Abstract

Average wages are considerably lower in agriculture than in the rest of the economy. We document this fact for thirteen countries ranging from rich (Canada, U.S.) to poor (India, Indonesia). We develop a broad measure of human capital by sector that takes into account observable and unobservable individual characteristics. We find that differences in broad human capital account for most of the wage gaps. We develop a model that rationalizes this findings and that allows us to quantify the distortions to the allocation of labor. We find that they are much smaller than those often derived in the literature.

Keywords: human capital gaps; misallocation of labor; wage gaps.

JEL classification: O1.

*For helpful discussions and suggestions, we would like to thank Tim Lee, Alessio Moro, Gustavo Ventura, and the audience of presentations at ASU, Católica de Chile, the Conference on “Structural Change and Macroeconomic Dynamics” in Paris, Mannheim, the SED Meetings in Toronto, and UCSD for comments. Herrendorf thanks the Spanish Ministry of Education for research support (Grant ECO2012–31358. The usual disclaimer applies.

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1 Introduction

In his Nobel prize lecture, Kuznets (1973) named the process of structural transformation as one of the six main features of modern economic growth. In this paper, we focus on a particular aspect of structural transformation, namely the reallocation of labor from agriculture to other sectors of the economy (“non–agriculture”). Perhaps surprisingly there are two rather different views within the macro–development literature of this aspect of structural transformation. One strand of the literature assumes that labor is allocated efficiently between sectors and characterizes the properties of preferences and technological progress that generate the reallocation of labor from agriculture to non–agriculture as a consequence of growth; see e.g. Herrendorf, Rogerson and Valentinyi (2013) and the references therein. In contrast, a second strand of the literature measures large gaps in labor productivity between non–agriculture and agriculture and, since it is difficult to account for these gaps, concludes that labor must be allocated inefficiently between sectors, with the reallocation of labor from agriculture to non–agriculture in poor countries hindered by what is typically referred to as barriers or wedges; see e.g. Caselli (2005) and Restuccia, Yang and Zhu (2008). According to this logic, the removal of barriers would allow labor to move out of agriculture, which would generate growth. This is precisely the opposite direction of causality from that in the first strand of the literature. It follows that given the same stylized fact these two strands of the macro–development literature will make completely different policy prescriptions.

The different views can coexist in the literature because there is little hard evidence on whether or not the allocation of labor between agriculture and non–agriculture is efficient. The contribution of this paper is to provide such evidence for multiple years and thirteen countries ranging from rich (Canada, U.S.) over middle income (Brazil, Mexico) to poor (India, Indonesia). The selection criterion for including a country in our analysis is that there is sufficiently detailed data to be able to calculate wages and construct human capital at the sectoral level. The resulting sample of countries covers 30% of the world population in 2010 and contains four of the five most populous countries (namely, India, US, Indonesia, Brazil). For the U.S. these data are from the CPS, the Census, and the American Community Survey (ACS) and they cover the period 1940–2012. For the other twelve countries, these data are from 32 population censuses that are harmonized by IPUMS and range from 1970 to 2010. We document that there are large gaps between the average wages per worker in non–agriculture and agriculture in all countries. We decompose the wage gaps into differences in the average sectoral human capital of workers (appropriately constructed) and
residual wage gaps. We view the result of this decomposition through the lens of a sorting model and derive bounds on the distortions to the allocation of labor between agriculture and non–agriculture.

We start by analyzing the period 1980–2012 for the U.S. for which we have the most detailed data. We document that even in the U.S. there are large gaps in average hourly wages: an average worker in non–agriculture makes almost twice as much as an average worker in agriculture. A natural candidate explanation for these wage gaps is that average human capital is higher in non–agriculture. We document that indeed an average non–agricultural worker went to school for three years more than an average agricultural worker. It is not immediately obvious, however, how to translate such gaps in years of schooling into gaps in human capital. A natural first step is to use the off–the–shelf Mincer returns that have been estimated for the aggregate economy and that are widely used in the development literature. Employing the numbers from Hall and Jones (1999), we find that this closes the wage gaps somewhat but leaves sizeable residual wage gaps: per unit of human capital (“efficiency unit”) the wage of an average worker in non–agriculture still is 40% higher than that of an average worker in agriculture. Some observers might conclude from this finding that even in the US there are large distortions/wedges to the allocation of labor between agriculture and non–agriculture. Since that seems rather implausible, a more likely explanation is that aggregate Mincer returns capture only part of sectoral human capital. Indeed, estimating Mincer returns to schooling by sector, we find that they are considerably larger in non–agriculture than in agriculture. Moreover, using these sectoral Mincer returns to construct human capital, it turns out that the resulting human capital gaps account for the entire wage gaps.

These results raise the question why workers in non–agriculture experience higher Mincer returns to schooling than workers in agriculture. We consider two possible answers. The “sectoral hypothesis” attributes the differences in Mincer returns to differences in sectoral technologies: schooling generates more human capital for a worker with the same characteristics in non–agriculture than in agriculture. In contrast, the “selection hypothesis” attributes the differences to differences in workers’ characteristics: schooling generates the same human capital in each sector, but workers sort so that those who have higher innate ability and therefore learned more per year of schooling work in non–agriculture. This type of sorting leads to higher Mincer returns to schooling in non–agriculture. Both views have the potential to explain why non–agriculture has higher Mincer returns than agriculture. To help us distinguish between them, we study the qualitative implications in a simple two–sector model in which workers are endowed with years of schooling and innate ability.
and choose in which sector they work. To be able to speak to the sectoral hypothesis, we allow for the possibility that sector technologies differ in the way in which they translates workers characteristics into human capital. We show that to account for our U.S. findings we need to restrict our model such that both sectors have the same technology and a given worker gets the same return to his characteristics in both sectors. Differences in observed Mincer returns are then entirely due to differences in worker characteristics, that is, the selection hypothesis prevails. In particular, if the returns to characteristics are the same in both sectors, then our model has a sorting equilibrium with the following properties: average wages per worker are higher in non–agriculture; observed Mincer returns are higher in non–agriculture; average wages per efficiency unit are equalized between the sectors. The restriction that both sectors have the same technology has the testable implication that individuals who switch between sectors should not experience sizeable changes in the returns to their observable characteristics. We provide some evidence from the CPS about the wages of switchers that is broadly consistent with that restriction.

For the larger set of countries, we find similar results. Specifically, there are sizeable wage gaps between non–agriculture and agriculture. Most of the wage gaps for by differences in human capital: non–agricultural workers again have more years of schooling and earn higher Mincer returns on schooling. Imposing the selection hypothesis that as in the US the technologies are the same in both sectors and differences in observed Mincer returns are due to differences in worker characteristics, we can use our model to derive bounds to barriers. We find that they are an order of magnitude smaller than those derived in studies like Restuccia et al. (2008), who used indirect evidence from labor productivity gaps instead of direct evidence from wage gaps. We conclude that barriers that lead to the mis–allocation of labor between the agriculture and non–agriculture are relatively small and account only for a small part of the raw wage gap between non–agriculture and agriculture.

Our work has several important implications for the literature. To begin with, our finding that even in poor countries like India and Indonesia the potential role for barriers is relatively small suggests that reality is closer to the first than the second view of structural transformation outlined above and that there is limited scope for policy reforms that aim to generate growth by removing barriers to the allocation of labor. It is important to keep in mind that this statement is purely about the allocation of wage workers, and so has nothing to say about the importance of barriers to the allocation of capital, proprietors, land, or intermediate goods. Second, our work implies that to construct human capital at the sector level one does not only need to take into account selection according to observed characteristics like years of schooling but also selection according to unobserved
characteristics like innate ability. Our analysis shows that Mincer returns that are estimated at the sectoral level deliver this, whereas Mincer returns that are estimated at the aggregate level by construction miss the selection according to unobserved characteristics. While we find that this is quantitatively important for the allocation of labor across sectors, it is potentially relevant in other contexts as well.

Our results are related to Gollin, Lagakos and Waugh (2011), who study misallocation between non–agriculture and agriculture in a large set of poor countries. Since for most of their countries wage data from population censuses is not available, they rely on data form household surveys which contains household characteristics but has no information on wages. They therefore focus on productivity gaps, which are available from NIPA for most countries, and they use off–the–shelf Mincer returns that are common across countries. Instead we focus on wage gaps and we use Mincer returns that are estimated on country data. In terms of results, they find that a sizeable part of the productivity gaps between non–agriculture and agriculture remains unaccounted for whereas we find that human capital differences account for most of the wage gaps.

Our results are also related to Young (2013), who documents for poor and middle–income countries that migration flows go in both directions: while on average one in five individuals born in rural areas moves to urban areas as an adult, one in four individuals born in urban areas moves to rural areas as an adult. Young develops a location model in which people sort depending on observed characteristics such as schooling and on unobserved characteristics such as skills that are acquired after leaving school. The basic idea is that if observed and unobserved characteristics are positively correlated and are more important as an input in production in urban areas, then sorting implies that on average individuals with higher observed and unobserved characteristics locate in urban areas and individuals with lower observed and unobserved characteristics locate in rural areas. Since our concept of human capital is broad in the sense that it includes the stocks of observed and unobserved characteristics, this prediction of Young is consistent with our finding that most of the wage gaps between non–agriculture and agriculture are accounted for by the fact that workers in non–agriculture have considerably more human capital.

The remainder of the paper is organized as follows. In the next section, we present our basic findings for the U.S. Section 3 views the basic findings through the lens of a simple multi–sector model. Section 4 presents evidence for the U.S. from workers who switch sector. Section 5 extends the U.S. analysis to 41 censuses from thirteen countries. Section 6 concludes and provides suggestions for future research.
2 Basic Facts About Sectoral Wages and Human Capital in the U.S.

2.1 Overview and Basics

Our goal in this section is to describe the stylized facts about wages in agriculture vs. non-agriculture in the U.S. We start with the U.S. because it has the richest data of all countries in our sample. In Section 5, we will turn to international data and show that similar broad patterns apply there.

Within the U.S. there are two data sets that are nationally representative, have data on wages, schooling, age, and so on, and have a sufficient sample size in agriculture to produce useful statistics: the population census and the Current Population Survey (CPS).\(^1\) Within the CPS there are two ways to construct data on wages. The first way is to use the monthly files. Workers in the outgoing rotation group (those in the fourth or eighth month in the sample) respond to a full battery of questions that we need, so we can use 1/4 of the sample every month. A second way is to use the March demographic oversample. For now we show results from all three data sets. They will agree on broad trends.

We restrict our attention for now to the period 1980–2012. The reason for starting in 1980 is that we lack some of the critical data (in particular on switchers) before 1980. In all three data sets we focus on the subsample of workers that are typically used in wage regressions, that is, workers who have valid responses to the questions of interest (industry of employment, income, and so on) and who are 18–65 years old. We use workers who are employed, work for wages, and report positive wage income for the relevant period. While these restrictions are all standard, we note that the restriction to wage workers is somewhat stronger here than is usually the case. The reason for this is that roughly half of the agricultural labor force is self-employed proprietors. While these individuals can be of interest, we avoid studying them here for two reasons. First, their income represents payments to both capital and labor, and it is unclear how to disentangle the fraction of proprietors’ income that is wage income. Second, there is evidence showing that these proprietors underreport their income by a large amount, in which case we want to avoid taking their stated income too seriously (Herrendorf and Schoellman 2013). In contrast, the income of wage workers is easier to interpret and better reported.

\(^1\)The 2000 Census was the last to include the “long form” that provides the detailed data on a sample of households. Since 2000 this information has been collected annually from a smaller sample of households through the American Community Survey (ACS). The questions and responses are quite similar, so we combine ACS data for year 2005–2012 with the Censuses of 1980, 1990, and 2000.
We classify workers into agriculture and non–agriculture on the basis of their reported industry of employment. We define agriculture as crop and livestock farming. All other industries are allocated to non–agriculture. The appendix includes details on the exact industry responses available by year and how they are allocated.

2.2 Stylized Fact 1: Large Raw Wage Gaps

We start by documenting the wage gap, defined as the ratio of the average hourly wages in non–agriculture to agriculture, both expressed in current dollars. A wage gap larger than one indicates that average wage in non–agriculture is larger than the average wage in agriculture. To find the wage gap, we estimate the following log–wage regression:

$$\log(w_{ijt}) = \beta_t d_t + \beta_j d_j + \beta_z Z_{ijt} + \varepsilon_{ijt}$$

where $w_{ijt}$ is the hourly wage of individual $i$ in sector $j$ during year $t$, $d_t$ are year dummies, $d_j$ is a sector dummy, $Z_{ijt}$ are controls for state and gender, $\beta_t$, $\beta_j$, and $\beta_z$ are the corresponding coefficients, and $\varepsilon_{ijt}$ is an iid error term with zero mean. This regression controls for average wage growth and inflation by year through the full set of year dummies and then estimates the average sectoral wage gap. Choosing agriculture as the omitted group, $\exp(\beta_n)$ is the wage gap between non–agriculture and agriculture which we are after here.

We estimate the above regression separately for all three data sources. Hourly wages for the different data sources are constructed as follows. In the Census/ACS, the wage is constructed as last year’s income divided by the product of hours usually worked in a week times weeks worked in the year. For the March CPS the wage is constructed in the same way. For the monthly CPS file the wage is constructed in a slightly different way, because workers report either their hourly wage directly or their weekly earnings and hours worked for the prior week.

Details aside, Table 1 shows that the picture is quite consistent across data sets. Hourly wages in non–agriculture are considerably larger than in non–agriculture and the differences are larger if we control for geography and gender (“adjusted wage gap”) than if we don’t (“raw wage gaps”). This is the essential stylized fact that we want to shed light on in this paper.
Table 1: Wage Gaps in the U.S. 1980–2011

<table>
<thead>
<tr>
<th></th>
<th>U.S. Census</th>
<th>March CPS</th>
<th>Monthly CPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>1.72</td>
<td>1.83</td>
<td>1.75</td>
</tr>
<tr>
<td>Adjusted</td>
<td>1.80</td>
<td>1.94</td>
<td>1.85</td>
</tr>
</tbody>
</table>

*a The wage gap is the ratio of average hourly wages in non–agriculture to agriculture

2.3 Stylized Fact 2: Differences in Observed Characteristics

A natural candidate explanation for wage gaps is sectoral differences in human capital. After all, existing theories of how workers choose their sector predict that the wage per efficiency unit of labor is crucial, not the wage per hour worked. The natural next step is therefore to adjust wages for sectoral differences in human capital. The data suggest that this adjustment is potentially important, because the observable characteristics typically associated with human capital turn out to differ across sectors. Table 2 shows this: non–agricultural workers have more than three more years of schooling than agricultural workers.2

Table 2: Gaps in Schooling and Standard Human Capital

<table>
<thead>
<tr>
<th></th>
<th>U.S. Census</th>
<th>March CPS</th>
<th>Monthly CPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Years of Schooling</td>
<td>3.50</td>
<td>3.32</td>
<td>3.33</td>
</tr>
<tr>
<td>Hall–Jones aggregate rate of return</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Human capital gap</td>
<td>1.42</td>
<td>1.39</td>
<td>1.39</td>
</tr>
<tr>
<td>Residual Wage gap</td>
<td>1.27</td>
<td>1.39</td>
<td>1.33</td>
</tr>
<tr>
<td>Estimated aggregate rate of return</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Human capital gap</td>
<td>1.30</td>
<td>1.29</td>
<td>1.28</td>
</tr>
<tr>
<td>Residual Wage gap</td>
<td>1.39</td>
<td>1.50</td>
<td>1.44</td>
</tr>
</tbody>
</table>

*a A gap is the ratio of non–agriculture to agriculture

To assess whether schooling gaps can account for wage gaps, we need to translate years of schooling into human capital. A useful first step is to follow the approach pioneered by Bils and Klenow (2000). They show that under some mild assumptions, the log–human capital gain from an additional year of schooling is equal to the log–wage gain ("Mincer

2In this context, the issue arises that some reported years of schooling are implausibly low or high. An example is an individual who reports zero years of schooling and professor as occupation. Appendix A.2 explains how we deal with this problem.
return”) from an additional year of schooling. We consider two applications of this idea that differ in the Mincer returns to schooling that we use to construct human capital stocks. We first assign every year a constant value of ten percent, consistent with Banerjee and Duflo (2005); we then work with the actual Mincer returns estimated from our data.

Using the actual estimated returns to schooling in our data turns out to be complicated slightly by the fact that the data are not well fit by a linear return to schooling. Instead, wages are a convex function of schooling in all three data sources that we use. This is consistent with recent work in the U.S. as well as in many other countries around the world (Lemieux 2006, Binelli 2012). To show the relationship in our data, we estimate regressions

Figure 1: Convexity in the Returns to Schooling
that are fully flexible in schooling:

\[ \log(w_{ijt}) = \beta_t d_t + \beta_j d_j + \beta_s s_{ijt} + \beta_z Z_{ijt} + \varepsilon_{ijt} \]

where \( d_s \) is a full set of dummies for years of schooling. The results are plotted in Figure 1. There is a notable change in slope that arises at roughly twelve years of schooling in all three figures. This suggests the parsimonious regression that is used for the remainder of our results:

\[ \log(w_{ijt}) = \beta_t d_t + \beta_j d_j + \beta_s s_{ijt} + \beta_z Z_{ijt} + \beta_c c_{ijt} + \varepsilon_{ijt} \]

where \( s \) is total years of schooling and \( c \) is years of college (or university), that is, years of schooling past the twelfth. This functional form allows for a linear return to schooling \( \beta_s \) in the standard way, but also captures through \( \beta_c \) that college has a higher return.\(^3\)

Table 2 shows the human capital gaps and the residual wage gaps estimated using the constant rate of return and our estimated rates of return. Although the figures differ slightly they reach a common conclusion: workers in non–agriculture have more human capital than do workers in agriculture, but the gap is not large enough to explain all of the wage gap. The residual wage gap is on the order of 25–50 percent. The reason that the figures are larger for the Banerjee and Duflo (2005) returns is that they apply a larger rate of return for the first twelve years of schooling than what we estimate in our data; this rate of return is the main factor in explaining our results, not the return to years of college.

### 2.4 Stylized Fact 3: Differences in Sectoral Mincer Returns

So far, we have constructed human capital under the assumption that the return of a year of schooling is the same in agriculture and non–agriculture. Now we relax this assumption and show that in the data some of the Mincer returns differ by sector. To establish this, we run the following regression:

\[ \log(w_{ijt}) = \beta_d d_t + \beta_x X_{ijt} + (\beta_d + \beta_s s_{ijt} + \beta_c c_{ijt})d_j + \varepsilon_{ijt} \]

\(^{3}\)Note that most of the literature follows Psacharopoulos (1994) and assumes that wages are a concave function of schooling, which turns out to be at odds with the current data we use.
We find that $\hat{\beta}_{sa} < \hat{\beta}_{sn}$ while $\hat{\beta}_{ca} \approx \hat{\beta}_{cn}$. A useful way of visualizing this result is by plotting the estimated log–wage function $\log(w_j(s))$ for each sector, i.e.,

$$\log(w_{ijt}) = (\beta_{sj} s_{ijt} + \beta_{cj} c_{ijt})d_j$$

As we can see from Figure 2, the returns to schooling are initially steeper in non–agriculture and subsequently similar. Table 3 reports the sectoral human capital and wages per efficiency unit that are implied by our estimates of the sectoral Mincer returns. In the first line, we calculate human capital gaps in each of our three data sources. These gaps are roughly twice as large as those computed with aggregate returns to schooling. Indeed, they are nearly as large as productivity gaps and the residual productivity gaps range from 2%
higher in non–agriculture to 6% higher in agriculture. Our preferred data set, the monthly CPS files, indicates a 3 percent difference. We conclude from this that measuring human capital with sector–specific Mincer returns all but accounts for the wage gaps between non–agriculture and agriculture.

<table>
<thead>
<tr>
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<th>U.S. Census</th>
<th>March CPS</th>
<th>Monthly CPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human Capital Gaps</td>
<td>1.75</td>
<td>1.97</td>
<td>1.89</td>
</tr>
<tr>
<td>Residual Wage Gaps</td>
<td>1.03</td>
<td>0.98</td>
<td>0.98</td>
</tr>
</tbody>
</table>

* A gap is the ratio of non–agriculture to agriculture.

One concern is that our way of obtaining human capital may eliminate wage gaps by construction. One can imagine that since we start with a sectoral wage gap and then use sectoral returns to schooling, then this “must” account for the sectoral wage gap somehow. We stress that this is not the case and there is nothing in our methodology that forces human capital to account for wage gaps. In particular, there is nothing that prevents us from estimating, say, that the return to school is higher in agriculture than non–agriculture. In this case we would conclude that the human capital gap was smaller than the traditional methodology, and the unexplained wage gap larger. This possibility is not academic. In Appendix A.3 we provide a falsification test by looking at an alternative wage gap that we do not expect to be explained entirely by human capital or selection: the union wage gap. We show that union workers earn higher wages than non–union workers but that union workers earn lower returns to schooling. Thus, we find that the residual wage gap is actually larger than the raw wage gap.

We now offer two interpretations for our finding that sectoral Mincer returns are larger in non–agriculture. The “sectoral hypothesis” attributes the differences in sectoral Mincer returns to sectoral technologies: schooling generates less human capital for workers who choose agriculture. The “selection hypothesis” attributes the differences in sectoral Mincer returns to the workers: schooling generates the same human capital in each sector, but workers sort according to their unobserved ability. As a result, non–agriculture is more human capital–intensive and has higher Mincer returns than agriculture. We first develop a simple model that will help us distinguish between the sectoral and the selection hypothesis. Afterwards, we look at the evidence from individuals who actually switched sector.
3 Model

3.1 Environment

Consider a static environment with a continuum of measure one of individuals. Each individual is endowed with one unit of time, an innate ability \( x \in [0, \bar{x}] \) and a non-negative number of years of schooling \( s \in [0, \bar{s}] \). For analytical convenience, we do not restrict \( s \) to be an integer but allow it to be a real number. As in the empirical part above, an individual with \( s \) years of schooling has \( c(s) \equiv \max\{0, s - 12\} \) years of college. We assume that an individual with characteristics \((x, s)\) who works in sector \( j \) has \( h_j(x, s) \) units of human capital, where \( h_j \) is a smooth function that is non-increasing in both of its arguments. We use \( L(x, s) \) to denote the measure of individuals with characteristics \((x, s)\) and \( \Omega \) to denote the set of individual characteristics.

There is an agricultural and non-agricultural consumption good. Individual preference over the consumption of the two goods are represented by the Cobb–Douglas utility function

\[
\alpha \log(y_a) + (1 - \alpha) \log(y_n)
\]

where the subscripts indicate the sector and \( \alpha \in (0, 1) \) is a relative weight. Individuals do not value leisure, implying that in equilibrium they will allocate their full time endowment of one to work.

The two goods are produced according to linear production functions that use labor as the only input factor:

\[
Y_j = H_j
\]

where \( H_j \) denotes total human capital (or efficiency units of labor) in sector \( j \). For future reference, we denote by \( L_j \) the measure of individuals which work in sector \( j \) and by \( \nu_j(x, s) \) the indicator functions that equal one when individual \((x, s)\) chooses sector \( j \) and zero otherwise.

The development literature considers barriers that prevent the free movement of labor from agriculture to non-agriculture and distort the efficient allocation of labor between the two sectors. A simple way of capturing the effects of such barriers on the allocation of labor is by assuming that there is a tax \( \tau \) on wages in non-agriculture that gets redistributed through a lump–sum transfer \( T \) to all individuals. This is similar to how Restuccia et al. (2008) modeled barriers.
3.2 Equilibrium definition

A competitive equilibrium is

- goods prices \((P_a, P_n)\)
- rental prices \((W_a, W_n)\)
- a tax rate \(\tau\)
- choices of consumption and sector \((y_a, y_n, \nu_a, \nu_n)(x, s)\) for all \((x, s) \in \Omega\)
- output and labor \((Y_j, H_j)\) in each sector \(j\)

such that:

- \((y_a, y_n, \nu_a, \nu_n)(x, s)\) solve the individual problem:
  \[
  \max_{y_a, y_n, \nu_a, \nu_n} \alpha \log(y_a) + (1 - \alpha) \log(y_n)
  \text{ s.t. } P_a y_a + P_n y_n = W_a h_a(x, s) \nu_a + (1 - \tau) W_n h_n(x, s) \nu_n + T
  \]

- \((Y_j, H_j)\) solve the firm problem in sector \(j\):
  \[
  \max_{Y, H} P_j Y - W_j H \quad \text{s.t. } Y = H
  \]

- markets clear:
  \[
  Y_j = \int_{(x, s) \in \Omega} y_j(x, s) dL(x, s)
  \]
  \[
  H_j = \int_{(x, s) \in \Omega} h_j(x, s) \nu_j(x, s) dL(x, s)
  \]

- government budget is balanced:
  \[
  T = \tau \int_{(x, s) \in \Omega} W_n h_n(x, s) \nu_n(x, s) dL(x, s)
  \]

One might be tempted to start solving this model by requiring the usual restriction that the rental rates of human capital are equalized across sectors, \(W_a = W_n\). For two reasons, this is not in general an equilibrium property of our model: since in general \(h_a(x, s) \neq h_n(x, s)\) the wages have to adjust such that the labor market clears and the “right” number of individuals chooses each sector; only \(W_n\) is taxed in our model, and so \(W_n > W_a\) even if the net wages are equalized across sectors.
3.3 Equilibrium sorting

Since in the data individuals in non-agriculture have more years of schooling and earn higher Mincer returns on each year of schooling, we are interested in equilibria that have these features. We therefore explore the possibility that sorting according to individual characteristics generates them. To ensure that an equilibrium exists and is unique in our model, we need to impose more structure on the environment. Given the empirical findings from subsection 2.4 from above, we make the following assumption:

\[ h_j(x, s) = \exp(\gamma_j xs + \beta_c c(s)) \]  

(5)

where \( j \) is the sector index and \( \gamma_j \) and \( \beta_c \) are non-negative rates of return to total years of schooling \( s \), innate ability \( x \), and years of college \( c(s) \equiv \max\{0, s-12\} \). The functional form for \( h_j \) has three key features. First, for an individual with zero schooling, human capital equals one irrespective of the sector. Second, the Mincer return to schooling depends on the product of a sector-specific technology parameter \( \gamma_j \) and innate ability \( x \). We assume that \( \gamma_a \leq \gamma_n \), which is inspired by our empirical findings that the Mincer returns are larger in non-agriculture than in agriculture. We will show below that if \( \gamma_a < \gamma_n \) then there is a unique sorting equilibrium such that individuals with higher \( xs \) choose non-agriculture. Third, the additional return to college is independent of sector and innate ability. This assumption is motivated by Figures 2 and it will greatly simplify the analysis.

Under these assumptions, we can derive three results that are crucial for interpreting our empirical findings:

**Proposition 1**

- Suppose that \( \gamma_a < \gamma_n \). Then there is a unique competitive equilibrium.

- In equilibrium, individuals sort into the sectors according to their years of schooling and their innate ability. In particular, there is a unique threshold \( \chi \in (0, \bar{x}s) \) such that:
  - individuals with \( xs = \chi \) are indifferent between the two sectors, i.e.
    \[ W_a \exp(\gamma_a \chi) = (1 - \tau)W_n \exp(\gamma_n \chi) \]  
    (6)
  - individuals with \( xs < \chi \) choose agriculture
  - individuals with \( xs > \chi \) choose non-agriculture

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The equilibrium has the following additional properties:

\[
\frac{P_a Y_a}{L_a} < \frac{P_n Y_n}{L_n}
\]  

(7)

Proof: See Appendix B.

Proposition 1 says that there is a unique sorting equilibrium that is consistent with the key fact that we want to explain: value added per worker is higher in non-agriculture. Note that while individuals in non-agriculture have higher \(xs\) than in agriculture, this does not in general imply that they have more years of schooling. To account for this particular feature of the data, one needs to introduce the plausible additional assumption that ability and schooling are positively correlated in the population. An obvious special case that works is that the correlation is one and \(s = s(x)\) is an increasing function.

Our empirical findings suggest that wages per efficiency unit are roughly equalized between agriculture and non-agriculture. The next proposition explores the implications of this finding:

**Proposition 2.** If \(W_a = W_n\) and \(\tau = 0\), then \(h_a(x,s) = h_n(x,s)\).

Proof: The proof follows directly from the indifference condition (6).

Making the standard additional assumption that there are no barriers that distort the allocation of labor between agriculture and non-agriculture in the US, Proposition 2 says that if wages per efficiency unit are equalized across sectors, then the technologies that translate characteristics into human capital are the same in both sectors. This, of course, means that the selection hypothesis prevails and that differences in the estimated Mincer returns to schooling are entirely due to the fact that innate abilities and years of schooling differ across sectors. In the next subsection, we provide evidence from individuals who switch sector (“switchers”) that is broadly consistent with this conclusion.

If the sectoral technologies are the same so that the selection hypothesis prevails, we have a third result:

**Proposition 3.** If \(h_a(x,s) = h_n(x,s)\), then barriers are determined by the gaps in wages in efficiency units:

\[
\tau = \frac{W_n - W_a}{W_n}
\]

Proof: The proof follows directly from the indifference condition (6).

Proposition 3 will be useful for interpreting the findings of our international analysis.
where we will find gaps in wages per efficiency unit of labor even after adjusting for sector-specific Mincer returns to schooling.

4 Mincer Returns for Switchers in the U.S.

We now study the wage patterns of workers who switch sectors ("switchers"). If switchers experience large changes in the return on their education, this indicates that the differences are intrinsic to the sectoral technology. This would contradict the conclusions derived so far. If switchers do not experience large changes in the return on their education, this indicates that they are intrinsic to the workers. This would support the conclusions derived so far.

Our ideal data set has a panel dimension so that we can compare the wages and wage structure before and after switching industries for the same worker. Our ideal data set also has a large sample so that we can observe a sufficient number of switchers, given the relatively small size of the agricultural labor force in the U.S. today. The only data set that we are aware of that satisfies these requirements is the CPS. The CPS provides the sample size that we need and includes a short panel structure: households are in the CPS for four months, then out for eight months, before returning for four more months. We focus on matching the fourth month of each spell, when extra data are collected (the so-called “outgoing rotation groups”). The resulting two observations are separated by one year and allow us to study the changes in wages and wage structure for workers who switch sectors in the intervening year.

Matching workers over time in the CPS is well known to be challenging. The basic problem stems from two points. First, the CPS is really a survey of addresses, not persons or households. That is, the CPS samples dwellings based on address and surveys whoever lives in that dwelling. In some cases, the family in that dwelling will differ over time. In principle the CPS carefully denotes when a household changes within a dwelling. However, the second point is that the within-dwelling household and person identifiers are known to have coding errors. Fortunately, there is a well-established procedure for dealing with these issues that we follow here (Madrian and Lefgren 1999, Madrian and Lefgren 2000). The basic idea is to start by matching all persons who share the same dwelling, household, and person identifiers. We then check whether the match is valid by checking whether variable responses are logically consistent across time within a match. Here, there is a tradeoff. If one checks more variables and/or requires stricter agreement over time, then one not only excludes more false matches, but also more valid matches where a code is misreported. We
adopt a fairly strict check by requiring that age, sex, and race all agree.\textsuperscript{4}

The matching process excludes a number of observations. Before analyzing the data, we want to make certain that the same basic facts apply also in the sample of matched workers. If so, then we can be reassured at least that the workers we can match do not differ in obvious ways from the workers we exclude. We focus on two moments that are of the most interest to our analysis. The first one is the wage gap. Table 4 shows the raw wage gap that prevails in the monthly CPS and the matched CPS. The two should agree closely because they start with the same observations; the only difference is that the matched file contains only households that can be matched across years. Indeed the gap is close in size. The Table also shows the gap after making a series of adjustments for state and gender; for schooling, using the observed aggregate return; and for schooling, using the observed sectoral return. Throughout the estimates are close. This is reassuring because it says that the matching process yields a data set with wage gaps similar to the baseline data.

<table>
<thead>
<tr>
<th>Table 4: Gaps for Matched and Unmatched Samples (U.S. 1980–2011)</th>
<th>Monthly CPS</th>
<th>Matched CPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted Wage Gap</td>
<td>1.85</td>
<td>2.06</td>
</tr>
<tr>
<td>Wage Gap with Aggregate Capital Adjustment</td>
<td>1.44</td>
<td>1.57</td>
</tr>
<tr>
<td>Wage Gap with Sector-Specific Adjustment</td>
<td>0.98</td>
<td>1.00</td>
</tr>
</tbody>
</table>

A gap is the ratio in non-agriculture and agriculture.

Given our interest in the sectoral return to schooling we also check whether the basic patterns are the same for matched and unmatched data sets. We estimate the same equation allowing for sectoral returns to schooling in each data set and plot the resulting wage as a function of schooling profiles in Figure 3. The two profiles are indeed quite similar, again reassuring us that the results we find for the matched CPS will apply to the other U.S. data sets discussed in the previous section.

Having established that the matched CPS appears to be a useful data set to study, we now turn to analyzing the experiences of switchers and non-switchers. We define four groups: those who work in agriculture both years; those who work in non-agriculture both years; those who switch from agriculture to non-agriculture; and those who switch from non-agriculture to agriculture. We focus on the determinants of the annual changes in

\textsuperscript{4}Agreement here means that the gender is the same; that the race report of white or non-white is the same; and that the age in the later period is between the same and two years older than the age in the earlier period. Note that since the CPS is not necessarily asked on the exact same date of the month each time, this is the strictest agreement on age that one can check.
wages. That is, we want to understand for worker $i$ who works in sectors $j$ and $j'$ in periods $t - 1$ and $t$ the determinants of $\Delta \log(w_{ijj'}t) \equiv \log(w_{ijj't}) - \log(w_{ijj't-1})$. As a simple exploratory regression we try:

$$\Delta \log(w_{ijj't}) = \beta_{djj'}d_{jj'} + \beta_{dt}d_t + \varepsilon_{ijj't}$$

where $jj'$ denotes a sector pair; for example, $jj' = a, a$ denotes workers who stay in agriculture, and $jj' = n, a$ denotes workers who switch from non–agriculture to agriculture. The idea of this regression is simply to capture the mean effect of staying in the same sector versus switching, controlling for trend wage growth with $d_t$. Table 5 shows the resulting estimates relative to the average annual wage growth of workers who are in non–agriculture. In particular, the average wages of workers who remain in agriculture grow by 2 percent less than the average wages of those who stay in non–agriculture. The more interesting figure is for switchers: the average wages of switchers from agriculture to non–agriculture and from non–agriculture to agriculture grow by 14 percent more and less than the average wages of stayers in non–agriculture, respectively. These figures are quite small relative to the total agricultural wage gap of roughly 40 percent. We view these results as providing evidence that most of wage gaps represent selection of workers of different types.

A common concern is selection. One can imagine that all workers have the chance to switch sectors and that there is some heterogeneity in the wage gain or loss to switching sectors. In most models, workers with larger gains (or smaller losses) will be more likely to switch. This logic suggests (for example) that the 12 percent wage loss from moving to
Table 5: Wage Changes for Stayers and Switchers (U.S. 1980–2011)

<table>
<thead>
<tr>
<th></th>
<th>ag to ag</th>
<th>ag to non–ag</th>
<th>non–ag to ag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage Change</td>
<td>-0.020</td>
<td>0.130</td>
<td>-0.124</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.015)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>6,720</td>
<td>1,910</td>
<td>1,602</td>
</tr>
</tbody>
</table>

Average annual wage growth relative to average annual wage growth of the workers who remain in non–agriculture. Standard errors given in parentheses. Wage changes are statistically different from zero, and wage changes of switchers are statistically different from those who stay in the same industry.

agriculture from non–agriculture may understate the wage loss that would occur if a random sample of workers were moved. Note, however, that the same logic works in reverse: the 13 percent wage gain from moving from agriculture to non-agriculture is probably higher than the wage gain that would occur if a random sample of workers were moved. The fact that these two numbers are similar but opposite in sign suggests that the selection concern may not be so strong in our data.

We now ask how switching affects the market value of education. Recall that the cross–sectional estimates indicate higher returns to education in non–agriculture than in agriculture. The estimated wage–schooling relationship for the two sectors is given in Figure 4a. The relationships in the matched CPS data suggest large differences in the return to education. In Figure 4b we add the returns to education for those who switch, as observed before the switch. We can see already that switchers are different even before they switch: their wage–return on their education is between that of workers who stay in agriculture and workers who stay in non-agriculture. This evidence suggests that selection may play a role. In Figure 4c, we confirm this suspicion: the value of education after switching is still between the two sectors, and not too different from the value of education before switching.

This last fact may be better represented by Figure 5, which shows, group by group, the value of education before and after. For workers who remain in agriculture or non–agriculture throughout the value is essentially unchanged. For workers who switch sectors, the changes are modest: workers who exit agriculture earn somewhat higher returns on their schooling, while workers who switch to agriculture experience almost no change in the relevant region. These two figures indicate that much of the gap in the return to schooling is attributable to selection: workers who are going to switch are already different from non–switchers in the same sector. Further, when switchers switch, their returns change little.

It may be useful to provide a quantitative sense of how much the data support the
sectoral differences versus selection views of why returns to schooling differ across sectors. We can perform a simple calculation that gives such a sense. The idea is to quantify the total change in the value of education that one would observe under each of these theories; to compute the actual change observed in the data; and then to compare the three values to assess how close the data is to each theory.

For the selection view, the answer is straightforward: rates of return differences reflect differences in the workers who select into the two sectors. When workers switch they take their returns with them. Hence, switchers would experience no change in the value of their education. This value is reported in column 2 of Table 7. For the sectoral view, the answer requires some calculation. We observe in the data $s_{ijt}$, $c_{ijt}$, $\beta_{sj}$, and $\beta_{cj}$. We can
Table 6: Changes in Returns to Schooling

<table>
<thead>
<tr>
<th></th>
<th>Years of Schooling</th>
<th>Years of College</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non–Ag Stayers</td>
<td>-0.002*</td>
<td>0.003*</td>
</tr>
<tr>
<td>Ag Stayers</td>
<td>0.001</td>
<td>-0.005</td>
</tr>
<tr>
<td>Non–Ag to Ag</td>
<td>-0.012</td>
<td>0.046</td>
</tr>
<tr>
<td>Ag to Non–Ag</td>
<td>0.022*</td>
<td>-0.039</td>
</tr>
</tbody>
</table>

Table gives the change in the returns to schooling for switchers and stayers.

* Difference is statistically significant at the 95% level.

Figure 5: Wages as a Function of Schooling, Before and After Switching

compute the total value of the schooling for a worker $i$ in sector $j$ as $\beta_{sijt}^j + \beta_{cijt}^j$. The average value of the human capital stock for sector $j$ is simply the average of this across
all workers in \( j \). Under the view that rates of return differences are due to sectoral factors, the counterfactual value of this education in sector \( j' \) is just \( \beta_{s'j's} + \beta_{c'j'c} \), with the change in the value of education defined as the difference between the two. In words, we can compute the change in the value of education for an individual by assigning them the red line instead of the blue or vice versa in Figure 4a. We compute the average change implied by this calculation for switching all agricultural workers to non–agriculture, and vice versa. The sectoral view implies large changes in the value of education that would raise or lower wages by over 50 percent.

<table>
<thead>
<tr>
<th>Table 7: Change in Value of Education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change Implied by:</td>
</tr>
<tr>
<td>Selection View</td>
</tr>
<tr>
<td>ag to non–ag</td>
</tr>
<tr>
<td>non–ag to ag</td>
</tr>
</tbody>
</table>

Table gives the wage change due to changing value of schooling for switchers. Values are provided for two stylized theories as well as the actual change observed in the model.

In the fourth column of the table we give the actual wage change induced by substituting the estimated “before” returns to schooling for the estimated “after” returns to schooling for the two groups of switchers. In words, we are quantifying the effect of moving from the purple to the pink lines in Figure 6 for the average worker who actually switches. The effects are much smaller than our counterfactuals. For workers who switch from ag to non–ag, the effect is a 22 percent increase in wages. This is closer to the selection view. For workers who switch in the opposite direction the actual change is even smaller, just a seven percent decline in wages. We conclude that the data are much closer to the selection than the sectoral view of why returns to schooling vary by sector.

5 Cross–country Analysis

5.1 Preliminaries

In the previous sections we analyzed wage gaps in the U.S. In this section, we extend our analysis to a larger sample that includes earlier U.S. censuses as well as 32 censuses from 13 other countries with the relevant variables in IPUMS International. We use Censuses from IPUMS because they are nationally representative and the IPUMS team has

The resulting sample of countries covers 30% of the world population in 2010 and contains four of the five most populous countries (India, US, Indonesia, Brazil). In addition to rich countries like Canada and the U.S., it comprises medium–income countries like Brazil and Mexico and poor countries like India and Indonesia. As a result, there is a large cross–country variation in GDP per capita of around a factor of 20. Our sample clearly shows the usual macro–development facts about agriculture: the largest productivity gaps between non–agriculture and agriculture is about 4 and the largest employment share in agriculture is almost 2/3. Although in 2010 the total population of our sample countries was more than twice that of Africa, it does not unfortunately contain any African countries. The reason for this is that IPUMS does not report sufficiently sufficiently detailed census information for African countries.

5.2 Cross–country facts about wages and human capital

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Wage Gap</td>
<td>1.42</td>
<td>1.82</td>
<td>3.57</td>
</tr>
<tr>
<td>Adjusted Wage Gap</td>
<td>1.36</td>
<td>1.74</td>
<td>3.09</td>
</tr>
<tr>
<td>Standard Human Capital</td>
<td>1.08</td>
<td>1.40</td>
<td>2.78</td>
</tr>
<tr>
<td>Sector–specific Returns</td>
<td>0.92</td>
<td>1.21</td>
<td>2.25</td>
</tr>
</tbody>
</table>

We now calculate wage gaps and assess the importance of human capital in accounting for them. We follow the same broad principles as before to the extent possible. In particular, we use only information from individuals who are at least 10 years old and have valid information for our key variables: sex, education, employment by sector and so on. Within the set of countries in our sample we again find that there are sizeable wage gaps between non–agriculture and agriculture. Table 8 gives the raw wage gaps and the adjusted wage gaps (which again control for differences in gender and region of residence in the country).
The median gap is actually quite comparable to the U.S., but there is substantial dispersion. There is also less correlation with GDP per capita than one would expect based on previous work on agricultural productivity gaps. For example, the largest gap is for Brazil 1980, but the smallest is for Venezuela 2001.

Next, we explore how far we can go to closing these gaps with various corrections for sectoral human capital differences. Table 8 shows that the answer is: quite far. Our preferred human capital correction closes wage gaps from 1.82 to 1.21 for the median country. Figure 6 visualizes the results. The x axis represents the raw gaps described in Table 8. Along the y axis we show the successive effects of making the same adjustments that we implemented for the U.S. The figure clearly brings out the importance of adjusting for human capital, using both years of schooling and the sectoral return to schooling. We are able to close more than 70% of the total wage gap in the median country. This limits the potential role of barriers. The next paragraph quantifies to what extent barriers matter.

The literature typically assumes that except for TFP differences, technology is the same across countries. Making that assumption in our context implies that $h_n(x, s) = h_a(x, s)$ also internationally. Proposition 3 from above then implies that $\tau = (W_n - W_a)/W_n \in (0, 1)$. In other words, viewed through the lens of our model, the observed gaps in residual wages
allow us to calculate the size of the distortion \( \tau \). Table 9 reports the implied values of distortions. We can see that they are an order of magnitude smaller than those calibrated in papers like Restuccia et al. (2008). In fact, their magnitude is consistent with more benign explanations such as difference in the cost of living between rural and urban areas or difference in the prevalence of the shadow economy in rural and urban areas.

Table 9: Implied \( \tau \)

<table>
<thead>
<tr>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.08</td>
<td>0.21</td>
<td>1.25</td>
</tr>
</tbody>
</table>

6 Conclusion

Our findings suggest that accounting for just one form of selection closes all of the residual wage gap for the US and most of the residual wage gaps across countries. We argued above that this implies that barriers do not play a major quantitative role for the allocation of labor between non–agriculture and agriculture. This statement implies that the assumptions made by the first strand of the structural transformation literature are fine to a first–order approximation. This statement also implies that productivity gaps between non–agriculture and agriculture, which are typically much larger than wage gaps, don’t manifest themselves in labor markets. This leaves two logical possibilities. First, productivity gaps may result from barriers that affect markets other than the labor market. Two obvious examples are subsidies to one sector but not the other and distortion to the land market; see Adamopoulous and Restuccia (2014) on the latter. We think that this is an important topic for further research. Second, measured productivity gaps may be exaggerated because it is notoriously difficult to measure agricultural value added (Herrendorf and Schoellman 2013). This may imply that actual productivity in agriculture is higher than measured productivity and productivity gaps are more in line with wage gaps.

Our work has an important implication for how to construct human capital at the sectoral level. It shows that one needs to use Mincer returns that are estimated at the sector level, instead of Mincer returns that are estimated at the aggregate level. The reason for this is that Mincer returns that are estimated at the sectoral level capture that unobserved characteristics differ across sectors, which Mincer returns that are estimated at the aggregate level miss by construction.
References


Appendix A: Details about the Data Work

Appendix A.1: Sectors

In the CPS and Census in sections 2 and 6, agriculture and non–agriculture are defined on industry codes. Agriculture is crop and animal production. Non-agriculture is the residual.

In the matched CPS of section 4, the definition is stricter. Here, agriculture and non–agriculture are defined on industry and occupation. We keep only those individuals who are in farm industries and have farmer occupations, or non–farm industries and non-farmer occupations. This is somewhat severe, but it is useful/necessary for thinking about switchers. In short, we want to be certain that switchers really do switch, and one way to enforce this is to require (as this procedure does) that they go from reporting farm and farmer to non–farm and non–farmer (or vice versa). We throw out everyone who has ambiguous responses (industry = finance and occupation = farmer, or industry = crop production and occupation = accounting, and so on)

Appendix A.2: Trimming

We encountered several reports of zero years of schooling. It is important to check the plausibility of these reports because 0’s can have a large effect on the estimated Mincer returns if the wages that go along with them are high. The most natural way of checking
for the plausibility of the reported years of schooling is to compare them to the reported occupation. To implement this, we study the distribution of schooling by occupation and focus on the 1st percentile. Anyone who has schooling strictly less than the average in the 1st percentile is discarded from the data. The idea is that this automated process detects implausibly low reports.

Two purely hypothetical examples may help. For the occupation landscapers, we likely find a 1st percentile of 0 years. This suggests that low schooling is not atypical for landscapers, and so even landscapers with no schooling should be considered plausible. For the occupation doctors, we might find a 1st percentile of high school graduates. We conservatively say that anyone with less than a high school diploma has likely made a mistaken school report and drop them.

For robustness, we also try cutting implausibly high school levels (above the 99th percentile) and changing the thresholds (0.5 or 2 percent, for example). We obtain similar results.

Appendix A.3: Falsification Test: the Union Wage Gap

In the text we explore the ability of human capital defined in different ways to explain the agricultural wage gap. A concern with this way of proceeding is that our method of constructing human capital with sectoral returns explains the entire gap by definition. Here we perform a simple falsification test to show that this is not the case.

To do so we explore an alternative gap that is widely viewed as arising through market power rather than differences in unobserved human capital and selection, namely the union wage gap. We show results for the monthly CPS files; workers from 1983 onward were asked whether they were union members. We then conduct the same empirical analysis of union wage gaps as we did for sectoral wage gaps. The results are shown in Table 10, with the results for the agricultural wage gap from the monthly CPS files shown for comparison.

<table>
<thead>
<tr>
<th>Table 10: Sectoral and Union Wage Gaps</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Wage Gap</td>
</tr>
<tr>
<td>Adjusted Wage Gap</td>
</tr>
<tr>
<td>Wage Gap with Aggregate Human Capital Adjustment</td>
</tr>
<tr>
<td>Wage Gap with Sector–specific Human Adjustment</td>
</tr>
</tbody>
</table>

A gap is the ratio of non–agriculture to agriculture or union to non–union.
First, the raw union wage gap is sizable; union members earn thirty percent higher hourly wages as compared to non-members. Adjusting for basic demographic information (state and gender) reduces this gap somewhat. Adjusting for schooling using the aggregate returns to school, however, makes almost no difference. Finally, adjusting for differences for the returns to schooling between union and non-union members actually makes the wage gap substantially worse. The reason is simple: the return to schooling for union members is much lower than the return to schooling for non-union members. Given this fact, our proposed measure of human capital actually implies that human capital is lower rather than higher for union workers. Figure 7 shows the estimated gap in wages per efficiency unit and returns to schooling for union and non-union workers.

![Figure 7: Returns to Schooling Vary with Union Status](image)

Appendix A.4: Robustness: Accounting for Immigration

A common concern with the US data is that the patterns may be explained in large part by the high percentage of immigrants working in the agricultural sector. The fact that the pattern also applies in other countries provides one piece of evidence against this supposition. In this section we re-compute wage and human capital gaps using only natives born
in the U.S. We perform this exercise using the monthly CPS files for the years 1994 onward; the variable on citizenship is not available in the monthly CPS before that time.

Table 11: Sectoral Wage Gaps for Natives

<table>
<thead>
<tr>
<th></th>
<th>All Workers</th>
<th>Natives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw Wage Gap</td>
<td>1.75</td>
<td>1.61</td>
</tr>
<tr>
<td>Adjusted Wage Gap</td>
<td>1.85</td>
<td>1.66</td>
</tr>
<tr>
<td>Wage Gap with Aggregate Human Capital Adjustment</td>
<td>1.39</td>
<td>1.41</td>
</tr>
<tr>
<td>Wage Gap with Sector–specific Human Adjustment</td>
<td>0.98</td>
<td>0.85</td>
</tr>
</tbody>
</table>

A gap is the ratio of non–agriculture to agriculture or union to non–union.

Our results are given in table 11. As one might expect, the gap in raw and adjusted wages are both smaller if we focus only on natives; part of the low wages in agriculture are explained by the presence of a high proportion of immigrants. Applying a standard human capital correction to the sample of natives would still imply a large residual wage gap of 41 percent to be explained. Most importantly, however, we find that there the sectoral gaps in returns to schooling are actually slightly larger when we focus on natives. For example, the gap in the baseline returns to schooling is 4.1 percent for the native sample as compared to 3.5 percent in the sample including immigrants. Thus, the gap in return to schooling in the U.S. is not explained by immigration. We also find adjusting for these differences more than closes the gap in wages per efficiency unit.

Appendix B: Proof of Proposition 1

We choose the agricultural good as the numeraire, $W_a = 1$. There are three different cases to consider:

1. If $$W_n = \frac{\exp((\gamma_a - \gamma_n)\bar{x}\bar{s})}{1 - \tau}$$ then individuals with ability and schooling $xs = \bar{x}\bar{s}$ are indifferent and individuals with ability and schooling $xs < \bar{x}\bar{s}$ prefer agriculture.

2. If $$W_n = \frac{1}{1 - \tau}$$ then individuals with ability and schooling $xs = 0$ are indifferent and individuals with ability and schooling $xs > 0$ prefer non–agriculture.
3. If
\[ W_n \in \left( \frac{\exp([\gamma_a - \gamma_n] \bar{x}s)}{1 - \tau}, \frac{\exp(0)}{1 - \tau} \right) \] (8)
then there is a unique threshold \( \chi(W_n) \). Individuals with ability and schooling \( xs = \chi(W_n) \) are indifferent, individuals with ability and schooling \( xs < \chi(W_n) \) prefer agriculture, and individuals with ability and schooling \( xs > \chi(W_n) \) prefer non-agriculture. To see this, note that, as \( xs \) increases from 0 to \( \bar{x}s \), \( \exp([\gamma_a - \gamma_n]xs) \) is monotonically decreases from \( \exp(0) \) to \( \exp([\gamma_a - \gamma_n] \bar{x}s) \).

4. \( \chi(W_n) \) is decreasing in \( W_n \), as can be seen from (6)

In equilibrium, it must be that \( P_a = W_a = 1 \) and \( P_n = W_n \). Moreover, individuals will spend the shares \( \alpha \) and \( 1 - \alpha \) of their income on agricultural and non-agricultural goods. Hence,
\[ \frac{W_n Y_n}{Y_a} = \frac{1 - \alpha}{\alpha} \]
or:
\[ W_n = \frac{1 - \alpha}{\alpha} \int_{xs \leq \chi(W_n)} \exp(\gamma_a xs + \beta_c c(s)) dL(x,s) \]
\[ \int_{xs \geq \chi(W_n)} \exp(\gamma_n xs + \beta_c c(s)) dL(x,s) \] (9)

For \( W_n \) satisfying (8), the left-hand side of (9) is monotonically increasing from \( \exp([\gamma_a - \gamma_n] \bar{x}s)/(1 - \tau) \) to \( \exp(0)/(1 - \tau) \) and the right-hand side of (9) is monotonically decreasing from \( \infty \) to 0. Since both sides are continuous, the intermediate-value theorem implies that there is a unique solution.

To obtain inequality (7), note that (6) implies for individuals with \( xs = \chi \) that:
\[ W_a \exp(\gamma_a xs + \beta_c c(s)) = W_n (1 - \tau) \exp(\gamma_n xs + \beta_c c(s)) \] (10)

Since \( \gamma_a \leq \gamma_n \), for individuals with \( xs < \chi \)
\[ W_a \exp(\gamma_a xs + \beta_c c(s)) < W_n (1 - \tau) \exp(\gamma_n xs + \beta_c c(s)) \] (11)
and for individuals with \( xs > \chi \)
\[ W_a \exp(\gamma_a xs + \beta_c c(s)) > W_n (1 - \tau) \exp(\gamma_n xs + \beta_c c(s)) \] (12)
Putting (10)–(12) together, we obtain:

\[
\frac{\int_{xs \leq \chi} W_a \exp(\gamma_a xs + \beta_c c(s)) dL(x, s)}{\int_{xs \leq \chi} dL(x, s)} < \frac{\int_{xs \geq \chi} W_n \exp(\gamma_n xs + \beta_c c(s)) dL(x, s)}{\int_{xs \geq \chi} dL(x, s)}
\]

Since the zero profit conditions for the stand–in firms imply that \(W_j = P_j\) and since the technology is such that \(Y_j = H_j\), this inequality can be rewritten to:

\[
\frac{P_a Y_a}{\int_{xs \leq \chi} dL(x, s)} < \frac{P_n Y_n}{\int_{xs \geq \chi} dL(x, s)}
\]

Defining

\[
L_a \equiv \int_{xs \leq \chi} dL(x, s) \quad (13)
\]
\[
L_n \equiv \int_{xs \geq \chi} dL(x, s) \quad (14)
\]

we obtain (7). \textbf{QED}