Returns to Experience and the Sectoral Allocation of Labor

Asif Islam, Remi Jedwab, Paul Romer, and Daniel Pereira *

October 1, 2019

Abstract

Work experience is a major component of human capital accumulation. Measuring how returns to experience vary across sectors and locations within and across countries is thus particularly important to understand economic growth. In this paper, we: (i) Study wage-experience profiles and obtain measures of returns to experience across various dimensions using data from 23 million individuals in more than 1,000 household surveys for 145 countries; (ii) Document that returns to experience vary across dimensions in both developing and developed countries, which suggests misallocation of labor: non-agricultural sectors, cognitive occupations, the formal sector, and urban areas exhibit higher returns than agriculture, manual occupations, the informal sector, and rural areas, respectively; (iii) Show that despite these gaps, reallocating labor to the best sector/location in the country might do little to bridge the gap in aggregate returns between developed and developing countries. Indeed, returns are significantly higher in richer countries, particularly so for manual occupations; and (iv) Through cross-country regressions show that a range of economic institutions, social institutions and values have served workers better in developed economies than developing economies in acquiring human capital at work plausibly by both reducing frictions and facilitating skill acquisition. Overall, this research encourages policies to focus on raising the returns to experience and labor mobility across various dimensions.

JEL: O11; O14; O18; R11; R12; J21; J24

Keywords: Returns to Experience; Income Gap; Labor Misallocation; Structural Change; Occupational Change; Formalization; Urbanization; Cities; Labor Mobility

---

*Corresponding author: Paul Romer: NYU Stern, paul@paulromer.net. Asif Islam: The World Bank, aislam@worldbank.org. Remi Jedwab: George Washington University, jedwab@gwu.edu. Daniel Pereira: George Washington University, pereirad@gwmail.gwu.edu. This paper served as a basis for the 5th chapter of the 2019 World Development Report on "The Changing Nature of Work". We gratefully thank Jan Brueckner, Barry Chiswick, Pierre-Philippe Combes, Gabriel Demombynes, Jonathan Dingel, Simeon Djankov, Gills Duranton, Edward Glaeser, Aaart Kray, Gabriel Kreindler, David Lagakos, Mushfiq Mobarak, Nancy Qian, Tommaso Porzio, Diego Puga, Stuart Rosenthal, Federica Saliola, Harris Selod, and Todd Schoellman for helpful comments. We also thank seminar audiences at George Washington, Harvard-Johns Hopkins Cities & Development Workshop, Pacifico (Lima), Syracuse, UC-Irvine, UC-San Diego, the UEA (Columbia), William & Mary and the World Bank for useful feedback. We are grateful to Claudio Montenegro, Minh Nguyen, and David Newhouse for helping us with using the I2D2 database. We gratefully acknowledge the generous support of the World Bank (Office of the Senior Vice-President and Chief Economist) and the Cities Program of the International Growth Center (Grant no. 89408).

Work experience is a major component of human capital (Lagakos et al., 2018a; World Bank, 2018b; Islam et al., 2019a). The average human in the world spends 10 years studying but works for up to 50 years. Thus, despite returns to experience being on average four times lower than returns to education, the contribution of experience to human capital accumulation is plausibly as large as the contribution of education itself (Islam et al., 2019a). A fairly consistent pattern observed is that returns to experience are significantly higher in developed countries than in developing countries, which has implications for cross-country divergence (Lagakos et al., 2018a; Islam et al., 2019a). To what extent such differences are driven by the distinct economic structure of developed and developing economies? The answers to this question can provide key insights for development. For example, if experience in urban areas generates more human capital than experience in rural areas, developed countries may show higher returns simply because they are more urbanized. As a result, policies aimed at removing constraints on urbanization may raise returns to experience and human capital in developing countries. Therefore, measuring how such returns vary across sectors and locations within and across countries is particularly important to understand economic growth.

Significant differences in productivity, wages, or assets have been disproportionately observed for developing countries across sectors (e.g., Gollin et al., 2014), between larger and smaller firms (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009) and between urban and rural areas (e.g., Gollin et al., 2014, 2017). While some studies question whether such gaps reflect sorting of better able workers across sectors or locations (e.g., Young, 2013; Hicks et al., 2017), overall the literature has argued that poorer economies are ineffective in allocating resources to their most productive use (e.g., Restuccia and Rogerson, 2017). While these differences are often interpreted as static wage gains – e.g., the immediate effect of moving to a new location –, Roca and Puga (2017) have shown using Spanish data that such differences also reflect dynamic wage gains – e.g., the effects of experience accumulated in a specific location. However, little is known about how dynamic wage gains may vary across countries.

This study explores how returns to experience vary across sectors, occupational types, formal statuses, and locations, within and across countries and assess whether reallocating workers could have measurable effects on aggregate returns to experience in developing countries. The analysis consists of the following steps.

First, we use the *International Income Distribution Database* (I2D2) of the World Bank to obtain wage-experience profiles and returns to experience for many countries and dimensions. Our sample includes 23 million individuals in 1,084 household surveys and census samples for 145 countries comprising 95% of the world's population.

Second, we document that returns to experience significantly vary across dimensions: non-agricultural sectors, cognitive occupations, the formal sector, and urban areas exhibit higher returns than agriculture, manual occupations, the informal sector, and rural areas, respectively. The gaps in the returns across dimensions are larger in developing countries than in developed countries, which could suggest misallocation of labor. However, despite these gaps, reallocating labor from the "worst" sector/location to the "best" sector/location in the country might do little to bridge the gap in aggregate returns between developed and developing countries. Indeed, returns are significantly higher in richer countries. In developing countries, wages increase by 1.2-1.5% and 1.8-2.1% for each extra year of experience in the "worst" and "best" sector/location, respectively. In contrast, in developed countries wages increase by 2.7-3.3% and 3.5-3.6% in the "worst" and "best" sector/location, respectively. Pushing this further, the "best" sector/location in developing countries still exhibits lower returns than the "worst" sector/location in developed countries (2.1% vs. 2.7%).

Third, we examine how robust these effects are by attempting to account for cohort, sorting and selection effects. As is well-documented in the literature, the collinearity between experience, time, and cohort effects precludes the inclusion of year of birth fixed effects in estimating returns to experience. We thus use two simple methods inspired by Heckman and Robb (1985). Given the size of our database, we can afford to include decade-of-birth fixed effects and/or cohort fixed effects tailored to match the historical political, economic and/or social circumstances faced by the different cohorts of the 145 countries. Furthermore, the advantage of focusing on returns to experience over studying static wage gains is that we can include sector-location fixed effects, thus comparing the wages of more experienced individuals with less experienced individuals *in the same sector-location*. As such, we capture the most important aspect of sorting. Our results also hold when including subsector, occupation and/or sublocation fixed effects, as in Roca and Puga (2017). We then deal with selection effects in various ways, e.g. we restrict our analysis to samples with low unemployment or very high labor force participation rates. Moreover, results hold if we: (i) consider wages instead of earnings; (ii) interact sectors, occupational types, formal statuses and/or locations; (iii) study subsectors and occupations; (iv) allow for complementarities between experience and education; and (v) account for measurement error in earnings or experience.

Fourth, if economic structure does not account for differences in aggregate returns between developed and developing countries, country-wide characteristics must be the main drivers of aggregate returns. Interestingly, the developed-developing gaps are the largest for manual occupations, suggesting that the characteristics of developed countries allow its less economically integrated workers to disproportionately gain from work experience. As explained by Lagakos et al. (2018a), there are two main explanations as to why experienced workers may receive relatively higher wages in developed countries. Workers in richer countries may accumulate more human capital over the life cycle than workers in poorer countries. Alternatively, labor market frictions in poor countries could prevent its workers from moving up the ladder to better jobs that fit their skills profile. Similar to Lagakos et al. (2018a), we are not able to distinguish the two mechanisms in our data. However, having estimates of the aggregate returns for 145 countries, we show that they correlate with measures of institutional quality, labor market flexibility and technological advancement, as well as values that may help reduce social frictions. These results hold if we control for income, suggesting that economic development, and economic capacity in particular, is not the only determinant of the returns. No matter their income level, countries may be able to implement policies promoting human capital accumulation at work and labor mobility.

This study makes significant contributions to the literature on returns to experience by estimating experience-wage profiles across many countries in several dimensions. Studies on wage dynamics have historical roots in the profession, going back to the early studies that explored returns to education and experience (Mincer, 1974). There are also more recent extensions (e.g., Heckman et al., 2006a; Polachek, 2008b). Most studies on how Mincer returns vary across sectors, occupations or locations for the world have mainly focused on the returns to education (Psacharopoulos and Patrinos, 2018a). To our knowledge, far fewer studies have studied returns to experience for the world. We build on the analysis of Lagakos et al. (2018a)—who estimate experience-wage profiles for 125 samples in 18 countries also using individual-level data— and expand it for

1,084 samples in 145 countries across various dimensions and development levels.[1] We also build on their paper by using different methods to deal with cohort effects. Our research question also forces us to deal with sorting effects. In a related paper, Islam et al. (2019a) use the same data to investigate the consequences for human capital accumulation and long-run growth of differences in aggregate returns to experience across countries. However, they do not examine the factors behind the higher returns to experience observed in developed economies, thus abstracting from the respective roles of economic structure and sector- or location-specific returns. In contrast, previous studies use far fewer samples, for possibly highly selected countries, and have not found that returns to experience differ by income level (e.g., Psacharopoulos, 1994; Bils and Klenow, 2000; King et al., 2012a). They also do not account for cohort, sorting and selection effects.[2]

Substantial urban wage premia have then been documented (Glaeser et al., 1992; Henderson et al., 1995; Duranton and Puga, 2004; Rosenthal and Strange, 2004a; Glaeser and Gottlieb, 2009; Puga, 2010; Combes et al., 2012c; Combes and Gobillon, 2015), especially in developing countries (Au and Henderson, 2006; Duranton, 2016; Chauvin et al., 2017; Combes et al., 2017; Quintero and Roberts, 2018). Much debate has emerged on whether this wage premium is attributable to the sorting of better-able workers to cities (Berry and Glaeser, 2005; Combes et al., 2008, 2012a; Eeckhout et al., 2014; Puga, 2017; Bilal and Rossi-Hansberg, 2018; Bosquet and Overman, 2019). Further debate exists on whether this wage premium is static or dynamic. As such, our paper is closely related to Roca and Puga (2017) who find using Spanish data that the dynamic premium is as large as the static premium. Other studies finding significant dynamic urban wage premium include Baum-Snow and Pavan (2012a) and D'Costa and Overman (2014). While we also examine static wage premia, it is not the main focus of this study, given the inherent difficulties in accounting for sorting. We find that developing countries have significantly larger urban-rural wage gaps than developed countries. However, this difference disappears when we allow for work experience to have differential effects

[1] Lagakos et al. (2018a) also use an expanded set of 263 samples in 35 countries for robustness checks. They are able to study wage-experience profiles separately for cognitive and manual occupations for 8 countries only. However, they do not necessarily find higher gaps between manual and cognitive occupations in developing countries (see their Fig. 10).

[2] Other studies of the returns to experience focus on one country or a few countries at a time.

across locations and countries.[3] Finally, most studies focus on one country or a few countries at a time – e.g., Chauvin et al. (2017) and Quintero and Roberts (2018) study 4 and 16 countries, respectively – whereas we estimate dynamic urban wage premia for as many as 132 countries and then examine how it varies with economic development. In particular, while it has been argued that developing countries might have stronger agglomeration economies than developed countries (e.g., Combes and Gobillon, 2015, p.312), we find lower returns to experience in the urban areas of developing countries (2.1%) than in both the urban *and* rural areas of developed countries (3.6% and 3.3%, respectively). These findings are a significant advancement in the literature as most studies of agglomeration economies focus on static wage gains in somewhat more successful developing economies (e.g., Brazil, China and India). However, as can be seen in Figure 1, our analysis includes 103 developing economies, including many low-income countries that often not analyzed due to lack of wage data.

Finally, the paper uncovers findings that are relevant for the misallocation literature. A wide range of studies have noted high dispersion rates of productivity levels even within narrowly defined industries and in various contexts (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Asker et al., 2014; Haltiwanger et al., 2018). Factor misallocation is seen as the main cause of such dispersion. Studies have found that reallocating capital may have large effects on aggregate productivity (Olley and Pakes, 1996; Hsieh and Klenow, 2009; Bartelsman et al., 2013; Gopinath et al., 2017). Likewise, studies have found significant wage gaps across sectors or locations (Gollin et al., 2014; Bryan et al., 2014; Gollin et al., 2017; Herrendorf and Schoellman, 2018a; Bryan and Morten, 2019). However, sorting may explain a significant share of these gaps (Lagakos and Waugh, 2013; Vollrath, 2014; Porzio, 2016) or their entirety (Young, 2013; Hicks et al., 2017; Alvarez, 2017).[4] We find that static wage gains disappear once we account for the effects of experience. Focusing on returns to experience, we do not find that sorting is consequential for our estimates. However, our estimates also suggest that gaps across sectors and/or locations are not large enough to explain why developed countries have higher returns to experience.

[3]We measure how experience is rewarded in each location rather than the effects of experience accumulated in each location. However, results hold if we restrict the sample to individuals who have never migrated. Indeed, experience for individuals born in cities reflects their urban experience.

[4]There are also studies on the misallocation of land (e.g., Duranton et al., 2015).

The rest of the paper is organized as follows. Section 1. describes the data from I2D2. Section 2. explains our econometric specification and methodological choices. Section 3. shows the estimated returns by economic sectors, occupational types, formal status, locations, and development status. In Sections 4.-7., we examine the robustness of the results. Section 8. investigates the mechanisms. Section 9. concludes.

1. Data

Data. Our main data source is the *International Income Distribution Database* (I2D2). I2D2 consists of a large number of individual-level household surveys, labor force surveys, and census samples harmonized by the Development Economics Research Group of the World Bank. We restrict our analysis to workers aged between 18 and 67 with data on age, education, and wages. The main sample includes 24,437,020 individuals from 1,073 surveys and 11 censuses in 145 countries from 1990-2016. We include samples from the 1990s to increase the number of countries in our sample.[5]

Sample. We have at least one sample for 145 countries comprising 94% of the world's population. Figure 1 shows the number of samples per country. 122 countries have two samples or more. The data is representative for both developed countries (76% of their population) and developing countries (98%). Developed countries are high-income countries circa 2017 according to the classification of the World Bank.[6] Developing countries are low-, lower-middle and upper-middle income countries.

Main Variables. We follow Lagakos et al. (2018a) and calculate *potential work experience* – which we call "experience" in the rest of the analysis – as follows: (i) For individuals with at least 12 years of education, we assume children start school at age 6 and calculate experience as age - years of education - 6; (ii) For individuals with less than 12 years of education, we assume that experience before age 18 is inconsequential and calculate experience as age - 18. Note that we drop the few observations with negative experience.

For many individuals, we have information on their main sector (ISIC-1) and subsector (ISIC-2) of activity as well as their main occupation (ISCO-08). We also have a set of variables that allows us to proxy for formal vs. informal employment. Finally, we

[5]The database has been largely used to study returns to education with relatively less focus on returns to experience (Montenegro and Patrinos, 2014; de Hoyos et al., 2015; Gindling and Newhouse, 2014a; Gindling et al., 2016a).

[6]datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups (01-05-2018).

know if workers live in urban areas or rural areas.

Limitations. While the I2D2 database is particularly useful in terms of external validity, the fact that all these surveys/censuses had to be harmonized implies that few variables are available (about 70, much less than for a typical survey). Also, most samples are surveys because censuses rarely include data on wages. Next, as we will discuss below, the variables in I2D2 do not include proper measures of: (i) work experience (instead, we measure potential work experience); (ii) ability (e.g., test scores); and (iii) sectoral and occupational history. The data on migration (i.e., locational history) is also limited. Finally, the data is not panelized. This will limit our ability to measure causal returns.

2. Methodology

Specification. To be consistent with the recent literature on returns to experience, we adapt the econometric framework of Lagakos et al. (2018a). For individual i in sector or location d and sample t, we use OLS for each country one by one to estimate:

$$lnW_{idt} = D_{idt} + \sum_{e=1}^{7} \beta_e exp_{idte} + \sum_{e=1}^{7} \beta_{ed} D_{idt} * exp_{idte} + \gamma edu_{idt} + X_{idt}\pi + \theta_t + \varepsilon_{idt} \qquad (1)$$

where the dependent variable is the log of monthly wages (lnW_{idt}). D_{idt} is a dummy for the sector or location of interest. We will sequentially consider four dummies that will capture for whether the worker's main activity is in the non-agricultural sector, a cognitive occupation, in the formal sector, or in an urban area. Experience is categorized into seven bins (exp_{idte}). The experience bins are [5-9 years] (which we call 5), [10-14] (10), [15-19] (15), [20-24] (20), [25-29] (25), [30-34] (30), and [35+] (35). The omitted bin is [0-4] (0). The experience bin dummies are then interacted with the sector or location dummy ($D_{idt} * exp_{idte}$).

We account for education through years of schooling as it is one of the main predictors of wages and also affects work experience. First, individuals that studied longer are mechanically less experienced for a given age. Second, individuals that studied more have higher wages if returns to education are positive, and education could also improve longevity. We control for whether the individual is male or female. Lastly, we include sample fixed effects (θ_t) to account for country-year-sample unobservables. We thus only compare individuals from the same country-year-sample.[7]

[7]For the few samples for which the number of years of education is missing whereas educational

We run the regression for each country, as running the regression for the world is computationally intensive. Since most countries have several samples of different sizes, we use individual weights (provided by I2D2) divided by the size of the sample. Finally, to ensure results are not driven by small samples, we keep samples with at least 10 observations in each sector-bin or location-bin.

The coefficient of D_{idt} represents the *static* wage difference in moving across sectors/locations, whereas the coefficients on the experience terms and their interactions with the sector/location dummy capture the *dynamic* wage differences associated with accumulated experience across sectors/locations. The focus of this study are the latter, because static wage differences are much more difficult to estimate causally, due to sorting. Given the sector or location fixed effect (D_{idt}), returns to experience are only estimated for individuals in the same sector or location, thus making sorting less consequential, as we will discuss in more details below.

Wage-Experience Profiles. The 7 experience dummy variables give the profile when the sector or location dummy variable is equal to 0, i.e. in agriculture, manual occupations, the informal sector, or rural areas. The 7 interacted experience dummy variables give the difference in the profile between this sector or location and its corresponding sector or location when the sector or location dummy variable is equal to 1, i.e. in non-agriculture, cognitive occupations, the formal sector, or urban areas. To obtain the profile for these latter, we add the coefficients of the uninteracted experience dummy variables and the coefficients of the interacted experience dummy variables.

To illustrate what can be learned from such profiles, Figure 2(a) and Figure 2(b) show the wage-experience profiles for the rural areas, the urban areas, and the whole economy of the U.S. and Honduras respectively. As can be seen, in the U.S., a worker with 30 years of experience earn almost twice more than a worker with 0 experience. Most of the steepness in the profile comes from the first 25 years, specifically the first 5 years. There is also a gap between urban areas and rural areas, but it is relatively small. In Honduras, the profiles are flatter, and the urban-rural gap is overall wider and increasing over time. Interestingly, the urban profile of Honduras is much below the rural profile of the U.S. These patterns are then replicated if we consider all developed countries (see Figure 3(a)) vs. all developing countries (see Figure 3(b)). To obtain these

attainment is not, we impute that number based on descriptions of educational stages in the country.

profiles, we obtain the average wage differential for each country (during the period 1990-2016). We then obtain the mean wage differentials for each group of countries using the population of each country in 2017. Doing so, we give more weight to larger countries. Note that the median developed country and the median developing country in terms of per capita income are Belgium and Jordan respectively.

Returns to Experience. Measures of the returns should take the integral below the profiles, what Lagakos et al. (2018a) call the "sum of heights". We estimate an annualized return for each bin/type of individuals (0-5, 0-10, 0-15, etc.) and take the mean of these annualized returns to obtain the *mean annualized return* throughout the experience distribution. Our specification has several advantages over the Mincerian specification that includes a quadratic function of experience: (i) It is more flexible and informative, especially given that the wage-experience profiles are not always monotonic;[8] (ii) It allows us to construct returns that are independent of the distribution of experience in the sector or location. Indeed, since we keep samples with at least 10 observations in each bin, and then give each bin/type of individuals the same weight, the constructed mean returns are relatively less affected by the facts that developed countries and developing countries tend to have more experienced workers and more inexperienced workers, respectively;[9] and (iii) We can construct measures using only specific parts of the experience distribution, which will prove important when dealing with changes in a country's economic system as well as selection effects in and out of the workforce or selection effects related to adult mortality in poor countries.

Methodological Choices. Our framework departs from Lagakos et al. (2018a) who study hourly wages and exclude females, part-time workers, self-employed workers and workers of the public sector. Using hourly wages necessitates data on the number of hours worked, which is available for fewer countries (N = 131). The number of hours worked could also be part of the returns. In addition, we keep female, part-time, self-employed and public sector workers for the following reasons. First, we want our sample to be as representative as possible. Second, many workers work part time in developing countries. Due to the lack of unemployment benefits, unemployment is often measured

[8] 34 out of the 145 countries have non-monotonic aggregate wage-experience profiles.

[9] A related issue with the Mincerian specification is how to calculate returns from the coefficients of experience (β_1) and its square (β_2). It is common to calculate the returns as $\beta_1 + \beta_2 \times$ the mean or median number of years of experience. However, this number varies across countries. This method then captures the *local* slope/return at the mean/median experience level, not for the full distribution of experience.

by underemployment. Also, most workers are self-employed in poor countries.

3. Baseline Results

Aggregate Returns. We obtain from Islam et al. (2019a) the average aggregate returns to experience for the 145 countries during the 1990-2016 period. Figure 4 shows the correlation between the aggregate returns and log per capita GDP (PPP; constant 2011 USD; two-year moving average around the mean year in the data for each country).[10] Note that we omit 7 outlying observations in the top and bottom 5% in returns. There is a strong positive relationship (coef. of log per cap. GDP = 0.33***). Developed countries thus have higher returns than developing countries, a result that Lagakos et al. (2018a) and Islam et al. (2019a) show for various data sets and specifications. In particular, Islam et al. (2019a) find average population-weighted returns of 1.8% and 3.6% for developing countries (N = 107) and developed countries (38), respectively. Overall, developed countries have returns that are double the returns of developing countries.

We now study how differences in these returns could be due to labor shares and/or sectoral/locational returns varying across developed and developing countries. Table 1 shows for both developed (henceforth, "D") and developing ("G") countries the shares (col. 1-2) and returns (col. 3-4) for agriculture (A) vs. non-agriculture (N) (first panel), manual (M) vs. cognitive (C) occupations (second panel), informal (I) vs. formal (F) status (third panel) and rural (R) vs. urban (U) areas (fourth panel). As the labor shares indicate, economic development is associated with structural transformation (non-agriculture), skill upgrading (cognitive), formalization and urbanization.

To test for the significance of the within-country differences in the returns, we regress the returns of one of the sectors/locations (e.g., urban in G) on the returns of the other sector/location (e.g., rural in G) for all available country observations using as weights country populations in 2017. The level of significance is indicated in columns (3)-(4), on the row labeled "N-A", "C-M", "F-I" and "U-R".

To test for between-country differences in the returns (e.g., urban in D vs. urban in G), we regress for all available observations the sectoral/locational returns on a dummy equal to one if the country is developed, also using as weights country populations in 2017. The level of significance is shown in column (5). Note that we ignore the fact

[10] For countries for which we have several samples and thus multiple years of data, the "mean" year is the average survey/census year using as weights the number of observations in each survey/census.

that the coefficients of the experience dummies in equation 1 might be imprecisely estimated. However, we will discuss later how most coefficients are precisely estimated given the size of our database. We will also implement various robustness checks.

Sectors (first panel): We find that: (i) The agricultural employment share is higher in developing countries (37%) than in developed countries (5%); (ii) For both groups of countries, returns are significantly higher in non-agriculture than in agriculture (see "N-A"). This gap is larger in developing countries ((2.0-1.2)/1.2*100 = 67%) than in developed countries (33%); (ii) Returns are significantly higher for developed countries than for developing countries ("D-G"); and (iii) Non-agricultural sectors in developing countries have lower returns than agriculture in developed countries ("A_D-N_G").

Occupations (second panel): We find that: (i) Developed economies have higher shares of cognitive occupations (79%) than developing economies (48%);[11] (ii) Returns are higher in cognitive occupations ("C-M"). The gap between cognitive occupations and manual occupations is larger in developing countries ((2.1-1.4)/1.4*100 = 50%) than in developed countries (9%); (iii) For both occupational types, returns are higher for developed economies ("D-G"); and (iv) Cognitive occupations in developing countries have lower returns than manual occupations in developed countries ("M_D-C_G").

Formal status (third panel): We find that: (i) Developed economies have higher formal shares (69%) than developing economies (50%);[12] (ii) Returns are higher in the formal sector ("F-I"). However, the formal-informal gap is not larger in developed countries ((1.8-1.5)/1.5*100 = 20%) than in developing countries (25%); (iii) For both sectors, returns are higher for richer countries ("D-G"); and (iv) The formal sector in developing countries has lower returns than the informal sector in developed countries ("I_D-F_G").

Location (fourth panel): We find that: (i) Developed economies have higher urban shares than developing economies (73% vs. 46%); (ii) Returns are higher in urban areas than in rural areas ("U-R"). This gap is larger in developing countries ((2.1-1.3)/1.3*100

[11] Following Lagakos et al. (2018a), we define cognitive occupations as managers, professionals, technicians, clerks, crafts and salespersons. Non-cognitive occupations are defined as machinists, elementary occupations, skilled agricultural workers, and other occupations.

[12] Many countries use information on contracts and social security to define formality. Other countries distinguish small firms and other firms, often using a firm size cut-off of 10. In our analysis, we combine both criteria and formal wage workers are those with a contract or health insurance or social security or union membership or those working in a firm of more than 10 employees. All other workers for which we have information on any of the dimensions above are considered to be informal. Samples for which we have no information on any of the elements are not included for this analysis.

= 61%) than in developed countries (9%); (iii) For all locations, returns are higher for developed economies than for developing economies ("D-G"); and (iv) Developing country urban areas have lower returns than developed country rural areas ("R_D-U_G").

Static Differences As shown by Roca and Puga (2017), wage differences between locations reflect both *static* wage gains – i.e. the immediate gain from moving across locations – and *dynamic* wage gains resulting from experience accumulated in the location, i.e. local learning effects. More precisely, they find that dynamic wage gains explain about half of inter-city wage differences in Spain. In this study, and as we explain below, we ignore static wage gains because it is difficult to accurately measure static effects in our context given the data limitations. Nonetheless, if we estimate equation 1 without including the experience dummies, we find mean (population-weighted) wage gaps of about 43-65% and 18-42% in developing countries and developed countries, respectively. As Web Appx. Table A.1 shows, the gaps for non-agriculture vs. agriculture, cognitive vs. manual occupations, and urban vs. rural locations, are significantly higher by 25, 12 and 33 percentage points in developing countries than in developed countries. However, the same table shows that these gaps become small and insignificant if we include the experience dummies. Thus, differences in wage gaps across countries are likely driven by dynamic wage gains, hence it is important to better understand the factors behind the higher returns to experience of developed countries.

Summary. These results provide our core contribution. We do find relatively higher returns for what we expected to be the "best" sectors/locations, in both developed and developing countries. The gaps are also more apparent in developing countries than in developed countries. However, the "best" sectors/locations of developing countries have much lower returns than the "worst" sectors/locations in developed countries. This suggests that even if reallocating labor in developing countries could increase aggregate returns, it may not contribute much to explaining why aggregate returns are twice lower there than in developed countries. We test that hypothesis now.

Reallocation Exercises. Equation 2 shows that for each sector/location, the aggregate return is equal to the weighted mean of the returns of all subsectors/sublocations s (e.g., non-agriculture and agriculture) using as weights the labor shares of the subsectors/sublocations:

$$\overline{expr} = \sum_s share_s * expr_s \tag{2}$$

Developed countries may have higher returns because they have higher returns across all subsectors/sublocations and/or because they have higher shares of workers in the higher-return subsector/sublocation. Table 2 shows the effects of various crude labor reallocation exercises on the gap in aggregate returns between developing and developed countries. Note that we take the returns as given, thus ignoring any general equilibrium effects that could alter the sectoral/locational returns as workers are moved across sectors/locations. We also abstract from the costs of such policies.

Rows 0a and 0b show for each dimension the implied aggregate returns for both groups of countries, whereas row 0c shows the developed-developing gap in aggregate returns. For example, knowing the labor shares and the returns of the agricultural sector and the non-agricultural sector, we estimate that aggregate returns should be equal to 1.7% in developing countries and 3.6% in developed countries. That is similar to what Islam et al. (2019a) found when estimating aggregate returns directly (1.8% and 3.6%). Rows 1-5 then show by how many percentage points the developed-developing gap is reduced when implementing various changes in the labor shares or the returns of developing countries. Reallocating labor, either by moving all workers to the high-return sector in developing countries (row 1), or by matching the labor structure of developed countries (row 2), always has smaller effects than increasing returns to the levels seen in developed countries but without changing the labor structure of developing countries (row 3). At best, changing labor shares reduces the gap by 26%. Changing returns then reduces the gap by at least 84%. If developing countries only get the developed country returns for their lower-return sector or their higher-return sector, the gap is reduced by 32-58% (see row 4) and 37-53% (see row 5), respectively. The contributions of the "worst" and "best" sectors thus appear relatively similar.

Limitations. The estimates shown so far do not account for cohort, sorting and selection effects. We now address each problem one by one, starting with cohort effects.

4. Dealing with Cohort Effects

Experience-Time-Cohort Problem. Experience is collinear with sample years and years of birth. Therefore, we cannot include year of birth fixed effects (see Web Appx. Section

A.1 for a detailed explanation). We also cannot distinguish the effects of experience and age (ditto).[13] To deal with that problem, we follow Heckman and Robb (1985, p.145) (henceforth, "HR") who simply propose to include cohort effects consisting of "a sequence of adjacent years (e.g., Depression or 1950s youth, etc.)".

"HR1" Approach. For countries with at least two years of data, and given our data sets are large, we include decadal cohort fixed effects, which we call the "HR1" approach. Since we focus on workers aged 18-67 in samples from 1990-2016, individuals are born between 1923 and 1998. We thus include 8 cohort fixed effects (1920s, ..., 1990s).

HR2 Approach. Alternatively, we can "tailor" our cohort fixed effects to match the historical political, economic and/or social circumstances faced by different cohorts of each country. We construct for each country periods based on "important" years, e.g. for the U.S., 1923-1928, 1929-1932, 1933-1940, 1941-1944, 1945-1953, 1954-1961, 1962-1963, 1964-1967, 1968-1973, 1974-1979, 1980-1989, 1990-1993 and 1994-2000, due to "important" events in 1929 (Great Depression), 1933 (New Deal), 1941 (Pearl Harbor), 1945 (World War II ends), 1954 (ends of racial segregation in schools), 1962 (Cuban Missile Crisis), 1964 (Civil Rights Act), 1968 (Martin Luther King assassinated), 1974 (Watergate), 1980 (Reagan's election), 1990 (Gulf War starts, Cold War ends), 1994 (Nafta), 2001 (9-11), and 2007 (Great Recession). Note that we arbitrarily define important years using information from Wikipedia and other sources (see Web Appx. Section A.2 for more examples). We then include in the regressions multiple country-specific period dummies equal to one if the individual was 18-67 years old during the period(s), and zero otherwise (again, only for countries with at least two years of data). Doing so captures the fact that each person was affected by multiple events during her lifetime. Although there may be heterogeneity in the effect of these events, with some having economy wide-effects, while others specific to certain sectors or areas within in the economy, we err towards including as many incidents as feasible to demand as much as possible from the data. We call this strategy the "HR2" approach.[14]

[13]We also do not measure true work experience, as employment history is unavailable in our data. We likely over-estimate experience for more experienced individuals, since they have by construction more months that could have been spent not working. We should thus under-estimate returns. However, it is unclear whether such measurement errors are correlated with the sector/location differentially across development status. Finally, we could think of potential work experience as "life experience".

[14]The HR1 approach is more flexible than the HR2 strategy, since it is a-historical. Indeed, with decadal cohort fixed effects, we ignore what may be driving the cohort effects. The latter approach is more thorough, and potentially more demanding, since our controls for the cohort effects follow real events,

"Combi" Approach. Finally, we combine both HR1 and HR2 approaches. Furthermore, we also add as a control the country's average per capita GDP growth rate for those years during which the individual was 18-67 years old, since the identified important years may not capture well uneventful periods of growth or recessions.

Results. Columns (1) and (5) of Table 3 replicate the baseline results whereas the HR1, HR2 and "Combi" approaches are implemented in columns (2) and (6), (3) and (7), and (4) and (8), respectively. As can be seen, returns decrease across all dimensions for both developing (col. (1)-(4)) and developed countries (col. (5)-(8)). Nonetheless, results are not qualitatively changed. Gaps, once computed in percentage terms (not shown), tend to be larger in developing countries than in developed countries. Returns are then much larger in developed countries than in developed countries, even when comparing the "worst" sector/location of the former with the "best" one of the latter (with the exception of agriculture vs. non-agriculture for the Combi approach, col. (12)).

Robustness. Web Appx. Table A.2 shows results hold if we (to reduce clutter, significance tests are omitted, but available on request): (i) use 20-year or 5-year cohort fixed effects. Using 5-year cohort fixed effects preserves the difference in returns between developed and developing countries. However, estimated returns are lower, since collinearity increases as one uses more and more refined cohort fixed effects; (ii) use periods based on ages 18-40 or 18-30, in case important events are more consequential in the first decades or years after high school; (iii) we also add country-specific period dummies equal to one if the individual was 0-17 years old during the period(s), and the individual's corresponding growth rate, in case important events are consequential during childhood; and (iv) we implement the main approach followed by Lagakos et al. (2018a) (they call it "HLT" because it is based on the work of Heckman et al. (1998a)). More precisely, they rely on theories of life cycle wage growth that claim that "there should be little or no effect of experience on wages near the end of the life cycle". Thus, older workers have no incentive to invest in human capital formation and the incentive to search for a better-paying job declines similarly. One can then "follow a fixed cohort across multiple cross sections for the last years of their working life" and attribute any wage changes for them to time effects. Once time effects are recovered, we estimate the experience and cohort effects of workers who are not near the end of

which take place every 6.5 years on average in our data. 11.5 period dummies are thus included in average.

the life cycle. However, wage profiles could decrease at the end of the life cycle because of human capital depreciation. Indeed, with age, all our body systems (e.g., the brain) decline. However, two parameters are required: "first, the number of years at the end of the life cycle for which there are no experience effects and, second, a number for the depreciation rate". Like them, we consider 5 or 10 years and 0 or 1%.[15]

5. Dealing with Sorting Effects

Sorting Problem. Returns to experience compare the wages of more experienced individuals with less experienced individuals. When comparing the different subdimensions of the same country, the sorting of workers may affect the results. For example, if there is rural-to-urban migration, and migrants are overall less experienced and positively selected, which means they would obtain higher wages anyway, the returns for urban (rural) areas will be under-(over-)estimated. When comparing the returns for urban and rural areas, the gap will be under-estimated. Likewise, if there is structural/occupational change and workers are little experienced when they decide which sector/occupation to specialize into and the ones choosing the "best" sector(s)/occupation(s) are positively selected, then the returns of the best (worst) sector(s)/occupation(s) will be under-(over-)estimated. When comparing the returns between the best and worst sectors/occupations, the gap will be under-estimated.

The main objective of this study is to show that the gap in the returns between the "best" and "worst" location/sector in developing countries is not large enough so that narrowing that gap would not bridge the gap in aggregate returns between developed and developing countries. Sorting is thus an issue if we under-estimate the gap between the best and worst sectors/locations in developing countries and over-estimate returns in the best sector/location in developed countries. Indeed, the aggregate returns of developed countries are driven by their best sectors/locations because they have high shares of workers in these. We will under-estimate the gaps in developing countries if the best sectors/locations disproportionately attract relatively more able younger workers or relatively less able older workers. We will over-estimate the returns of the best sectors/locations in developed countries if they disproportionately attract relatively less able younger workers or relatively more able older workers. Sorting would

[15]We do not use this approach as well as the other approach they implement as our main strategies because these approaches may have limitations in our sample (see Web Appx. Section A.1 for details).

thus need to work in opposing directions between developing and developed countries.

Therefore, sorting is problematical if and only if experience is correlated with workers sorting differentially across locations/sectors *and* development status. As such, this is a strong condition. Regardless, we attempt to control for sorting directly.

Controls for Sorting. In this study, we focus on dynamic rather than static wage differences associated with sectors/locations. Thus, we do not directly compare the wages of individuals working in the agricultural/rural sector with the wages of individuals working in the non-agricultural/urban sector. Instead, since we include the sector/location dummy as a control (see eq. 1), we compare the wages of more experienced individuals with the wages of less experienced individuals *for a same sector/location*. As such, we already capture the most important aspect of sorting. We can also push this further by adding refined sectoral or locational fixed effects.

Columns (1), (5) and (9) of Table 3 replicate the baseline results. In columns (2), (6) and (10), we show the results hold when including controls for broad sectoral and occupational skill groups. Indeed, as shown by Roca and Puga (2017) (henceforth, "DRP") for Spain, there appears to be limited sorting on unobserved ability once such DRP controls are included. In particular, in addition to the number of years of education and the male dummy, we now include 3 (ISIC-1) sector fixed effects, 10 occupation fixed effects, the four sectoral/locational dummies, and the square of the number of years of education.[16] As can be seen, returns decrease for both developing and developed countries but the gap remains and the results are not qualitatively changed. In Web Appendix Table A.3, we push this further and add 10 (ISIC-2) subsector x 10 occupation = 100 sector-occupation fixed effects. Results are unchanged (to reduce clutter, significance tests are omitted, but available on request). However, this leads to over-controlling if the choice of a sector/occupation is part of the returns.

In columns (3), (7) and (11), we show results hold when including the DRP controls as well as first-level administrative units fixed effects which we interact with the urban dummy. In the U.S., this corresponds to 51 units (50 states and the District of Columbia) x urban/rural. As can be seen, we lose countries, especially developed countries, because not all countries report spatial information.[17] In Web Appendix Table A.3, we

[16]The three sectors are agriculture, industry and services.

[17]Many European countries do not provide location details because of privacy concerns.

push this further and add second-level administrative units fixed effects which we also interact with the urban dummy. In the U.S., this corresponds to about 3,000 counties x urban/rural. Results are unchanged. However, this leads to over-controlling if the choice of a specific sublocation is part of the returns.[18]

Next, in columns (4), (8) and (12), we show results hold when including the DRP controls as well as accounting for whether we know if the individual has ever migrated, first domestically and then internationally, and whether this information comes from the last migration episode or from comparing the place of current residence with the place of previous residence or the place of birth. For this analysis, we use the available spatial levels of the place of previous residence and the place of birth, thus either first-level units (e.g., states in the U.S.) or second-level units (e.g. counties).[19]

Alternatively, Web Appendix Table A.3 shows results hold when including the DRP controls as well as place of birth fixed effects (either the first-level or second-level unit depending on the country). Indeed, it has been shown that the place of birth is a significant predictor of talent.

Finally, unlike Roca and Puga (2017), we do not have data on the locational, sectoral or occupational history of each individual. We thus measure how experience is rewarded in each location/sector/occupation rather than the effects of experience specifically accumulated in each location/sector/occupation. To remedy that issue, at least regarding locational choices, Web Appendix Table A.3 shows results hold if we restrict the analysis to individuals who have never migrated, i.e. individuals who have always lived in the same location. Indeed, the stock of experience for individuals born in urban (rural) areas reflects their urban (rural) experience.[20] Regarding sectoral choices, if most workers enter their career field just after school, the fact that we restrict our analysis to the workers of the same broad sectoral/occupational group may partially address that issue. We will also discuss later how results hold when estimating the returns for 10 subsectors or 10 occupations separately. Indeed, some subsectors and

[18]For this exercise, and since very few developed countries have information on the second-level administrative unit in I2D2, we also use the IPUMS database for 7 developed countries with available wage data as well as labor force survey (LFS) data for 3 other developed countries. Before doing so, we verify that similar baseline returns are obtained when using I2D2 data or IPUMS/LFS data.

[19]For this exercise, and since few developed countries have information on migration in I2D2, we also use for that test the IPUMS and LFS data sets mentioned in the previous footnote.

[20]However, this might not be entirely true if some rural locations are reclassified as urban over time.

occupations likely have low entry-exit rates among higher experience bins.

6. Dealing with Selection Effects

Selection Problem. Our regressions only include waged workers and are thus susceptible to selection problems particularly in samples with disproportionately high unemployment or low labor force participation rates. This could bias the results but only if experience is correlated with selection differentially across sectors/locations *and* development status. This is another particularly strong condition.

We address the selection through a battery of checks. First, we check correlations between unemployment rates and development, and find that unemployment / labor force participation rates are not correlated with development. For each country, we obtain the mean unemployment rate and the mean NEET rate across all available years (using as weights the number of observations in each sample). In our case, the NEET rate (NEET stands for "Not in Education, Employment, or Training") is the ratio of the number of 18-67 year old workers to the number of 18-67 year old individuals who are not currently enrolled in school. We then regress these rates on log per capita GDP (PPP, constant 2011 international $) for the country-specific "mean" year in the data.[21] No relationship is found for unemployment (not shown, but available upon request). Indeed, poor countries do not offer unemployment benefits, which may force most people to work in order to survive. Conversely, rich countries have more dynamic economies, which may reduce unemployment, but they also offer unemployment benefits and other subsidies, thus raising the reservation wage of non-workers. Likewise, no effect is found for the NEET rate.

Second, I2D2 does not include data on ability, an important individual characteristic to explain unemployment/labor force participation. However, results hold if we control for factors such as the sector, the occupation, the place of residence or the place of birth, which are all important proxies for individual ability. The question is how much unobserved ability is unaccounted for to make selection into work an issue.

Third, selection disproportionately affects female workers given several constraints they face in many sectors/locations. Furthermore, work experience for women is mis-measured as many of them may leave the labor force due to childbearing and childcare

[21] For countries with only one sample, it is the year of the sample. For countries with multiple samples, we obtain the mean year in the data using as weights the number of observations in each sample.

activities which would not be captured in our measure or potential work experience. Thus, in columns (2), (6) and (10) of Table 5, we show results hold when we exclude female workers (see col. (1), (5) and (9) for the baseline results).

Fourth, columns (3), (7) and (11) show results hold if we keep samples with low unemployment, i.e. country-year samples with unemployment rates below the median unemployment rate in the sample, which is 7%. Web Appx. Table A.4 shows results hold if we keep samples with high unemployment, i.e. country-year samples with unemployment rates above 7%. Alternatively, we use as the threshold the mean unemployment rate in the sample (10%). Finally, Web Appx. Table A.4 shows results hold if we keep samples with high, or low, NEET rates, using the median NEET rate in the sample – 35% – as the cut-off (35% is also the mean rate in the sample).

Finally, we attempt to correct for selection bias using the Heckman correction method. The selection equation includes the variables of equation 1 (e.g., the male dummy) and as external variables marital status dummies (married, non-married, divorced, widowed or single) and the number of children and its square. Results hold (see col. (4), (8) and (12)). However, these results should be taken with caution since marital status and the number of children may not be good "instruments" for selection.

7. Robustness

Monthly vs. Hourly Wages. The same analysis is repeated in Table 6 but using log hourly wages (Panel A) and the log of number of hours worked (Panel B) as dependent variables. By construction, the monthly wage is equal to the product of the hourly wage and the number of hours worked. Overall, the patterns remain consistent whether monthly or hourly wages are used. However, experience in the non-agricultural sectors in developing countries now has the same returns as experience in the agricultural sectors in developed countries. Next, the returns are close to zero for hours in developing countries and usually greater than zero in developed countries. This suggests that experience makes workers work relatively more hours in developed countries. There are a couple of plausible reasons for this. It could be because hourly wages are higher in developed economies, which makes them increase their labor supply. Or it could be that demand for the labor of experienced workers is higher in developed countries. However, no particular gaps are observed within countries. These observations combined with the fact that there are gaps in the returns for hourly wages between developed and developing economies suggests that the gaps in monthly wages are driven by gaps in hourly wages, hence labor productivity.

Selected Bins. Results hold if we use specific segments of the experience profile. Panel C only considers the 5-35 experience bins, in case the large magnitude of returns for experience bin 5 in developed countries distorts the average. Panel D only considers the first 25 years of experience to capture the returns for younger workers. In addition, focusing on the first 25 years abstracts away from issues that affect returns estimated for older workers such as selective adult mortality in poorer countries, selective pre-retirement in richer countries, and the fact that a change in the economic system of ex-USSR countries may have made pre-liberalization experience obsolete.

Sample Restrictions. Table 7 shows results hold if we exclude self-employed, part-time, female and public sector workers, to mimic Lagakos et al. (2018a), considering both monthly wages (Panel A) and hourly wages (Panel B). Note that returns are not significantly different between employed and self-employed workers (not shown).

Complementarities between Experience and Education. Developed countries may have higher returns to experience because they have more educated workers. Education can amplify the returns to experience given the complementarities between experience and education. According to Unesco (2012), individuals finish high school after about 12 years of education. We estimate the returns if we restrict the sample to individuals with less (Panel C), or more (Panel D), than 12 years of education. Returns are higher for more educated individuals. However, results are not qualitatively changed .[22]

Aggregation Issues. Web Appx. Table A.6 shows the returns when we interact sectors, occupations, formality and/or locations. Returns are consistently higher in what we expect to be the "best" sector-location (e.g., urban x cognitive or urban x formal).[23] We push this further by estimating returns for non-agricultural sectors x cognitive work x formal work x urban location (henceforth, "NCFU"). Row 1 of Table 8 reports the estimated labor shares and returns. NCFU shows much higher returns in developed

[22]We use 12 years as the cut-off because the number of years of education is available for more countries than educational achievement based on stages in I2D2. However, Web Appx. Table A.5 shows results hold if we compare individuals who completed high school vs. not. Alternatively, results hold if we use 10 years or 13 years as the cut-off since the average number of years of education in the world is 10 in our data and since there are countries where people finish high school after 13 years (not shown).

[23]In developed countries: (i) non-agriculture involves more cognitive work and is more formal/urban; (ii) cognitive occupations are more formal/urban; (iii) the formal sector involves more cognitive work and is more urban; and (iv) the urban sector involves more cognitive work and is more formal.

countries than in developing countries (3.6 vs. 2.2). The returns of the NCFU sector are then *not* significantly higher than the best sector- or location-specific baseline returns from Table 1 (3.7 and 2.2, respectively). The returns of the NCFU sector in developing countries is also lower than the return for agriculture in developed countries (2.6). Thus, if everyone worked in NCFU in developing countries, the developed-developing gap in aggregate returns would still not be bridged (see row 6 of Table 2).

Subsectors and Occupations. We can then estimate the returns for each of the 10 subsectors and each of the 10 occupations. Rows 2-8 of Table 8 shows these returns for selected subsectors. Returns are the highest in transportation & communications and finance, real estate & business services. In both developing and developed countries, non-agricultural sectors tend to have significantly higher returns than agriculture (see the stars in col. (3)-(4)). Rows 9-17 then show the returns for selected occupations. Technicians, managers and professionals have the highest returns. Next, in developing countries, most occupations show significantly higher returns than in elementary occupations (col. (3)), but that is not the case in developed countries (col. (4)). Again, whether we consider subsectors or occupations, the lowest return in developed countries is higher than the highest return in developed countries.

Measurement Errors and Sampling. Results could be sensitive to measurement errors in experience and wages or sampling. Web Appx. Table A.5 shows results generally hold if we: (i) Use country-specific ages of entry in primary school, include child labor, or drop samples exhibiting age heaping; (ii) Restrict the sample to post-2000 samples to minimize issues arising from ex-USSR countries; (iii) Use three- or seven-year bins; (iv) Keep workers for which the wage was reported for a period of at least a month since the monthly wage may be mis-measured for workers paid hourly, daily or weekly; (v) Include the wage of any secondary occupation; (vi) Use mean wages, experience and education in the household in case there is intra-household optimization; (viii) Keep samples for which the estimated labor shares are less than 10 percentage points than the official labor shares;[24]; (ix) Keep samples with at least 100 observations per experience bin; and (x) Only compare high-income countries and low- and lower-middle income

[24]The labor shares of the non-agricultural sector, cognitive occupations and the formal sector, and urban areas come from World Bank (2018a), International Labour Organization (2018), and United Nations (2018b) respectively. When including observations for which a discrepancy is observed, the respective correlations between the estimated and official shares are 0.84, 0.78, 0.76 and 0.58, respectively. Once we exclude these observations, the correlations become 0.98, 0.95, 0.97 and 0.92, respectively.

countries, thus excluding upper-middle income countries from the analysis.

Standard Errors. Standard errors in the main tables do not account for the fact that the coefficients of the fourteen experience dummies may be imprecisely estimated in equation 1. However, the medians of the mean and max standard errors across the fourteen coefficients in our sample of countries are relatively low, at 0.04-0.08 and 0.05-0.09, respectively (the corresponding median mean and max coefficients are 0.21-0.25 and 0.49-0.54). Web Appx. Table A.5 then shows that results hold if we use countries whose mean or max standard error is below the median of the mean/max standard error in the sample. Besides, results hold with bootstrapped standard errors (not shown).

8. Mechanisms

8.1. Manual vs. Cognitive Occupations

As shown in the previous sections, the higher returns in developed countries are driven by hourly wages, and thus driven by labor productivity if workers are paid their marginal product. Returns are steeper for lower-experience bins in developed economies relative to developing economies. What factors could explain why wages, and possibly labor productivity, increases disproportionately faster for less experienced workers in developed countries relative to developing countries?

Manual vs. Cognitive Occupations. As shown earlier, the developed-developing gap is mostly driven by higher returns across all sectors and locations in developed countries and is unlikely to be bridged if developing economies mimicked the economic structure of developed countries. Now, which sectors and/or locations disproportionately account for the higher returns in developed countries? In Figure 5, we plot the returns for each of the 10 occupations separately for developed countries and developing countries (from Table 8) against the returns of the same occupation for the whole world (using the population of each country as weights). The slope of the relationship is relatively flatter - i.e., within-country gaps are smaller – for developed countries. Interestingly, the developed-developing gap - i.e. the local difference between the two regression lines – is much larger for more manual occupations, which carry the bulk of employment in poorer countries. This raises the question as to why more manual, and not more cognitive, occupations offer higher wages over time in developed countries.[25]

[25] If we give developing countries the occupational labor shares of developed countries, the developed-

Robustness. The estimated slope coefficient for developed and developing countries is 0.21 and 1.09*** (N = 10; not shown), respectively. The slope coefficients remain similar if we: (i) use the labor shares of each occupation as weights (0.30*** vs. 1.09***; not shown); (ii) use as a control the labor share in case occupation-specific returns decrease with occupation-specific labor supply (0.23 vs. 1.08***, not shown); and (iii) exclude skilled agriculture (0.32** vs. 1.08***, not shown). In Web Appx. Figure 1(a), 1(b) and A.2, we push this further by showing the same patterns for the 10 occupations interacted with the formal employment dummy, the urban dummy or the 10 subsector dummies.[26]

8.2. Mechanisms

As explained by Lagakos et al. (2018a), there are three potential explanations for the higher returns to experience in developed countries: (i) *Long-term contracts:* It could be that contracts are relatively more (less) back-(front-)loaded in developed countries. With back (front) loaded contracts, younger/less experienced workers are paid less (more) than marginal labor productivity, which would then lead to steeper (flatter) experience profiles. Note that in that case wages do not always reflect productivity; (ii) *Human capital:* The human capital theory suggests that richer economies have higher returns to experience as workers accumulate more human capital over the life cycle than workers in poorer countries.; and (iii) *Search and matching frictions:* The search and match theory suggests that there are large labor market frictions in poor countries. As a result, lower market fluidity in developing economies prevents workers from moving up the ladder to better jobs that fit their skills profile.

Long-term contracts. For this explanation to matter, contracts would have to be relatively more back-loaded in developed countries. If developed countries are more likely to pay less experienced workers their marginal product, this explanation may not hold. Furthermore, we showed that results are similar whether we focus on workers who report their wage on a monthly, semi-annual or annual basis - i.e., are more likely to have a long-term contract – or workers who report their wage on a weekly, daily or hourly basis. Results were also similar for employed vs. self-employed workers, since

developing gap in the aggregate returns is only reduced by 26% vs. 88% if we give them the returns of developed countries. If we give developing countries the returns of the five "best" occupations or five "worst" occupations in developed countries, the gap is reduced by 25% vs. 63%, respectively.

[26] For these analyses, we keep returns for which at least 10 country observations are available (N = 18, 18 and 51, respectively). Slope coefficients also remain similar (see the notes under the figure).

self-employed workers are more likely to receive their marginal product.[27]

Human Capital. Wages may increase with work experience because workers obtain skills from working, whether hard skills - i.e., teachable and measurable abilities – or soft skills – traits that make you a good employee. Thus, it could be that manual occupations in developed countries disproportionately require workers to achieve specialized and/or complex tasks, as the result of which they can develop hard skills over time. In particular, manual occupations in developed countries could involve the use of technologies that would reward workers that have become more familiar with these technologies. Alternatively, manual workers could disproportionately learn soft skills in the firms of developed countries. These soft skills could have significant effects on productivity, if workers become more persistent, creative and better able to work in teams.

Frictions. With reduced frictions in the economy, workers could find the job that matches the best their skill profile and help them realize their productive potential. In particular, frictions could prevent workers from finding the "right" position, firm, sector and/or location for them. Spatial frictions could then contribute to isolating workers from existing opportunities. Likewise, social frictions related to group-based discrimination (e.g., across gender or ethnic groups) could prevent a significant share of the labor force from accessing existing opportunities. Finally, such frictions might be particularly prevalent and consequential for manual workers, which constitute the brunt of the labor force in developing countries, especially as manual workers are often disproportionately affected by labor market regulations, spatial frictions and social frictions.

In practice, much like Lagakos et al. (2018a), we are not be able to distinguish the human capital and frictions channels. Frictions constrain human capital accumulation, since workers are less likely to find the job that will help them obtain skills and realize their potential. Conversely, reducing frictions in a society may be accelerated by human capital accumulation at work, for example soft skills that may contribute to changing attitudes or hard skills that may help societies find solutions to spatial frictions. However, unlike Lagakos et al. (2018a), we have estimated returns for a large

[27]The earnings of self-employed workers may nonetheless include returns to capital, and thus not entirely measure returns to work experience. However, we also studied returns for self-employed individuals who did not have employees and were thus less likely to own a capital-intensive company.

number of countries, which allows us to investigate how they correlate with various country-level proxies for economic institutions, social institutions and values.

8.3. Cross-Country Correlates of the Returns

Returns Used. Differences in the aggregate returns are mostly driven by manual occupations. Indeed, the coefficient of correlation between the returns for manual occupations and the aggregate returns is 0.90. However, the manual returns are available for 127 countries vs. 145 countries for the aggregate returns. Since some of the country-level factors examined below are available for a small number of countries, we use the aggregate returns in order to maximize the number of observations.

Specifications. We focus on 24 factors among the hundreds of variables now available at the country level in various databases. We first regress the returns on each factor one by one. Table 9 shows the 24 estimated coefficients in 24 separate panels. We then examine how the coefficients change if we control for log per capita GDP (PPP; constant 2011 USD; two-year moving average around the mean year in the I2D2 data for each country). This tells us whether the factor might partially account for the higher returns in developed countries. This might also indicate whether countries with similar income levels have different returns as a result of these factors.[28] Next, we test for each factor whether any significant correlation survives when we control for the other factors. More precisely, for each factor and each specification, we re-estimate the coefficient when sequentially including each of the other 23 controls. We then show in the row "Sh. Sign." the percentage share of the 23 re-estimated coefficients that are of the same sign as the baseline coefficient and significant. Indeed, it is not obvious which other controls should be included or not, since we do not want to over-control. In addition, some variables are available for less than half of the sample. Finally, these results should be taken with caution, as they only capture correlations.

Political and Economic Institutions. We first investigate the relationship between the aggregate returns and measures of governance from the *World Governance Indicators* of the World Bank (we use averages in 2000-2018). We find strong correlations between the returns and the following measures: control of corruption (Panel A), government

[28]When we regress the returns on log per capita GDP, we find a slope coefficient of 0.41*** and a R2 of 0.18, thus much lower than 1. In other words, even when comparing two countries with the same income, there are still significant differences in the returns.

effectiveness (Panel B), political stability (Panel C), rule of law (Panel D) and regulatory quality (Panel E). These survive the inclusion of income. When adding the other controls one by one, they also tend to survive. For example, control of corruption always survives (sh .sign. = 100%). We then regress the aggregate returns on a measure of economic freedom from the *Doing Business Indicators* (DBI) of the World Bank. Panel F shows a strong positive effect of the ease of doing business score (average in 2000-2018) which, however, does not survive once income is included in the specification. We find similar results for all doing business sub-indicators (not shown).

The DBI database also includes measures of labor regulations. However, these are not summarized in one sub-indicator, hence the need to examine their correlation with the returns one by one. We use the most recent year, 2018, since this data has only been recently added to the DBI database. As explained by the "Employing Workers" webpage of the website of the DBI database, "the regulation of employment is necessary [...] to protect workers from arbitrary or unfair treatment and to ensure efficient contracting between employers and workers. [...] The challenge for governments is to avoid the extremes of over- and under-regulation by balancing labor flexibility with worker protection." We find that constraints on redundancy rules and working hours lower the returns, possibly because inflexible labor markets prevent firms and workers from making socially optimal decisions. As a result, a significant share of workers may not be in the "right" position, firm, sector and/or location. More precisely, returns are higher if dismissal due to redundancy is allowed by law (Panel G), if firms have to pay a premium for overtime work (Panel H), if overtime work is simply restricted (Panel I), or if the redundancy cost – i.e., severance pay – is high (Panel J). However, not all labor regulations lower returns to experience. The length of the notice period for redundancy dismissal increases returns (Panel K), possibly because it gives workers made redundant more time to search for a job that better matches their skill profile. These results largely survive the inclusion of income in the specification.

Spatial and Informational Frictions. We then examine how the returns correlate with a simple measure of spatial frictions, the Freedom of Domestic Movement subcomponent of the Human Freedom Index of the Cato Institute. As can be seen in Panel L, we find that reduced spatial frictions is associated with higher returns. However, this effect does not survive controlling for income. In Panels M, N and O, we then study the correlation between the returns and three measures of informational technologies: the share of households with computers (2012-2016; source: World Bank TCdata360), the share of individuals with a broadband subscription (2000-2016; source: World Development Indicators of the World Bank), and the share of individuals 15 year old and older who use digital payments (2017; source: Global Findex Database). As can be seen, the correlations are positive, survive the inclusion of income, and tend to survive the inclusion of other controls (see "Sh. Sign."). While such technologies could be used to reduce informational frictions (e.g., help workers find the "right" job), they may also capture the fact that manual occupations in developed countries also involve the use of technologies, which might facilitate human capital accumulation at work.

Social Frictions. We obtain measures of "values" from the *World Values Surveys* (WVS) available for 70 countries in our sample. In particular, once we control for income, we find no effect for the Secular Values Index of the WVS (Panel P). According to Welzel (2014a), "secular values dissociate people from external sources of quasi-sacred authority, like religion, the nation, the state and group norms". Panel Q then shows a strong correlation between the Emancipative Values Index and the returns, even when including income and the other controls (one by one). According to Welzel (2014a), "emancipative values appreciate a life free from external domination, for which reason these values emphasize equal freedoms for everyone. Thus, emancipative values involve a double emphasis on freedom of choice and equality of opportunities." In other words, holistic freedom, not just specific to "quasi-sacred authorities", matters.[29]

We push this further and investigate the correlation between measures of discrimination against economic and non-economic minorities. Panel R and S show a positive correlation between the returns and measures showing weaker legal disparities between men and women from the World Bank *Women, Business and the Law* database: the legal disparities score (Panel R) and its component "Getting a Job" (Panel S). However, these correlations do not survive the inclusion of income. But if we use a measure of whether race, color, sex, religion, political opinion, and social origin are prohibited grounds for dismissal (Panel T; source: ILO EPLex), then the positive correlation survives the inclusion of income and tends to survive the inclusion the

[29]We obtain similar results if we focus on components of these indexes. We find a positive correlation for measures of "equality" (between men and women), "choice of life" and "autonomy" (not shown).

controls (one by one). Panel U shows a negative correlation between the returns and a measure of racism (source: *World Values Surveys*), in particular the share of survey respondents that say they would dislike having a neighbor from a different race. This is true if we include income or other controls (one by one). We find similarly negative effects for the shares of respondents that dislike having neighbors from a different religion (Panel V) or neighbors that are immigrants/foreign workers (Panel W). Interestingly, ethnic fractionalization does not have any effect once we control for income, thus showing it that is discrimination, not ethnic diversity per se, that matters. Thus, societies where specific groups are discriminated show lower returns, possibly because discriminated workers cannot find the right job for them over time.

9. Concluding Discussion

We use data from 23 million individuals in more than 1,000 household surveys for 145 countries to show that there are significant differences in the returns to experience across dimensions within and between countries. We are particularly careful to test the robustness of these results by implementing methods that account for cohort, sorting and selection effects. While reallocating labor across subdimensions may increase aggregate returns in developing countries, it does little to bridge the gap in aggregate returns between developed and developed countries. Indeed, returns are significantly higher in richer countries, particularly so for manual occupations. Developed economies thus appear to serve their workers better at acquiring human capital at work. Cross-country regressions suggest that this may be due to the better quality of their political and economic institutions as well as technologies and values that may reduce labor market frictions. Finally, our results should be taken with caution because the estimated aggregate and dimension-specific returns, and the effects of the country-level factors, are not necessarily causal. Future work should thus keep investigating how to account for cohort, sorting and selection effects, not just for one country at a time. Likewise, more detailed analysis of the mechanisms by which developed country workers accumulate human capital at work are warranted.

REFERENCES

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

Ades, Alberto F. and Edward L. Glaeser, "Trade and Circuses: Explaining Urban Giants," *The Quarterly Journal of Economics*, 1995, *110* (1), 195–227.

aglar zden, Michael Packard, and Mathis Wagner, "International Migration and Wages," *Revue d'conomie du dveloppement*, 2017, *25* (3), 93–133.

Almeida, Rita K. and Emanuela Galasso, "Jump-starting Self-employment? Evidence for Welfare Participants in Argentina," *World Development*, May 2010, *38* (5), 742–755.

Altonji, Joseph G. and Charles R. Pierret, "Employer Learning and Statistical Discrimination," *The Quarterly Journal of Economics*, 2001, *116* (1), 313–350.

Alvarez, Jorge, "The Agricultural Wage Gap: Evidence from Brazilian Micro-data," Technical Report 2017.

Amodio, Francesco and Michele Di Maio, "Making Do With What You Have: Conflict, Input Misallocation and Firm Performance," *The Economic Journal*, 2017.

Arias, O., I. Santos, and D.K. Evans, *The Skills Balancing Act in Sub-Saharan Africa: Investing in Skills for Productivity, Inclusivity, and Adaptability* Africa Development Forum, World Bank Publications, 2019.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn, "Revisiting the risk of automation," *Economics Letters*, 2017, *159*, 157 – 160.

Ashworth, Jared, V. Joseph Hotz, Arnaud Maurel, and Tyler Ransom, "Changes across Cohorts in Wage Returns to Schooling and Early Work Experiences," Working Paper 24160, National Bureau of Economic Research December 2017.

Asker, John, Allan Collard-Wexler, and Jan De Loecker, "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy*, 2014, *122* (5), 1013–1063.

Attanasio, Orazio, Adriana Kugler, and Costas Meghir, "Subsidizing Vocational Training for Disadvantaged Youth in Colombia: Evidence from a Randomized Trial," *American Economic Journal: Applied Economics*, July 2011, *3* (3), 188–220.

__ , Arlen Guarn, Carlos Medina, and Costas Meghir, "Vocational Training for Disadvantaged Youth in Colombia: A Long-Term Follow-Up," *American Economic Journal: Applied Economics*, April 2017, *9* (2), 131–143.

Au, Chun-Chung and J. Vernon Henderson, "How migration restrictions limit agglomeration and productivity in China," *Journal of Development Economics*, August 2006, *80* (2), 350–388.

Ayerst, Stephen, Loren Brandt, and Diego Restuccia, "Market Constraints, Misallocation, and Productivity in Vietnam Agriculture," 2018. Copyright - Copyright Federal Reserve Bank of St Louis 2018; Last updated - 2018-08-26.

Banerjee, Abhijit V. and Esther Duflo, "Chapter 7 Growth Theory through the Lens of Development Economics," in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Amsterdam: Elsevier Science, 2005, pp. 473 – 552.

__ and __ , "Growth Theory through the Lens of Development Economics," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1 of *Handbook of Economic Growth*, Elsevier, July 2005, chapter 7, pp. 473–552.

Bank, World, *World Development Report 2019: The Changing Nature of Work* World Development Report, World Bank Publications, 2018.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta, "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, February 2013, *103* (1), 305–34.

Baum-Snow, Nathaniel and Ronni Pavan, "Understanding the City Size Wage Gap," *The Review of Economic Studies*, 2012, *79* (1), 88–127.

__ and __ , "Understanding the City Size Wage Gap," *The Review of Economic Studies*, January 2012, *79* (1), 88–127.

Beaudry, Paul and Ethan Lewis, "Do Male-Female Wage Differentials Reflect Differences in the Return to Skill? Cross-City Evidence from 1980-2000," *American Economic Journal: Applied Economics*, April 2014, *6* (2), 178–94.

Becker, Gary S., "Investment in Human Capital: A Theoretical Analysis," *Journal of Political Economy*, 1962, *70*, 1–9.

Beegle, Kathleen, Emanuela Galasso, and Jessica Goldberg, "Direct and indirect effects of Malawi's public works program on food security," *Journal of Development Economics*, 2017, *128* (C), 1–23.

Behrens, Kristian, Gilles Duranton, and Frédéric Robert-Nicoud, "Productive Cities: Sorting, Selection, and

Agglomeration," *Journal of Political Economy*, 2014, *122* (3), 507–553.

Behrman, Jere R., Barbara L. Wolfe, and David M. Blau, "Human Capital and Earnings Distribution in a Developing Country: The Case of Prerevolutionary Nicaragua," *Economic Development and Cultural Change*, 1985, *34* (1), 1–29.

Belfield, Clive R, Milagros Nores, Steve Barnett, and Lawrence Schweinhart, "The High/Scope Perry Preschool Program: Cost-Benefit Analysis Using Data from the Age-40 Followup," *Journal of Human Resources*, 2006, *41* (1).

Bento, Pedro and Diego Restuccia, "Misallocation, Establishment Size, and Productivity," *American Economic Journal: Macroeconomics*, July 2017, *9* (3), 267–303.

Berg, Erlend, Sambit Bhattacharyya, D. Rajasekhar, and R. Manjula, "Can public works increase equilibrium wages? Evidence from India's National Rural Employment Guarantee," *World Development*, 2018, *103* (C), 239–254.

Berhane, Guush, Daniel Gilligan, John Hoddinott, Neha Kumar, and Alemayehu Taffesse, "Can Social Protection Work in Africa? The Impact of Ethiopia's Productive Safety Net Programme," *Economic Development and Cultural Change*, 2014, *63* (1), 1 – 26.

Bernal, Maria Laura Snchez Puerta Alexandria Valerio Marcela Gutirrez, *Taking Stock of Programs to Develop Socioemotional Skills: A Systematic Review of Program Evidence*, The World Bank, 2016.

Berry, Christopher R. and Edward L. Glaeser, "The divergence of human capital levels across cities*," *Papers in Regional Science*, 2005, *84* (3), 407–444.

Besley, Timothy and Hannes Mueller, "Predation, Protection, and Productivity: A Firm-Level Perspective," *American Economic Journal: Macroeconomics*, April 2018, *10* (2), 184–221.

Bhuller, Manudeep, Magne Mogstad, and Kjell G. Salvanes, "Life-Cycle Earnings, Education Premiums, and Internal Rates of Return," *Journal of Labor Economics*, 2017, *35* (4), 993–1030.

Bigsten, Arne, Anders Isaksson, Måns Söderbom, Paul Collier, Albert Zeufack, Stefan Dercon, Marcel Fafchamps, Jan Willem Gunning, Francis Teal, Simon Appleton, Bernard Gauthier, Abena Oduro, Remco Oostendorp, and Cathy Pattillo, "Rates of Return on Physical and Human Capital in Africa's Manufacturing Sector," *Economic Development and Cultural Change*, 2000, *48* (4), 801–827.

Bilal, Adrien and Esteban Rossi-Hansberg, "Location as an Asset," NBER Working Papers 24867, National Bureau of Economic Research, Inc July 2018.

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

Björklund, Anders and Christian Kjellström, "Estimating the return to investments in education: how useful is the standard Mincer equation?," *Economics of Education Review*, 2002, *21* (3), 195 – 210.

Bolt, Jutta and Jan Luiten van Zanden, "The Maddison Project: collaborative research on historical national accounts," *Economic History Review*, 2014, *67* (3), 627–651.

Bonjour, Dorothe, Lynn F. Cherkas, Jonathan E. Haskel, Denise D. Hawkes, and Tim D. Spector, "Returns to Education: Evidence from U.K. Twins," *American Economic Review*, December 2003, *93* (5), 1799–1812.

Borghans, Lex, Angela Lee Duckworth, James Heckman, and Bas ter Weel, "The Economics and Psychology of Personality Traits," *Journal of Human Resources*, 2008, *43* (4).

Bosquet, Clment and Henry G. Overman, "Why does birthplace matter so much?," *Journal of Urban Economics*, 2019, *110* (C), 26–34.

Braga, Breno, "Earnings dynamics: The role of education throughout a worker's career," *Labour Economics*, 2018, *52*, 83 – 97.

Bryan, Gharad and Melanie Morten, "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia," *Journal of Political Economy*, 2019, *0* (0), 000–000.

—, Shyamal Chowdhury, and Ahmed Mushfiq Mobarak, "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, September 2014, *82* (5), 1671–1748.

Caggese, Andrea, Vicente Cuñat, and Daniel Metzger, "Firing the wrong workers: Financing constraints and labor misallocation," *Journal of Financial Economics*, 2018.

Card, David, "The causal effect of education on earnings," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, Vol. 3 of *Handbook of Labor Economics*, Elsevier, May 1999, chapter 30, pp. 1801–1863.

—, Jochen Kluve, and Andrea Weber, "What Works? A Meta Analysis of Recent Active Labor Market Program Evaluations," *Journal of the European Economic Association*, 2018, *16* (3), 894–931.

Carlsen, Fredrik, Jorn Rattso, and Hildegunn Stokke, "Education, experience and dynamic urban wage premium," Working Paper Series, Department of Economics, Norwegian University of Science and Technology 2013.

Carneiro, Pedro, Claire Crawford, and Alissa Goodman, "The Impact of Early Cognitive and Non-Cognitive

Skills on Later Outcomes," CEE Discussion Papers 0092, Centre for the Economics of Education, LSE October 2007.

Caselli, Francesco, Jacopo Ponticelli, and Federico Rossi, *A new dataset on mincerian returns*, Princeton: Princeton University Press,

Cawley, John, James Heckman, and Edward Vytlacil, "Three observations on wages and measured cognitive ability," *Labour Economics*, 2001, *8* (4), 419–442.

Chang-Tai, Hsieh and Peter J. Klenow, "The Reallocation Myth," 2018. Copyright - Copyright Federal Reserve Bank of St Louis 2018; Last updated - 2018-06-26.

Chauvin, Juan Pablo, Edward Glaeser, Yueran Ma, and Kristina Tobio, "What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States," *Journal of Urban Economics*, 2017, *98*, 17 – 49. Urbanization in Developing Countries: Past and Present.

Chen, Chaoran, "Untitled Land, Occupational Choice, and Agricultural Productivity," *American Economic Journal: Macroeconomics*, October 2017, *9* (4), 91–121.

Cho, Yoon Y. and Ummul Ruthbah, "Does Workfare Work Well? The Case of the Employment Generation Program for the Poorest in Bangladesh," IZA Discussion Papers 11473, Institute of Labor Economics (IZA) April 2018.

Cho, Yoonyoung and Maddalena Honorati, "Entrepreneurship programs in developing countries: A meta regression analysis," *Labour Economics*, 2014, *28* (C), 110–130.

Cohn, Elchanan and John T. Addison, "The Economic Returns to Lifelong Learning in OECD Countries," *Education Economics*, 1998, *6* (3), 253–307.

Collard-Wexler, Allan and Jan De Loecker, "Reallocation and Technology: Evidence from the US Steel Industry," *American Economic Review*, January 2015, *105* (1), 131–71.

Combes, Pierre-Philippe and Laurent Gobillon, "The Empirics of Agglomeration Economies," in "in," Vol. 5, Elsevier, 2015, chapter Chapter 5, pp. 247–348.

— , Gilles Duranton, and Laurent Gobillon, "Spatial wage disparities: Sorting matters!," *Journal of Urban Economics*, 2008, *63* (2), 723 – 742.

— , — , — , and Sbastien Roux, "Sorting and local wage and skill distributions in France," *Regional Science and Urban Economics*, 2012, *42* (6), 913 – 930. special issue In honor of Jacques Thisse.

— , — , — , Diego Puga, and Sébastien Roux, "The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection," *Econometrica*, November 2012, *80* (6), 2543–2594.

— , — , — , — , and Sïbastien Roux, "The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection," *Econometrica*, November 2012, *80* (6), 2543–2594.

— , Sylvie Demurger, and Shi Li, "Productivity gains from agglomeration and migration in Chinese cities over 2002-2013," Technical Report 2017.

Costa, Paul and Robert R. McCrae, "Age changes in personality and their origins: Comment on Roberts, Walton, and Viechtbauer (2006)," *Psychological Bulletin*, 1 2006, *132* (1), 26–28.

Crpon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora, "Do Labor Market Policies have Displacement Effects? Evidence from a Clustered Randomized Experiment," *The Quarterly Journal of Economics*, 2013, *128* (2), 531–580.

Cunha, Flavio, James J. Heckman, and Lance Lochner, *Interpreting the Evidence on Life Cycle Skill Formation*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, June

D'Costa, Sabine and Henry G. Overman, "The urban wage growth premium: Sorting or learning?," *Regional Science and Urban Economics*, 2014, *48*, 168 – 179.

de Hoyos, Rafael, John Kennan, and Rebecca Lessem, "Returns to Investments in Human Capital, within and across Countries," 2015. Mimeo.

Deaton, Angus, *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy.*, Washington, DC: World Bank., 1997.

Dias, Daniel A., Carlos Robalo Marques, and Christine Richmond, "Misallocation and productivity in the lead up to the Eurozone crisis," *Journal of Macroeconomics*, 2016, *49*, 46 – 70.

Dower, Paul Castaneda and Andrei Markevich, "Labor Misallocation and Mass Mobilization: Russian Agriculture during the Great War," *Review of Economics and Statistics*, May 2018, *100* (2), 245–259.

Duflo, Esther, "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," *American Economic Review*, September 2001, *91* (4), 795–813.

Duhigg, C., *The Power of Habit: Why We Do What We Do in Life and Business* Concentrated Knowledge for the Busy Executive, Random House Publishing Group, 2012.

Duranton, Gilles, "Agglomeration Effects In Colombia," *Journal of Regional Science*, 03 2016, *56* (2), 210–238.

— and Diego Puga, "Micro-foundations of urban agglomeration economies," in J. V. Henderson and J. F.

Thisse, eds., *Handbook of Regional and Urban Economics*, Vol. 4, Elsevier, 2004, chapter 48, pp. 2063–2117.

— , Ejaz Ghani, Arti Grover Goswami, and William R. Kerr, *Effects of Land Misallocation on Capital Allocations in India*, The World Bank, 2015.

Durlak, Joseph A., Roger P. Weissberg, Allison B. Dymnicki, Rebecca D. Taylor, and Kriston B. Schellinger, "The Impact of Enhancing Students' Social and Emotional Learning: A Meta-Analysis of School-Based Universal Interventions," *Child Development*, 2011, *82* (1), 405–432.

Dutta, Puja, Rinku Murgai, Martin Ravallion, and Dominique van de Walle, *Right to Work? Assessing India's Employment Guarantee Scheme in Bihar* number 17195. In 'World Bank Publications.', The World Bank, 2014.

Eckert, Fabian, Conor Walsh, and Mads Hejlesen, "The Return to Big City Experience: Evidence from Danish Refugees," in "2018 Meeting Papers" number 1214 Society for Economic Dynamics 2018.

Eeckhout, Jan, Roberto Pinheiro, and Kurt Schmidheiny, "Spatial Sorting," *Journal of Political Economy*, 2014, *122* (3), 554 – 620.

Engbom, Niklas, "Worker Flows and Wage Growth over the Life-Cycle: A Cross-Country Analysis," May 2017.

Farber, Henry S. and Robert Gibbons, "Learning and Wage Dynamics," *The Quarterly Journal of Economics*, 1996, *111* (4), 1007–1047.

Fu, Shihe and Stephen L. Ross, "Wage Premia in Employment Clusters: How Important Is Worker Heterogeneity?," *Journal of Labor Economics*, April 2013, *31* (2), 271–304.

Garcia, Jorge Luis, James Heckman, Duncan Ermini Leaf, and Mara Jos Prados, "The Life-cycle Benefits of an Influential Early Childhood Program," NBER Working Papers 22993, National Bureau of Economic Research, Inc 2016.

Gertler, Paul, James Heckman, Rodrigo Pinto, Arianna Zanolini, Christel Vermeersch, Susan Walker, Susan M. Chang, and Sally Grantham-McGregor, "Labor market returns to an early childhood stimulation intervention in Jamaica," *Science*, 2014, *344* (6187), 998–1001.

Gilligan, Daniel, John Hoddinott, and Alemayehu Taffesse, "The Impact of Ethiopia's Productive Safety Net Programme and its Linkages," *Journal of Development Studies*, 2009, *45* (10), 1684–1706.

Gindling, T. H., Nadwa Mossaad, and David Newhouse, "How Large are Earnings Penalties for Self-Employed and Informal Wage Workers?," *IZA Journal of Labor & Development*, Dec 2016, *5* (1), 20.

— , — , and — , "How Large are Earnings Penalties for Self-Employed and Informal Wage Workers?," *IZA Journal of Labor & Development*, December 2016, *5* (1), 1–39.

Gindling, T.H. and David Newhouse, "Self-Employment in the Developing World," *World Development*, 2014, *56*, 313 – 331.

— and — , "Self-Employment in the Developing World," *World Development*, 2014, *56* (C), 313–331.

Glaeser, Edward L., *Triumph of the City: How Our Greatest Invention Makes Us Richer, Smarter, Greener, Healthier, and Happier.*, New York: Penguin Press, 2011.

— and David C. Maré, "Cities and Skills," *Journal of Labor Economics*, 2001, *19* (2), 316–342.

— and Joshua D. Gottlieb, "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States," *Journal of Economic Literature*, December 2009, *47* (4), 983–1028.

Glaeser, Edward L, Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer, "Growth in Cities," *Journal of Political Economy*, December 1992, *100* (6), 1126–52.

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

— , Martina Kirchberger, and David Lagakos, "In Search of a Spatial Equilibrium in the Developing World," CEPR Discussion Papers 12114, C.E.P.R. Discussion Papers June 2017.

Gopinath, Gita, Şebnem Kalemli-Özcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, "Capital Allocation and Productivity in South Europe," *The Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Grogger, Jeffrey, "Welfare Reform, Returns to Experience, and Wages: Using Reservation Wages to Account for Sample Selection Bias," *The Review of Economics and Statistics*, August 2009, *91* (3), 490–502.

Guner, Nezih, Andrii Parkhomenko, and Gustavo Ventura, "Managers and productivity differences," *Review of Economic Dynamics*, 2018, *29*, 256 – 282.

Hall, R. E., "Technical Change and Capital from the Point of View of the Dual," *The Review of Economic Studies*, 1968, *35* (1), 35–46.

Haltiwanger, John, Robert Kulick, and Chad Syverson, "Misallocation Measures: The Distortion That Ate the Residual," Working Paper 24199, National Bureau of Economic Research January 2018.

Hayashi, Fumio and Edward C. Prescott, "The Depressing Effect of Agricultural Institutions on the Prewar Japanese Economy," *Journal of Political Economy*, August 2008, *116* (4), 573–632.

Heckman, James and Pedro Carneiro, "Human Capital Policy," NBER Working Papers 9495, National Bureau of Economic Research, Inc February 2003.

— and Richard Robb, "Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations," in W.M. Mason and S.E. Fienberg S.E., eds., *Cohort Analysis in Social Research*, Springer, New York, NY, 1985, pp. 137–150.

— and Tim Kautz, "Hard evidence on soft skills," *Labour Economics*, 2012, *19* (4), 451–464.

Heckman, James J., "Skill Formation and the Economics of Investing in Disadvantaged Children," *Science*, 2006, *312* (5782), 1900–1902.

— and V. Joseph Hotz, "An Investigation of the Labor Market Earnings of Panamanian Males Evaluating the Sources of Inequality," *The Journal of Human Resources*, 1986, *21* (4), 507–542.

— , Lance J. Lochner, and Petra E. Todd, "Chapter 7 Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond," in E. Hanushek and F. Welch, eds., *Handbook of the Economics of Education*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, 2006, pp. 307 – 458.

— , — , and — , *Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, June

Heckman, James J, Lance Lochner, and Christopher Taber, "Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents," *The Review of Economic Dynamics*, 1998, *1*, 1–58.

— , — , and — , "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1* (1), 1 – 58.

Heckman, James J., Seong Hyeok Moon, Rodrigo Pinto, Peter A. Savelyev, and Adam Yavitz, "The rate of return to the HighScope Perry Preschool Program," *Journal of Public Economics*, February 2010, *94* (1-2), 114–128.

Heckman, James, John Humphries, and Gregory Veramendi, "Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking," *Journal of Political Economy*, 2018, *126* (S1), S197 – S246.

— , Jora Stixrud, and Sergio Urzua, "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 2006, *24* (3), 411–482.

— , Rodrigo Pinto, and Peter Savelyev, "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes," *American Economic Review*, October 2013, *103* (6), 2052–2086.

Heineck, Guido and Silke Anger, "The returns to cognitive abilities and personality traits in Germany," *Labour Economics*, June 2010, *17* (3), 535–546.

Heise, Sebastian and Tommaso Porzio, "Why Do Spatial Wage Gaps Persist? Evidence from the Enduring Divide between East and West Germany," *mimeo*, 2018.

Hendel, Igal and Yossi Spiegel, "Small Steps for Workers, a Giant Leap for Productivity," *American Economic Journal: Applied Economics*, January 2014, *6* (1), 73–90.

Henderson, Vernon, Ari Kuncoro, and Matt Turner, "Industrial Development in Cities," *Journal of Political Economy*, October 1995, *103* (5), 1067–1090.

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

— , "A database of Mincerian earnings regressions," 2004.

Herrendorf, Berthold and Todd Schoellman, "Wages, Human Capital, and Barriers to Structural Transformation," *American Economic Journal: Macroeconomics*, April 2018, *10* (2), 1–23.

— and — , "Wages, Human Capital, and Barriers to Structural Transformation," *American Economic Journal: Macroeconomics*, April 2018, *10* (2), 1–23.

Hicks, Joan Hamory, Marieke Kleemans, Nicholas Y Li, and Edward Miguel, "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata," Working Paper 23253, National Bureau of Economic Research March 2017.

Hirshleifer, Sarojini, David McKenzie, Rita Almeida, and Cristobal Ridao?Cano, "The Impact of Vocational Training for the Unemployed: Experimental Evidence from Turkey," *Economic Journal*, November 2016, *126* (597), 2115–2146.

Hoddinott, John, Guush Berhane, Daniel O. Gilligan, Neha Kumar, and Alemayehu Seyoum Taffesse, "The Impact of Ethiopia's Productive Safety Net Programme and Related Transfers on Agricultural Productivity," *Journal of African Economies*, November 2012, *21* (5), –786.

Hoque, Mohammad Mainul, Elizabeth M. King, Claudio E. Montenegro, and Peter F. Orazem, "Revisiting the relationship between longevity and lifetime education: global evidence from 919 surveys," *Journal of Population Economics*, April 2019, *32* (2), 551–589.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *The*

Quarterly Journal of Economics, 2009, *124* (4), 1403–1448.

Ibarraran, Pablo, Laura Ripani, Bibiana Taboada, Juan Villa, and Brigida Garcia, "Life skills, employability and training for disadvantaged youth: Evidence from a randomized evaluation design," *IZA Journal of Labor & Development*, December 2014, *3* (1), 1–24.

Imbert, Clment and John Papp, "Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee," *American Economic Journal: Applied Economics*, April 2015, *7* (2), 233–263.

International Labour Organization, *Ilostat* 2018.

International Monetary Fund, *World Economic Outlook Databse* 2018.

Islam, Asif, Remi Jedwab, and Paul Romer, "Human Capital Accumulation at Work: Estimates for theWorld and Implications for Growth," Mimeo 2019.

—, —, —, and Daniel Pereira, "Returns to Experience and the Sectoral and Spatial Allocation of Labor," Mimeo 2019.

Jeong, Hyeok, Yong Kim, and Iourii Manovskii, "The Price of Experience," *American Economic Review*, February 2015, *105* (2), 784–815.

Kautz, Tim, James J. Heckman, Ron Diris, Bas ter Weel, and Lex Borghans, "Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success," NBER Working Papers 20749, National Bureau of Economic Research, Inc December 2014.

Kerr, Gilles Duranton Ejaz Ghani Arti Grover Goswami William R., *Effects of Land Misallocation on Capital Allocations in India*, The World Bank, 2015.

King, Elizabeth M., Claudio E. Montenegro, and Peter F. Orazem, "Economic Freedom, Human Rights, and the Returns to Human Capital: An Evaluation of the Schultz Hypothesis," *Economic Development and Cultural Change*, 2012, *61* (1), 39–72.

—, —, and —, "Economic Freedom, Human Rights, and the Returns to Human Capital: An Evaluation of the Schultz Hypothesis," *Economic Development and Cultural Change*, 2012, *61* (1), 39–72.

Knudsen, Eric I., James J. Heckman, Judy L. Cameron, and Jack P. Shonkoff, "Economic, neurobiological, and behavioral perspectives on building America's future workforce," *Proceedings of the National Academy of Sciences*, 2006, *103* (27), 10155–10162.

Krueger, Alan B and Jorn-Steffen Pischke, "A comparative analysis of East and West German labor markets: before and after unification," in "Differences and changes in wage structures," University of Chicago Press, 1995, pp. 405–446.

la Roca, Jorge De, "Selection in initial and return migration: Evidence from moves across Spanish cities," *Journal of Urban Economics*, 2017, *100*, 33 – 53.

—, Gianmarco I. P. Ottaviano, and Diego Puga, "City of Dreams," Working Papers wp2016 1609, CEMFI December 2016.

Lagakos, David and Michael E. Waugh, "Selection, Agriculture, and Cross-Country Productivity Differences," *American Economic Review*, April 2013, *103* (2), 948–80.

—, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

—, —, —, —, and —, "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

—, —, —, —, and —, "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

Lassibille, Gérard, "Wage gaps Between the public and private sectors in Spain," *Economics of Education Review*, 1998, *17* (1), 83 – 92.

laura Alza, Mara, Guillermo Cruces, and Carolina Lopez, "Long-Run Effects Of Youth Training Programs: Experimental Evidence From Argentina," *Economic Inquiry*, October 2016, *54* (4), 1839–1859.

Lemieux, Thomas, "The "Mincer Equation" Thirty Years After Schooling, Experience, and Earnings," in Shoshana Grossbard, ed., *Jacob Mincer A Pioneer of Modern Labor Economics*, Boston, MA: Springer US, 2006, chapter 11, pp. 127–145.

Levitt, Steven D., John A. List, and Chad Syverson, "Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant," *Journal of Political Economy*, August 2013, *121* (4), 643–681.

Li, Hongbin, Pak Wai Liu, and Junsen Zhang, "Estimating returns to education using twins in urban China," *Journal of Development Economics*, 2012, *97* (2), 494–504.

Limam, Imed and Abdelwahab Ben Hafaiedh, "Education, Earnings and Returns to Schooling in Tunisia," Working Papers 1162, Economic Research Forum June 2017.

Maddison, Angus, *Statistics on World Population, GDP and Per Capita GDP, 1-2008 AD* 2008.

Maitra, Pushkar and Subha Mani, "Learning and earning: Evidence from a randomized evaluation in India," *Labour Economics*, 2017, *45* (C), 116–130.

Mark, William Darity Jr. Paul and Darrick Hamilton, "Why we Need a Federal Job Guarantee," Jacobin 2017.

McCaig, Brian and Nina Pavcnik, "Export Markets and Labor Allocation in a Low-Income Country," *American Economic Review*, July 2018, *108* (7), 1899–1941.

McCrae, R.R. and P.T. Costa, *Personality in Adulthood: A Five-factor Theory Perspective* EBL-Schweitzer, Guilford Publications, 2003.

McKenzie, David, "How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence," *World Bank Research Observer*, 2017, *32* (2), 127–154.

McMillan, Margaret, Dani Rodrik, and Íñigo Verduzco-Gallo, "Globalization, Structural Change, and Productivity Growth, with an Update on Africa," *World Development*, 2014, *63*, 11 – 32. Economic Transformation in Africa.

Meghir, Costas, Renata Narita, and Jean-Marc Robin, "Wages and Informality in Developing Countries," *American Economic Review*, April 2015, *105* (4), 1509–46.

Midrigan, Virgiliu and Daniel Yi Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, February 2014, *104* (2), 422–58.

Mincer, Jacob A, "Schooling and earnings," in "Schooling, experience, and earnings," NBER, 1974, pp. 41–63.

Mion, Giordano and Paolo Naticchioni, "The spatial sorting and matching of skills and firms," *Canadian Journal of Economics/Revue canadienne d'économique*, January 2009, *42* (1), 28–55.

Montenegro, Claudio E. and Harry Anthony Patrinos, "Comparable Estimates of Returns to Schooling around the World," Working Paper 7020, The World Bank September 2014.

Mueller, Gerrit and Erik Plug, "Estimating the Effect of Personality on Male and Female Earnings," *ILR Review*, 2006, *60* (1), 3–22.

Muller, Wendy Cunningham Pablo Acosta Nol, *Minds and Behaviors at Work: Boosting Socioemotional Skills for Latin America's Workforce*, The World Bank, 2016.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar, "General Equilibrium Effects of (Improving) Public Employment Programs: Experimental Evidence from India," NBER Working Papers 23838, National Bureau of Economic Research, Inc September 2017.

Murgai, Rinku, Martin Ravallion, and Dominique van de Walle, "Is Workfare Cost-effective against Poverty in a Poor Labor-Surplus Economy?," *World Bank Economic Review*, 2016, *30* (3), 413–445.

Ngai, L. R., Christopher A. Pissarides, and Jin Wang, "China's Mobility Barriers and Employment Allocations," 2018. Copyright - Copyright Federal Reserve Bank of St Louis 2018; Last updated - 2018-06-26.

Nordman, Christophe J. and François-Charles Wolff, "On-the-job learning and earnings: Comparative evidence from Morocco and Senegal," 2009. Copyright - Copyright FEDERAL RESERVE BANK OF ST LOUIS 2009; Last updated - 2015-10-03.

Olivetti, Claudia, "Changes in Women's Hours of Market Work: The Role of Returns to Experience," *Review of Economic Dynamics*, 2006, *9* (4), 557–587.

Olley, G. Steven and Ariel Pakes, "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Osborne, Melissa, Herbert Gintis, and Samuel Bowles, "The Determinants of Earnings: A Behavioral Approach," *Journal of Economic Literature*, December 2001, *39* (4), 1137–1176.

Osikominu, Aderonke, "Quick Job Entry or Long-Term Human Capital Development? The Dynamic Effects of Alternative Training Schemes," *Review of Economic Studies*, 2013, *80* (1), 313–342.

Papageorgiou, Theodore, "Worker sorting and agglomeration economies," *mimeo*, 2017.

Patrinos, Harry and Maria Paula Savanti, "The Screening Hypothesis and the Returns to Schooling in Argentina," *Research in Applied Economics*, 08 2014, *6*, 28.

Payton, John, Roger P. Weissberg, Joseph A. Durlak, Allison B. Dymnicki, Rebecca D. Taylor, Kriston B. Schellinger, Molly Pachan, Roger P. Weissberg, Phd Joseph, and A. Durlak, "The positive impact of social and emotional learning for kindergarten to eighth-grade students: Findings from three scientific reviews. Chicago, IL: Collaborative for Academic, Social, and Emotional Learning," 2008.

Peet, Evan D., Gnther Fink, and Wafaie Fawzi, "Returns to education in developing countries: Evidence from the living standards and measurement study surveys," *Economics of Education Review*, 2015, *49* (C), 69–90.

Polachek, Solomon, "Earnings Over the Life Cycle: The Mincer Earnings Function and Its Applications," *Foundations and Trends(R) in Microeconomics*, 2008, *4* (3), 165–272.

Polachek, Solomon W., "Earnings Over the Life Cycle: The Mincer Earnings Function and Its Applications," *Foundations and Trends® in Microeconomics*, April 2008, *4* (3), 165–272.

Porzio, Tommaso, "Distance to the Technology Frontier and the Allocation of Talent," Technical Report 2016.

Psacharopoulos, George, "Returns to investment in education: A global update," *World Development*, 1994, *22* (9), 1325 – 1343.

— and Harry Anthony Patrinos, "Returns to investment in education: a further update," *Education Economics*, 2004, *12* (2), 111–134.

— and — , "Returns to investment in education: a decennial review of the global literature," *Education Economics*, June 2018, *26* (5), 445–458.

— and — , "Returns to investment in education: a decennial review of the global literature," *Education Economics*, September 2018, *26* (5), 445–458.

Puga, Diego, "The Magnitude and Causes of Agglomeration Economies," *Journal of Regional Science*, February 2010, *50* (1), 203–219.

— , "The changing distribution of firms and workers across cities," Development Working Papers 418, Centro Studi Luca d'Agliano, University of Milano February 2017.

Quintero, Luis and Mark Roberts, "Explaining spatial variations in productivity: evidence from Latin America and the Caribbean," Policy Research Working Paper Series 8560, The World Bank 2018.

Ravallion, Martin, "Guaranteed employment or guaranteed income?," *World Development*, 2019, *115* (C), 209–221.

Restuccia, Diego and Richard Rogerson, "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic Dynamics*, October 2008, *11* (4), 707 – 720.

— and — , "The Causes and Costs of Misallocation," *Journal of Economic Perspectives*, August 2017, *31* (3), 151–74.

Roca, Jorge De La and Diego Puga, "Learning by Working in Big Cities," *The Review of Economic Studies*, 2017, *84* (1), 106–142.

Rolnick, Art and Rob Grunewald, "Early Childhood Development: Economic Development with a High Public Return. Minneapolis, MN: Federal Reserve Bank of Minneapolis," 2003.

Rosenthal, Stuart and William Strange, "Evidence on the nature and sources of agglomeration economies," in J. V. Henderson and J. F. Thisse, eds., *Handbook of Regional and Urban Economics*, 1 ed., Vol. 4, Elsevier, 2004, chapter 49, pp. 2119–2171.

Rosenthal, Stuart S. and William C. Strange, "Chapter 49 - Evidence on the Nature and Sources of Agglomeration Economies," in J. Vernon Henderson and Jacques-François Thisse, eds., *Cities and Geography*, Vol. 4 of *Handbook of Regional and Urban Economics*, Elsevier, 2004, pp. 2119 – 2171.

Rubinstein, Yona and Yoram Weiss, "Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning," in E. Hanushek and F. Welch, eds., *Handbook of the Economics of Education*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, 2006, pp. 1 – 67.

— and — , "Chapter 1 Post Schooling Wage Growth: Investment, Search and Learning," in E. Hanushek and F. Welch, eds., *E. Hanushek and F. Welch, eds.*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, 2006, pp. 1 – 67.

Shenoy, Ajay, "Market failures and misallocation," *Journal of Development Economics*, 2017, *128*, 65 – 80.

Sukhtankar, Sandip, "India's National Rural Employment Guarantee Scheme: What Do We Really Know about the World's Largest Workfare Program?," India Policy Forum 2017.

Tansel, Aysit, "PublicPrivate Employment Choice, Wage Differentials, and Gender in Turkey," *Economic Development and Cultural Change*, 2005, *53* (2), 453–477.

— and Fatma Bircan Bodur, "Wage Inequality and Returns to Education in Turkey: A Quantile Regression Analysis," *Review of Development Economics*, 2012, *16* (1), 107–121.

Unesco, *International Standard Classification of Education: ISCED 2011* 2012.

United Nations, *World Population Prospects: The 2018 Revision* 2018.

— , *World Urbanization Prospects: The 2018 Revision* 2018.

Vollrath, Dietrich, "How important are dual economy effects for aggregate productivity?," *Journal of Development Economics*, 2009, *88* (2), 325 – 334.

— , "The efficiency of human capital allocations in developing countries," *Journal of Development Economics*, 2014, *108*, 106 – 118.

Walsh, D.A. and N. Bennett, *Why Do They Act that Way?: A Survival Guide to the Adolescent Brain for You and Your Teen* Instant book club, Free Press, 2004.

Welzel, Christian, "Evolution, Empowerment, and Emancipation: How Societies Climb the Freedom Ladder," *World Development*, 2014, *64*, 33 – 51.

— , "Evolution, Empowerment, and Emancipation: How Societies Climb the Freedom Ladder," *World Development*, 2014, *64*, 33 – 51.

Wheeler, Christopher H., "Cities and the growth of wages among young workers: Evidence from the NLSY," *Journal of Urban Economics*, 2006, *60* (2), 162 – 184.

World Bank, *World Development Indicators* 2018.

—, *World Development Report: The Future of Work* 2018.

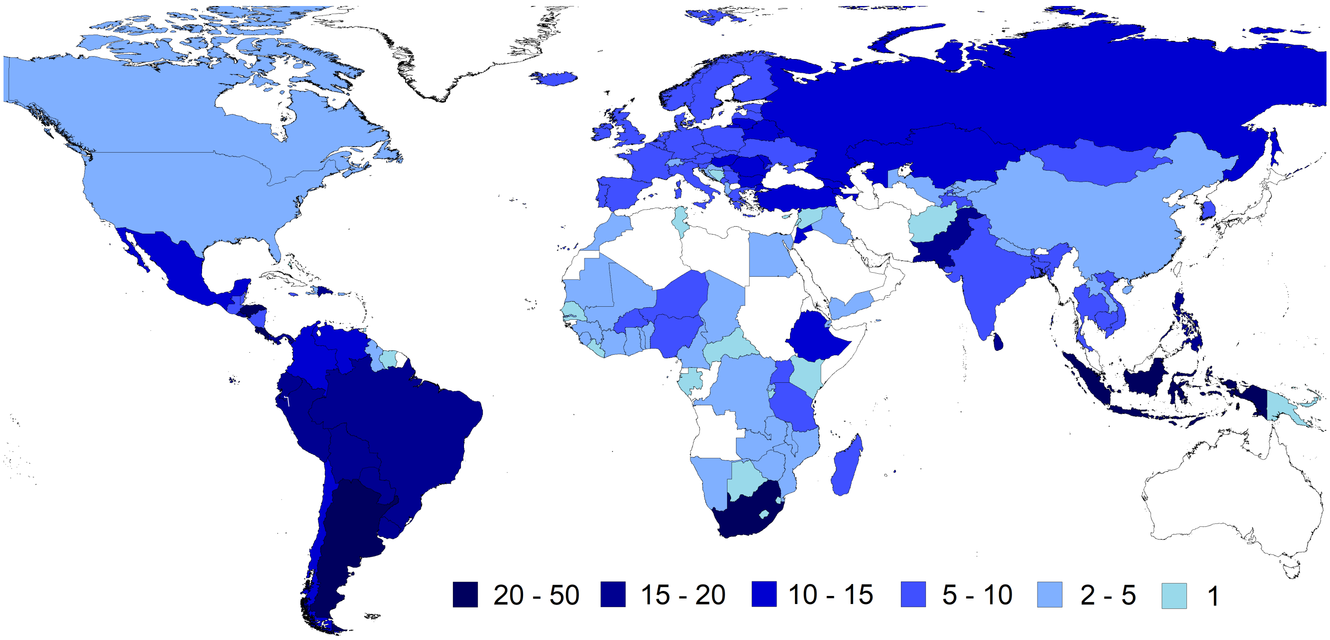
Yang, Dennis Tao, "Determinants of schooling returns during transition: Evidence from Chinese cities," *Journal of Comparative Economics*, 2005, *33* (2), 244 – 264. Returns to Schooling in Translation: The Chinese, European, and Russian Experiences.

Young, Alwyn, "Inequality, the Urban-Rural Gap, and Migration," *The Quarterly Journal of Economics*, 2013, *128* (4), 1727–1785.

—, "Structural Transformation, the Mismeasurement of Productivity Growth, and the Cost Disease of Services," *American Economic Review*, November 2014, *104* (11), 3635–67.

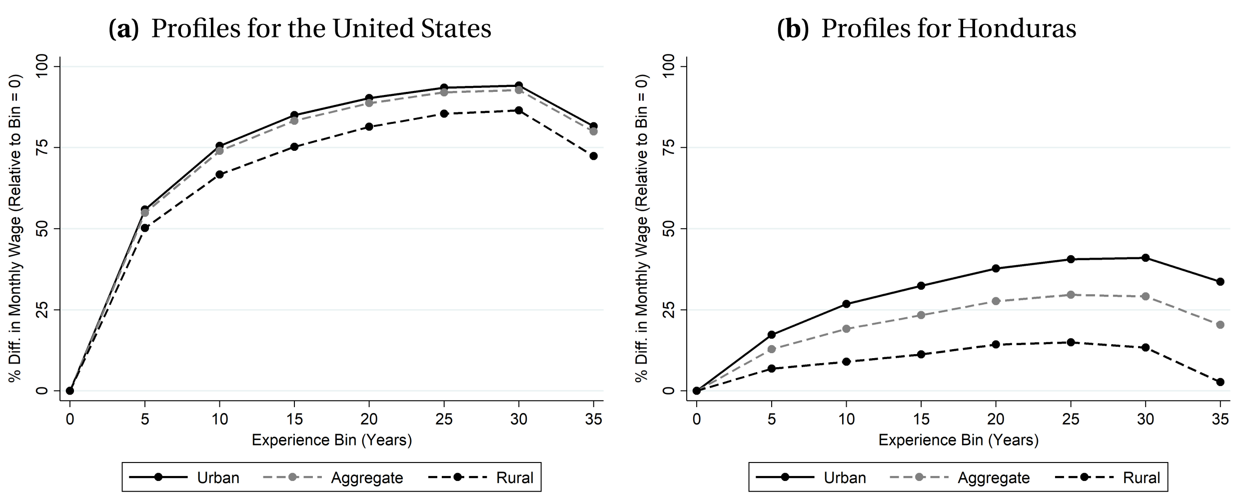
Zimmermann, Laura, "Why Guarantee Employment? Evidence from a Large Indian Public-Works Program," University of Georgia Working Paper 2014.

Figure 1: NUMBER OF SURVEY/CENSUS SAMPLES BY COUNTRY, 1990-2016



Notes: This figure shows the number of household and labor force surveys and population censuses used for each of the 145 countries with at least one survey or one census from 1990-2016 (median number of surveys/censuses per country in the sample = 6; mean = 7.5; min = 1; max = 44; N = 1,084).

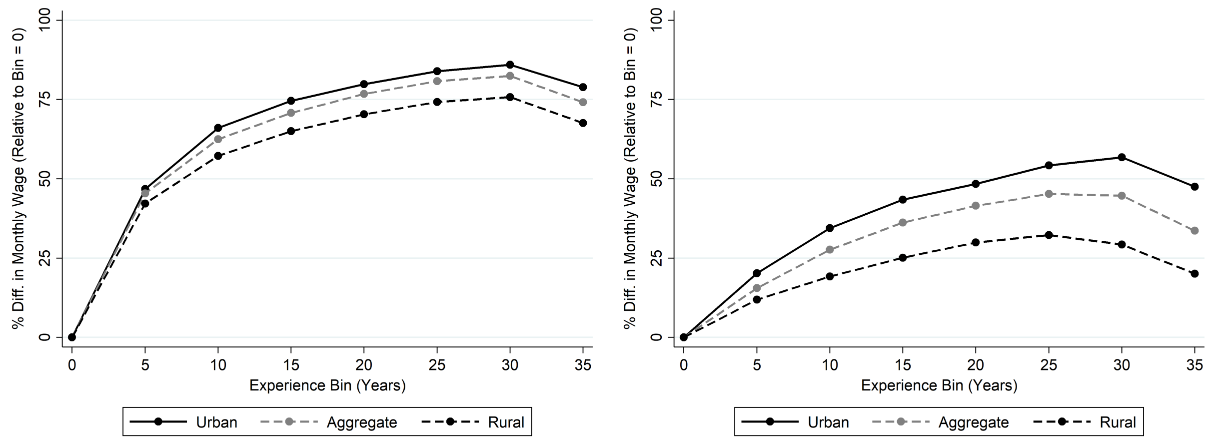
Figure 2: WAGE-EXPERIENCE PROFILES FOR THE U.S. VS. HONDURAS



Notes: The figure shows the wage differential for the seven experience bins ("5" for 5-9 years, ..., "30" for 30-34 years, "35" for 35-49 years) for rural areas, urban areas, and the whole economy of both the U.S. (Subfigures 2(a)) and Honduras (Subfigures 2(b)). The "0" experience bin (0-4 years) is the omitted group.

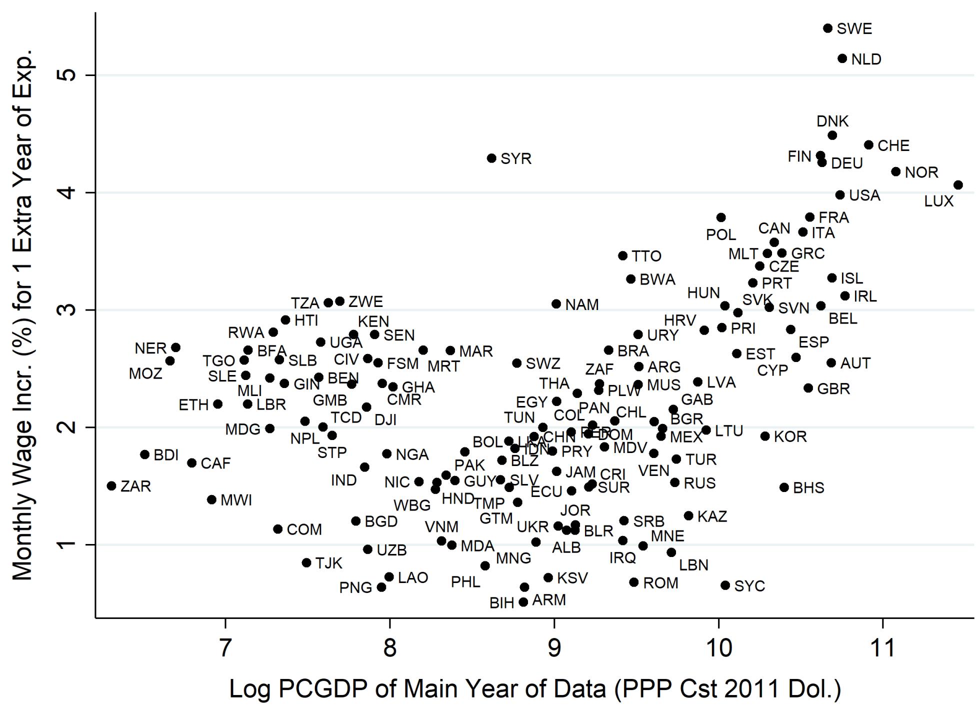
Figure 3: WAGE-EXPERIENCE PROFILES BY DEVELOPMENT STATUS

(a) Profiles for Developed Countries **(b)** Profiles for Developing Countries



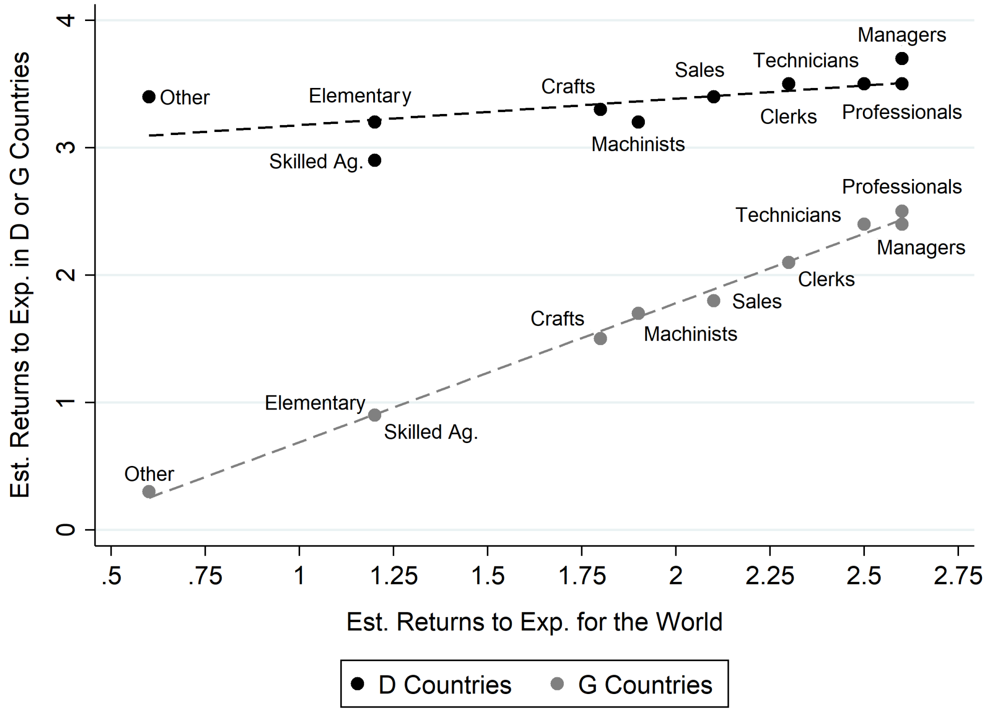
Notes: The figure shows the average (population-weighted) wage differential for the seven experience bins ("5" for 5-9 years, ..., "30" for 30-34 years, "35" for 35-49 years) for rural areas, urban areas, and the whole economy of both developed countries (Subfigures 3(a)) and developing countries (Subfigures 3(b)). The "0" experience bin (0-4 years) is the omitted group. We obtain the wage differentials for each country one by one. We then obtain the average wage differentials for developed countries and developing countries using as weights the population of each developed/developing country in 2017. Developed countries are high-income countries according to the 2017 classification of the World Bank (the median developed country in terms of per capita GDP is Belgium). Developing countries are low-, lower middle and upper middle income countries (the corresponding median developing country is Jordan).

Figure 4: AGGREGATE RETURNS TO EXPERIENCE AND ECONOMIC DEVELOPMENT



Notes: Figure 4 plots the relationship between aggregate returns (using observations from 1990-2016) and log per capita GDP (PPP; constant 2011 USD; for the mean year in the data for each country). The sample consists of 138 countries (145 countries - 7 countries in the top and bottom 5% in estimated returns).

Figure 5: OCCUPATION-SPECIFIC RETURNS AND ECONOMIC DEVELOPMENT



Notes: The figure shows for both developed (D) and developing (G) countries the relationship between the estimated occupation-specific returns to experience and the estimated occupation-specific returns to experience for the whole world (using as weights the population of each country in 2017).

Table 1: BASELINE RETURNS TO EXPERIENCE ACROSS DIMENSIONS

	Labor Shares			Baseline Returns to Experience		
Countries:	G	D		G	D	D - G:
Dimension:	(1)	(2)		(3)	(4)	(5)
Agriculture (A)	0.37	0.05		1.2	2.7	***
Non-Agriculture (N)	0.63	0.95		2.0	3.6	***
			N - A:	***	**	[A_D-N_G: ***]
Manual (M)	0.52	0.21		1.4	3.3	***
Cognitive (C)	0.48	0.79		2.1	3.6	***
			C - M:	***		[M_D-C_G: ***]
Informal (I)	0.50	0.31		1.5	2.8	***
Formal (F)	0.50	0.69		1.8	3.5	***
			F - I:		**	[I_D-F_G: ***]
Rural (R)	0.54	0.27		1.3	3.3	***
Urban (U)	0.46	0.73		2.1	3.6	***
			U - R:	***		[R_D-U_G: ***]
Countries	92-121	31-39		82-103	19-36	111-132

Notes: This table shows for 18-67 y.o. workers the average (population-weighted) labor shares and estimated returns to experience for each group of countries (G = Developing; D = Developed) and each dimension. Developed countries are "high-income" countries according to the classification of the World Bank in 2017. We use the population of each country in 2017 as weights. The stars shown in brackets in column (5) indicate for each dimension whether the returns of the "worst" subdimension in developed countries are significantly higher than the returns of the "best" subdimension in developing countries. *, **, *** = 10, 5, 1% significance.

Table 2: EFFECTS OF THE LABOR SHARES OR THE RETURNS ON THE D-G GAP

	Estimated Aggregate Returns to Experience			
	(1)	(2)	(3)	(4)
0a. Agg. Returns in G	1.7	1.7	1.7	1.7
0b. Agg. Returns in D	3.6	3.5	3.3	3.5
0c. D-G Gap (0b - 0a)	1.9	1.8	1.6	1.8
1. Move to Best in G	16	22	6	22
2. Labor Shares of D	16	17	0	11
3. Returns of D for All	84	94	94	94
4. Returns of D for Worst	32	56	37	56
5. Returns of D for Best	53	44	50	39
6. Move to NCFU in G	26	28	31	28
Sectors/Locations	NoAg-Ag	Man-Cog	Inf-For	Rur-Urb
Num. Countries	111	127	112	132

Notes: This table shows by how many percentage points the gap in aggregate returns between developed countries (D) and developing countries (G) is reduced when implementing five changes in the labor shares or the returns of G countries: 1. Moving all workers of G countries to the higher-return sector in G countries; 2. Giving G countries the labor shares of D countries. 3. Giving G countries the returns of D countries. 4. Giving the lower-return sector in G countries the return of the lower-return sector in D countries. 5. Giving the higher-return sector in G countries the return of the higher-return sector in D countries. 6. Moving all workers of G countries to non-agriculture ("N") x cognitive ("C") x formal ("F") x urban ("U") in G countries.

Table 3: RETURNS TO EXPERIENCE ACROSS DIMENSIONS, COHORT EFFECTS

Countries:	(1)-(4) Developing (G)				(5)-(8) Developed (D)				(9)-(12) D-G			
Approach:	Base	HR1	HR2	Combi	Base	HR1	HR2	Combi	Base	HR1	HR2	Combi
Dimension:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ag. (A)	1.2	0.6	0.0	0.2	2.7	2.0	1.8	1.8	***	***	***	***
Non-Ag. (N)	2.0	1.5	1.1	1.3	3.6	2.9	2.7	2.8	***	***	***	***
N-A [A_D-N_G]:	***	***	***	***	**	**	**	**	[***]	[*]	[*]	[]
Man. (M)	1.4	0.9	0.4	0.7	3.3	2.7	2.4	2.6	***	***	***	***
Cogn. (C)	2.1	1.8	1.4	1.5	3.6	3.0	2.8	3.0	***	***	***	***
C-M [M_D-C_G]:	***	***	**	**					[***]	[***]	[***]	[***]
Inf. (I)	1.5	1.1	0.6	1.0	2.8	2.3	2.1	2.2	***	***	***	***
Form. (F)	1.8	1.4	0.9	1.3	3.5	3.1	2.9	3.0	***	***	***	***
F-I [I_D-F_G]:					**	**	**	**	[***]	[***]	[***]	[***]
Rur. (R)	1.3	0.8	0.4	0.6	3.3	2.7	2.5	2.6	***	***	***	***
Urb. (U)	2.1	1.7	1.4	1.6	3.6	3.1	2.9	3.0	***	***	***	***
U-R [R_D-U_G]:	***	***	***	***					[***]	[***]	[***]	[***]
Countries (Min)	82	58	58	54	19	18	18	16	111	87	87	81
Countries (Max)	103	83	83	75	36	31	31	28	132	111	111	101

Notes: HR1: We add decadal cohort FE in the 1st-step regressions. *HR2:* For each country, we construct periods based on important years and include in the 1st-step regressions country-specific period dummies equal to one if the person was 18-67 years old during the period(s). *Combi:* We combine HR1 and HR2 and also add as a control in the first-step regressions the country's average per capita GDP growth rate for those years during which the individual was 18-67 years old. *, **, *** = 10, 5, 1% significance.

Table 4: RETURNS TO EXPERIENCE ACROSS DIMENSIONS, SORTING EFFECTS

Countries:	(1)-(4) Developing (G)				(5)-(8) Developed (D)				(9)-(12) D-G			
Approach:	Base	DRP	REGU	MIG	Base	DRP	REGU	MIG	Base	DRP	REGU	MIG
Dimension:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ag. (A)	1.2	0.8	0.8	0.7	2.7	2.4	2.7	3.4	***	***	***	***
Non-Ag. (N)	2.0	1.6	1.6	1.9	3.6	3.2	3.4	3.7	***	***	***	**
N-A [A_D-N_G]:	***	***	***	***	**				[***]	[**]	[***]	[]
Man. (M)	1.4	1.2	1.1	1.2	3.3	3.1	3.4	3.5	***	***	***	***
Cogn. (C)	2.1	1.8	1.7	2.1	3.6	3.3	3.6	3.7	***	***	***	**
C-M [M_D-C_G]:	***	***	**	***					[***]	[***]	[***]	[**]
Inf. (I)	1.5	1.4	1.4	1.5	2.8	2.5	2.9	3.2	***	***	***	***
Form. (F)	1.8	1.7	1.7	2.2	3.5	3.2	3.6	4.0	***	***	***	**
F-I [I_D-F_G]:	*			***	**				[***]	[**]	[***]	[**]
Rur. (R)	1.3	1.2	1.1	1.2	3.3	3.0	3.3	3.6	***	***	***	***
Urb. (U)	2.1	1.9	1.9	2.1	3.6	3.3	3.6	3.7	***	***	***	**
U-R [R_D-U_G]:	***	***	***	***					[***]	[***]	[***]	[**]
Countries (Min)	82	71	67	38	19	17	10	10	111	92	84	48
Countries (Max)	103	83	83	45	36	27	15	11	132	110	99	56

Notes: DRP: We add various controls for sorting: the non-agriculture, cognitive occupation, formal sector and urban dummies, 3 sector FE, 10 occupation FE, a male dummy, and the square of education. *REGU:* We add the DRP controls and first-level administrative units FE interacted with the urban dummy. *MIG:* We add the DRP controls and dummies for whether the individual is a domestic migrant or an international migrant and whether this information comes from the last migration episode or from comparing the place of current residence with the place of previous residence or the place of birth. *, **, *** = 10, 5, 1% significance.

Table 5: RETURNS TO EXPERIENCE ACROSS DIMENSIONS, SELECTION EFFECTS

Countries:	(1)-(4) Developing (G)				(5)-(8) Developed (D)				(9)-(12) D-G			
Approach:	Base	Male	U≤7	HSM	Base	Male	U≤7	HSM	Base	Male	U<7	HSM
Dimension:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ag. (A)	1.2	0.9	1.2	1.3	2.7	3.0	2.9	2.7	***	***	***	***
Non-Ag. (N)	2.0	2.1	2.0	2.0	3.6	4.2	3.5	3.7	***	***	***	***
N-A [A_D-N_G]:	***	***	***	***	**	***	*	**	[***]	[***]	[***]	[*]
Man. (M)	1.4	1.4	1.3	1.4	3.3	3.6	3.3	3.1	***	***	***	***
Cogn. (C)	2.1	2.3	2.1	2.2	3.6	4.2	3.5	3.5	***	***	***	***
C-M [M_D-C_G]:	***	***	***	***		**			[***]	[***]	[***]	[***]
Inf. (I)	1.5	1.8	1.5	1.5	2.8	3.3	2.5	2.8	***	***	**	***
Form. (F)	1.8	2.1	1.8	1.8	3.5	3.9	2.9	3.5	***	***	***	***
F-I [I_D-F_G]:	*				**	*		**	[***]	[***]	[]	[***]
Rur. (R)	1.3	1.3	1.2	1.2	3.3	3.9	3.2	3.0	***	***	***	***
Urb. (U)	2.1	2.4	2.2	2.2	3.6	4.2	3.5	4.5	***	***	***	**
U-R [R_D-U_G]:	***	***	***	***					[***]	[***]	[***]	[**]
Countries (Min)	82	78	56	67	19	16	9	15	109	109	72	95
Countries (Max)	103	101	66	91	36	36	19	33	132	132	81	119

Notes: Male: We restrict the sample to male workers only. *U<7:* We keep samples for which the unemployment rate of 18-67 y.o. active individuals is below 7%. *HSM:* We keep both active and inactive 18-67 y.o. individuals and implement a two-step Heckman selection model with fixed effects for each marital status (married, never married, living together, divorced/separated, widowed) and the number of children in the household and its square as external variables in the first-step equation. *, **, *** = 10, 5, 1% significance.

Table 6: RETURNS TO EXPERIENCE ACROSS DIMENSIONS, ROBUSTNESS 1/2

Panel:	*A:* Log Hourly Wage			*B:* Log Num. Hours Worked			*C:* 5-35 Exp. Bins Only			*D:* 0-25 Exp. Bins Only		
Countries:	G	D	D-G	G	D	D-G	G	D	D-G	G	D	D-G
Ag. (A)	1.1	2.1	***	0.1	0.7	***	1.2	2.1	***	1.4	3.3	***
Non-Ag. (N)	2.1	3.1	***	0.0	0.6	***	1.8	2.9	***	2.4	4.4	***
N-A [A_D-N_G]:	***	**	[]			[***]	***	**	[]	***	**	[**]
Man. (M)	1.5	2.9	***	0.0	0.4	**	1.3	2.6	***	1.7	3.9	***
Cogn. (C)	2.3	3.4	***	0.0	0.4	*	2	3	***	2.6	4.5	***
C-M [M_D-C_G]:	***		[**]			[**]	***	*	[***]	***		[***]
Inf. (I)	1.5	2.8	***	0.0	0.1		1.3	2.3	***	1.9	3.4	***
Form. (F)	2.1	3.5	***	-0.1	0.1		1.7	2.9	***	2.3	4.2	***
F-I [I_D-F_G]:	***	*	[**]			[]	**	***	[***]		**	[***]
Rur. (R)	1.5	3.1	***	-0.2	0.3	*	1.1	2.7	***	1.6	4	***
Urb. (U)	2.3	3.4	***	0.1	0.5	*	1.9	3	***	2.6	4.4	***
U-R [R_D-U_G]:	***		[***]			[]	***		[***]	***		[***]
Countries (Min)	71	15	92	77	22	99	82	19	109	81	18	109
Countries (Max)	87	34	117	90	35	118	103	36	132	103	36	132

Notes: The stars shown in brackets indicate whether the returns of the "worst" subdimension in developed countries are significantly higher than the returns of the "best" subdimension in developing countries. *, **, *** = 10, 5, 1% significance.

Table 7: RETURNS TO EXPERIENCE ACROSS DIMENSIONS, ROBUSTNESS 2/2

Panel:	*A:* Lagakos et al (2018) (monthly)			*B:* Lagakos et al (2018) (hourly)			*C:* Num. Yrs. Educ. $\leq$ 12			*D:* Num. Yrs. Educ. $\geq$ 12		
Countries:	G	D	D-G	G	D	D-G	G	D	D-G	G	D	D-G
Ag. (A)	0.9	3.2	***	0.7	3.0	***	1.0	1.8		1.7	3.0	**
Non-Ag. (N)	2.3	3.7	***	2.3	3.5	***	1.7	3.5	***	2.5	3.7	***
N-A [A_D-N_G]:	***		[***]	***		[*]	***	**	[]		*	[]
Man. (M)	1.6	3.4	***	1.6	3.2	***	1.2	2.9	***	2.0	3.3	***
Cogn. (C)	2.3	3.9	***	2.4	3.7	***	1.9	3.4	***	2.5	3.7	***
C-M [M_D-C_G]:	***	*	[***]	***		[***]	***		[***]	***		[***]
Inf. (I)	1.5	3.4	***	1.6	3.3	***	1.2	2.6	***	1.9	2.9	***
Form. (F)	2.0	3.7	***	2.1	3.6	***	1.5	3.0	***	2.2	3.6	***
F-I [I_D-F_G]:	*		[***]	***		[***]			[**]		**	[**]
Rur. (R)	1.6	3.7	***	1.6	3.5	***	1.0	3.1	***	2.0	3.4	***
Urb. (U)	2.3	3.8	***	2.4	3.7	***	2.0	3.1	***	2.5	3.7	***
U-R [R_D-U_G]:	***		[***]	***		[***]	***		[***]			[***]
Countries (Min)	64	9	73	58	7	65	81	15	105	43	14	57
Countries (Max)	79	31	105	76	30	101	102	35	130	68	34	96

Notes: The stars shown in brackets indicate whether the returns of the "worst" subdimension in developed countries are significantly higher than the returns of the "best" subdimension in developing countries. *, **, *** = 10, 5, 1% significance.

Table 8: RETURNS FOR SELECTED SUBSECTORS AND OCCUPATIONS

	Labor Shares		Estimated Returns to Experience		
Dimension:	(1) G	(2) D	(3) G	(4) D	(5) D-G
1. Non-Ag.*Cognitive*Formal*Urban	0.24	0.43	2.2	3.6	***
Countries	80	27	67-92	18-25	92-110 [88]
2. Agriculture	0.37	0.05	1.0	2.6	***
3. Construction	0.06	0.08	1.4***	3.2	***
4. Manufacturing	0.12	0.17	1.7***	3.5**	***
5. Wholesale & Retail & Trade	0.16	0.19	1.9***	3.6**	***
6. Transportation & Communications	0.05	0.07	2.1***	3.7***	***
7. Administration	0.10	0.18	2.2***	3.2	***
8. Finance, Real Est. & Business & Services	0.03	0.12	2.2***	3.6**	***
Countries	76	36	71-98	18-33	103-130 [89]
9. Elementary Occupation	0.15	0.08	0.9	3.2	***
10. Skilled Agriculture	0.27	0.03	0.9	2.9	***
11. Crafts	0.10	0.12	1.5***	3.3	***
12. Machinists	0.05	0.10	1.7***	3.2	***
13. Salespersons	0.15	0.14	1.8***	3.4	***
14. Clerks	0.06	0.14	2.1***	3.5	***
15. Technicians	0.05	0.14	2.3***	3.5	***
16. Managers	0.05	0.10	2.4***	3.7	***
17. Professionals	0.06	0.16	2.5***	3.5	***
Countries	72	39	46-87	11-36	66-123 [111]

Notes: The stars in columns (3)-(4) show for selected subsectors and occupations in both developing and developed countries whether the estimated returns to experience are significantly different from the estimated returns to experience for the lowest-return subsector / occupation at the world level, i.e. "Agriculture" and "Elementary Occupations". *, **, *** = 10, 5, 1% significance.

Table 9: CROSS-COUNTRY CORRELATES OF THE RETURNS TO EXPERIENCE

	Dependent Variable: Estimated Returns to Experience							
Panel:	**A:** Ctrl of Corruption		**B:** Gvt Effectiveness		**C:** Pol. Stability		**D**: Rule of Law	
Coef.	0.03***	0.03***	0.03***	0.03***	0.02***	0.02***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	145	145	145	145	145	145	145	145
R2	0.38	0.39	0.33	0.34	0.23	0.26	0.37	0.38
Sh. Sign.	100%	100%	92%	92%	88%	84%	96%	92%
Panel:	**E:** Regu. Quality		**F:** Doing Business		**G:** Dismissal Allowed		**H:** Prem. Overtime	
Coef.	0.03***	0.03***	0.03***	0	0.35***	0.41**	-0.01***	-0.01***
	[0.00]	[0.01]	[0.01]	[0.01]	[0.10]	[0.19]	[0.00]	[0.00]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	145	145	145	145	145	145	144	144
R2	0.29	0.29	0.12	0.18	0	0.19	0.07	0.25
Sh. Sign.	72%	76%	60%	0%	22%	61%	68%	64%
Panel:	**I:** Restrict. Overtime		**J:** Severance Pay		**K:** Notice Period		**L:** Dom. Movement	
Coef.	-0.41**	-0.37**	-0.02***	-0.01*	0.07***	0.06***	0.09**	-0.00
	[0.20]	[0.19]	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]	[0.04]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	145	145	143	143	143	143	131	131
R2	0.02	0.20	0.05	0.20	0.06	0.23	0.05	0.18
Sh. Sign.	28%	36%	48%	8%	100%	100%	52%	0%
Panel:	**M:** Perso. Computers		**N:** Broadband Subscr.		**O:** Digital Payments		**P:** Secular Values	
Coef.	0.02***	0.02***	0.07***	0.08***	0.02***	0.03***	0.03*	-0.02
	[0.00]	[0.01]	[0.01]	[0.02]	[0.00]	[0.00]	[0.02]	[0.02]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	125	125	143	143	128	128	72	72
R2	0.26	0.26	0.32	0.33	0.37	0.38	0.04	0.27
Sh. Sign.	72%	76%	80%	92%	100%	100%	20%	12%
Panel:	**Q:** Emancip. Values		**R:** WBL Score		**S:** WBL: Getting a Job		**T:** Proh. Work Disc.	
Coef.	0.08***	0.07***	0.02***	0.00	0.02***	0.01	1.67***	1.13***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.46]	[0.35]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	72	72	145	145	145	145	77	77
R2	0.45	0.45	0.07	0.19	0.13	0.20	0.14	0.38
Sh. Sign.	88%	96%	36%	0%	60%	0%	80%	76%
Panel:	**U:** Dislike Ot. Races		**V:** Dislike Ot. Relig.		**W:** Dislike Immigrants		**X:** Ethnic Frac.	
Coef.	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.01*	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Ctrl Lpcgdp	N	Y	N	Y	N	Y	N	Y
Obs.	72	72	63	63	72	72	137	137
R2	0.29	0.39	0.43	0.51	0.14	0.34	0.03	0.20
Sh. Sign.	92%	92%	96%	96%	68%	68%	24%	4%

Notes: This table shows the effects of various country-level factors on the estimated aggregate returns to experience. The factors are estimated circa 2000-2017. For each factor, we show the effects for two specifications, first without any control and then controlling for log per capita GDP (PPP; constant 2011 USD; two-year moving average around the mean year in the I2D2 data for each country). Sh. Sign.: For each factor and each specification, we re-estimate the coefficient when sequentially including each of the other 23 controls. We then show the percentage share of the 23 re-estimated coefficients that are of the same sign as the baseline coefficient (without any control except log per capita GDP for the second specification) and significant. *, **, *** = 10, 5, 1% significance.

FOR ONLINE PUBLICATION: Appendix

A.1 Details on the Experience-Time-Cohort Problem

The Experience-Time-Cohort Problem. As Heckman and Robb (1985, p.137) show, the literature considers earnings W of individuals i as a function of schooling s, work experience e, age a, time t (e.g., the survey is from 2008) and cohort c (e.g., individual i is born in 1982). For the sake of simplicity, we consider a linear function and the number of years of experience instead of experience bins:

$$W_i = \alpha + \alpha_s s + \alpha_e e + \alpha_a a + \alpha_t t + \alpha_c c + \epsilon_i \tag{A.1.1}$$

Wages increase with schooling ($\alpha_s > 0$) and work experience ($\alpha_e > 0$). Age could have an effect that is independent of the effect of work experience. As Heckman and Robb (1985, p.137) explain, "age may be a direct determinant of earnings through maturation and other physiological effects". In that case, wages increase with age ($\alpha_a > 0$). However, employers could also discriminate against older workers ($\alpha_a < 0$). There are then time effects. In contexts where the economy is growing (declining), time effects will be positive (negative), and thus $\alpha_t > 0$ ($\alpha_t < 0$). Finally, there could be cohort effects. For example, Heckman and Robb (p.138 1985) explain that "workers reared in the Depression may be pessimistic or risk averse while workers reared in the 1950s may be overly optimistic". We could also imagine that people born earlier did not have access to a good health infrastructure in countries where modern health systems were established later on. In that case, and if past health investments matter for productivity, wages will increase with the year of birth/cohort ($\alpha_c > 0$).

Without retrospective data on individual employment, experience tends to be estimated as age minus schooling ($e_i = a_i - s_i$). Time is then equal to age plus the year of birth ($t = a_i + c_i$). This implies that one cannot simultaneously include schooling, experience, age, time fixed effects and cohort fixed effects. In that case, and not including age and cohort fixed effects, we de facto estimate:

$$W_i = \alpha + (\alpha_t + \alpha_c) * t + (\alpha_s + \alpha_a - \alpha_c) * s + (\alpha_e + \alpha_a - \alpha_c) * e + \epsilon_i \tag{A.1.2}$$

In other words, the coefficient of experience (and schooling) captures the age and cohort effects.

Distinguishing Experience Effects and Age Effects. One cannot distinguish the effects unless one has separate data on age and past employment. However, if one considers experience as *life experience* rather than work experience per se, one may be interested in $\alpha_e + \alpha_a$. Obviously, there is still an issue if employers discriminate relatively more against older (or younger) workers. Also, since we are mostly interested in the difference between developed and developing countries, that is only an issue for us if richer countries discriminate more (or less) against older (or younger) workers than poorer countries. Without country-level data on age-based discrimination, we abstract from this issue in our analysis and acknowledge that our experience effects may capture age affects.

Distinguishing Experience Effects and Cohort Effects. As can be seen in equation A.1.2, the coefficient of experience captures the cohort effects. In particular, if later cohorts benefit from say new technologies raising productivity, we expect positive cohort effects ($\alpha_c > 0$). In that case, the estimated effect of experience (+ age) will be lower than the true effect ($\alpha_e + \alpha_a - \alpha_c < \alpha_e + \alpha_a$), and the returns are downward-biased. Conversely, if there is fast population growth and cohort size negatively affects wages, we expect negative cohort effects ($\alpha_c < 0$) and the returns to be upward-biased. Again, that is only an issue for us if richer countries have different cohort effects than poorer countries.

Specific Related Issues in our Sample of 145 Countries. Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals born between 1923 and 1998. Without controls for cohort effects, various factors may affect our results. First, investments in human capital and/or new technologies may lead to positive cohort effects ($\alpha_c > 0$), where later cohorts have better unobservable abilities over time. Returns are then downward-biased. The question is whether this is more true in developed countries or in developing countries.[1] Second, faster population growth in poorer countries could have reduced their cohort effects. Indeed, if cohort size negatively affects wages, one could expect fast population growth to reduce wages over time ($\alpha_c < 0$). In that case, the returns of poorer countries are upward-biased. Third, there may be selection effects due to very high child and adult mortality rates in the past in poorer countries (or in countries with major pandemics such as HIV). If "survivors" from these times were positively selected, older workers still alive in the data may be intrinsically more productive. In that case, cohort effects may end up negative ($\alpha_c < 0$), and the returns of poorer countries are upward-biased. Finally, the experience of older cohorts may be less valuable ceteris paribus than the experience of younger cohorts in countries that have experienced a dramatic change in their economic system, for example in the ex-USSR. Given a same level of experience, older cohorts will be paid less than younger cohorts, so cohort effects are positive ($\alpha_c > 0$). Therefore, the returns of these countries may be downward-biased.

DH Approach Followed by Lagakos et al. (2018). Their first approach, which they call the Deaton-Hall (DH) approach, is inspired by Hall (1968) and Deaton (1997). As Lagakos et al. (p.799, 2018) explain, one can try to resolve the difficulty of collinearity by imposing "one additional linear restriction on the set of cohort and time effects in equation (2)" (eq. 1 in our analysis). One version of this approach attributes all labor productivity growth to cohort effects and uses year dummies to capture only cyclical fluctuations. They implement this by estimating their equation (2) with birth cohort dummies and time dummies, with the restriction that the time dummies are orthogonal to a time trend. A clear limitation with that approach, as acknowledged by the authors themselves (p.814), is that it does not capture time trends in fast-growing countries such as Brazil and Jamaica (3.5% and 2.1% per year, respectively; see their footnote 8). In such cases, very steep wage-experience profiles may be

[1] Developed countries have grown relatively fast during the 1923-1998 period, since they became "developed". However, life expectancy has dramatically improved in developing countries even when per capita incomes did not. Since increases in life expectancy reflects major health improvements, and since health is a major determinant of productivity, one could expect productivity to have dramatically increased across cohorts over time in developing countries.

obtained (see their Figure 4A). Indeed, Lagakos et al. (2018) explain that with "time effects shut down, all wage growth by individual cohorts over their lifetimes is attributed to their increased experience."[2] Symmetrically, this method has limitations for countries experiencing economic decline. In our sample of 145 countries between 1950 and 2017, 454 out of 931 country-decades for which we have per capita GDP data – 48.8% of the sample – saw an average annual growth rate higher than 2% whereas 166 country-decades – 17.8% of the sample – saw a negative average annual growth rate.[3]

HLT Approach Followed by Lagakos et al. (2018). Their second approach, which they call the HLT approach, is inspired by Heckman, Lochner and Taber (1998). As Lagakos et al. (2018) explain, they rely on theories of life cycle wage growth that claim that "there should be little or no effect of experience on wages near the end of the life cycle". In other words, more experienced/older workers have no incentive to invest in human capital formation and the incentive to search for a better-paying job declines similarly. One can then "follow a fixed cohort across multiple cross sections for the last years of their working life" and attribute any wage changes for them to time effects. Once aggregate time effects are recovered, "it is straightforward to estimate the experience and cohort effects of workers who are not near the end of the life cycle". However, wage profiles could decrease at the end of the life cycle because of human capital depreciation. Indeed, with age, all our body systems (e.g., the brain) decline. As the authors acknowledge, "this approach requires assumptions about two main parameters: first, the number of years at the end of the life cycle for which there are no experience effects and, second, a number for the depreciation rate". They consider 5 or 10 years and 0 or 1%.

While this approach has several clear merits, it posits that there are no experience effects near the end of the life cycle, which may be less true in developed countries than in developing countries. Also, selective early retirement in developed countries, and more importantly selective mortality in developing countries, complicates the analysis, since estimated time effects near the end of the life cycle could capture unobservable compositional changes in the population of the older cohorts across years. We focus on workers aged between 18 and 67. Given how work experience is constructed, the correlation between experience and age is mechanically high, at 0.90 or more in most samples. However, among our 145 countries, life expectancy is lower than 60 for 390 country-decades, i.e. 39.0% of the sample (source of the life expectancy data: United Nations (2018)). Therefore, because our sample includes 45 lower-middle income countries and 26 low income countries and given that life expectancy is strongly correlated with income across countries, this approach might create issues of its own. Finally, since we have 145 countries and we have multiple years of data for most of them, wages are not necessarily comparable across years *within* a same country, due to changes in (i) the

[2]Lagakos et al. (2018) tries two other versions of this approach, one where productivity growth is attributed to time effects and another one where it is attributed in equal parts to cohort and time effects. However, they explain on p.799 that "one does not know in general what fraction of growth is due to time effects, and this fraction could differ across countries".

[3]The main source for GDP is Bolt and van Zanden (2014) who update Maddison (2008)'s data set. The data show per capita GDP in constant 1990 international $ (i.e. PPPs). We extend the data to 2017 using the levels in the data in 2010 and annual per capita GDP growth rates reported by World Bank (2018) for the period 2000-2017 (constant 2011 international $).

domestic currency, (ii) inflation, and (iii) possibly changes in the methodology to estimate wages across surveys/censuses. In equation 1, we include country-year-sample fixed effects so as to only compare individuals facing the same currency and national level of prices and for which wages were obtained similarly. Their HLT approach requires that all wages of a same country be estimated in a same currency and be deflated. While currency changes are easy to track (we use Wikipedia for all countries), inflation may be poorly measured in poor countries, especially in high-inflation contexts (we use the GDP deflator from International Monetary Fund (2018)). The HLT approach also requires that we restrict the analysis to surveys/censuses that are similar enough methodologically. This makes us drop about 6% of our sample, mostly low-income countries.

Nonetheless, we show in Web Appx. Table A.2 that results hold if we implement this approach, whether focusing on the last 5 or 10 years of experience and/or using a depreciation rate of 0 or 1%. In order to do so, we do our best to express wages in a single currency for each country.

A.2 More Examples of Countries for the HR2 Approach

We show below the identified "important" years for five different countries:

Haiti 1923-2016: 1915 (U.S. occupation), 1934 (U.S. withdraws troops), 1947 (U.S. maintains fiscal control until 1947), 1856 (Duvalier seizes power in military coup), 1964 (Duvalier declared president for life), 1971 (Duvalier dies and is succeeded by his son), 1986 (Duvalier's son flees Haiti, civilian government installed in 1988), 1991 (President Aristide ousted in a coup, triggering sanctions), 1994 (transition to a civilian government, Aristide returns), 1999 (President Preval begins ruling by decree), 2002 (becomes full member of the Caribbean Community trade bloc), 2010 (earthquake).

Honduras 1923-2016: 1925 (American troops landing), 1932 (dictatorship of General Andino), 1949 ("New Reform" and movement away from Carias regime), 1954 (general strike, coup in 1955), 1963 (coup), 1969 (El Salvador invades Honduras), 1974 (hurricane), 1980 (peace treaty with El Salvador), 1981 (first civilian government), 1984 (General Alvarez deposed), 1995 (WTO), 1998 (Hurricane Mitch), 2003 (trade agreement with the U.S.), 2006 (trade deal with the U.S.), 2009 (President Zelaya removed).

Kenya 1923-2016: 1920 (Crown Colony of Kenya), 1940 (Italian forces attack), 1944 (Kenyan African Union), 1947 (Kenyatta becomes KAU leader), 1952 (Mau Mau rebellion), 1956 (rebellion ends), 1960 (state of emergency ends), 1963 (Independence), 1969 (assassination of Mboya, ethnic unrest), 1978 (Kenyatta dies, rule of Moi starts), 1982 (one-party state), 1987 (opposition groups suppressed), 1992 (elections, tribal conflict), 1996 (constitution amended), 2002 (Moi's reign ends), 2007 (electoral violence), 2010 (new constitution, East African common market), 2013 (terrorist attacks).

Paraguay 1923-2016: 1922 (Paraguayan civil war), 1932 (Chaco War), 1936 (February revolution, coup), 1947 (2nd Paraguayan civil war), 1954 (General Stroessner seizes power in coup, beginning of dictatorship), 1959 (liberalization reforms), 1963 (multi-party dictatorship), 1989 (Stroessner deposed in coup), 1992 (new democratic constitution, joins Mercosur in 1991), 1996 (avoided coup, joins WTO in 1995), 2002 (state of emergency), 2012 (President Lugo ousted).

Venezuela 1923-2016: 1935 (Gomecista dictatorship), 1945 (military Coup, 1948 too), 1958 (return to Democracy), 1976 (oil nationalized), 1983 (Venezuelan Black Friday), 1989 (Caracazo Riots), 1992 (Chávez coup, Mercosur in 1991, WTO in 1995), 1998 (election of Chávez), 2002 (armed forces rebel), 2006 (Chávez wins 3rd term, various companies nationalized in 2007), 2013 (Chávez dies).

REFERENCES

Bolt, Jutta and Jan Luiten van Zanden, "The Maddison Project: collaborative research on historical national accounts," *Economic History Review*, 2014, *67* (3), 627–651.

Deaton, Angus, *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy.*, Washington, DC: World Bank., 1997.

Hall, R. E., "Technical Change and Capital from the Point of View of the Dual," *The Review of Economic Studies*, 1968, *35* (1), 35–46.

Heckman, James and Richard Robb, "Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations," in W.M. Mason and S.E. Fienberg S.E., eds., *Cohort Analysis in Social Research*, Springer, New York, NY, 1985, pp. 137–150.

Heckman, James J, Lance Lochner, and Christopher Taber, "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1* (1), 1 – 58.

International Monetary Fund, *World Economic Outlook Databse* 2018.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Life Cycle Wage Growth across Countries," *Journal of Political Economy*, 2018, *126* (2), 797–849.

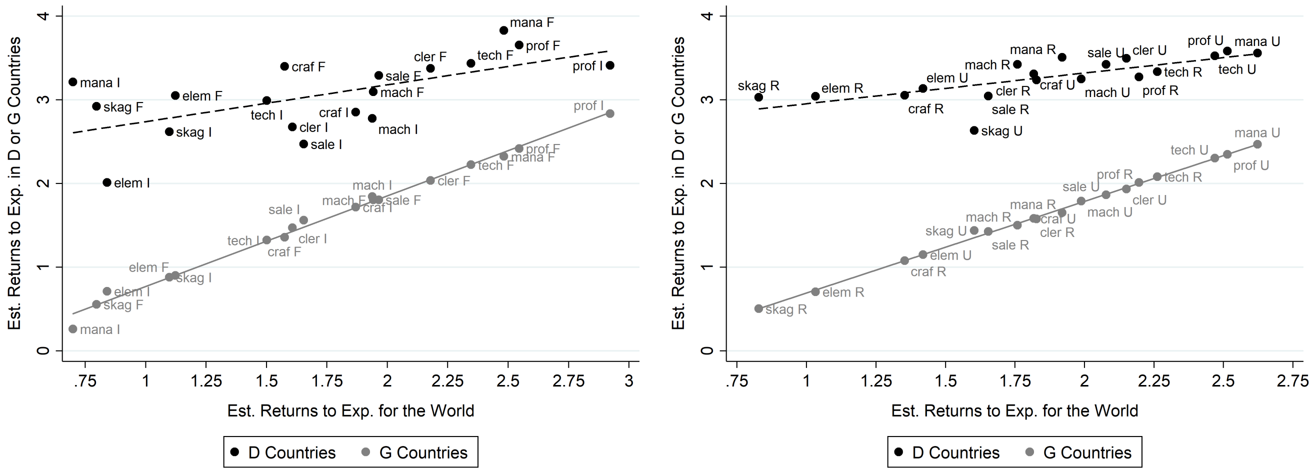
Maddison, Angus, *Statistics on World Population, GDP and Per Capita GDP, 1-2008 AD* 2008.

United Nations, *World Population Prospects: The 2018 Revision* 2018.

World Bank, *World Development Indicators* 2018.

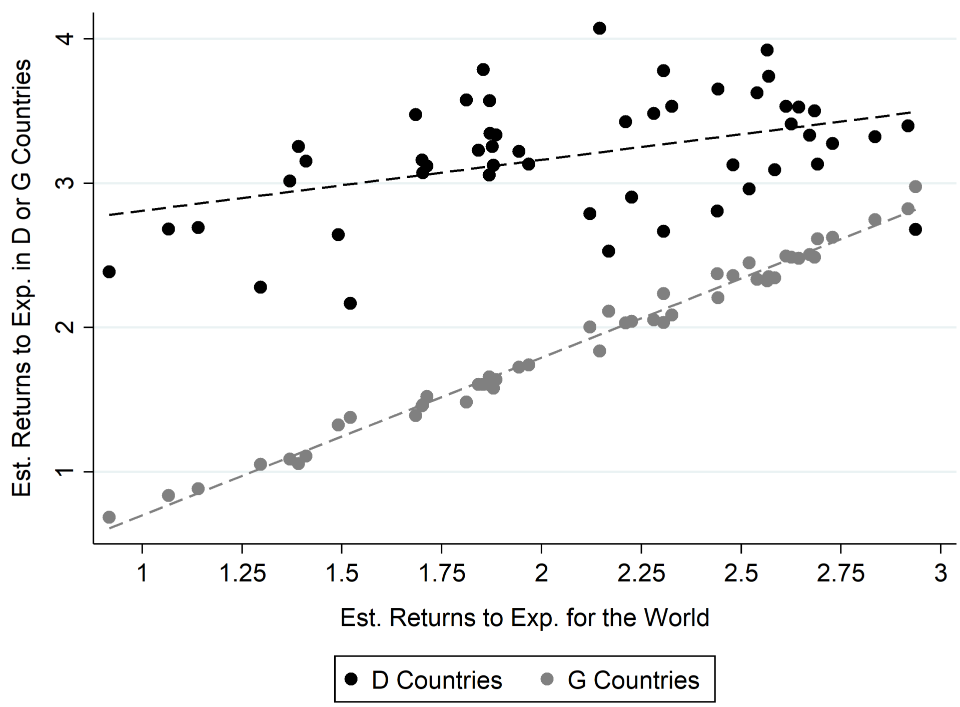
Figure A.1: OCCUPATION SPECIFIC RETURNS AND DEVELOPMENT, ROBUSTNESS

(a) 10 Occupations x Formal Status **(b)** 10 Occupations x Urban Area



Notes: Subfigure 1(a) shows for both developed (D) and developing (G) countries the relationship between the occupation x formal specific returns to experience and the occupation x formal specific returns to experience for the whole world (using as weights the population of each country in 2017). The estimated slope coefficient is 0.44** and 1.08*** for developed and developing countries, respectively (N = 18; not shown). We omit two occupation x formal categories because returns are available for fewer than 10 developed or developing countries. Subfigure 1(b) shows for both D and G countries the relationship between the occupation x urban specific returns to experience and the occupation x urban specific returns to experience for the whole world (using as weights the population of each country in 2017). The estimated slope coefficient is 0.37*** and 1.09*** for developed and developing countries, respectively (N = 18; not shown). We omit two occupation x urban categories because returns are available for fewer than 10 developed or developing countries.

Figure A.2: OCCUPATION-SECTOR SPECIFIC RETURNS AND DEVELOPMENT



Notes: The figure shows for both developed (D) and developing (G) countries the relationship between the estimated occupation x sector specific returns to experience and the estimated occupation x sector specific returns to experience for the whole world (using as weights the population of each country in 2017). The estimated slope coefficient is 0.35*** and 1.09*** for developed and developing countries, respectively (N = 51; not shown). While there are potentially 10 occupations x 10 sectors = 100 occupation-sectors, returns are available for at least 10 countries for 51 of them only.

Table A.1: STATIC WAGE DIFFERENCES ACROSS DIMENSIONS

	Dependent Variable: Estimated Wage Difference (%) for Each Dimension							
Sect./Loc.	NoAg-Ag (1)	Man-Cog (2)	Inf-For (3)	Rur-Urb (4)	NoAg-Ag (5)	Man-Cog (6)	Inf-For (7)	Rur-Urb (8)
	Col. (1)-(4): Not Including the Experience Dummies				Col. (5)-(8): Including the Experience Dummies			
Developed	-24.6***	-11.6***	-1.0	-32.8***	-16.4	7.1	-0.9	-10.4
	[8.7]	[4.2]	[10.1]	[10.3]	[10.6]	[6.0]	[6.6]	[7.8]
Mean	62.7	43.2	42.6	46.7	28.1	8.9	16.6	14.5
Max	183.5	183.3	173.9	161.7	174.4	153.9	104.7	128.4
Observations	111	127	112	132	111	127	112	132

Notes: Col. (1)-(4): We show the coefficients of the sector/location dummy when not including the experience dummies (we include the number of years of education and the male dummy). Col. (5)-(8): We show the coefficients of the sector/location dummy when including the experience dummies (we include the number of years of education and the male dummy). These regressions correspond to the baseline regressions of Table **??**. We use as weights the population of each country in 2017. *, **, *** = 10, 5, 1% significance.

Table A.2: RETURNS ACROSS DIMENSIONS, COHORT EFFECTS, ROBUSTNESS

Approach:	Base (1)	20-Yr Cohort FE (2)	5-Yr Cohort FE (3)	18-40 Period Dum. (4)	18-30 Period Dum. (5)	18-67 & 0-17 Dum. (6)	18-67 Dum. & Gr. (7)	HLT 5 Yrs 0% Dep. (8)	HLT 5 Yrs 1% Dep. (9)	HLT 10 Yrs 0% Dep. (10)	HLT 10 yrs 1% Dep. (11)
Panel A:	Developing Countries										
Ag.	1.2	1.1	-0.3	0.2	0.3	-0.6	-0.2	1.1	1.1	1.1	1.1
Non-Ag.	2.0	1.8	0.8	1.2	1.3	0.5	1.0	1.9	1.8	1.7	1.8
Man.	1.4	1.3	0.2	0.5	0.6	-0.1	0.3	1.3	1.3	1.2	1.3
Cogn.	2.2	2.0	1.2	1.5	1.5	1.0	1.2	2.0	2.1	2.0	2.0
Inf.	1.6	1.5	0.4	0.7	0.9	0.1	0.7	1.4	1.5	1.3	1.5
Form.	1.9	1.7	0.7	1.0	1.2	0.4	1.0	1.7	1.7	1.7	1.7
Rur.	1.3	1.2	0.2	0.5	0.6	0.0	0.3	1.3	1.2	1.2	1.4
Urb.	2.2	2.0	1.3	1.5	1.6	1.0	1.4	2.0	2.1	1.9	2.0
Obs (Min)	82	58	58	58	58	58	54	51	51	51	51
Obs (Max)	103	83	83	83	83	83	75	72	72	72	72
Panel B:	Developed Countries										
Ag.	2.7	2.3	1.0	2.0	2.1	1.0	1.4	2.3	2.5	2.4	2.3
Non-Ag.	3.6	3.1	2.1	2.9	3.0	2.1	2.4	3.1	3.2	3.3	3.1
Man.	3.2	3.0	2.0	2.7	2.8	2.0	2.3	3.0	3.1	3.0	3.0
Cogn.	3.7	3.3	2.4	3.1	3.1	2.5	2.7	3.4	3.3	3.5	3.5
Inf.	2.9	2.6	1.6	2.3	2.3	1.8	2.0	2.6	2.7	2.7	2.6
Form.	3.6	3.3	2.5	3.1	3.1	2.7	2.8	3.4	3.4	3.3	3.2
Rur.	3.4	3.0	2.1	2.8	2.9	2.2	2.4	3.0	3.1	2.9	3.0
Urb.	3.7	3.3	2.5	3.1	3.2	2.6	2.8	3.4	3.3	3.4	3.3
Obs (Min)	19.0	18.0	18.0	18.0	18.0	18.0	16.0	13.0	13.0	13.0	13.0
Obs (Max)	36.0	31.0	31.0	31.0	31.0	31.0	28.0	26.0	26.0	26.0	26.0

Notes: 20-Year Cohort FE: We include 20-year cohort fixed effects. 5-Year Cohort FE: We include 5-year cohort fixed effects. 18-40 Period Dum.: We use country-specific periods based on ages 18-40. 18-30 Period Dum.: We use country-specific periods based on ages 18-30. 18-67 & 0-17 Dum.: In addition to country-specific periods based on ages 18-67, we add period dummies equal to one if the individual was 0-17 years old during the period(s). 18-67 Dum. & Gr.: We use the 18-67 and 0-17 dummies, and the individual's corresponding growth rates. HLT: We implement the algorithm of Lagakos et al. (2018), separately for each subdimension and for countries with at least 3 years of data. At the end of the life cycle, we consider 5 or 10 years as the number of years for which there are no experience effects and 0% or 1% as the depreciation rate of human capital. *, **, *** = 10, 5, 1% significance.

Table A.3: RETURNS ACROSS DIMENSIONS, SORTING EFFECTS, ROBUSTNESS

Countries:	Columns (1)-(5): Developing Countries					Columns (6)-(10): Developed Countries				
Approach:	Base	10 Sect. *10 Occ.	Region2* Urban FE	Region Birth FE	Never Movers	Base	10 Sect. *10 Occ.	Region2 *Urban	Region Birth FE	Never Movers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ag.	1.2	0.8	0.7	1.4	1.1	2.7	2.4	2.8	4.2	3.6
Non-Ag.	2.0	1.6	1.5	2.0	1.9	3.6	3.1	3.3	4.1	3.6
Man.	1.4	1.1	1.1	1.6	1.4	3.2	3.0	3.0	4.0	3.7
Cogn.	2.2	1.8	1.6	2.1	2.0	3.7	3.2	3.3	4.1	3.6
Inf.	1.6	1.4	1.4	2.0	1.5	2.9	2.5	3.5	3.5	3.1
Form.	1.9	1.7	1.4	1.9	1.8	3.6	3.2	4.0	4.4	4.4
Rur.	1.3	1.2	1.0	1.4	1.1	3.4	3.0	3.0	4.0	3.6
Urb.	2.2	1.8	2.0	2.1	2.1	3.7	3.2	3.3	4.1	3.6
DRP Ctrls	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Obs (Min)	82	71	37	25	31	19	17	8	8	7
Obs (Max)	103	83	45	31	37	36	27	9	8	10

Notes: Col. (2)-(5) & (7)-(10): We add the DRP controls for sorting: the non-agriculture, cognitive occup., formal sector and urban dummies, 3 sector FE, 10 occupation FE, a male dummy, and the square of education. 10 Sect.*10 Occ.: We include 10 subsector * 10 occupation = 100 subsector-occupation FE. Region2*Urban FE: We include 2nd-level admin. units FE which we interact with the urban dummy. 2nd-level admin. units (e.g., counties in the U.S.). Region Birth FE: We include region of birth FE. Depending on the country, they include 1st-level or 2nd-level admin. units. Never Movers: We restrict the sample to individuals who have never migrated, i.e. individuals who still live in the same place as their place of birth. *, **, *** = 10, 5, 1% significance.

Table A.4: RETURNS ACROSS DIMENSIONS, SELECTION EFFECTS, ROBUSTNESS

Countries:	Columns (1)-(6): Developing Countries						Columns (7)-(12): Developed Countries					
Approach:	Base	Unemp. ≥7%	Unemp. ≤10%	Unemp. ≥10%	NLFP ≤35%	NLFP ≥35%	Base	Unemp. ≥7%	Unemp. ≤10%	Unemp. ≥10%	NLFP ≤35%	NLFP ≥35%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ag.	1.2	1.4	1.2	1.2	1.5	0.6	2.7	3.1	2.8	2.0	2.9	2.2
Non-Ag.	2.0	2.2	2.0	2.2	2.0	1.9	3.6	4.0	3.5	3.5	3.6	3.0
Man.	1.4	1.7	1.3	1.9	1.5	1.3	3.2	3.5	3.4	3.1	3.4	3.0
Cogn.	2.2	2.2	2.1	2.1	2.2	2.0	3.7	4.0	3.6	3.8	3.6	3.6
Inf.	1.6	1.9	1.5	1.8	1.7	1.4	2.9	3.0	2.8	3.0	2.7	2.9
Form.	1.9	2.0	1.8	1.7	1.7	1.9	3.6	3.7	3.4	3.8	3.5	3.7
Rur.	1.3	1.5	1.2	1.5	1.3	1.3	3.4	3.7	3.3	3.3	3.3	3.2
Urb.	2.2	2.1	2.1	1.9	2.2	2.0	3.7	4.1	3.6	3.7	3.6	3.6
Obs (Min)	82	42	68	27	54	46	19	15	15	8	14	6
Obs (Max)	103	67	82	47	67	63	36	28	31	19	29	16

Notes: Unemp.: We keep country-year samples whose unemployment rate among active 18-67 y.o. individuals is above 7%, the world's median unemployment rate in the sample, or below or above 10%, the world's mean unemployment rate in the sample. NLFP: We keep country-year samples whose non-labor force participation rate among both active and inactive 18-67 y.o. individuals is below or above 35%, the world's median and mean non-labor force participation rates in the sample. *, **, *** = 10, 5, 1% significance.

Table A.5: RETURNS ACROSS DIMENSIONS, OTHER ROBUSTNESS CHECKS

	Base (1)	≤ High School (2)	≥ High School (3)	Cntry Age Entry (4)	Incl. Teen Labor (5)	Age Heap < 150 (6)	Post 2000 Samp. (7)	3-Yr Exp. Bins (8)	7-Yr Exp. Bins (9)	Wage Info ≥ Month (10)	Incl. Second Job (11)	Agg. HH Level (12)	Close Official Stats (13)	≥ 100 Obs. Bin (14)	Excl. UMI Cntries (15)	Low Mean SE (16)	Low Max SE (17)
Panel A:	Developing Countries																
Ag.	1.2	1.0	2.6	1.2	1.4	1.3	1.0	1.2	1.2	1.7	1.2	0.2	1.3	1.2	1.0	1.1	1.1
Non-Ag.	2.0	1.7	3.7	2.0	2.3	2.1	1.9	2.5	1.8	2.2	2.1	1.7	2.0	2.1	2.1	2.0	2.0
Man.	1.4	1.2	3.1	1.4	1.8	1.6	1.3	1.6	1.2	1.8	1.4	0.8	1.4	1.3	1.3	1.3	1.3
Cogn.	2.2	1.9	3.8	2.2	2.4	2.3	2.1	2.4	2.0	2.4	2.3	2.0	2.1	2.1	2.3	2.2	2.2
Inf.	1.6	1.2	2.9	1.6	2.1	1.7	1.6	1.9	1.4	1.9	1.6	1.4	1.5	1.4	1.5	1.5	1.5
Form.	1.9	1.4	3.8	1.9	2.2	1.8	1.7	2.0	1.7	2.0	2.0	1.8	2.0	1.7	2.1	1.9	1.9
Rur.	1.3	1.0	3.5	1.3	1.7	1.3	1.2	1.4	1.1	1.7	1.3	1.0	1.2	1.2	1.4	1.2	1.2
Urb.	2.2	1.9	3.7	2.2	2.3	2.2	2.1	2.5	1.9	2.3	2.2	2.0	2.2	2.1	2.2	2.2	2.2
Obs (Min)	82	68	15	82	82	58	79	72	81	61	82	82	74	45	56	35	32
Obs (Max)	103	98	33	103	102	73	99	98	103	84	103	102	91	71	70	51	51
Panel B:	Developed Countries																
Ag.	2.7	1.8	4.1	2.7	3.3	2.7	2.7	3.9	2.2	2.7	2.7	2.2	2.7	3.1	2.7	2.9	2.9
Non-Ag.	3.6	2.5	4.2	3.7	3.9	3.6	3.6	4.9	2.8	3.6	3.6	3.2	3.6	3.9	3.6	3.8	3.8
Man.	3.2	2.0	3.2	3.2	3.6	3.2	3.3	4.4	2.5	3.3	3.2	2.9	3.3	3.4	3.2	3.2	3.1
Cogn.	3.7	2.5	3.7	3.7	3.9	3.7	3.7	4.7	2.9	3.7	3.7	3.3	3.7	3.6	3.7	3.7	3.6
Inf.	2.9	1.9	2.9	2.8	3.1	2.9	2.8	3.8	2.1	2.8	2.9	3.0	2.8	2.7	2.9	2.7	2.7
Form.	3.6	2.3	3.3	3.6	3.7	3.6	3.5	4.6	2.8	3.5	3.6	3.2	3.5	3.4	3.6	3.5	3.5
Rur.	3.4	2.0	3.4	3.4	3.6	3.3	3.4	4.4	2.6	3.3	3.4	3.0	3.3	3.4	3.4	3.4	3.4
Urb.	3.7	2.5	3.7	3.7	3.9	3.7	3.7	4.7	2.9	3.6	3.7	3.3	3.6	3.7	3.7	3.8	3.8
Obs (Min)	19	44	4	20	16	19	19	8	24	18	19	18	19	4	19	5	5
Obs (Max)	36	68	27	36	36	36	35	35	36	34	36	34	36	24	36	24	25

Notes: High School: We exclude/keep individuals who have completed at least high school. Cntry Age Entry: We use the country-specific age of entry into primary school to calculate potential work experience. Incl. Teen Labor: We include potential teen labor from age 15 when to calculating potential work experience. Age Heap < 150: We only use samples for which the Whipple Index, which measures age heaping, is not "rough" (< 150). Post 2000 Samples: We only use samples from 2000-2016. 3-Year Exp. Bins: We categorize experience into 3-year bins. 7-Year Exp. Bins: We categorize experience into 7-year bins. Wage Info ≥ Monthly: We keep workers workers for which the wage was reported for a period of at least a month (e.g., monthly, semi-annually or annually). Incl. Second. Job: We include the monthly wage of any secondary occupation. Agg. HH Level: We use mean wages, experience and education in the household. Close Official Stats: We use country-years for which the estimated labor share in I2D2 is less than 10 percentage points from the official labor share. ≥ 100 Obs. Bin: We keep samples with at least 100 obs. per experience bin. Excl. UMI Cntries: We exclude upper-middle income countries from the developing group. Low Mean SE 1st-Step: We use countries whose mean standard error across the fourteen coefficients is below the median mean standard error in the sample. Low Max SE 1st-Step: We use countries whose maximal standard error across the fourteen coefficients is below the median maximal standard error in the sample. *, **, *** = 10, 5, 1% significance.

Table A.6: RETURNS TO EXPERIENCE WHEN INTERACTING DIMENSIONS

	Labor Shares			Estimated Returns to Experience		
Countries:	G	D		G	D	D-G:
Dimension:	(1)	(2)		(3)	(4)	(5)
Agriculture (A)	0.33	0.05		1.2	2.7	***
Non-Agri. & Manual (NM)	0.20	0.17		1.6	3.2	***
Non-Agri. & Cognitive (NC)	0.47	0.79		2.1	3.6	***
			NM-A:	**		[A_D-NM_G: ***]
			NC-A:	***	**	[A_D-NC_G: *]
Agriculture (A)	0.25	0.06		1.1	2.3	***
Non-Agri. & Informal (NI)	0.32	0.27		1.7	2.6	**
Non-Agri. & Formal (NF)	0.43	0.67		1.9	3.4	***
			NI-A:	***		[A_D-NI_G: **]
			NF-A:	***	***	[A_D-NF_G:]
Agriculture (A)	0.37	0.05		0.9	2.7	***
Non-Agri. & Rural (NR)	0.24	0.23		1.5	3.4	***
Non-Agri. & Urban (NU)	0.39	0.72		2.2	3.6	***
			NR-A:	*		[A_D-NR_G: ***]
			NU-A:	***	**	[A_D-NU_G: *]
Manual (M)	0.40	0.23		1.4	3	***
Cognitive & Informal (CI)	0.25	0.23		2.1	2.9	***
Cognitive & Formal (CF)	0.34	0.55		2	3.6	***
			CI-M:	***		[M_D-CI_G: ***]
			CF-M:	***		[M_D-CF_G: ***]
Manual (M)	0.52	0.21		1.3	3.2	***
Cognitive & Rural (CR)	0.17	0.18		1.6	3.4	***
Cognitive & Urban (CU)	0.31	0.61		2.3	3.7	***
			CR-M:			[M_D-CR_G: ***]
			CU-M:	***		[M_D-CU_G: ***]
Informal (I)	0.49	0.31		1.5	2.8	***
Formal & Manual (FM)	0.16	0.14		1.5	3.3	***
Formal & Cognitive (FC)	0.34	0.55		1.9	3.6	***
			FM-I:			[I_D-FM_G: ***]
			FC-I:	**	**	[I_D-FC_G: ***]
Informal (I)	0.49	0.31		1.5	2.8	***
Formal & Rural (FR)	0.26	0.15		1.4	3.4	***
Formal & Urban (FU)	0.30	0.53		2	3.6	***
			FR-I:		*	[I_D-FR_G: ***]
			FU-I:	**	**	[I_D-FU_G: ***]
Rural (R)	0.52	0.26		1.2	3.3	***
Urban & Manual (UM)	0.24	0.21		1.8	3.3	***
Urban & Cognitive (UC)	0.30	0.53		2.3	3.7	***
			UM-R:	***		[R_D-UM_G: ***]
			UC-R:	***		[R_D-UC_G: ***]
Rural (R)	0.56	0.26		1.2	3.1	***
Urban & Informal (UI)	0.14	0.13		1.9	2.9	***
Urban & Formal (UF)	0.31	0.61		2.2	3.5	***
			UI-R:	***		[R_D-UI_G: ***]
			UF-R:	***		[R_D-UF_G: ***]
Countries	84-115	28-36		67-87	16-30	81-111

Notes: The stars shown in brackets indicate whether the returns of the "worse" subdimension in developed countries are significantly higher than the returns of the "best" subdimension in developing countries. *, **, *** = 10, 5, 1% significance.