it effectively controls for the size of the gap in GDP per worker. The results are given in Table 3. We find no strong support for imperfect substitution: the proportional wage gains are roughly the same for all workers with at least a high school degree, and are lower for high school dropouts, whereas a theory with imperfect substitution would predict that it is higher. Indeed, it is apparent from our confidence intervals that we cannot reject that the wage change is the same across groups, implying that we cannot reject \(\sigma = \infty\), the case of perfect substitutes.
Figure 5: Wages and Education Level

Table 3: Robustness: Human Capital Share in Development Accounting by Education

<table>
<thead>
<tr>
<th>Robustness Check</th>
<th>Human Capital Share</th>
<th>95% Confidence Interval</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.63</td>
<td>(0.55, 0.71)</td>
<td>974</td>
</tr>
<tr>
<td>&lt;HS</td>
<td>0.55</td>
<td>(0.38, 0.71)</td>
<td>139</td>
</tr>
<tr>
<td>HS</td>
<td>0.65</td>
<td>(0.45, 0.84)</td>
<td>196</td>
</tr>
<tr>
<td>SC</td>
<td>0.62</td>
<td>(0.33, 0.91)</td>
<td>94</td>
</tr>
<tr>
<td>CD</td>
<td>0.64</td>
<td>(0.55, 0.74)</td>
<td>545</td>
</tr>
</tbody>
</table>

6 Skill Transferability

Finally, we explore the evidence on skill transferability. Utilization of skills is clearly not directly measurable in the data. We proxy for skill utilization by comparing immigrants’ pre- and post-migration occupations. This allows us to capture many common ideas of immigrants who cannot practice their chosen profession because of problems of accreditation, licensure, discrimination, or other barriers. 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, e.g., that they may simply have been unqualified. On the other hand, our measure does not capture within-occupation skill loss. For example, we capture
Table 4: Occupational Changes at Migration

<table>
<thead>
<tr>
<th>GDP category</th>
<th>Same Occ. (Narrow)</th>
<th>Same Occ. (Broad)</th>
<th>Median Wage Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;1/16</td>
<td>6%</td>
<td>13%</td>
<td>-30%</td>
</tr>
<tr>
<td>1/16–1/8</td>
<td>26%</td>
<td>43%</td>
<td>-2%</td>
</tr>
<tr>
<td>1/8–1/4</td>
<td>10%</td>
<td>22%</td>
<td>-19%</td>
</tr>
<tr>
<td>1/4–1/2</td>
<td>9%</td>
<td>22%</td>
<td>-15%</td>
</tr>
<tr>
<td>&gt;1/2</td>
<td>32%</td>
<td>48%</td>
<td>0%</td>
</tr>
</tbody>
</table>

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 includes over 450 possible occupational choices. With these two caveats in mind, we now turn to analyzing occupational switches. \(^{12}\)

We begin by looking at the fraction of workers who have the exact same narrowly defined occupation. The results are given in Table 4 for each of the five GDP per worker categories used above. We find that maintaining the same narrow occupation is uncommon, with only 6–32% of immigrants reporting this. There is perhaps some evidence of a trend: immigrants from the poorest countries are least likely to report maintaining the same occupation and immigrants from the richest countries most likely. On the other hand, the groups in between are mixed.

Given the fineness of the codes, many of these changes will happen between closely related occupations. For example, the Census includes codes for 28 different kinds of managers. This leads us to also construct occupational switches between broad occupation categories; the Census occupational coding scheme includes 25 such broad groupings. The corresponding results for broad occupational groupings are given in the third column of Table 4. Obviously we find more occupational persistence by this measure, but the same basic patterns apply as for occupational persistence in narrowly defined occupations.

A change in occupation does not indicate whether the new occupation is better or worse, or by how much. As a proxy for the “quality” of an occupation, we construct for each occupation the mean wage of natives in that occupation using the 2000 U.S. Census.\(^{13}\) We merge this mean wage by occupation with both the pre- and post-migration occupations of immigrants in the NIS. This procedure provides us a quantitative ranking of each immigrant’s pre- and post-migration occupation. We compute the difference for each immigrant

\(^{12}\)We have also explored repeating all this analysis using industry data and find similar results throughout.

\(^{13}\)Calculated as mean log wage of wage workers aged 18–70. Data from Ruggles et al. (2010).
to provide a quantitative estimate of how well their skills transferred to the U.S.

The median value of occupational change is given in the last column of Table 4. There are again two main take-aways. First, the median immigrant in each category is moving to an occupation that pays the same or less as their pre-migration occupation. One interpretation of this finding is that some of immigrants’ skills do not transfer to the U.S. Quantitatively, this effect can be large. The median occupation from the poorest countries switches to an occupation that pays natives 30% less than his pre-migration occupation. Second, the size of the median wage gap is larger for immigrants from poorer countries. One interpretation of this finding is that immigrants from poorer countries have a harder time transferring their skills to the U.S.

If we interpret these findings as evidence of skill non-transferability, then these findings have important implications for our development accounting results. The logic is as follows: immigrants’ U.S. are a downward biased estimate of their true human capital because they cannot transfer all of their skills. In the absence of this effect their wages would be higher, and we would calculate a larger wage gain at migration. Larger wage gains at migration would lead us to attribute a larger role to country and a smaller role to human capital in development accounting.

To explore this idea quantitatively, we conduct some simple experiments where we consider alternative possible wages for immigrants who have been downgraded, e.g., immigrants whose post-migration occupation is “worse” than their pre-migration occupation as judged by mean earnings of natives. For each of these immigrants we construct estimates of the counterfactual wage the immigrant could have earned, if he had been able to transfer all of his skills to the U.S. One simple estimate is to assume that if the immigrant had been able to work in his pre-migration occupation, he would have earned the mean wage of natives in that occupation. In some cases an immigrant’s reported wage is higher than this alternative; in such cases we use instead the reported wage, to insure that the calculation is conservative.

We then repeat all of our exercises on this alternative sample. The results are reported in Table 5. The first row repeats the baseline results from above: an implied share for human capital of 0.63 with a fairly tight confidence interval. We also report the median post-migration hourly wage in our sample, which is $9.00 per hour. The second line reports the results of giving downgraded immigrants the mean wage of natives in their pre-migration occupation. Doing so raises the median wage among immigrants by more than two-thirds. In this case, immigrants would actually out-earn natives. By raising the wage of immigrants
Table 5: Development Accounting and Skill Transfer

<table>
<thead>
<tr>
<th>Robustness Check</th>
<th>Human Capital Share</th>
<th>95% C.I.</th>
<th>Median Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.63</td>
<td>(0.55,0.71)</td>
<td>$9.00</td>
</tr>
<tr>
<td>Skill Transfer: Mean Wage</td>
<td>0.49</td>
<td>(0.42,0.56)</td>
<td>$15.59</td>
</tr>
<tr>
<td>Skill Transfer: Mean + 1 S.D. Wage</td>
<td>0.35</td>
<td>(0.27,0.42)</td>
<td>$24.37</td>
</tr>
<tr>
<td>Skill Transfer: Mean + 2 S.D. Wage</td>
<td>0.20</td>
<td>(0.12,0.28)</td>
<td>$40.73</td>
</tr>
</tbody>
</table>

we also raise their wage gain at migration. Thus, we reduce the role for human capital, which now accounts for only half of cross-country income differences.

We can alter this calculation further to imagine the possibility that immigrants were not just the equal of natives in their occupation but were exceptional. Doing so will further reduce the importance of human capital in development accounting. Two examples will help. Suppose first that we assume that immigrants would have earned not the mean wage of natives, but one standard deviation above the mean. This pushes immigrant wages up still further, to nearly $25 per hour, and implies that human capital accounts for only one-third of cross-country income differences. This result would still be larger than what is typically found in the development accounting literature. In order to find results in line with that literature we would have to attribute to a wage two standard deviations above the mean to downgraded immigrants, effectively assuming that they are at the 98th percentile of the native wage distribution for their pre-migration occupation. This assumption would push the human capital share in development accounting down to 20 percent. However, in this case the implied median hourly wage for immigrants is $40.73, more than four times their reported median wage and more than three times the wage of natives. Put differently, this calculation would imply that more than four-fifths of immigrants’ true skills are lost upon migration to the U.S.; if they were able to fully utilize these skills, they would out-earn natives by a factor of three.

7 Conclusion

In this paper we use unique 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. We infer that human capital accounts for roughly two-thirds of cross-country income differences. We conduct a range of robustness checks and consistently find results between one-half and three-fourths.

We also provide novel evidence on two issues frequently raised in the literature. First, we find that immigrants’ experiences are consistent with the assumption of perfect substitution across labor types. The key finding here is that immigrants with different education levels have similar wage gains at migration, which is inconsistent with imperfect substitution. Second, we study skill transfer through immigrants’ changes in occupation. We find evidence that immigrants move to lower-paying occupations upon arrival, particularly immigrants from poor countries. We provide calculations to show that reasonable corrections for this possible skill loss at migration do not substantially lower our estimate of the importance of human capital in development accounting.
References


_ , _ , and _ , Penn World Table Version 7.1, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, November 2012.

_ , _ , and _ , Penn World Table, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.


Table 6: Sample Size by Adjustment

<table>
<thead>
<tr>
<th></th>
<th>Pre-Migration Wages</th>
<th>Post-Migration Wages</th>
<th>Both</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hourly Wage</td>
<td>4,770</td>
<td>5,752</td>
<td>2,378</td>
</tr>
<tr>
<td>Valid Country</td>
<td>4,664</td>
<td>5,612</td>
<td>2,308</td>
</tr>
<tr>
<td>Adjusted Wage</td>
<td>3,927</td>
<td>5,612</td>
<td>2,095</td>
</tr>
<tr>
<td>Matched GDP</td>
<td>3,914</td>
<td>5,548</td>
<td>2,085</td>
</tr>
<tr>
<td>No Devaluations</td>
<td>3,577</td>
<td>5,173</td>
<td>1,907</td>
</tr>
<tr>
<td>No US Schooling</td>
<td>3,059</td>
<td>3,814</td>
<td>1,589</td>
</tr>
<tr>
<td>Arrived After 1983</td>
<td>2,747</td>
<td>3,383</td>
<td>1,464</td>
</tr>
</tbody>
</table>

A Sample Details