Wages, Human Capital, and Barriers to Structural Transformation[*]

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Abstract

We document for 13 countries ranging from rich (Canada, U.S.) to poor (India, Indonesia) that average wages are considerably lower in agriculture than in the other sectors. Moreover, agriculture has less educated workers and lower Mincer returns. We view these findings through the lens of a multi-sector model in which workers differ in observed and unobserved characteristics and sectors differ in their human–capital intensities. We derive expressions for the implied barriers to the reallocation of labor out of agriculture. We find that in our sample these barriers are considerably smaller than what the macro–development literature has argued.

Keywords: barriers; human capital gaps; wage gaps.

JEL classification: O1.

1   Introduction

It is well known that in poor countries most workers are in agriculture where labor productivity is low. This fact has led a large literature in development economics to argue that reallocating labor from agriculture to non–agriculture would increase aggregate output in poor countries, but that barriers to the mobility of labor prevent this structural transformation from happening.[1] Despite the popularity of this argument, it is not clear what exact nature the barriers to structural transformation take in reality and how important they are quantitatively. Of course, there are prominent examples for barriers like the hukou system of China or the caste system of India.[2] However, to the best of our knowledge, there is no systematic direct evidence on the size of barriers to structural transformation across countries.

This paper assesses how large the barriers to structural transformation are by using micro data about wages and years of schooling from a sample of 13 countries during the last seventy years. Our data are from 42 population censuses that are harmonized by the Integrated Public Use Microdata Series International [IPUMS International, Minnesota Population Center (2015)]. The countries in our sample range from rich (Canada, U.S.) over middle income (Brazil, Mexico) to poor (India, Indonesia). Our sample covers 30 percent of the world population and includes four of the five most populous countries (namely, India, the U.S., Indonesia, Brazil). All countries in our sample have detailed census data that allow us to construct measures of wages and human capital at the sectoral level.[3]

We document that there are large gaps between the average wages per hour in non–agriculture and agriculture: at the median of our sample the wage gap is a factor of 1.8 and at the 90th percentile it is a factor of 2.7. Since non–agriculture is a large and heterogenous sector, we disaggregate it into industry, unskilled services, and skilled services. We find that the largest wage gaps are between skilled services and agriculture. A natural explanation is that average human capital differs across sectors. We document that indeed an average worker in non–agriculture went to school more years than an average worker in agriculture, with the largest difference between skilled services and agriculture. It is not immediately obvious, however, how to translate gaps in sectoral years of schooling into gaps in sectoral human capital. Gollin et al. (2014) suggested to combine information about

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[1]See e.g. Caselli and Coleman (2001), Caselli (2005), Restuccia et al. (2008), Vollrath (2009), and McMillan and Rodrik (2011).

[2]Hnatkovska and Lahiri (2013) argue that urban–rural wage gaps in India have declined in recent years. We remain silent on the behavior of wage gaps over time.

[3]Barro and Lee (2010), which is the standard data source for human capital stocks around the world, does not contain schooling and wage information at the sector level, which is required for our analysis.

years of schooling with off–the–shelf aggregate Mincer returns from the macro–development literature. Following the spirit of their suggestion, we estimate our own aggregate Mincer returns for each of our sample countries and use them to construct sectoral human capital. We find that while this reduces the raw wage gaps, sizable adjusted wage gaps remain: at the median the wage gap is a factor of 1.3 and at the 90th percentile it is a factor of 1.7. This finding is related to the finding of Gollin et al. (2014) that taking into account their measure of sectoral human reduces the raw productivity gaps while leaving sizeable adjusted productivity gaps.

Since we have disaggregate micro data on wages, we are in the unique position to go beyond using aggregate Mincer returns. Running Mincer regressions by sector for each country of our sample, we find that the sectoral Mincer returns differ significantly from each other and from the aggregate Mincer returns. We interpret this finding as suggesting that aggregate Mincer returns do not capture all information relevant for the determination of wages at the sector level. To think about what that implies for the importance of barriers, we look for guidance from a model.

We develop a variant of the multi–sector model that is standard in the macro–development literature. Our model has the following key features: workers are heterogeneous with respect to observable and unobservable characteristics (years of schooling and innate ability); sectors have different human–capital intensities. Our model encompasses the approach of Gollin et al. (2014) as the special case in which all workers have the same innate ability and all sectors have the same human–capital intensity. Our model highlights the two explanations for sector–specific Mincer returns that come to mind immediately: the selection view attributes differences in sectoral Mincer returns to differences in sectoral innate ability; the technology view attributes differences in sectoral Mincer returns to differences in technology, and in particular to differences in sectoral human–capital intensities. Under both views, we derive explicit expressions for the model–implied barriers in terms of observables sectoral wages.

We then turn to additional panel evidence for workers who leave agriculture for another sector, which is available for three countries of our sample. Panel data has the advantage that one can control for selection because one sees the same worker at least two times. Doing this for the Panel Study of Income Dynamics (PSID), we estimate the average wage gains of such "switchers" in the U.S. We complement these estimates with those of Alvarez (2017) and Hicks et al. (2017) about the average wage gains of switchers in Brazil and Indonesia, respectively. In all three cases, the average wage gains from switching are positive but small compared to both the raw wage gaps and the wage gaps adjusted with human

capital constructed from aggregate Mincer returns. This means that there is little scope for barriers of structural transformation. We also find for the three countries that the barriers to structural transformation implied by the wage gains of switchers are close to the model–implied values under the selection view and far away from the model–implied values under the technology view. We conclude from this evidence that the selection view is a reasonable approximation to reality for the three countries and present estimates of the model–implied barriers under the selection view for all countries of our sample. We find similar results: the model–implied barriers under the selection view are relatively small for all countries of our sample.

The remainder of the paper is organized as follows. In the next section, we briefly review the most closely related literature. We then present our empirical findings. Section 4 views the basic findings through the lens of a multi–sector model. Section 5 presents our evidence on barriers. Section 6 concludes.

2   Related Literature

In a broad sense, our work is related to the literature on structural transformation, which has assumed that there are no barriers to the mobility of labor across sectors and has then characterized the properties of preferences and technological progress that generate the reallocation of labor from agriculture to non–agriculture as a consequence of growth. Herrendorf et al. (2014) provide a review of that strand of the literature. Key contributions to it include Echevarria (1997), Kongsamut et al. (2001), Ngai and Pissarides (2007), Rogerson (2008), Buera and Kaboski (2012), Herrendorf et al. (2013), Boppart (2016), and Herrendorf et al. (2015).

More narrowly, our results are related to those of Gollin et al. (2014), 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 are not available, they rely on data from household surveys which contain household characteristics but have no information on wages. They therefore focus on productivity gaps, which are available from NIPA for most countries, and they use an off–the–shelf aggregate Mincer return for all countries. Instead we focus on wage gaps and we use Mincer returns that are estimated on country census data. In terms of results, they find that a sizable part of the productivity gaps between non–agriculture and agriculture remains unaccounted for. In contrast, we find that most of the wage gaps can be accounted for if one takes selection into account.

Our results are also related to Lagakos and Waugh (2013) and Young (2014), who

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develop variants of the Roy model to study the selection of workers according to unobserved characteristics as a potential explanation for the existence and evolution of productivity gaps. Here we focus on the more direct statistic of interest – wages – and show how selection on unobserved characteristics can be measured in a simple way that is disciplined by micro data.

Lastly, our results are related to Young (2013), who develops a location model in which people with better observed and unobserved characteristics sort into urban areas and workers with worse observed and unobserved characteristics sort into rural areas. This prediction of Young is consistent with our finding that most of the wage gap between non–agriculture and agriculture is accounted for by the fact that workers in non–agriculture have more human capital.

3   Evidence

In this section, we first describe the data and show that our sample of countries captures the standard macro–development facts. We then document new stylized facts about sectoral wages and sectoral human capital.

3.1   Data

We use census data from IPUMS for the U.S. during 1940–2015 and from IPUMS International for 12 other countries during 1970–2010 (Minnesota Population Center, 2014). These data are nationally representative and the IPUMS team has put forth a great deal of effort into harmonizing variables such as education and industry that are critical for our analysis.[4] Table 1 reports the country–year pairs for which we have sufficient data to be able to construct wages by sector.

For our main analysis, we focus on the subsample of wage workers that are typically used in wage regressions, that is, workers who have valid responses to the questions of interest (industry of employment, wage income, and so on) and who are firmly attached to the labor force, which we define as being 10–70 years old.[5] Studying only wage workers is more restrictive in agriculture than in other sectors because a sizeable part of the agricultural labor is self–employed proprietors. There are three reasons why we nonetheless do not

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[4]We have conducted the analysis that follows in this section also with data from the Current Population Survey (CPS) for the U.S. since 1980. The findings are similar; see the working–paper version, Herrendorf and Schoellman (2017).

[5]Note that since in poor countries many children work full time, we have lowered the age bar from the usual 15 years to 10 years or older when such children are included in the data.

Table 1: Country–Year Pairs in Our Sample

Brazil (1991,2000,2010)	Canada (1971,1981,1991,2001)
Dominican Republic (1981)	India (1983,1987,1993,1999,2004)
Indonesia (1976,1995)	Israel (1995)
Jamaica (1982,1991,2001)	Mexico (1990,2000,2010)
Panama (1970,1990,2000,2010)	Puerto Rico (1990,2000)
U.S. (1940,1950,1960,1970,1980,1990,2000,2005,2010,2015)	Uruguay (2006)
Venezuela (1981,1990,2001)	

include them in the main analysis. First, we do not have information about proprietors' income for all countries of our sample. Second, proprietors' income represents payments to both capital and labor and it is unclear how to disentangle the fraction that is wage income. Third, there is evidence that proprietors underreport their income by a large amount, implying that we do not want to take their stated income too seriously (Herrendorf and Schoellman, 2015). In contrast, the income of wage workers is clearly due to labor and tends to be more precisely reported.

One might be worried that excluding self–employed proprietors does not leave sufficiently many wage workers to be able to calculate statistically meaningful average wages. We emphasize that wage workers are more common in agriculture in our sample than is often supposed. For the median country, 42 percent of the agricultural labor force works for wages; the range is wide, from 15 to 73 percent; the countries at the low end (particularly Indonesia) have such large agricultural labor forces that we still have a large number of agricultural wage workers for them. One might also be worried that excluding self–employed proprietors leads to a bias if proprietors differ from wage workers because of selection. For a subset of countries in our sample, we have sufficient information to calculate the income of self–employed proprietors. Below, we will use that information for a crude robustness check that suggests that this is not a major concern.

We distinguish between the following sectors: agriculture and non–agriculture; agriculture, industry, and services; agriculture, industry, unskilled services, and skilled services. The dividing line between unskilled and skilled services is the average years of schooling in the U.S. in 2000: subsectors in unskilled services have at most 13 years of average schooling and subsectors in skilled services have at least 13 years of average schooling. The cross–walk between our sectors and the fifteen–sector split of IPUMS International is as follows:[6]

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[6] "Other services" comprise all services that are not obviously part of any other category. Examples include "Architectural, engineering, and related services", "Employment services", "Other amusement,

- Agriculture: agriculture, forestry, and fishing.

- Industry: construction; manufacturing; mining.

- Unskilled services: hotels and restaurants; private household services; communication and transportation; wholesale and retail trade.

- Skilled services: education; financial services and insurance; health; public administration; other services; real estate and business services; utilities.

The first two of the sectors splits that we study are common in the literature on structural change. The third sector split is introduced because services is a big and rather heterogenous category, with subcategories that are rather different (Jorgenson and Timmer, 2011; Duarte and Restuccia, 2016; Duernecker et al., 2016)].

Figure 1: Structural Transformation in our Sample of Countries
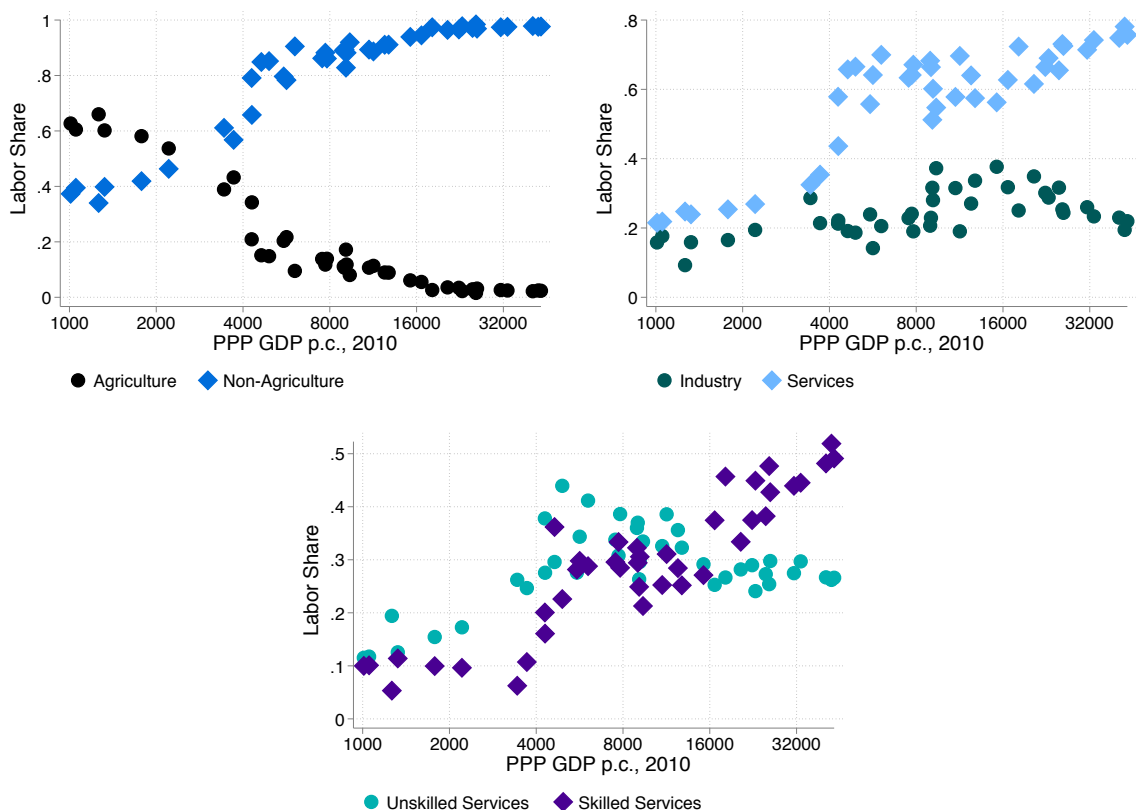
Before we present new stylized facts about gaps of sectoral wages, years of schooling, and human capital, it is useful to establish that our sample of countries captures the standard

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gambling, and recreation industries", "Beauty salons", and "Religious organizations". Other services are part of skilled services because they happen to have more than 13 years of schooling on average.

macro–development facts. It covers about one–third of the world population in 2010 and contains four of the five most populous countries, namely, India, the U.S., Indonesia, and Brazil. In addition to rich countries like Canada and the U.S., it comprises middle–income countries like Brazil and Mexico and low–income countries like India and Indonesia. The cross–country variation in GDP per capita in our sample is about a factor of 20. Moreover, the largest employment share in agriculture is almost 2/3 and the largest productivity gap between non–agriculture and agriculture is about four. The countries of our sample exhibit the standard patterns of structural transformation that were summarized by Herrendorf et al. (2014). Figure 1 shows that the agricultural labor share declines sharply as the level of development as measured by GDP per capita increases. The pattern for industry shows the hump shape that one would expect, while the service share is increasing. Disaggregating services into skilled and unskilled services, Figure 1 also shows for middle–income and high–income countries that skilled services grow with GDP per capita whereas unskilled services are unrelated to GDP per capita. This is consistent with the theory of Buera and Kaboski (2012).

3.2   Gaps in Wages, Years of Schooling, and Human Capital

Stylized Fact 1: Large Raw Wage Gaps

We define raw wage gaps as the ratio of the average wages in a non–agricultural sector relative to agriculture. We express wages in current units of the currency of each country. Depending on what is reported in the data, we calculate wages as the reported hourly wage or the reported weekly earnings divided by the reported hours worked in the prior week. A wage gap larger than one indicates that the average wage in the sector is larger than the average wage in agriculture.

To document that there are large raw wage gaps, we estimate the following log–wage regression for each country–year:[7]

$$\log(w_{ij}) = \beta_j d_j + \beta_z Z_{ij} + \varepsilon_{ij}$$

We omit the country–year index to economize on notation. w_{ij} is the hourly wage of worker i in sector j in the country–year pair under consideration, d_j is a sector dummy, Z_{ij} are controls for state and gender, β_j and β_z are the corresponding coefficients in the country

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[7]Since our samples are large and we just estimate straightforward sectoral averages, the point estimates of our regression coefficients are statistically significant at the 99% level. We therefore omit reporting standard errors.

Table 2: Gaps of Wages, Schooling, and Human Capital relative to Agriculture

		10th Pctl.	Med.	90th Pctl.
Non–Agriculture				
Stylized Fact 1	Raw wages	1.51	1.80	2.71
	Wages adjusted for gender and geography	1.50	1.69	2.27
Stylized Fact 2	Years of schooling	1.92	3.93	5.02
	Wages adjusted for gender etc. and human capital	1.18	1.33	1.72
Industry				
Stylized Fact 1	Raw wages	1.49	1.77	2.62
	Wages adjusted for gender and geography	1.41	1.66	1.91
Stylized Fact 2	Years of schooling	1.32	2.90	3.64
	Wages adjusted for gender etc. and human capital	1.16	1.40	1.75
Services				
Stylized Fact 1	Raw wages	1.51	1.88	2.91
	Wages adjusted for gender and geography	1.53	1.78	2.65
Stylized Fact 2	Years of schooling	2.20	4.21	6.54
	Wages adjusted for gender etc. and human capital	1.15	1.33	1.79
Unskilled services				
Stylized Fact 1	Raw wages	1.21	1.52	2.29
	Wages adjusted for gender and geography	1.19	1.45	1.94
Stylized Fact 2	Years of schooling	1.54	3.00	4.46
	Wages adjusted for gender etc. and human capital	1.03	1.19	1.57
Skilled services				
Stylized Fact 1	Raw wages	1.65	2.25	3.57
	Wages adjusted for gender and geography	1.70	2.19	3.26
Stylized Fact 2	Years of schooling	2.91	5.25	7.91
	Wages adjusted for gender etc and human capital	1.31	1.58	1.95

under consideration, and ε_{ij} is an i.i.d. error with zero mean. Choosing agriculture as the omitted group, $\exp(\beta_j)$ is the raw wage gap between sector j and agriculture.

Table 2 shows that the raw wage gaps are sizable: the average wages in the non–agricultural sectors can be more than three times larger than in agriculture. The smallest raw wage gap is with unskilled services and the largest wage gap is with skilled services. Not surprisingly there is substantial dispersion. Table 2 also shows that controlling for geography and gender tends to reduce the raw wage gaps somewhat, but leaves sizeable adjusted wage gaps.

A valid concern is that agricultural wages are depressed by an unusually high incidence of seasonal or part–time labor. Indeed, it is true that agricultural labor is more cyclical than other sectors: the number of workers and hours per worker both rise in the harvest months. However, in terms of wages, the seasonal effects remain relatively small. Using the Current Population Survey (CPS) for the U.S., we find that over the year agricultural wages differ by at most 5% from the average agricultural wage. This suggests that cyclical variation in the agricultural labor force does not account for much of the wage gaps.

In sum, we conclude that there are large raw wage gaps between the non–agricultural sectors and agriculture. This is the main stylized fact that we want to shed light on in this paper.

Stylized Fact 2: Sizeable Wage Gaps Adjusted with Aggregate Mincer Returns

A natural explanation for the raw wage gaps is sectoral differences in human capital. Indeed, as the row "Years of schooling" of Table 2 shows, the observable characteristics typically associated with human capital differ across sectors: on average, non–agricultural workers have more years of schooling than agricultural workers. The largest difference again turns out to be between skilled services and 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), who 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 return"). We apply this idea by estimating the aggregate Mincer returns for each of our

country–year pairs. Specifically, we run the following parsimonious regression:[8]

$$\log(w_{ij}) = \beta_j d_j + \beta_z Z_{ij} + \gamma s_{ij} + \varepsilon_{ij}$$

where s is total years of schooling (including college) and γ is the aggregate Mincer return. Table 2 shows the resulting human capital gaps and the wage gaps after adjusting for aggregate Mincer returns. We find that workers in non–agriculture have more human capital than workers in agriculture. However, the gap is not large enough to account for the entire raw wage gap, leaving sizeable adjusted wage gaps of up nearly a factor of 2.

One may be concerned about the fact that we have excluded self–employed individuals ("proprietors") from our analysis and focused exclusively on wage workers. Doing this is natural in our context because proprietors' income is not available for all countries of our sample and is more difficult to interpret than wage income because proprietors tend to under–report their incomes (Herrendorf and Schoellman, 2015). Moreover, the income that they do report includes compensation for their labor together with the capital and land in their businesses. One may still wonder what we would find if we ignored these issues and included proprietors' income, pretending it were all labor income. Re–conducting our analysis for the countries for which we have information about proprietors' income, we find that the raw wage gaps (for wage workers) are somewhat smaller than the raw income gaps (for wage workers and proprietors). This can be seen by comparing the second with the fourth columns of Table 3. This finding is attributable mostly to the fact that agricultural proprietors report somewhat lower incomes than agricultural wage workers. Turning now to the gaps adjusted for human capital, it turns out that the gaps in human capital are somewhat larger for proprietors than for wage workers.[9] Hence, the adjusted income gaps are only somewhat larger than the adjusted wage gaps. This can be seen by comparing the third and fifth columns of Table 3. Overall, none of the conclusions that we have reached so far changes when we take proprietors' income into account.[10]

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[8]In this estimation, we follow the common approach in the macro–development literature and do not control for experience. We will control for experience later when we estimate Mincer returns by sector. In the working–paper version, Herrendorf and Schoellman (2017), we take into account that the Mincer returns to schooling tend to be smaller than the Mincer returns to college; see Lemieux (2006) and Binelli (2015). Here, we abstract from this feature of the data because it does not affect our quantitative results much. Moreover, for the poor countries of our sample it is impossible to separately estimate the returns to college in agriculture with precision, because only very few college graduates work in agriculture.

[9]To be specific, the education gaps are similar, but the aggregate returns to human capital are somewhat larger when estimated for income cum wages than for wages only.

[10]Note that since we do not have information on the income of proprietors for all poor countries of our sample, the raw and adjusted median wage gaps tend to be smaller than those of Table 2.

Table 3: Median Gaps of Wages and Income in a Subsample of Countries (Income includes Wages and Proprietors' Income)

	Wage Gaps		Income Gaps	
	Raw	Adjusted	Raw	Adjusted
Non–agriculture	1.78	1.34	2.05	1.48
1. Industry	1.83	1.41	2.01	1.49
2. Services	1.87	1.33	2.03	1.43
2.1 Unskilled services	1.51	1.19	1.76	1.37
2.2 Skilled services	2.07	1.51	2.28	1.60

Stylized Fact 3: Differences in Sectoral Mincer Returns

The previous construction of human capital restricted the Mincer returns to be the same for all sectors of a country. Given that we have access to micro data about wages, we are in the unique position to go further and test this restriction. To do so, we run the following regression for each sector j and country–year pair:

$$\log(w_{ij}) = \beta_j d_j + \beta_x X_{ij} + \gamma_j s_{ij} + \varepsilon_{ij} \tag{1}$$

Note that the coefficient γ_j on years of schooling is now indexed by sector. Since this regression is in the spirit of what labor people would do, the controls X_{ij} include a quartic in experience in addition to state and gender where experience is measured as usual as potential experience (age minus years of schooling minus six years).

We find that the restriction of equal sectoral Mincer returns is rejected by the data. Figure 2 shows this by plotting the Mincer returns to schooling by sector and country depending on GDP per capita. Although there is some heterogeneity across countries, we can see that skilled services consistently offers a high return, while agriculture offers a low return. Since our samples come from censuses, they are large and so the slopes are precisely estimated, implying that the slope differences are statistically significant.

A useful way of visualizing that the slopes differ across sectors is to plot the estimated log–wage function implied by regression (1) after leaving out demographics, i.e.,

$$\widehat{\log(w_j(s))} = \widehat{\beta}_j + \widehat{\gamma}_j s$$

Note that again we have dropped the country–year index for notational convenience. Figure 3 plots the resulting wage schedules for Brazil and the U.S. The figures show two generic features of the wage schedules in our sample: the intercept of the agricultural wage schedule

may be either smaller or larger than the intercept of the other wage schedules; the slope of
the agricultural wage schedule is smaller than the slope of the other wage schedules.

Figure 2: Sectoral Mincer Returns to Schooling
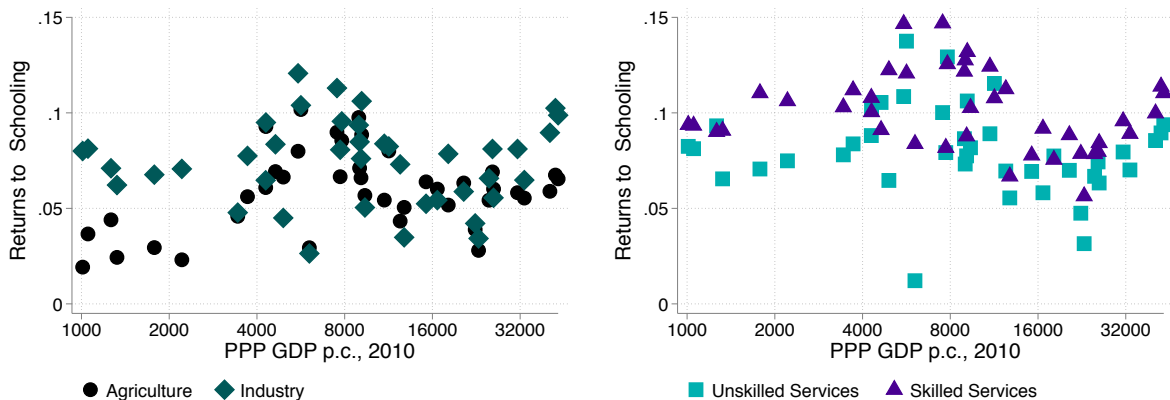
Figure 3: Sectoral Log Wages in Brazil and the U.S.
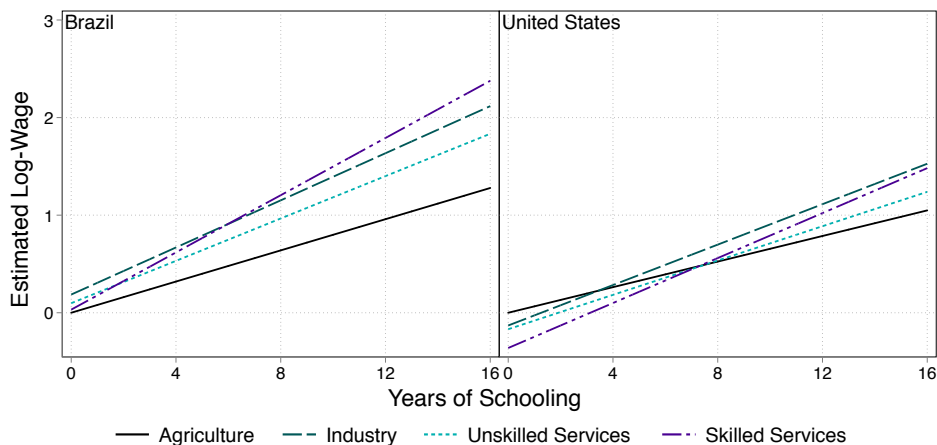
The finding that the slopes of the Mincer regressions differ across sectors suggests that
we will miss something when we estimate the barriers to structural transformation from
wage gaps that are adjusted with aggregate Mincer returns. To figure out what to do
instead, we need a model, which we develop in the next section.

4   Model

In this section, we develop a simple model that guides us how to estimate the unobserved barriers to structural transformation from the observed sectoral wage schedules when aggregate Mincer returns differ from sectoral Mincer returns. We demand that our model encompass as a special case the standard multi–sector model of barriers from the macro–development literature, see e.g. Restuccia et al. (2008). This special case is straightforward to analyze because it implicitly assumes workers have the same unobserved characteristics and that sectors have the same human–capital intensity. It then follows that aggregate and sectoral Mincer returns are equal and the barriers of moving are equal to the observed average wage gaps adjusted for human capital, which we calculated for Stylized Fact 2.

The logic from the special case does not work in general when aggregate and sectoral Mincer returns differ. The reason is that the wage gap averaged over all workers differs from the marginal wage gap of the worker who is indifferent between moving and not moving. To be able to analyze the general case, we combine the standard multi–sector model from the macro–development literature with a human–capital technology akin to those underlying Mincer regressions. There are two features that can generate differences in the observed Mincer returns across sectors: sectoral differences in innate ability and sectoral differences in human–capital intensity. The working–paper version of this paper, Herrendorf and Schoellman (2017), contains a general equilibrium version of the model and identifies conditions under which equilibrium exists. Here we focus on the partial equilibrium version of the labor market, which suffices for deriving expressions for barriers to labor mobility between agriculture and non–agricultural sectors.

4.1   Environment

There is one period and two sectors indexed by j. Sector $j = a$ is agriculture and sector $j = n$ is any non–agricultural sector from above.[11]

There is a continuum of measure one of workers. Each worker is endowed with one unit of time, an innate ability $x \in [0, \bar{x}]$ and a number of years of schooling $s \in [0, \bar{s}]$. For analytical convenience, we allow s to be a real number instead of an integer. The density function over workers' types is denoted by $m(x, s)$. Note that although $m(x, s)$ is exogenous in our model, nothing prevents it from capturing the notion that innate ability and years of schooling are positively correlated.

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[11] Having two sectors suffices for deriving expressions for barriers which is our purpose here. The working–paper version, Herrendorf and Schoellman (2017), contains a more general analysis with four sectors.

A worker with characteristics (x, s) has human capital

$$h(x, s) = \exp(xs) \tag{2}$$

This functional form generalizes the usual functional form $h(s) = \exp(s)$ from the human–capital literature. Like the usual functional form, the specification in (2) is log–linear and imposes the restriction that workers with zero years of schooling have human capital of 1. Different from the usual functional form, the specification in (2) features innate ability and assumes that innate ability and years of schooling complement each other in a multiplicative way.

Individuals value wage income but not leisure. Hence, they allocate their entire time endowment to working in the sector which pays them the higher wage. The two sectors produce different categories of value added according to

$$Y_j = \int h(x, s)^{\gamma_j} m_j(x, s) dx ds \tag{3}$$

where $\gamma_j \in (0, 1)$ is the human–capital intensity of sector j and $m_j(x, s)$ is the measure of type (x, s) in sector j.

There are moving costs ("barriers"): given an equilibrium allocation of workers to the two sectors, if a worker moves from sector i to j, then the wage in the destination sector is "taxed" at rate $\tau_j \in [0, 1)$. The tax revenue is thrown away.

4.2   Equilibrium definition

Denote by P_j the price per unit of value added in sector j and by $W_j(x, s)$ the wage of a worker of type (x, s) in sector j, both expressed in units of the same numeraire.

Definition. *A competitive equilibrium is*

$$\{P_j, W_j(x, s), m_j(x, s), \tau_j\}_{\{j \in \{a, n\}, (x, s) \in [0, \bar{x}] \times [0, \bar{s}]\}}$$

such that:

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- *Workers are paid their marginal value products in each sector:*[12]

$$W_j(x, s) = P_j h(x, s)^{\gamma_j} \tag{4}$$

- *If $m_j(x, s) > 0$, then in sector i worker (x, s) does not earn a higher wage net of moving costs:*

$$W_j(x, s) \geq (1 - \tau_i) W_i(x, s)$$

- *For each worker type (x, s) the labor market clears:*

$$m(x, s) = m_a(x, s) + m_n(x, s)$$

Before we explore what we can say about the equilibrium relationship between observed sectoral wages and barriers, it is useful to define for each sector j the total sectoral efficiency units of labor, the average sectoral ability, and the average sectoral wages for all workers and for workers with s years of schooling:

$$L_j \equiv \int h(x, s)^{\gamma_j} m_j(x, s) dx ds \tag{5}$$

$$X_j \equiv \frac{\int x m_j(x, s) dx ds}{\int m_j(x, s) dx ds} \tag{6}$$

$$W_j \equiv P_j L_j \tag{7}$$

$$W_j(s) \equiv P_j \frac{\int h(x, s)^{\gamma_j} m_j(x, s) dx}{\int m_j(x, s) dx} \tag{8}$$

It is also useful to note that the functional form (2) implies that workers with zero years of schooling earn the wage $W_j(0) = P_j$. Using this, we can write the wages of the other workers of sector j as:

$$W_j(x, s) = W_j(0) h(x, s)^{\gamma_j} = W_j(0) \exp(\gamma_j x s) \tag{9}$$

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[12]The marginal product of worker type (x, s) in sector j follows by taking the derivative of the sectoral production function (3) with respect to $m_j(x, s)$.

A robust feature of our data is that each sector has workers of a given year of schooling $s \in [0, \bar{s}]$. In what follows, we will consider only equilibria in which that is the case. We will first analyze the case where differences in sectoral Mincer returns result from different sectoral innate ability ("selection view"). We will then analyze the case where differences in sectoral Mincer returns result from different sectoral technology ("technology view"). In both cases, we study equilibria that are consistent with the generic features of the wage schedules that are highlighted in Figure 3, that is, the intercepts of the wage schedule are either smaller or larger in agriculture than in the other sectors while the slope is smaller in agriculture. We will focus on barriers of moving from agriculture to the non–agricultural sector. While there may also be barriers in the opposite direction, or between two non–agricultural sectors, these are not the focus of the macro–development literature.

4.3 Selection view: $\gamma_a = \gamma_n$

We start characterizing the equilibrium properties of our model for the selection view under which differences in observed sectoral Mincer returns are due to differences in the unobserved sectoral abilities and there are no differences in the sectoral technologies, $\gamma_a = \gamma_n$. We focus on the case in which the wages for workers with zero years of schooling are at least as large in the non–agricultural sector as in agriculture, $W_n(0) > W_a(0)$. Otherwise, no worker wants to move from agriculture to non–agriculture anyways and barriers for moving between agriculture and non–agriculture are zero.

We begin by noting that (7) and (8) immediately imply that:

$$\frac{W_n/L_n}{W_a/L_a} = \frac{W_n(0)}{W_a(0)}$$

On the left–hand side is the adjusted average wage gaps after taking into account differences in sectoral labor.[13] On the right–hand side is the wage gap of workers with zero years of schooling. Given that $W_n(0) > W_a(0)$, keeping workers with zero schooling in agriculture requires barriers such that $(1 - \tau_n)W_n(0)/W_a(0) \leq 1$. Since the sectoral human–capital intensities are the same, barriers that keep workers with zero schooling in agriculture also keep all other workers in agriculture: $(1 - \tau_n)W_n(0)h(x, s)^\gamma \leq W_a(0)h(x, s)^\gamma$. Hence, we have calculated barriers that are consistent with equilibrium under the selection view.

The equilibrium size of barriers is indeterminate in our model, because if an equilibrium with barriers exists, then the same equilibrium allocation is part of another equilibrium

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[13]Note that in general L_j is not the human capital of sector j, as it depends not only on the human capital of the workers in sector j but also on sector j's human–capital intensity.

with larger values of barriers. While all these equilibria have the same allocation of workers between the two sectors, only the equilibrium with the smallest values of barriers will have workers in agriculture that are indifferent between the two sectors. In all other equilibria, all workers in agriculture strictly prefer to be there. This distinction is critical, because a robust feature of the panel data, which we will turn to in the next section, is that some workers move between the sectors. Since we want our model to be consistent with this feature of the data, we will focus on the equilibrium that has the smallest possible barriers and has workers who are indifferent between the two sectors.

Result 1 (Barriers under Selection View)
Suppose that $\gamma_n = \gamma_a$. Then the smallest barriers that keep workers of all years of schooling in agriculture are given by:

$$\frac{1}{1-\tau_n} = \max\left\{1, \frac{W_n/L_n}{W_a/L_a}\right\} = \max\left\{1, \frac{W_n(0)}{W_a(0)}\right\} \tag{10}$$

To bring expression (10) to the data, we first need to check whether $W_a(0) > W_n(0)$ or $W_n(0) > W_a(0)$. In the former case, we are done because no worker wants to move from agriculture to other sectors and $1/(1-\tau_n) = 1$. In the latter case, workers want to move from agriculture to other sectors.

To find the required minimum barriers that prevent them from moving in practice, take logs of equation (4) to obtain:

$$\log(w_j(x,s)) = \log(W_j(0)) + \gamma x s$$

We can then run a Mincer regression of the observed log wages on the left–hand side on the observed years of schooling on the right–hand side. The results of the Mincer regression can be used in two ways to calculate τ_n: we can use the estimated Mincer returns or we can use the estimated intercepts. In particular, for $\gamma \equiv \gamma_n = \gamma_a$ we have:

$$L_j = \int \exp(\gamma x s) m_j(x,s) dx ds$$

If all workers have the same ability $x = 1$, then the Mincer regression yields an estimates of γ. Given a value for γ, it is straightforward to calculate L_j from this expression. This is in the spirit of what Gollin et al. (2014) did; they calculated sectoral human capital by combining an off–the–shelf aggregate Mincer return γ from the literature with information on years schooling from living–standards surveys. This way of proceeding imposes the

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restriction that the Mincer returns are the same across sectors. As we have shown in the previous section, this restriction is rejected by the data. If x differs across workers while $\gamma_n = \gamma_a$, then the estimated Mincer returns $M_j = \gamma X_j$ differ across sectors when the average sectoral innate abilities X_j differ. We then have a crude approximation to L_j:

$$L_j \approx \int \exp(M_j s) m_j(x, s) dx ds$$

Since W_j is observable, one could use this approximation to calculate $(W_n/L_n)/W_a/L_a)$ and estimate barriers. In fact, this is what we used to do in the working–paper version of this paper, Herrendorf and Schoellman (2017). In the current version of the paper, we instead use the information about the intercept gap $W_n(0)/W_a(0)$. This way of proceeding is more direct and does not require an approximation.

The reason why there are two ways of estimating barriers when $\gamma_a = \gamma_n$ is that all workers are marginal, in that they all gain the same percentage wage increase by moving from sector a to n. Average and marginal wage gains are then the same and either one can be used to calculate barriers. One important implication of this observation is that the equilibrium of Result 1 is consistent with the fact that workers of all years of schooling move between the two sectors. In contrast, equilibria in which the marginal and the average wage gains are not equal are only consistent with moves of the marginal worker.

4.4   Technology View: $\gamma_a \neq \gamma_n$

Under the technology view, the two sectoral technologies have different human–capital intensities, $\gamma_a \neq \gamma_n$. In this case, the wage gain of moving sectors is no longer the same for the marginal and the average worker. In what follows, we will only consider the empirically relevant case $\gamma_a < \gamma_n$. The gains from moving from sector a to n then increase with the worker's innate ability and years of schooling, irrespective of how the intercepts line up. Consequently, workers with the highest ability and the highest years of schooling, i.e., type $(\bar{x}, \bar{s})$, have the most to gain from moving out of agriculture. Unfortunately, we do not know whether these workers work in both sectors. Instead, all we know is that workers with the highest years of schooling are in both sectors. An additional complication arises because for workers who have $\bar{s}$ years of schooling, we only observe the average wages (8) by sector over the unknown sectoral ability distribution. In general, this distribution will differ between sectors.

In the next section, we will turn to additional evidence from three panel data sets that report wages for workers who move sector, which allows for controlling for unobserved

ability. For now, we see how far we can go without that information. To obtain sharp results, we restrict attention to the special case in which all workers have the same ability normalized to one, $x = 1$. A similar intuition as in the example of the last paragraph then applies. Irrespective of the intercepts, workers with maximum years of schooling, $s = \bar{s}$, are the marginal workers who have most to gain from moving from agriculture to non–agriculture. If $W_a(\bar{s}) > W_n(\bar{s})$, then no worker wants to move and no barriers are required. In contrast, if $W_n(\bar{s}) > W_a(\bar{s})$, then barriers that prevent the workers with the highest years of schooling from moving prevent all workers from moving. To see this, choose the smallest barriers that prevent workers with $\bar{s}$ years of schooling from moving:

$$\frac{(1 - \tau_n)W_n(\bar{s})}{W_a(\bar{s})} = 1 \tag{11}$$

The claim follows because $\gamma_a < \gamma_n$ implies that for all $s \in [0, \bar{s}]$,

$$\frac{(1 - \tau_n)W_n(0)\exp(\gamma_n s)}{W_a(0)\exp(\gamma_a s)} < \frac{(1 - \tau_n)W_n(0)\exp(\gamma_n \bar{s})}{W_a(0)\exp(\gamma_a \bar{s})} = 1 \tag{12}$$

Hence, we have shown the following result:

Result 2 (Barriers under Technology View: $\gamma_a < \gamma_n$)
Suppose that $\gamma_a < \gamma_n$ and $x = 1$ and that the equilibrium is such that workers with all years of schooling are in both sectors. Then the smallest barriers that are consistent with equilibrium are:

$$\frac{1}{1 - \tau_n} = \max\left\{1, \frac{W_n(\bar{s})}{W_a(\bar{s})}\right\} \tag{13}$$

In the general case where $x \neq 1$ and $\gamma_a \neq \gamma_n$, it is impossible to calculate barriers unless we have panel data that allows us to restrict the possible selection patterns. The reason for this is that in the presence of barriers the differences in human–capital intensities can lead to very different selection patterns. For example, as sector n offers higher returns to innate ability, a natural selection pattern is that sector n attracts workers with higher innate ability. Nonetheless, sufficiently large barriers can also support the opposite selection pattern in equilibrium. All we can say here is that there are selection patterns such that part of the difference in the observed $W_j(\bar{s})$ comes from the fact that higher ability workers work in the sector with the higher human–capital intensity. This kind of selection implies that the smallest value of barriers consistent with equilibrium is strictly smaller than the

value in (13), if of course that value is larger than one.[14]

5   Evidence on Barriers

In this section, we will present evidence from workers who switched sector in the U.S., Brazil, and Indonesia. In our context, the key advantage of having panel data is that one can estimate the wage gains of switchers while controlling for selection according to unobserved human capital. That is not possible in cross sections which do not track workers. For the three countries, we will also compare the barriers implied by the evidence from switchers with the barriers implied by Results 1–2 above. We will conclude with a decomposition of raw wage gaps for the entire sample of countries that is in the development–accounting tradition.

5.1   Evidence from switchers in the U.S.

This subsection studies the wage changes of U.S. switchers in the Panel Survey of Income Dynamics (PSID). The PSID is a true panel survey that follows workers over many years irrespective of whether they move residence. The PSID has high re–contact rates of between 95 and 98% and its response rate is high even among respondents that require tracking because they moved; see Schoeni et al. (2013) for further discussion. Notwithstanding this advantage, the PSID has two limitations: its sample size for agriculture is relatively small and it is designed as a survey of heads of households that collects only limited information about other members of the household.[15]

We estimate the wage changes of switchers in the PSID during the period 1968–1997 for the subsample of male heads of household who worked for wages, were less than 70 years old, and had 0–50 years of potential experience in each period.[16] We exclude workers who report switching industries but not occupations in order to minimize the chances of analyzing miscoded switches. After doing this, we are left with a sample of 64,677 workers

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[14]The working–paper version, Herrendorf and Schoellman (2017), analyzes the following selection pattern: there is a threshold $\chi \in (0, \bar{x}\bar{s})$ such that workers with $x_a s_a < \chi$ are in sector a and workers with $x_n s_n > \chi$ are in sector n. It shows that this selection pattern can arises in the equilibrium of our model when the observed wage schedules intersect. This selection pattern implies that the smallest value of barriers consistent with equilibrium is strictly smaller than the value in (13).

[15]The Current Population Survey (CPS) is not suitable as an alternative for studying switchers because it samples dwellings based on their addresses and surveys whoever lives in that dwelling. As a result, it loses the workers who move dwellings when they switch sector, which potentially have most to gain from switching.

[16]In 1997, the PSID changed to biannual data collection, making it more difficult to analyze switchers.

Table 4: Wage Changes of Switchers from Agriculture in the PSID

Destination sector	Adjusted Wage Gaps	Wage Changes Switchers	Number PSID Observations
Non–agriculture	1.76	1.06	293
1. Industry	1.83	1.01	153
2. Services	1.72	1.14	140
2.1 Unskilled services	1.67	1.11	72
2.2 Skilled services	1.81	1.17	68

that are matched across one–year periods, including 5,602 who switch sectors at a four–sector level. Our goal is to estimate the wage gap for worker i who is in sector a in period $t-1$ and sector n in period t:

$$\Delta \log(w_{iant}) \equiv \log(w_{int}) - \log(w_{iat-1})$$

We regress the log–wage change on a dummy for the sector pair d_{an} and a year dummy d_t:

$$\Delta \log(w_{iant}) = \beta_{an} d_{an} + \beta_t d_t + \varepsilon_{iant}$$

This regression captures the mean effect of switching to sector n versus staying in sector a, while controlling for trend wage growth though the year dummy d_t.

Table 4 reports the results: workers who leave agriculture have positive yet small wage gains. The first line of Table 5 puts the wage gains of U.S. switchers from agriculture to non–agriculture into perspective by comparing them to the values of barriers according to the selection view and technology view. It shows that the wage gains of U.S. switchers are close to the model–implied barriers under the selection view and far away from the model–implied barriers under the technology view. Moreover, the model–implied barriers under the technology view are larger than the wage gaps adjusted with aggregate Mincer returns, which seems implausible. The U.S. finding suggest that the selection view explains most of the observed differences in the sectoral wage schedules and Result 1 is the empirically relevant one.

5.2   Evidence from switchers in other countries

We continue with evidence from three papers that studied switchers from agriculture to non–agriculture in panel data sets from other countries in our sample. All three papers share

Table 5: Barriers to Moving to Non–agriculture in Three Specific Countries

| | Wage Gaps | | Model–implied Barriers | | Wage Gains of |
	Raw	Adjusted	Selection View	Technology View	Switchers
U.S. 1990	1.48	1.31	1.00	1.32	1.06 (own estimate)
Brazil 2000	2.29	1.28	1.06	2.00	1.01–1.12 (Alvarez)
Indonesia 1995	1.81	1.12	1.00	1.73	1.05 (Hicks etal)

Adjusted wage gaps are adjusted for gender, geography, and human capital constructed with aggregate
Mincer returns.

our finding that the estimated gains are relatively small compared to the adjusted wage gaps and the implied barriers are close to the model–implied barriers under the selection view.

Alvarez (2017) studied formal workers in Brazil during 1996–2013. He found that switchers have average gains in hourly wages of $1.01 - 1.11$, depending on the subperiod and whether they switch to industry or services. Table 5 shows that these wage gains are close to the model–implied barriers under the selection view and far away from the model–implied barriers under the technology view. Hicks et al. (2017) used panel data from Indonesia 1993–2008 and found that switchers gained just 1.05 in wages per hour. Table 5 shows that again these wage gains are close to the model–implied barriers under the selection view and far away from the model–implied barriers under the technology view. Note that in both cases, the model–implied barriers under the technology view are now much larger than the wage gaps adjusted with aggregate Mincer returns. Swiecki (2017) also used panel data from Indonesia. The main difference from the previous paper is that he considered a longer period 1993–2014 and focused on changes in income instead of wages. He found that the income gain from switching from agriculture to non–agriculture is somewhat larger than the wage gain of the previous study, but is still relatively small compared to the raw wage gaps. Hicks et al. (2017) also provided evidence from Kenya during 2003–2014. Although that country is not in our sample, additional evidence from an African country is very valuable. Again, they found relatively small wage gains from switching from agriculture to non–agriculture.[17]

In sum, the results on the gains from switchers between agriculture and non–agricultural sectors in the U.S., Brazil, and Indonesia imply values of barriers to the structural transformation that are small and close to the model–implied values under the selection view. These findings provide evidence in factor of the selection view. An additional argument

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[17]Beegle et al. (2011) offered panel evidence for Tanzania during 1991–2004, but focused on consumption changes which are not immediately comparable with our results on wage changes.

in favor of the selection view is that it is consistent with the fact that all panel studies find that workers with different years of schooling move sectors. According to the model of the previous section, this is not consistent with the technology view, which implies that only workers with the highest years of schooling are indifferent and move between the two sectors.[18]

5.3 Decomposition of raw wage gaps

We conclude our analysis with a decomposition of the raw wage gaps into gaps of efficiency units and barriers. This exercise is in the spirit of development accounting that imposes that all countries use the same sectoral technologies.[19] Given that the U.S., Brazil, and Indonesia are reasonably approximated by the selection, imposing in our context that all countries use the same sectoral technology implies that $\gamma_a = \gamma_n$ everywhere. Result 1 from above implies that we can then calculate barriers as

$$\frac{1}{1-\tau_n} = \max\left\{1, \frac{W_n(0)}{W_a(0)}\right\}$$

Table 6: Model–implied Barriers according to the Selection View

10th Pctl.	Med.	90th Pctl.
1.00	1.11	1.45

Table 6 reports the barriers implied by the selection view. The Table shows that the implied barriers are relatively small and are considerably smaller than what the macro development literature typically finds; see for example Restuccia et al. (2008). For most countries, barriers are consistent with benign explanations such as difference in the cost of living between rural and urban areas or differences in the prevalence of the shadow economy in rural and urban areas. We pointed out in the introduction that the Chinese hukou system and the Indian caste system are well established examples for barriers of moving freely between locations or sectors. While we do not have data for China, our sample of countries does contain several observations from India. A natural year to consider is the first year for

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[18]Of course, we could add shocks to the above model and get more types of workers to move under the technology view. However, we would still have the conclusion that under the selection view similar numbers of workers with any year of schooling move whereas under the technology view workers with the highest years of schooling move the most. The latter is not borne out by the PSID data.

[19]See Hall and Jones (1999), Hendricks (2002), and Schoellman (2012) for development accounting exercises at the aggregate level and Herrendorf and Valentinyi (2012) for a development accounting exercise at the sectoral level.

which we have data for India, which is 1983. The reason why this is natural is that since India grown it was poorest in 1983. It turns out that the model–implied barriers under the selection view equal 1.38 for India in 1983. That is a sizeable barrier, which is close to the barriers at the 90th percentile of our sample. A barrier of this size is consistent with the view that the caste system considerably reduced mobility in India. Notwithstanding this example of sizeable barriers, overall our results suggest that barriers alone will not be able to explain why the raw wage gaps between non–agriculture and agriculture are so large.

6   Conclusion

We have documented for 13 countries ranging from rich (Canada, U.S.) to poor (India, Indonesia) that average wages are considerably lower in agriculture than in the other sectors and that agriculture has less educated workers and lower Mincer returns. We have viewed these stylized facts through the lens of a multisector model in which workers differ in observed and unobserved characteristics and sectors differ in their human–capital intensity. Our model encompasses the two obvious reasons why Mincer returns are lower in agriculture: agricultural workers have lower innate ability ("selection view"); agriculture is less human–capital intensive ("technology view"). We have presented evidence from workers who leave agriculture in the U.S. suggesting that the implied barriers are close to those under the selection view. We have referred to additional evidence from Alvarez (2017) and Hicks et al. (2017) suggesting that the same conclusion holds for Brazil and Indonesia. We have calculated the barriers under the selection view for all 13 countries of our sample and found that they are considerably smaller than what the macro–development literature typically argues.

Our findings imply that productivity gaps between non–agriculture and agriculture, which are typically larger than wage gaps, do not manifest themselves in large barriers to mobility 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 distortions to the land market; see Adamopoulos 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, 2015). This may imply that actual productivity in agriculture is higher than measured productivity gaps and actual productivity gaps are more in line with wage gaps.

References

Adamopoulos, Tasso and Diego Restuccia, "The Size Distribution of Farms and International Productivity Differences," *American Economic Review*, 2014, *104* (6), 1667–97.

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

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

Beegle, Kathleen, Joachim De Weerdt, and Stefan Dercon, "Migration and economic mobility in Tanzania: Evidence from a tracking survey," *Review of Economics and Statistics*, 2011, *93* (3), 1010–1033.

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

Binelli, Chiara, "How the Wage-Education Profile Got More Convex: Evidence from Mexico," *The B.E. Journal of Macroeconomics*, 2015, *15* (2), 509–560.

Boppart, Timo, "Structural Change and the Kaldor Facts in a Growth Model with Relative Price Effects and Non–Gorman Preferences," *Econometrica*, 2016, pp. 2167–2196.

Buera, Francisco J. and Joseph P. Kaboski, "The Rise of the Service Economy," *American Economic Review*, 2012, *102*, 2540–2569.

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

_ **and Wilbur John Coleman**, "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation," *Journal of Political Economy*, 2001, *109*, 584–616.

Duarte, Margarida and Diego Restuccia, "Relative Prices and Sectoral Productivity," Manuscript, University of Toronto 2016.

Duernecker, Georg, Berthold Herrendorf, and Ákos Valentinyi, "Unbalanced Growth Slowdown," Manuscript, University of Mannheim, Arizona State University, and Cardiff Business School 2016.

Echevarria, Cristina, "Changes in Sectoral Composition Associated with Economic Growth," *International Economic Review*, 1997, *38*, 431–452.

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

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

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

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

_ **and Todd Schoellman**, "Why is Measured Labor Productivity so Low in Agriculture?," *Review of Economic Dynamics*, 2015, *18*, 1003–1022.

_ **and** _ , "Wages, Human Capital, and Structural Transformation," Working Paper 6426, CESifo 2017.

_ , **Christopher Herrington, and Ákos Valentinyi**, "Sectoral Technology and Structural Transformation," *American Economic Journal – Macroeconomics*, 2015, *7*, 1–31.

_ , **Richard Rogerson, and Ákos Valentinyi**, "Two Perspectives on Preferences and Structural Transformation," *American Economic Review*, 2013, *103*, 2752–2789.

_ , _ , **and** _ , "Growth and Structural Transformation," in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 2, Elsevier, 2014, pp. 855–941.

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

Hnatkovska, Viktoria and Amartya Lahiri, "Structural Transformation and the Rural–Urban Divide," Manuscript, University of British Columbia 2013.

Jorgenson, Dale W. and Marcel P. Timmer, "Structural Change in Advanced Nations: A New Set of Stylised Facts," *Scandinavian Journal of Economics*, 2011, *113*, 1–29.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie, "Beyond Balanced Growth," *Review of Economic Studies*, 2001, *68*, 869–882.

Lagakos, David and Mike Waugh, "Selection, Agriculture, and Cross–Country Productivity Differences," *American Economic Review*, 2013, *103*, 948–980.

Lemieux, Thomas, "The Mincer Equation Thirty Years After *Schooling, Experience, and Earnings*," in S. Grossbard, ed., *Jacob Mincer, A Pioneer of Modern Labor Economics*, Springer Verlag, 2006, pp. 127–145.

McMillan, Margaret and Dani Rodrik, "Globalization, Structural Change, and Economic Growth," in Marc Bachetta and Marion Jansen, eds., *Making Globalization Socially Sustainable*, Geneva: International Labor Organization and World Trade Organization, 2011, pp. 49–84.

Minnesota Population Center, "Integrated Public Use Microdata Series — International: Version 6.3 [Machine-readable database].," Minneapolis: University of Minnesota. 2014. http://www.ipums.org.

_ , "Integrated Public Use Microdata Series, International: Version 6.4," Machine–Readable Database, Minneapolis: University of Minnesota 2015.

Ngai, L. Rachel and Christopher A. Pissarides, "Structural Change in a Multisector Model of Growth," *American Economic Review*, 2007, *97*, 429–443.

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

Rogerson, Richard, "Structural Transformation and the Deterioration of European Labor Market Outcomes," *Journal of Political Economy*, 2008, *116*, 235–259.

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

Schoeni, Robert F., Frank Stafford, Katherine A. McGonagle, and Patricia Andreski, "Response Rates in National Panel Surveys," *The ANNALS of the American Academy of Political and Social Science*, 2013, *645*, 60–87.

Swiecki, Tomasz, "Mobility Costs or Sorting? Sources and Aggregate Implications of Income Gaps across Sectors and Locations in Indonesia," 2017. Manuscript, University of British Columbia.

Vollrath, Dietrich, "How Important are Dual Economy Effects for Aggregate Productivity?," *Journal of Development Economics*, 2009, *88*, 325–334.

Young, Alwyn, "Inequality, the Urban–Rural Gap, and Migration," *Quarterly Journal of Economics*, 2013, *128*, 1727–1785.

 ̲ , "Structural Transformation, the Mismeasurement of Productivity Growth, and the Cost Disease of Services," *American Economic Review*, 2014, *122*.