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Marcio Cruz
Emmanuel Milet
Marcelo Olarreaga

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Abstract

This paper estimates the mobility costs of workers across sectors and regions in a large sample of developing countries. The paper develops a new methodology that uses cross-sectional data only. This is motivated by the fact that panel data typically are not available for most developing countries. The results suggest that, on average, sector mobility costs are higher than regional mobility costs. The costs of moving across sectors and regions are higher than the costs of moving across only sectors or only regions. In poorer countries, workers face higher mobility costs. The paper provides evidence suggesting that mobility costs, particularly across sectors, are partially driven by information assimetries and access to the Internet can mitigate these costs.

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Labor Adjustment Costs across Sectors and Regions[*]

Marcio Cruz[†] Emmanuel Milet[‡] Marcelo Olarreaga[§]

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[†]World Bank and UFPR. email: marciocruz@worldbank.org
[‡]University of Geneva, email: emmanuel.milet@unige.ch .
[§]University of Geneva, CEPII, CEPR and FERDI, email: marcelo.olarreaga@unige.ch.

1 Introduction

We estimate labor mobility costs across sectors and regions for a large number of developing countries. Given that labor surveys in developing countries rarely provide longitudinal data, the methodology we developed only requires cross-sectional data. We rely on the assumption, borrowed from the urban literature, that workers' intertemporal utility net of mobility cost is equalized across sectors and regions. We start by estimating for each worker in our sample their hypothetical wage in other sectors and regions given their observed characteristics. We then compare their level of intertemporal utility in each location or sector. Differences in intertemporal utility capture mobility costs, which are identified using the time horizon faced by each worker in their intertemporal maximization, i.e., the number of years until retirement. After correcting for self-selection of workers into regions and sectors, we find that the sector mobility costs are larger than regional mobility costs and represent about 1.4 times the average annual wage. The cost of moving across sectors and regions simultaneously is larger and represents almost 1.8 times the average annual real wage. We also find that workers in poorer countries face higher mobility costs. In addition, we provide evidence suggesting that information costs partly explain labor mobility costs, which can be mitigated by better access to the Internet.

Estimating labor mobility costs across sectors and regions is important for several reasons. First, moving sector and location is often a joint decision in less developed countries. As economies get richer, the share of jobs in agriculture shrinks and workers migrate to urban areas to find job opportunities in other sectors. Bustos et al. (2016a) provide evidence that technological change in agriculture that is labor-saving can foster industrialization and labor reallocation towards manufacturing. These gains are also extended to other sectors and regions by capital reallocation through bank branch networks (Bustos et al., 2016b). However, if the workforce is not sufficiently mobile across sectors and regions, the gains from labor-saving technological change are unlikely to be realized to their fullest extent, which may slow the speed of structural transformation. Gollin et al. (2014) suggest that even after controlling for sector differences in hours worked and human capital per worker, there is still a large productivity gap in agriculture across developing countries associated with misallocation of factors across sectors. Their findings are supported by Hsieh and Klenow (2009) who suggest that resource misallocation is also existent in manufacturing.[1]

Second, for the gains from trade to materialize, workers and capital must be able to move freely within countries into sectors in which the country has a comparative advantage. Significant gains from trade integration accrue from the reallocation of labor from declining sectors into booming sectors. While capital can move relatively freely within a country, the same cannot be said about workers' mobility. Workers are endowed with sector-specific skills that are not easily transferable

[1] The authors use microdata on manufacturing firms to quantify the potential extent of misallocation of labor and capital across plants within industries in China and India compared to the United States.

to another sector, and new skills are costly to acquire. Furthermore, if changing sector also involves moving to another location workers incur an additional moving cost. This cost includes the cost of physically moving to another location (finding a new house), as well as the loss of the social environment people develop over time, which has a strong geographic component. If workers are stuck in some sector or region because of high mobility costs, gains from trade (or other productivity shocks) are likely to be small or even negative for workers.

Third, understanding what are the forces behind each of these costs (e.g. information costs, retraining costs, moving costs) can further help policy makers pinpoint the strategies needed to promote more labor mobility and ultimately a more efficient and equal wage distribution.[2]. Whether the lack of observed relocation of workers is driven by the difficulty of moving across sectors or across regions is highly relevant for policy makers who have to decide whether to allocate resources to the reduction of sector or regional mobility costs. Most of the existing literature has typically focused on one of these two adjustment costs separately. Our aim is to simultaneously identify the costs incurred by workers when they move to another region and when they become employed in a different sector. Ignoring the various dimensions of mobility costs can lead to an overestimation of the true cost of moving to another sector and/or to another location.

We face several challenges to estimate region and sector mobility costs in developing countries. First, if our methodology does not require longitudinal data, it does require cross sectional data that are comparable across countries. The World Bank has recently put together a series of labor and households surveys which are harmonized along some key dimensions, such as sector, location and other workers' characteristics. The richness of the International Income Distribution Data set (I2D2) allows us to account for workers' heterogeneity, which is an important component of our methodology.[3]

The second challenge has to do with the bias that workers' self-selection into regions or sectors may introduce in our analysis (Roy, 1951). If more skilled workers select in one sector or region, the comparison of wages across sectors and regions is not providing information on mobility costs, but on different returns to skills. To provide meaningful comparisons of predicted wages we estimate mobility costs by controlling for differences in observed heterogeneity, such as age differences, education, gender, and occupation across sector and regions. In addition, we deal with self-selection of workers into regions and sectors based on unobservables characteristics by applying a correction method suggested by Dahl (2002).

The third challenge we face is that workers base their migration decision on real wages, and not nominal wages. Information on the cost of living at the regional level in developing countries is unfortunately not available. We bypass this issue by using the average wage in each region to

[2]Based on a quasi-experiment using detailed information on rural road construction in India Asher and Novosad (2016) suggest that poor rural transportation infrastructure is a major constraint on the sectoral allocation of labor in low-income countries

[3]See Montenegro and Hirn (2009) for more details on the I2D2 database.

proxy for the local cost of living and compute real wages. This has the additional advantage as will become clearer in the empirical methodology section that our estimates of adjustment costs can be interpreted in terms of average real wages.

The fourth challenge has to do with the fact that the methodology we propose relies on cross-sectional data only, but the question at stake is fundamentally dynamic. To account for the fact that younger workers are more "footloose" than older ones, we use the difference between observed age and (expected) retirement age as a measure of workers' time horizon.[4] This introduces worker-level variation that will prove to be important in the estimation of the mobility cost and allow us to introduce dynamic considerations when estimating mobility costs.

The literature has recently produced various estimates of mobility cost (Hollweg et al., 2014). Kennan and Walker (2011) develop a model of individual migration, where expected income is the main force influencing migration. They test their model using detailed US data on individual workers. They find that interstate migration is strongly influenced by the prospect of higher income in other states, and estimate an elasticity of 0.5 between wages and migration decision. One important difference with our paper is that they do not consider sector mobility costs and exclusively focus on region mobility costs.

Using the same kind of theoretical tools but in a context of trade shocks, Artuç et al. (2010) propose a structural estimation of the reallocation cost of workers across sectors. Using panel data where workers' movements can be observed over time, they estimate the structural parameters of their model on US data and find an average moving cost of about 13 times the average worker's annual wage. In their model, workers are homogeneous, which may explain the large moving-cost they obtain. Dix-Carneiro (2014) develops a model where worker's heterogeneity is taken into account. Using panel data for Brazilian workers, he estimates an average moving cost of about 2 times the average annual worker's wage. Taking into account heterogeneity across workers appears to affect greatly the magnitude of the moving cost. Artuç et al. (2015) estimate sector mobility costs in a large number of countries by adapting the methodology in Artuç et al. (2010) to be implemented using repeated cross-sectional data on sectoral employment in manufacturing in each country. They found sector mobility costs that are on average 3 times annual wages. One important difference between all these papers and what we do is that we simultaneously allow for regional and sector mobility costs, whereas the previous papers have exclusively focus on only one of these two components. We find that simultaneously accounting for both matters. Moreover, we explore some potential channels that may explain labor mobility costs, including costs associated with information asymmetries , and investigate how access to Internet can reduce mobility costs.

The rest of the paper is organized as follows. In section 2 we present the methodology to estimate sectoral and regional adjustment costs using cross-sectional data. Section 3 describes the

[4] Younger workers may have acquired less skills than older workers, and their social network is likely to be less dense than that of their elders.

I2D2 database and provides some descriptive statistics regarding wage dispersion across region, sectors and age groups. Section 4 presents the estimates of regional and sector mobility costs, as well as a description of their correlation with variables such as income per capita, wage inequality and the geographic and sectoral concentration of employment. Section 5 explores the extent to which the estimates of mobility costs are driven by information costs and analyzes how access to the Internet is associated with reduction in mobility costs. Section 6 concludes.

2 Methodology

Consider a worker of type l (a type being given by characteristics such as age, gender, education, occupation, etc.) working and living in sector-region k.[5] Making this distinction right now would uselessly flood the text with subscript and indices. Her utility $U_{l,k}$ is given by:

$$U_{l,k} = w_{l,k} + \gamma_l, \tag{1}$$

where $w_{l,k}$ is the log of real wage received by the worker; γ_l represents worker's characteristics (orthogonal to wages) that are common across the different region/industries. We assume that (i) workers are rational and maximize their intertemporal utility, and (ii) what we observe in the data is an equilibrium. Workers of type l will decide to move from sector-region k to sector-region k' until their intertemporal utility $V_{l,k}$ is equal to the intertemporal utility in sector-region k' ($V_{l,k'}$) net of mobility costs ($C_{k,k'}$). Workers of different age maximize over different time horizons. We assume they maximize over (T_l-t_0) years, where T_l is the retirement age and t_0 their current age. This is an important feature of our model since our empirical strategy will strongly rely on the time horizon of workers until retirement (therefore on their age) for identification. This implies that for all $V_{l,k'}>V_{l,k}$ we should observe in equilibrium:

$$\begin{aligned} V_{l,k} &= V_{l,k'} - C_{k,k'} \\ \sum_{t=t_0}^{T_l} \beta^t U_{l,k} &= \sum_{t=t_0}^{T_l} \beta^t U_{l,k'} - C_{k,k'}, \end{aligned} \tag{2}$$

where β is the intertemporal discount factor. Substituting (1) into (2) and solving for the difference in gross intertemporal utilities yields:

[5]We consider jointly the sector in which workers are employed and the place where they live. In the empirical analysis we distinguish between industry and region.

$$C_{k,k'} = V_{l,k'} - V_{l,k} = \sum_{t=t_0}^{T_l} \beta^t [\widehat{w}_{l,k'} - w_{l,k}]$$

$$C_{k,k'} = V_{l,k'} - V_{l,k} = \sum_{t=t_0}^{T_l} \beta^t \Delta w_{l,k,k'} \tag{3}$$

where $C_{k,k'}$ is the cost (in utility terms) of moving from sector-region k to sector-region k', and $\Delta w_{l,k,k'} = \widehat{w}_{l,k'} - w_{l,k}$ is the difference between the hypothetical real wage of worker l in sector-region k' and her current (observed) real wage $\mathrm{w}_{l,k}$. We will use the equilibrium condition (3))to estimate the moving costs. With β lower than one, we have: $\sum_{t=t_0}^{T_l} \beta^t = \frac{1-\beta^{(T_l - t_0)}}{1-\beta}$. Solving equation (2) for the wage difference yields:

$$\Delta w_{l,k,k'} \quad = \quad C_{k,k'} \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}}, \tag{4}$$

Following Artuç et al. (2010) we assume that that mobility costs are symmetric and identical across sector-regions (i.e. $C_{k,k'} = C$). The parameter β is not observed and we follow the literature by using a discount factor equal to 0.95 and test for the robustness of results using estimates in the [0.9;0.99] range. This discount factor corresponds to the usual annual discount factor, which implies that the mobility costs C we estimate can be interpreted as a share of annual wages. To control for any other unobserved heterogeneity in sector-regions k and k' we add fixed effects to obtain our estimating equation:

$$\Delta w_{l,k,k'} \quad = \quad C_{k,k'} \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} + \alpha_k + \alpha_{k'} + \epsilon_{l,k,k'}. \tag{5}$$

The set of dummies α_k and $\alpha_{k'}$ can be thought as capturing local amenities in each sector-region, or anything other factor that may explain average differences in real wages in different sector-regions. This is somehow analogous to the idiosyncratic shocks ξ_j that workers receive in industry j in Artuç et al. (2010), or to the unexplained part of the utility flow viewed as preference shocks, or shocks to the cost of moving in Kennan and Walker (2011). Retrieving the moving cost $\mathrm{C}_{k,k'}$ from equation (5) can be done via simple OLS. Because equation (2) is an equilibrium condition if and only if $\mathrm{V}_{l,k'} > \mathrm{V}_{l,k}$, which from (3) necessarily implies $w_{l,k'} > w_{l,k}$, we impose this condition in the estimation.

We are interested in estimating separately three mobility costs. First, we want to estimate the cost for workers to move across sectors while remaining in the same region. We use the subscript

j to denote this mobility cost ($C_{j,j'}$). Second, we want to estimate the cost for workers to move across regions within a country while remaining employed in the same sector, and use the subscript r to denote characterize this mobility cost ($C_{r,r'}$). Finally, we are interested in estimating the cost for workers when they change sector and move to another region. We use the subscript jr to label this cost ($C_{jr,j'r'}$). Note that these three costs are orthogonal to each other, and that the "general" mobility cost ($C_{k,k'}$) is simply their union. Equation (6a) illustrate this strategy. We also want to compare these mobility costs with estimates where we ignore either the sector or the region dimension. To do so, we estimate equations (6b) and (6c) where we consider the cost of moving across sectors ($C2_{j,j'}$) (ignoring whether workers move to another location), and the cost of moving across regions ($C2_{r,r'}$) while ignoring that workers may also be moving across sectors.

$$\Delta w_{l,jr,j'r'} = [C_{j,j'} + C_{r,r'} + C_{jr,j'r'}] \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} + (\alpha_{r'} - \alpha_r) + (\alpha_{j'} - \alpha_j) + \xi_{l,jr,j'r'} \tag{6a}$$

$$\Delta w_{l,j,j'} = [C2_{j,j'}] \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} + (\alpha_{j'} - \alpha_j) + \epsilon_{l,j,j'} \tag{6b}$$

$$\Delta w_{l,r,r'} = [C2_{r,r'}] \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} + (\alpha_{r'} - \alpha_r) + \varepsilon_{l,r,r'} \tag{6c}$$

To estimate equations (6a)-(6c) we need an estimate of the left-hand-side $\Delta w_{l,k,k'}$. While $w_{l,k}$ is observed, $\widehat{w}_{l,k'}$ is not observed and has to be estimated. To properly estimate wages we need to account for both observable and unobservable characteristics. The I2D2 provides us with many individual characteristics we can directly use to predict wages. Unobserved characteristics are an issue if they are a determinant of wages, via the self-selection of workers into specific sector-regions for instance. We tackle this issue by estimating the probability for a worker to be observed in a specific sector-region using the methodology proposed by Dahl (2002). We then use this predicted probability as an additional determinant of wages. The next section describes the method in detail.

2.1 Expected wages and selection bias

Expected wage is a key variable in our analysis. We assume that workers are heterogeneous based on observable characteristics, including age, skills, gender, and occupation. To correct for self-selection based on other unobserved characteristics when estimating ($\widehat{w}_{l,k'}$) we adapt the methodology proposed by Dahl (2002), also used by Bourguignon et al. (2007) and Bertoli et al. (2013). The selection bias may happen because workers can choose among several industries-regions to work based on unobservable characteristics that may be correlated with their expected wages across different industries-regions. Thus, differences in wages accross industry-regions might be partly capturing differences in worker's ability unrelated to age, gender, schooling, or occupation. Note that in our cross-sectional data set we do not have information on the share of workers who migrate across sector-regions to estimate the selection probability of migration, as in Dahl (2002). Instead, we adapt a Roy model of occupational choice where workers choose from many alternative of jobs across sectors and regions, taking into consideration the relative concentration of jobs across sectors and regions. We proceed in two steps. First, we estimate Dahl's correction function based on the probabilities for a worker l to be in a different sector-region k using a multinomial logit model, following equation 7.

$$P(k_l = n|x_l) = \frac{exp(x_l'\beta_n)}{\left[1 + \sum_{h=1}^{N} exp(x_l'\beta_h)\right]}, \qquad n = 1, ..., N. \tag{7}$$

where x_l is a matrix made of the location quotient, $Z_{l,k}$, and a set of individual observable characteristics: age, age^2, occupation dummies, skill dummies, and a gender dummy. We estimate this equation using a multinomial logit and construct the predicted probability of observing worker l across different sector-regions k_n.

The location quotient, $Z_{l,k}$, is defined as:

$$Z_{l,k} = \frac{\#workers_{l,k}}{\#workers_k} / \frac{\#workers_l}{\#workers}.$$

where $\#workers_{l,k}$ is the number of workers at age l in sector-region k, $\#workers_k$ is the total number of workers in sector-region k, $\#workers_l$ is the number of workers at age l in the country, and $\#workers$ is the total number of workers in the country.

The predicted probability for each sector-region $\widehat{k}$ and its quadratic term $\widehat{k}^2$ is then used as correction fuction in the second stage to estimate expected wages ($\widehat{w}_{l,k'}$). We do this by adding $\widehat{k}$ and $\widehat{k}^2$ as additional explanatory variables in the following mincer equation:[6]

$$\begin{aligned} w_{l,k} = {} & \alpha + \beta_1 age_{l,k} + \beta_2 age^2_{l,k} + \beta_3 occup_{l,k} + \beta_4 skill_{l,k} + \beta_5 gender_{l,k} \\ & + \beta_6 age_{l,k} * K + \beta_7 age^2_{l,k} * K \ + \beta_8 occup_{l,k} * K + \beta_9 skill_{l,k} * K \\ & + \beta_{10} gender_{l,k} * K \ + \sum_1^N K + \sum_1^N \widehat{k} + \sum_1^N \widehat{k}^2 + \epsilon_{l,k} \end{aligned} \tag{8}$$

where $w_{l,k}$ refers to real wage of worker l in region k, α is a constant, *age* is the age of the worker, *agesq* is age square, *occup* is a dummy variable indentifying managerial occupations, *skill* is a dummy variable differentiating workers by education attainment (high-school or above), K is a set of fixed effects by sector-region based on the observed location of worker l, $\widehat{k}$ is the estimated probability of workers being in sector-region z, and ϵ is the error term. To capture the heterogeneity

[6] Our specification leads to similar results as using the selmlog routine develped by Bourguignon et al. (2007). Yet, instead of running a separate second stage for each industry-region, we capture the differences in the return of workers' observable characteristics (e.g. age, occupation, skills, and gender) through interactions terms using weights at the national level.

of the marginal returns to workers' characteristics (e.g. experience, skills, occupation, and gender) across sector-region k we interact *age*, *agesq*, *occup*, *skill*, and *gender* with the sector-region dummies K.

3 Data: The I2D2

We use the International Income Distribution Database (I2D2) developed at the World Bank. The I2D2 is a global harmonized household survey database, covering 120 countries. Data are collected from more than 1,000 surveys, and harmonized in order to be used for quantitative analysis. For the purpose of this study, we had to select surveys for which some key information on worker's gender, age, education, occupation, industry affiliation and location of residence (administrative region and rural/urban area) is non-missing. We also selected individuals working as paid employees between the age of 15 and 65. There are 10 occupations in the database: Senior officials, professionals, technicians, clerks, service and market sales workers, skilled agricultural workers, craft workers, machine operators, elementary occupations workers, and military. We define two broad categories of occupation: a managerial-type occupation (senior officials, professionals, and technicians) and a non-managerial occupation comprised of the remaining occupations. Similarly, we define 17 age categories by grouping individuals in a three years of age interval. For instance, individuals between 15 and 17 (included) are given the age of 16; individuals between 18 and 20 (included) are given the age of 19 and so on. The reason for this is that we need to reduce the dimensionality of worker characteristics for the selection equation to be able to perform appropriately.

Sectors are defined in 10 categories: agriculture, mining, manufacturing, public utilities, construction, commerce, transport and communications, financial and business services, public administration, and other services. Because some sectors have a very small size in some surveys, we aggregate them into 7 categories by merging agriculture with mining, public utilities with construction, and public administration with other services. Unlike sectors, the definition of regions as a geographical unit is not harmonized across surveys. Most of the countries in our final data set consist of on average 6 regions. Our final data set is a collection of 234 worker-level surveys covering 47 (almost exclusively) developing countries over the period 1981-2012. Table 1 provides the full list of surveys.

Our identification strategy relies on the age of workers. If older workers are less likely to move, i.e. they face higher mobility costs, then we should observe larger wage differences across sectors and/or regions for them than for younger workers. This implies a positive correlation between the age of workers and the variance of wages within this age group. To investigate this, we estimate the following equation:

$$ln\Big(\sigma(wage_{lct})\Big) = \alpha ln(age_{lct}) + \gamma_c t + \epsilon_{lct}, \quad (9)$$

where $ln(\sigma(wage_{kct}))$ and $ln(age_{kct})$ are respectively the log of the standard deviation of the wage distribution and the age of workers with of age l in country c in year t; $\gamma_c t$ are country×year fixed effects and ϵ_{kct} is the error term. A positive correlation between wage dispersion and age would imply α positive. Figure 1 plots the conditional correlation between $ln(\sigma(wage_{kct}))$ and $ln(age_{kct})$. The correlation is positive and statistically significant, with $\hat{\alpha}$ equal to 0.7 and very precisely estimated. Similarly, one can look at the dispersion of wages across sectors and regions. For each survey, we compute the variance of wages across these two dimensions. Results are shown in figure 2. The horizontal axis represents the dispersion of wages across sectors and the vertical axis represents the dispersion of wages across regions. Both are computed as the log standard deviation of the sample distribution. Each point in the figure represents a survey. Points to the right of the 45 degree lines indicate surveys for which the dispersion of wages across sectors is greater than the dispersion of wages across regions. This is the case for 80% of the surveys in our data and suggest that sector mobility costs may be larger than mobility costs across regions.

4 Results

4.1 Baseline results: With correction

The estimation of equations (7) and (8) is performed at the country× level, using worker level information, and three mobility costs are estimated each time for each of the 235 country-year surveys separately. This means that we have a total of 705 estimates. To avoid flooding the text with long tables, we present summary statistics of the estimates in table 2. The upper panel of table 2 presents the average, median and standard deviation for each mobility costs based on the estimates where we correct for the self-selection of workers into sectors and regions. The lower panel restricts the summary statistics to the mobility costs which are statistically significant at the 10% level.

Columns (1) reports the estimates for the sector mobility costs. On average, across the 235 country×year surveys we find that an average cost of moving across sectors (while remaining within the same region) is about 1.4 times the average annual real wage. The median mobility cost is slightly smaller, at around 1.3 times the average annual wage. Using only the significant estimates produces a larger average sector mobility cost.

Columns (2) reports the estimates for the region mobility costs. These costs are lower than the sector mobility costs. On average, region mobility costs represent about 86 percent of the average annual wage, while the median mobility cost is about 80 percent of the average annual wage.

Finally, column (3) reports summary statistics for the mobility cost incurred by workers when the change sectors and move to another location. On average, this cost is 1.8 times the average annual real wage, which is larger than the sector-only and region-only mobility costs. Note that the number of estimates which are statistically significant is much larger than for the other mobility costs. Using only the significant estimates produces a larger average sector-region mobility cost.

Yet, the mobility costs across countries are heterogeneous. Sector mobility cost range from one time the average annual wage in countries such as Honduras or Argentina to more than 10 times the average annual wage in Cameroon, Ethiopia, or South Africa. Regional mobility costs range from around 30% of the average annual wage in places like Uguanda and Malawi to more than 5 times in Timor-Leste or Ethiopia. The costs incurred by individuals moving across sectors and regions ranges from at least one time the average annual wage (Argentina, the Republic of Yemen, Chile) to more than 10 times in Ethiopia or South Africa. In the next subsection we investigate some of the determinants of mobility costs.

4.2 Explaining the mobility costs

The historical patterns of structural transformation in high income countries suggest that as economies develop workers move from agriculture activities in rural areas towards urban jobs in industry and services. This has been well documented in the literature (Clark, 1940; Rostow, 1959; Lewis, 1954). Yet, depending on the pattern of technological progress and frictions in labor market, workers may be misallocated across sectors and regions, slowing down structural transformation. To provide some description of the mobility costs and its association with development, we estimate the following equation:

$$\hat{C_{c,t}} \quad = \quad \alpha + \beta Country_{c,t} + \gamma_c + \gamma_t + \varepsilon_{c,t}, \tag{10}$$

where $\mathrm{C}_{c,t}$ is the estimated mobility costs of moving between industry/region k and k' and $\varepsilon_{c,t}$ is the error term. γ_c and γ_t are country and year fixed effects respectively. In the empirical analysis we use them alternatively. Because the left-hand side variable of equation (10) is estimated with error, we weight the observations by the inverse of the standard error of each mobility cost Lewis and Linzer (2005). We estimate equation (10) for each mobility cost and using a single country characteristics at a time. The country characteristics we use are the log of GDP per capita, The Gini coefficient, and the share of agriculture, manufacturing and services in employment. We expect GDP per capita to be negatively correlated with mobility costs, both across countries, and within countries over time as financial constraints which restrict mobility are likely to be lower as countries get richer. We also expect the Gini index to be positively correlated with mobility costs.[7]

[7] We computed the GINI index based on the information available in the surveys. It is therefore a measure of wage inequalities rather than total income inequalities.

Without claiming any causal link between mobility costs and income inequalities, we argue that high mobility costs can lead to divergent trajectories for wages both across industries and across regions. We then use the share of the three large sectors (agriculture, industry, and service) in total employment with the aim of capturing the extent of structural change across and within countries. Industry or services activities are likely to be more mobile than agriculture, which is strongly tied to land. Similarly, service activities are also likely to be more mobile than industry, where capital is less mobile in the short-run than in the long-run. We then use three measures of the concentration of jobs within industries, regions and industry× regions. We define an index aiming at capturing such specialization:

$$\textit{Specialization Index}_k = \sum_{k=1}^{K} \left[\frac{L_k}{L}\right]^2 \qquad k \in \{j, r, jr\},$$

where L is total employment, and L_k is employment in sector/region k. The index is a herfindahl index based on the share of sector, region or sector×region k in overall employment. It ranges from zero to 1/K. We expect the specialization index to be positively correlated with the mobility cost. Everything equal, the more concentrated jobs are in a particular sector and/or region the more difficult it is to move to another sector/region. Finally, we look at whether large countries face higher mobility costs. We use the average internal distance within a country to proxy for its size. We expect the regional cost to be positively correlated with internal distance. Because there is no time variation in this variable we only use it with time fixed effects.

Results are presented in table 3. Each coefficient (with its associated standard error) comes from a separate regression. In columns (1) and (4) the dependent variable is the sector mobility cost ($\widehat{C}_{j,j'}$), and we control for country or year fixed effect respectively. The same logic applies to columns (2) and (5) for the region mobility cost ($\widehat{C}_{r,r'}$), and to columns (3) and (6) for the sector× region mobility cost ($\widehat{C}_{jr,j'r'}$). Results indicate that the difference in mobility costs is significant between richer and poorer countries. The coefficients on GDP per capita are significant in columns (1)-(3). As countries get richer, the sector mobility cost and the sector×region mobility costs get smaller. On average, a 1% increase in GDP per capita lowers the sector mobility cost by 0.3%, and the sector-regional mobility cost by 0.6%, when controlling for country fixed effects. Note that variation in GDP per capita is not correlated with the regional mobility costs. The second country characteristics we use is the Gini index. Results indicate that more unequal countries, or countries that become more unequal over time, have higher sector and sector×regional mobility costs (columns 1 and 3, and 4 and 6). This finding supports the view that wage convergence is difficult when mobility costs are larger.

Finally, we look at whether sector and/or regional mobility costs are correlated with the structure of the economy. We alternatively regress each mobility cost on the share in employment of the agricultural, manufacturing, and service sector. Results indicate that countries with a larger agricultural sector also have higher mobility costs (columns 1-3). Results in columns (4-6) suggest that, as the share of the agricultural sector declined in most countries over time, so did on the average the mobility costs. Symmetrically, we obtain opposite results when considering the share of the manufacturing sector in the economy. More industrialized countries face lower sector mobility costs. Results are similar when considering the share of the service sector, but with a much smaller magnitude than for the manufacturing sector. Although we do not claim any causal link, our results suggest that larger mobility costs are correlated with the level and speed of structural change.

One constraint of our analysis is that the definition of a region is not identical across countries and we had to restrict ourselves to a limited number of regions for computational reasons, which means that large countries may have too few regions compared to smaller countries. We re-estimated the regression using only small countries (we dropped countries for which the average internal distance is above 1,000 km). The intuition is simple and merely assumes that greater distances between regions increases the cost of moving.Larger countries may also have developed denser road and railway networks, which would ease regional mobility. To capture these two effects, we use data on internal distance from CEPII.[8] and data on the length (in km) of the railway network from the World Development Indicators. Results presented in table 3 show that internal distance is positively correlated with the regional mobility costs, but results are less precisely estimated when using only statistically significant estimates of reginal mobility costs. The size of the railway network (which we interpret here as a proxy for transport infrastructure) is negatively correlated with regional mobility costs. Yet, when controlling for both variables (distance and railway network), none of them are statistically significant.[9]

5 Information costs and Internet access

For policy makers it is not only important to know whether sector or regional mobility costs are larger, but it is also key to understand what is driving these costs and what policies are available to reduce them. We explore this question by putting forward a potential explanation associated with information costs and analyze how access to the Internet may mitigate them. Other determinants (e.g. retraining costs and social network) have also been explored by the literature. For example, Dix-Carneiro (2014) suggests a moving subsidy as a better policy than retraining to compensate the fact that sector-specific experience is not perfectly transferable across sectors.[10]

A potential driver of mobility costs is lack of information associated with searching costs. Work-

[8] Mayer and Zignago (2011).

[9] These results are not fully comparable due to limitation of observations available for rail lines, which significantly reduces the sample.

[10] In a simulation of welfare change as a function of shocks in prices of high-tech manufacturing, he finds that moving subsidy policies seem to be more effective than retraining.

ers have to learn about job opportunities in other sectors and regions, while employers need to learn about the availability of workers, including those in other sectors and regions. An increase in Internet labor market connections should improve the efficiency with which workers are matched to jobs (Autor, 2001). Yet, the empirical literature evaluating the effects of Internet access on job search is not conclusive. Kroft and Pope (2014) find no effect of Craigslist, a major website aiming to advertise jobs and items for sale, at virtually no cost to the user, on the unemployment rate in the United States. Kuhn and Skuterud (2004) also find that Internet job search was ineffective in reducing unemployment durations, but in a more recent paper Kuhn and Mansour (2014) suggest that unemployment duration is about 25% shorter for those workers who search for jobs online. However, most of these findings are based on the United States and do not focus on the effect of Internet access on labor mobility costs.

We explore the importance of this channel by looking at how sector and regional mobility costs differ for workers with and without Internet access. We use a similar correction procedure, following Dahl (2002), to take into account self-selection of workers into sectors and regions. To capture the "access to internet" effect on mobility costs, we construct a variable that measures the relative concentration of access to Internet at the industry-region across different age groups.[11]

$$int_k = \left[\frac{Share\ of\ workers\ at\ age\ (l)\ in\ industry-region\ (k)\ with\ access\ to\ internet}{Share\ of\ workers\ at\ age\ (l)\ in\ country\ (y)\ with\ access\ to\ internet}\right],$$

We then re-estimate eq.(6c) adding the variable int_k in level and its interaction with each mobility costs (across sectors, regions, and both). More specifically, we estimate eq.11:

$$\begin{aligned}\Delta w_{l,jr,j'r'} &= [C2_{j,j'} + C2_{r,r'} + C2_{jr,j'r'}] \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} + int_k \\ &+ [C2_{j,j'} \times int_k + C2_{r,r'} \times int_k + C2_{jr,j'r'} \times int_k] \times \frac{1-\beta}{1-\beta^{(T_l - t_0)}} \\ &+ (\alpha_{r'} - \alpha_r) + (\alpha_{j'} - \alpha_j) + \xi_{l,jr,j'r'}\end{aligned} \tag{11}$$

Because int_k is a continuous variable, we compare the differences in the coefficients (with and without interaction with int_k) assuming different values for int_k. First we compare having no access to the Internet in the industry-region $int_k = 0$ versus having access equivalent to int_k national average. We call this comparison "average versus non-access to Internet." We then compare relative low-access to Internet, defined as one standard deviation below to the national average in a given industry-region, to a relative high-access to the Internet, defined as one standard

[11] We use the location quotient at the industry-region level across age groups instead of a dummy variable identifying access to the internet at the household level because we believe this is a better proxy to capture information flow provided by access to the Internet. The larger the proportional number of workers in a given industry-region with access to the internet at home, the more likely the workers in this industry-region will benefit from access to more information. We assume that this is valid if for workers who do not have access to the Internet at home.

deviation above the national average. Table 4 shows the results for these comparisons.[12]

Our results suggest that the mobility costs, particularly across industry and industry-region, tend to be smaller for workers with relatively more access to the Internet (table 4). This effect is not robust for mobility costs across regions when using only statistically significant estimates. Also, there are fewer statistically significant estimates for mobility costs across regions.[13] For example, on average sector mobility costs in Brazil would reduce from 1.1 to 0.97 times the average annual wage if access to the Internet for a worker in a given age l in region-industry k increases from low- to high-access status. A similar pattern is observed for Costa Rica, Honduras, Peru, Paraguay and Uruguay. The costs of moving to another industry-region in Brazil reduces from 1.3 to 1.02 times the average annual wage if workers move from low- to -high-access to Internet statuts. This pattern is followed by other countries (Chile, Peru, Paraguay, Uruguay, and the Republica Bolivariana de Venezuela) in figure 5, except Honduras. Other exceptions, where the Internet effect seems to be negative are Chile, for sector, and Honduras, for region. But both countries also have significant coefficients that suggest positive effects of the Internet on industry or industry-region mobility costs.

The numbers of significant coefficients are smaller for regions, which may suggest that other factors (e.g. infrastructure, differences on amenities, or social network) might be more important as a driver of mobility costs across regions. These results also suggest that lack of access to information may play an important role in determining mobility costs across sectors. In addition to facilitate access to information on jobs' opportunities in other sectors (and regions) access to the Internet can also reduce the costs of acquiring skills to perform in other sectors (e.g. online courses platform).

6 Concluding remarks

This paper estimates mobility costs of workers across sectors and regions in a very large sample of developing countries. Our results suggest that on average sector mobility costs are larger than regional mobility costs. The average sector mobility cost is about 1.4 times the average real wage and is larger than the regional mobility costs (0.9 times the average real wage). The cost of moving both sector and region (1.8 the average real wage) is larger than the costs of moving only sector or only region, but smaller than the sum of these two costs. Our results also suggest that increasing access to the Internet can reduce mobility costs across sectors and sector-regions. Thus, facilitating access to information might be an important policy to be considered by governments aiming to reduce mobility costs.

[12]Table 1 provides the country and year of surveys included in the sample and estimations at the country-year level.

[13]The number of surveys available is significantly smaller for this section due to lack of data availability on Internet access. The analysis covers 67 surveys for 17 countries, most of them from Latin America and the Caribbean region.

References

Artuç, E., S. Chaudhuri, and J. McLaren (2010). Trade Shocks and Labor Adjustment: A Structural Empirical Approach. *American Economic Review 100*(3), 1008–45.

Artuç, E., D. Lederman, and G. Porto (2015). A Mapping of Labor Mobility Costs in the Developing World. *Journal of International Economics 95*(1), 28 – 41.

Asher, S. and P. Novosad (2016). Market Access and Structural Transformation: Evidence from Rural Roads in India. mimeo.

Autor, D. H. (2001). Wiring the Labor Market. *Journal of Economic Perspectives 15*(1), 25–40.

Bertoli, S., J. Fernndez-Huertas Moraga, and F. Ortega (2013). Crossing the Border: Self-selection, Earnings and Individual Migration Decisions. *Journal of Development Economics 101*(C), 75–91.

Bourguignon, F., M. Fournier, and M. Gurgand (2007). Selection Bias Corrections Based On The Multinomial Logit Model: Monte Carlo Comparisons. *Journal of Economic Surveys 21*(1), 174–205.

Bustos, P., B. Caprettini, and J. Ponticelli (2016a). Agricultural Productivity and Structural Transformation: Evidence from Brazil. *American Economic Review 106*(6), 1320–1365.

Bustos, P., B. Caprettini, and J. Ponticelli (2016b). Capital Allocation Across Regions, Sectors and Firms: Evidence from a Commodity Boom in Brazil. mimeo.

Clark, C. (1940). *The Conditions of Economic Progress*. Macmillan and co., limited.

Dahl, G. B. (2002). Mobility and the Return to Education: Testing a Roy Model with Multiple Markets. *Econometrica 70*(6), 2367–2420.

Dix-Carneiro, R. (2014). Trade Liberalization and Labor Market Dynamics. *Econometrica 82*(3), 825–885.

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

Hollweg, C. H., D. Lederman, D. Rojas, and E. R. Bulmer (2014). *Sticky Feet: How Labor Market Frictions Shape the Impact of International Trade on Jobs and Wages*. The World Bank.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and Manufacturing TFP in China and India. *The Quarterly Journal of Economics 124*(4), 1403–1448.

Kennan, J. and J. R. Walker (2011). The Effect of Expected Income on Individual Migration Decisions. *Econometrica 79*(1), 211–251.

Kroft, K. and D. G. Pope (2014). Does Online Search Crowd Out Traditional Search and Improve Matching Efficiency? Evidence from Craigslist. *Journal of Labor Economics 32*(2), 259–303.

Kuhn, P. and H. Mansour (2014). Is internet job search still ineffective? *Economic Journal 124*(581), 1213–1233.

Kuhn, P. and M. Skuterud (2004). Internet Job Search and Unemployment Durations. *American Economic Review 94*(1), 218–232.

Lewis, J. B. and D. A. Linzer (2005). Estimating Regression Models in Which the Dependent Variable Is Based on Estimates. *Political Analysis 13*(04), 345–364.

Lewis, W. (1954). Economic Development with Unlimited Supplies of Labor. Manchester school of economics ans social studies, 139-191.

Mayer, T. and S. Zignago (2011). Notes on CEPII's Distances Measures: The GeoDist Database. CEPII Working Papers 2011-25.

Montenegro, C. E. and M. Hirn (2009). A new disaggregated set of labor market indicators using standardized household surveys from around the world. *Background paper prepared for World Development Report*.

Rostow, W. W. (1959). The Stages of Economic Growth. *The Economic History Review 12*(1), 1–16.

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers 3*(2), pp. 135–146.

Appendix

Figure 1: Correlation between worker age and wage dispersion

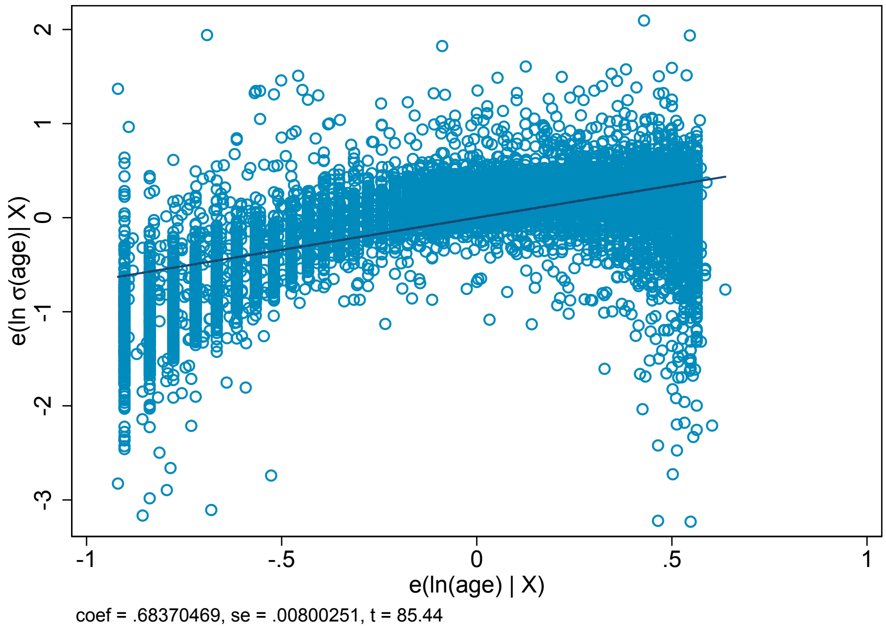


Figure 2: Dispersion of wages across industries and regions

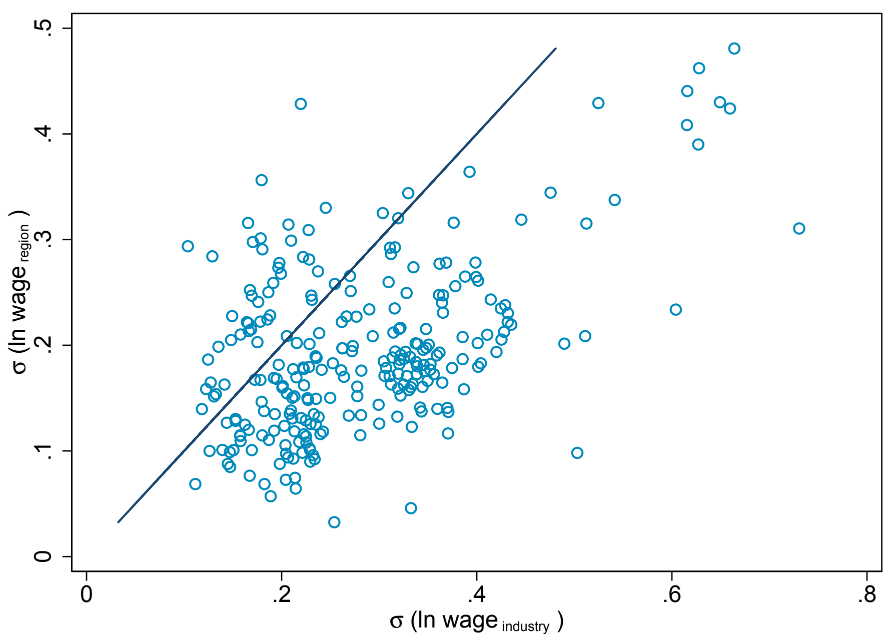
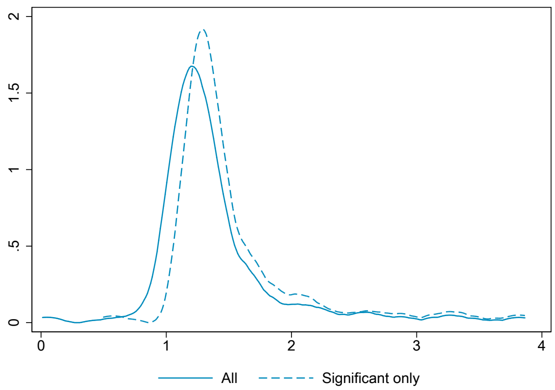
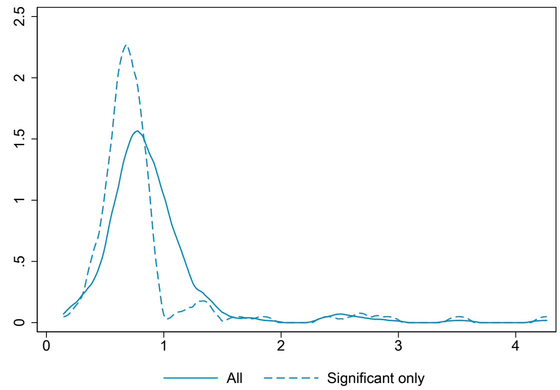


Figure 3: Distribution of mobility costs (corrected for selection)

(a) Sector



(b) Regional



(c) Sector×Regional

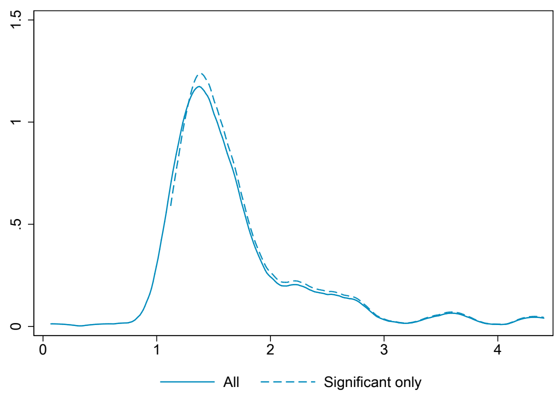
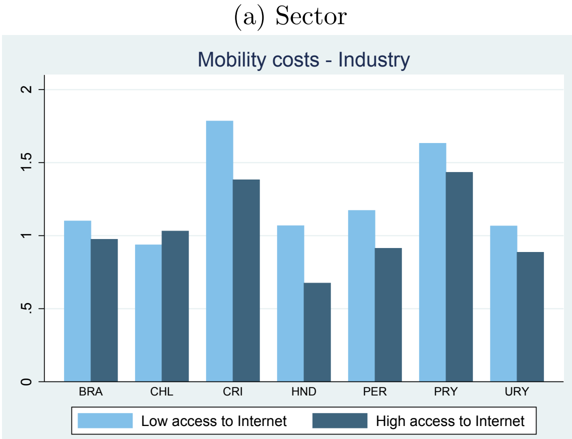


Figure 4: Comparing mobility costs with High- versus Low-access to Internet

(a) Sector



(b) Sector×Regional

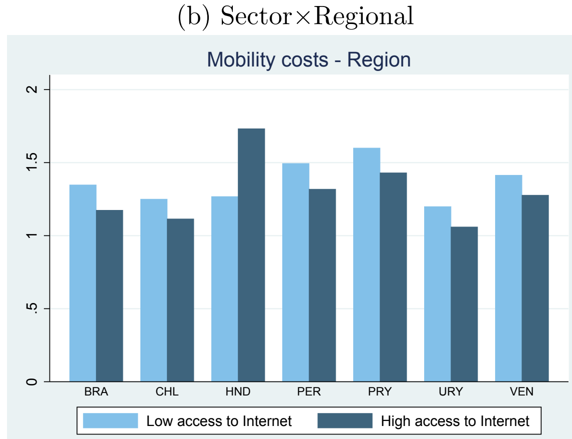


Table 1: List of surveys in our sample

Cty	#Years	# regions	# sectors	Surveys
ALB	1	4	7	2005*
ARG	6	6	7	2003, 2006, 2007, 2009, 2010, 2012
AUS	9	8	7	2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010
BGD	1	6.5	7	2000
BIH	1	2	7	2001
BRA	23	5	7	1981, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1989, 1990, 1993, 1995, 1996, 2002*, 2003*, 2004*, 2005*, 2006*, 2007*, 2008*, 2009*, 2011*, 2012*
CHL	9	5	7	1992, 1994, 1996, 1998, 2000*, 2003*, 2006*, 2009*, 2011*
CHN	1	6	7	2002
CMR	2	7	7	2001, 2007*
CRI	9	6	7	2001, 2002, 2003, 2004, 2005*, 2006*, 2007*, 2008, 2009*
DOM	2	9	7	2011, 2012
ECU	5	3	7	2000, 2004, 2005, 2006, 2007
GTM	5	3	7	2000*, 2002, 2003, 2004, 2006*
HND	18	6	7	1992, 1993, 1994, 1995, 1996, 1997, 1998, 2001, 2002, 2003, 2004*, 2005, 2006*, 2007*, 2008*, 2009*, 2010*, 2011*
IDN	2	5.7	7	1996, 1998
IND	1	6	7	2007
JAM	3	3	7	1990, 2001, 2002
JOR	1	3	7	2010*
KHM	4	5	7	2003, 2006, 2008, 2012
LBR	1	5	7	2010
LKA	10	7	7	1993, 1996, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2008
MEX	7	6	7	1989, 1992, 1994, 1996, 1998, 2000, 2002*
MKD	2	6.7	7	2003, 2004
MNG	3	4.2	7	2002, 2006, 2011*
MWI	1	3	7	2013
NIC	5	4	7	1993, 1998, 2001, 2005, 2009*
NPL	2	5	7	2008, 2010*
PAN	18	4	7	1989, 1995, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012
PER	15	7	7	1997, 1998, 1999, 2000*, 2001*, 2002*, 2004*, 2005*, 2006*, 2007*, 2008*, 2009*, 2010*, 2011*, 2012*
PHL	5	16.8	7	2006, 2007, 2008, 2009, 2010
PNG	1	20	7	2009*
PRY	2	4	7	2010*, 2012*
RUS	3	8	7	2005, 2006, 2009*
SLB	1	10	7	2005
SLV	6	5	7	1995, 1998, 1999, 2000, 2001*, 2003*
THA	11	5	7	1981, 1983, 1984, 1986, 1987, 1988, 1989, 1991, 1995, 2006*, 2009*
TMP	2	5	7	2007*, 2010

Table 1: List of surveys in our sample (cont'd)

Cty	#Years	# regions	# sectors	Surveys
TUN	1	7	7	2001
TZA	2	20.5	7	2000, 2006
UGA	1	4	7	2002
URY	14	5	7	1998, 2000, 2001*, 2002*, 2003*, 2004*, 2005*, 2006*, 2007*, 2008*, 2009*, 2010*, 2011*, 2012*
USA	1	4	7	2010
VEN	6	9	7	1989, 1992, 1995, 1998, 2005*, 2006*
VNM	1	6	7	2010
WBG	11	2	7	1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008
YEM	1	6	7	2005
ZAR	1	11	7	2004

Asterisks indicate surveys for which information on internet access is available.

Table 2: Mobility costs - with correction

	Sector	Region	Sector×Region
	(1)	(2)	(3)
Average	1.44	0.86	1.83
Median	1.28	0.82	1.54
Standard Deviation	2.27	1.86	2.01
#Estimates	235	235	235
Using only significant estimates:			
Average	1.73	0.80	1.93
Median	1.37	0.69	1.57
Standard Deviation	2.37	2.19	1.96
#Estimates	153	120	217

This table reports the average, median, and standard deviation of 235 country-year level estimations carried at the worker's level. We estimate the mobility cost for each country-year survey separately, correcting for self-selection into sector-region, based on equation (6c). Results at individual country level are available under request.

Table 3: Explaining mobility costs

dependent variable:	$\widehat{C2}_{j,j'}$	$\widehat{C2}_{r,r'}$.	$\widehat{C2}_{jr,j'r'}$	$\widehat{C2}_{j,j'}$	$\widehat{C2}_{r,r'}$	$\widehat{C2}_{jr,j'r'}$
	(1)	(2)	(3)	(4)	(5)	(6)
Ln GDP per capita	-0.271^a	-0.082	-0.375^a	-0.306^b	-0.248	-0.617^a
	(-2.85)	(-0.91)	(-4.78)	(-2.20)	(-1.54)	(-3.83)
Ln Gini	0.958^c	-0.627	0.974^b	0.974^a	-0.214	0.991^a
	(1.79)	(-1.36)	(2.04)	(3.60)	(-0.47)	(3.73)
Share of employment:						
Agriculture	0.015^a	0.006	0.019^a	0.021^a	0.015^c	0.028^a
	(3.15)	(0.86)	(3.98)	(4.98)	(1.79)	(6.42)
Manufacturing	-0.043^a	-0.013	-0.055^a	-0.023^c	-0.016	-0.035^b
	(-2.83)	(-0.70)	(-3.54)	(-1.74)	(-1.30)	(-2.37)
Service	-0.016^a	-0.006	-0.020^a	-0.016^b	-0.012	-0.019^a
	(-2.87)	(-0.89)	(-3.45)	(-2.58)	(-1.25)	(-2.89)
Ln Spec. Index$_j$	3.454			1.055		
	(1.60)			(0.63)		
Ln Spec. Index$_r$		0.346			-0.118	
		(1.41)			(-0.07)	
Ln Spec. Index$_{jr}$			2.557			6.261^c
			(1.27)			(1.94)
Ln Internal dist.	-0.126	-0.012	-0.114^c			
	(-1.11)	(-0.26)	(-1.93)			
Ln Internal dist.<1000	-0.153	0.022	-0.009			
	(-0.75)	(0.21)	(-0.07)			
Year FE	✓	✓	✓			
Country FE				✓	✓	✓

Robust standard errors, t-statistics in parentheses. Significance levels: ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01. Each cell corresponds to a single regression. Column (1) reports the regression of the industry mobility cost on alternatively: log of GDP per capita (N=235), log Gini (N=235), the share of employment in agriculture/manufacturing/services (N=213), Ln Specialization Index$_j$/Specialization Index$_r$/Specialization Index$_j r$ (N=235). We also include year dummies. Column (2) and (3) replicates column (1) using respectively the regional mobility cost or the industry×region mobility as the dependent variable instead. Columns (4)-(6) replicate columns (1)-(3) replacing the year dummies by country dummies.

Table 4: Differences in mobility costs estimates: with access to Internet

	All estimates				Significant estimates only			
	median	average	sd	N	median	average	sd	N
Average versus no-access to Internet								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{C2}_{j,j'}$	-0.04	-0.06	0.07	67	-0.08	-0.10	0.08	29
$\widehat{C2}_{r,r'}$	-0.00	0.01	0.11	67	0.05	0.02	0.15	19
$\widehat{C2}_{jr,j'r'}$	-0.02	-0.03	0.09	67	-0.09	-0.08	0.10	29
High- versus low-access to Internet								
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$\widehat{int_C 2}_{j,j'}$	-0.06	-0.07	0.11	67	-0.09	-0.12	0.10	29
$\widehat{int_C 2}_{r,r'}$	-0.00	0.04	0.19	67	0.09	0.09	0.17	19
$\widehat{int_C 2}_{jr,j'r'}$	-0.02	-0.00	0.13	67	-0.06	-0.02	0.16	29

Note: Estimations refer to the difference between the respective mobility costs ($\widehat{C2}_{j,j'}$, $\widehat{C2}_{r,r'}$,. and $\widehat{C2}_{jr,j'r'}$) coefficients (in log) with different levels of access to Internet. Because the variable used as a proxy for access to Internet can be treated as a continuous varible in order to compare the mobility costs with and without access to Internet, we assume different values for access to Internet. First we compare average access ($int_k = mean(int_k)$) versus no-access to Internet ($int_k = 0$). Results are shown in columns (1)-(8). Then we commpare a scenario with low-acess ($int_k = mean(int_k) - 1sd$) with high acess to Internet ($int_k = mean(int_k) + 1sd$).Results are shown in columns (9)-(16). Robust standard errors are used to keep significan estimates at 95%. This table reports the average, median, and standard deviation of 67 country-year level estimations carried at the worker's level. We estimate the effect of access to Internet on mobility cost for each country-year survey for which data is available separately, based on equation 11. Results at individual country level are available under request.