

Labor Market Flows and Development*

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Abstract

We build a new cross-country dataset of harmonized rotating panel labor force surveys covering thirteen countries with widely varying average income. We document two main new facts. First, poor country labor markets are characterized by flows between labor states 2–3 times higher than in rich countries. Second, tenure hazards and tenure-wage profiles are steeper in poor countries. A model where match productivity is learned through production in poorer countries can rationalize these findings. Imprecise ex ante signals lead workers and firms to start more ex post unproductive matches, explaining higher job finding rates. Production reveals these matches, explaining higher employment exit rates. More learning through production explains steeper tenure hazards and tenure-wage profiles. We provide accounting results that link these findings to skill: less skilled workers have higher flows and steeper tenure hazards everywhere; poor countries have much higher employment shares for such workers.

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1 Introduction

A recent literature has harmonized and compared microdata from a wide range of countries to document new facts about how the characteristics of workers and firms vary with development. Many of these facts suggest possible mechanisms or causal forces that might help explain differences in gross domestic product (GDP) per capita. For example, it has been shown that the wages of workers and size (employment) of firms grow much less over their respective life cycles in poor countries than in rich ones (Lagakos et al., 2018; Hsieh and Klenow, 2014).¹ These findings hint at an underlying dynamic process that is difficult to capture fully with cross-sectional data. Our goal is to contribute to this literature by harmonizing labor force surveys for thirteen countries across a wide range of development. We establish new facts about labor market flows and the role of job tenure and how they correlate with development.

We start by building a new cross-country dataset of the respective countries' labor force surveys. In all cases these are the official survey administered by the government for the purpose of creating labor force statistics such as the unemployment rate. We further restrict our attention to countries that utilize a rotating panel design, which allows us to track people over two consecutive quarters and learn about labor market dynamics. We were able to identify thirteen countries satisfying these criteria. They span a broad range of development, with purchasing power parity (PPP) adjusted GDP per capita ranging from roughly \$4,000 (Nicaragua, Palestine) to \$40,000–50,000 (United Kingdom, United States) (Feenstra et al., 2015). The underlying microdata are rich and typically include information on labor force status (salaried, self-employed, unemployed, inactive), demographics (age, gender), skill (education, occupation), firm characteristics (size, industry), and job characteristics (tenure, formality, wage). We have devoted substantial effort to harmonizing these responses across countries.

We document that our data imply cross-country patterns for standard moments in line with the existing literature. We then turn to our main contribution, which is to document new facts about labor market dynamics in poor versus rich countries. We highlight two main findings about dynamics. First, we use the panel dimension of the data to document that labor market flows are 2–3 times higher in poor countries. For example, the exit rate from employment to non-employment is 15 percent per quarter in our poorest countries

¹See also Bick et al. (2018) for data on hours worked by workers. Other work comparing firms across countries emphasizes productivity dispersion (Hsieh and Klenow, 2007), management practices (Bloom and Van Reenen, 2007), and firm organization (Bloom et al., 2012).

but only 5 percent in the richest. We show similar results for job-to-job transitions and the job finding rate, although for the latter we have to correct for the fact that unemployment and inactivity (not in the labor force) are less distinct states in poor countries than in rich ones.² Second, we use the patterns with respect to tenure to document that tenure hazards and tenure-wage profiles are steeper in poorer countries. Notably, this last fact applies even though we re-confirm the finding of [Lagakos et al. \(2018\)](#) that experience-wage profiles are flatter in poor countries.

At first glance these findings suggest a puzzle: why would workers and firms destroy matches more frequently in poor countries when the “returns to tenure” are higher? We show that these results arise naturally in a model of learning about match quality through production motivated by [Jovanovic \(1979\)](#) and [Menzio and Shi \(2011\)](#). In particular, the findings are consistent with the view that matches in rich countries are more “inspection goods”, whose quality is known in advance, while matches in poor countries are more “experience goods”, whose quality is learned through production. When match quality is initially unknown but rapidly learned through production, workers and firms endogenously choose higher match formation and match exit rates. In essence, they sample matches to learn which are productive.

This model also explains steeper tenure-wage profiles in poor countries. The key is that tenure-wage profiles are generated by selection. The pool of newly formed matches in poor countries includes many more (ex post) unproductive matches. As matches produce and tenure accumulates, these less productive matches are identified and endogenously destroyed, which raises wages and induces a steep tenure-wage profile. Thus, tenure-wage profiles are not really the private returns to tenure, as is well-known in the literature ([Topel, 1991](#)).

We then investigate why matches in poor and rich countries might behave differently. We find an important role for skill, defined based on the education and occupation of the worker. Less skilled workers – those with less education, or who work in elementary or manual occupations – consistently have higher rates of labor market transitions as well as steeper tenure hazards in all countries. Further, workers in poor countries are on average much less educated and much more likely to work in less skill-intensive occupations. These findings suggest that matches with unskilled workers may generally be experience goods, perhaps because firms find it harder to inspect workers ex ante or easier to learn through experience.

²In particular, we show that job finding rates from unemployment and inactivity are more similar in poorer countries, which is similar to the test proposed by [Flinn and Heckman \(1983\)](#) of the distinctness of labor market states.

For example, the output of many manual occupations is easier to measure and attribute to a specific worker than the output of white-collar workers. We use accounting exercises to show that these findings are important at the aggregate: over half of the cross-country differences in labor market flows are accounted for by education and occupation. Plausible alternative factors such as firm structure or demographics account for more modest shares.

Our results relate to two additional literatures. First, an existing literature compares labor market dynamics among subsets of *rich* countries. That literature finds large variation in labor market flows among rich countries and ties this variation to the underlying labor market institutions. In particular, rigid labor market institutions in many European countries are found to inhibit the efficient reallocation of labor.³ By contrast, our goal is to look at countries representing a much wider range of development and to capture the underlying relationship between labor market flows and development. In this sense, our work is closer to recent work by [Martellini and Menzio \(2018\)](#) that explores the long-run trends in labor market dynamics within the United States. Their work differs from ours in that the job finding and employment exit rates have not changed much in the U.S. over time, which leads them to formulate a theory that can explain this lack of trend in spite of the large presumed technological improvements in the matching technologies.

Second, our work relates to a literature in development economics that studies labor market policies or interventions. For example, [Blattman and Dercon \(forthcoming\)](#) alters directly the jobs of workers to measure the impact on wages and health, while [Groh et al. \(2016\)](#) subsidizes employers to hire certain workers to see if they move faster up the job ladder. Closer in spirit to our work, [Franklin \(forthcoming\)](#) and [Abebe et al. \(2017\)](#) reduce frictions to job search to see if workers find better jobs. Our work suggests that interventions aimed at helping workers and firms screen match quality in advance would likely have an important impact on labor market dynamics. [Bassi and Nansamba \(2018\)](#) provide some experimental evidence along this dimension.

The structure of our paper is as follows. In Section 2 we outline the data, our harmonization procedures, and the basic facts. In Section 3 we construct and compare labor market dynamics across countries. Section 4 provides the model that can jointly explain the facts. Section 5 provides the accounting exercises. Finally, section 6 concludes.

³See, for example, [Ljungqvist and Sargent \(1998\)](#), [Ridder and Berg \(2003\)](#), [Jolivet et al. \(2006\)](#), [Jung and Kuhn \(2014\)](#), and [Krause and Uhlig \(2012\)](#).

2 Data

We start by building a new cross-country dataset of harmonized rotating panel labor force surveys. By labor force survey, we mean the official survey administered by the government for the purpose of creating labor force statistics such as the unemployment rate. We have collected the underlying microdata for as many countries as possible, generally obtained directly from the relevant government’s data repository.

We focus on countries that have a rotating panel labor force survey. By far the most common design is for each household to be followed for two quarters, with half of the sample rolled over each quarter. We incorporate some additional countries that utilize alternative designs that allow for measurement of quarterly transitions.⁴ We focus further on countries where consistent individual identifiers are available to us over time. This restriction eliminates most European countries because identifiers are often re-anonymized each quarter to prevent matching of people over time. The European Union publishes some aggregate labor force statistics including quarterly transition rates. We incorporate these in figures when possible to facilitate comparison with the existing literature that focuses mostly on the United States and European Union.

We were able to identify thirteen countries with labor force surveys meeting these criteria. The countries are listed in Table 1. The duration of data availability varies widely, ranging from 3 years in Nicaragua and Paraguay to 39 years in the United States. We merge our data with annual purchasing power parity-adjusted GDP per capita from Penn World Tables when describing development trends.⁵ Our countries cover a wide range of development, with Palestine and Nicaragua having purchasing power parity adjusted GDP per capita around \$4,000 and the United States over \$50,000 in recent years (Feenstra et al., 2015).

We use the identifiers to match people for two consecutive quarters. We follow the standard protocol from the United States of checking the validity of these matches by requiring that they be unique and that they agree on age, sex, and (in the United States only) race, following Madrian and Lefgren (2000). These checks have little effect in most countries but do lead us to discard matches in the United States, particularly in earlier years. We adjust the provided cross-sectional weights for attrition so that our sample of matched observations

⁴For example, the United States Current Population Survey (CPS) allows us to measure quarterly transitions by matching households between their first and fourth or fifth and eighth months in the sample. See Drew et al. (2014) for general details on the design and matching of the CPS.

⁵Penn World Tables 9.0 stops in 2014. We use the growth rate of PPP GDP per capita from 2014–2016 from World Development Indicators to extend the data when possible.

Table 1: Sample Overview

Country	Years Covered	Obs. (Thousands)	PPP GDP per capita ^a
Argentina	2003 – 2017	671	12,500 – 20,200
Brazil	2002 – 2015	2,208	8,500 – 14,900
Chile	2010 – 2017	1,664	19,000 – 21,600
Costa Rica	2010 – 2017	299	12,600 – 14,200
Ecuador	2007 – 2015	184	8,000 – 11,000
Mexico	1994 – 2017	15,714	10,900 – 15,900
Nicaragua	2013 – 2015	194	4,200 – 4,500
Palestine	2000 – 2015	558	3,700 – 4,300
Paraguay	2013 – 2015	18	8,100 – 8,300
Peru	2003 – 2017	236	5,400 – 11,000
South Africa	2008 – 2017	1,050	11,400 – 12,100
UK	1997 – 2017	3,514	30,900 – 40,200
US	1979 – 2018	6,325	29,500 – 52,300
Total		32,633	

^a Range of PPP GDP per capita (rdgpe/pop) from [Feenstra et al. \(2015\)](#), rounded to the nearest one hundred dollars. Most recent data available from 2014.

agrees with the unmatched cross-section on key dimensions; see Appendix A.1 for details. We de-seasonalize the quarterly data and aggregate to the country-year level; for the rest of the paper we treat a country-year as an observation. We restrict our attention to the largest possible sample that we can get consistently for all countries, which turns out to be the urban population aged 16–65. Table 1 shows the number of observations per country, where an observation is a person matched for two consecutive quarters. Altogether, we have over 32 million observations.

We harmonize and use the data for labor force status, demographics, skill, employer characteristics, and job characteristics. Labor force status is key for our results, particularly about flows. We first categorize people as employed or not employed, which is generally straightforward. The main issue we need to deal with is unpaid family workers; we include as employed those with at least 15 hours a week of unpaid family work, in line with the convention in the United States.

At some points we break these labor force statuses down further. For the employed, we distinguish between wage and salaried workers (who work for someone else) and the self-employed, where the latter includes employers and unpaid family workers. For people who

are not employed we distinguish between those who are unemployed and inactive (not in the labor force). Unemployment is measured consistently as people who are not employed but who satisfy the standard three-part test: i) they want a job; ii) they have actively searched for a job in the last four weeks; iii) they are available to start a job. Poorer countries generally ask less specific questions about layoffs and other temporary absences from work, likely because such events are relatively rare. People who fail any of these three questions are labeled inactive.

We also harmonize a number of the characteristics of people and firms that might help understand our labor market flows patterns. For brevity we report our basic coding scheme here and discuss details further when relevant below. We start with demographics, meaning age, sex, and marital status. Age and gender are straightforward to harmonize. Marital status is a simple binary variable distinguishing whether a person is married at the moment or not.

We have two measures of a worker's skill: education and occupation. We recode education into the [Barro and Lee \(2013\)](#) coding scheme of none, some primary, primary complete, some secondary, secondary complete, some tertiary, and tertiary complete. We harmonize occupation at the one-digit level, following [Minnesota Population Center \(2014\)](#). At the one-digit level occupation codes largely capture skill level. For example, professionals or legislators, senior officials, and managers are generally highly skilled; clerks or crafts and related trade workers are moderately skilled; and elementary occupations are unskilled.

The main characteristics of the firm are size and industry. Our measure of size is number of employees in the establishment. Most surveys were careful to distinguish establishment from firm, but in some poorer countries the distinction was not so clearly made. The rarity of multi-establishment firms in poor countries makes this less important. In most countries respondents are presented with a discrete number of firm size bins to choose from. We can measure employment in three bins consistently for most countries: small (1–9 employees); medium (10–50 employees); and large (51+ employees). The most complex variable to harmonize is industry. Here we build on the work of [Minnesota Population Center \(2014\)](#), who suggest a hybrid 1/2-digit industry coding scheme with 15 possible codes that turns out to map well into our data.

Finally, we harmonize three job (match) characteristics. In many countries we have information on (observed) tenure, that is, how long a worker has been with his or her current employer. It is measured in years in most countries although some allow workers to report in months for short spells. Second, we know whether wage workers are employed

on a formal or informal basis in many countries. A formal job is one where the employer makes payments into social programs (such as pensions) on the worker's behalf. This test is not clearly defined, and the question often not asked, for the self-employed. Note that this is a job characteristic because some firms employ workers on both a formal and an informal basis. Finally, in many countries we have information on wages, which is typically constructed as the monthly income divided by 4.33 times the hours worked in the reference week. Although we have some information on the income of the self-employed, there are well-known measurement difficulties with this, so we limit our focus to the wages of wage and salary workers throughout.

2.1 Overview of Cross-Sectional Facts

Before proceeding to the baseline analysis, we overview cross-sectional facts that do not use the panel data. Doing so serves two roles. First, it allows us to highlight some important labor market institutions that will be of interest in what follows. Second, it allows us to show that our data generally line up with existing results when possible. To conserve space, details and figures are reserved to Appendix B.1.

We start by constructing two standard labor market indicators, the employment to population ratio and the unemployment rate. We find substantial variation among countries but little evidence of any relationship with development for these standard labor market indicators, in line with existing work (Bick et al., 2018; Feng et al., 2017). One difference is that existing work finds much higher employment to population ratios and much lower unemployment rates in the poorest countries; we have no such countries in our sample. These figures reveal that we have an important outlier (Palestine, the poor country outlier in both figures). The Palestinian labor market is subject to a number of unusual frictions that likely do not carry over to other countries (Amodio et al., 2017; Mansour, 2010). Our general approach is to include Palestine in figures but exclude it from any regressions or best fit lines.

Although employment does not vary systematically with development, we find that the type of employment does, again consistent with the literature. First, self-employment is much more common in poor countries, consistent with Gollin (2002). In our poorest countries, self-employment accounts for half of all employment. Second, informal employment is much more common among wage workers in poor countries, consistent with La Porta and Shleifer (2014). Again, for the poorest countries, half of wage work is on an informal basis. Thus,

our data broadly agree with other sources on the key cross-sectional facts.

3 Aggregate Labor Market Dynamics and Development

In this section we develop our main results on the patterns between labor market dynamics and development. We emphasize two new sets of dynamic results derived from our short rotating panel data. The first are facts about quarterly labor market flows; the second are facts about patterns with respect to job tenure.

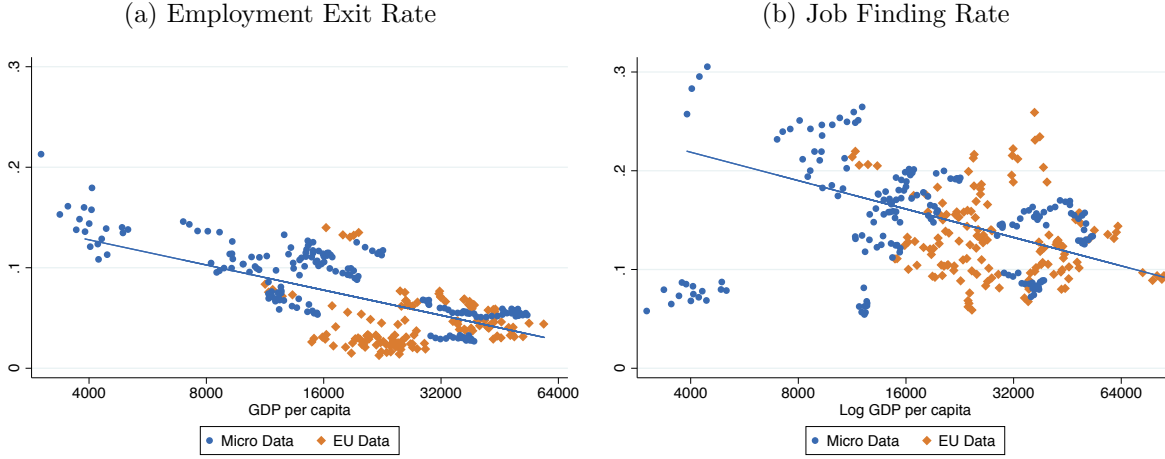
3.1 Labor Market Flows and Development

The first main feature we emphasize is higher rates of labor market flows in poor countries. We decompose the population into the standard groups of employed and not employed, denoted by E and N . We focus on transitions between these two states because we find that unemployment and inactivity in poor countries are fairly close substitutes. For example, inactive people in our poorest countries find employment at more than half the rate that unemployed people do. Further, most inactive people in poor countries would be classified as marginally attached to the labor force in the United States: they report that they want a job but that they do not have one because of a lack of skills or employment opportunities. These findings suggest to us that the clean distinction between unemployment and inactivity in rich countries does not apply in poor countries and so we pool them. See Appendix B.2 for further details and B.3 for transition rates when we distinguish between unemployment and inactivity.

We denote by T_{ij} the quarterly transition rate from i to j , meaning the share of people in i at quarter t who are in j at quarter $t + 1$. As in the previous section we de-seasonalize the quarterly data, aggregate to the country-year level, and merge with PPP GDP per capita. Note that since we only observe people at a quarterly frequency we may miss some transitions due to time aggregation (Shimer, 2012). Standard corrections to produce the implied hazard rates assume that hazards are constant over the intervening quarter and hence do not affect the relative trends by development that we focus on.

Figure 1 shows our baseline result. It plots the average transition rates for each country-year against PPP GDP per capita (on a log scale). Each blue circle marker corresponds to a

Figure 1: Quarterly Transition Rates



country-year in our data set. We also include the average quarterly transitions published by Eurostat. These country-years are denoted by yellow diamond markers. There are two main lessons from these figures. First, we confirm the finding in the literature that there is large variation in transition rates across countries. For example, they vary by more than a factor of three even among rich countries, which previous work has linked to differences in labor market institutions. A second and novel finding is that there is also an important trend with development. The best fit lines included in the figures suggest that poor countries have employment exit rates roughly three times those in rich countries, and job finding rates nearly twice as high.

One might also wonder if the results are driven by country-specific effects. Fortunately, we have long panels for several countries that make it possible for us to test the relationship between labor market flows and development while controlling for fixed effects (see Table 1). Thus, we run the regression:

$$Transition\ Rate_{ct} = \alpha \log(y_{ct}) + \theta_c + \gamma_t + \varepsilon_{ct}$$

where θ_c and γ_t are country and time fixed effects, and $\log(y_{ct})$ is real GDP per capita. The results are in Table 2. The estimated coefficient on GDP per capita is actually larger (in absolute value) when we control for country and year fixed effects, although the standard errors are wider. Still, the estimated effects are statistically different from zero at conventional levels in all cases.

Table 2: Labor Market Turnover and Income

	Exit Rate			Job Finding Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP per capita	-0.036 (0.003) ^{***}	-0.035 (0.004) ^{***}	-0.076 (0.008) ^{***}	-0.042 (0.003) ^{***}	-0.016 (0.008) ^{**}	-0.083 (0.018) ^{***}
Sample Average	0.067	0.067	0.067	0.142	0.142	0.142
Country FE	N	Y	Y	N	Y	Y
Year FE	N	N	Y	N	N	Y
Obs.	301	301	301	301	301	301
R^2	0.372	0.969	0.979	0.229	0.933	0.941

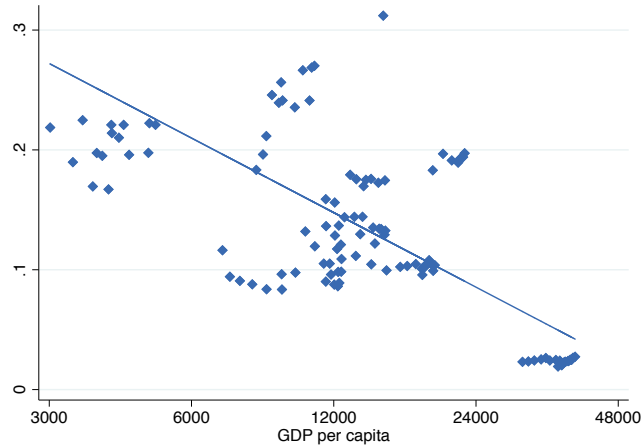
A second important form of labor market dynamics is job-to-job transitions. We can track such transitions for a subsample of countries. For most countries we measure these transitions using tenure. That is, we infer a job-to-job transition when a worker is employed in consecutive quarters and their tenure falls to fewer than three months in the second quarter.⁶ In doing so we label as job-to-job transitions all changes of employment that have an unobserved intervening spell of non-employment; again, we could correct for this in the standard way, but it would not affect our trends.

Figure 2 shows the implied transition rates. There is again a strong negative trend with development: while workers in poorer countries have a 20 percent chance of switching employers in a quarter, workers in rich countries (here, just the United States) have less than a 5 percent chance. This finding is consistent with Figure 1: labor market flows are higher in poor countries.

The interpretation of these findings is less clear. High rates of labor market flows can be inefficient (churn among similar jobs) or efficient (reallocation of labor to more productive uses, climbing a job ladder). In the next section we introduce additional information by looking at dynamics and tenure.

⁶The U.S. CPS data are again an outlier. There we measure tenure using dependent coding: we focus on people we can follow for four consecutive months from 1994 onward and utilize the fact that the CPS specifically asks workers in months 2–4 whether they work the same job as in the previous month. We measure a job-to-job transition as someone who says no in any month, following [Fallick and Fleischman \(2004\)](#).

Figure 2: Quarterly Job-to-Job Transition Rates



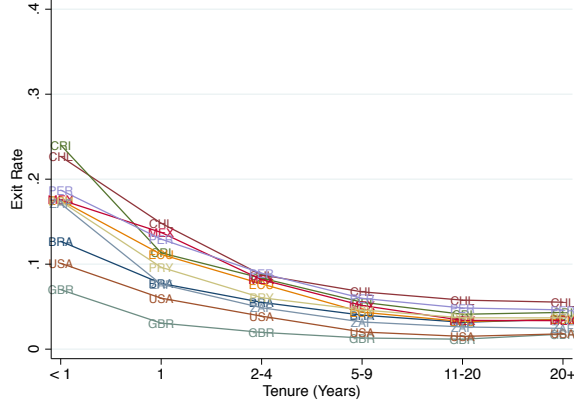
3.2 Tenure Dynamics and Development

We augment the above facts by looking at the importance of job tenure for outcomes of interest. The idea is that doing so allows us to speak to the dynamics of a particular match in addition to the overall dynamics of the labor market. In line with previous work, we focus on the evolution of the employment exit rate (tenure hazards) and wages (tenure-wage profiles).

We start with tenure hazards, or the probability that a match is destroyed between two quarters as a function of the tenure of the match in the first quarter. Figure 3 plots the hazards for all countries in which we can compute it. Tenure is binned in many of our countries, so we aggregate somewhat to make the figure comparable. There are two main features. First, the hazard slopes down in all countries, consistent with existing evidence. Second, the hazard is generally flatter for richer countries (for example, the U.S. and the U.K. are on the bottom) and steeper for poorer countries. These findings show that much of the gap in employment exit rates between poor and rich countries is accounted for by higher turnover at new jobs; the exit rates are much more similar for long-tenured matches.

Finally, we document the facts of wage-tenure profiles. We focus on wage and salary workers, because wage data are generally not available or not reliable for the self-employed. To investigate the relative importance of returns to experience and returns to tenure, we estimate an augmented Mincer wage equation motivated by [Topel \(1991\)](#) and [Lagakos et](#)

Figure 3: Tenure Hazard



al. (2018). We pool all available years for each country and regress:

$$\log(w_{it}) = \alpha + \sum_{x \in X} \phi_x D_{it}^x + \sum_{\tau \in T} \psi_\tau D_{it}^\tau + \theta s_{it} + \gamma t + \varepsilon_{it}. \quad (1)$$

w_{it} is the hourly wage of individual i observed at time t . x_{it} is their potential experience, constructed as age minus expected school duration minus 6. D_{it}^x is a dummy variable that takes the value of one if a worker is in experience group $x \in X = \{2 - 4, 5 - 9, 10 - 19, 20+, \dots\}$, with 0 – 1 years of experience serving as the omitted reference group. D_{it}^τ is a dummy variable that takes the value of one if a worker is in tenure group $\tau \in T = \{1, 2 - 4, 5 - 9, 10 - 19, 20+\}$, with < 1 years of tenure serving as the omitted reference group. s_{it} is a vector of education dummies corresponding to the seven Barro-Lee categories and t is a vector of year dummies.⁷ ε_{it} is a mean-zero error term.

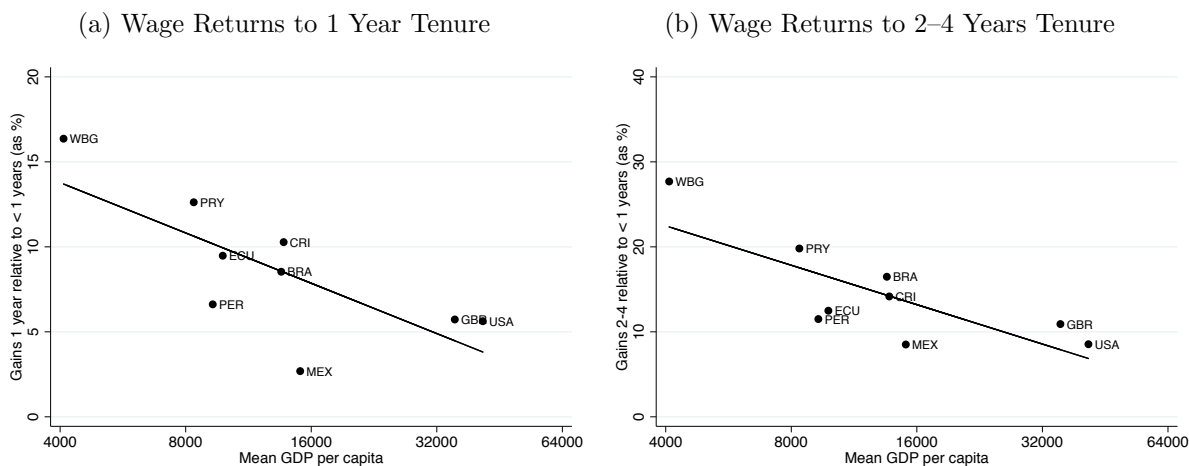
The functional form for estimating returns to experience follows Lagakos et al. (2018). Figure B7 in the Appendix shows that we obtain a similar result as they do for returns to experience: the estimated wage gain to 10–19 and 20 or more years of experience (as compared to 0–1 years of experience) is increasing with development. This finding holds independently of whether we control for tenure.

We add to this by estimating separately tenure-wage profiles. Figures 4a and 4b show the estimated percentage wage difference between 1 and 2–4 years of tenure (as compared to less than one year of tenure) plotted against GDP per capita. Unlike for experience, the

⁷Lagakos et al. (2018) also consider allowing for cohort effects but generally find a small role for them empirically.

trend is negative: workers' wages rise *more* quickly with job tenure in poor as compared to rich countries. We find similar patterns if we look at longer tenures, or if we cut tenure into different bins.

Figure 4: Tenure-Wage Profiles



This last finding will turn out to be important for interpreting higher rates of labor market turnover in poorer countries. There are two well-known theories of wage-tenure profiles: accumulation of job-specific human capital; or differential selection of workers into longer job tenures (Topel, 1991). It is difficult to reconcile the former theory with lower overall returns to experience and higher rates of labor market turnover in poor countries. However, we show in the next section that a theory of differential selection motivated by Jovanovic (1979) and Menzio and Shi (2011) provides a natural explanation for all of these facts.

4 Model

We have used our data set to show a number of new facts. Broadly, our results show that, relative to rich countries, poor countries have higher rates of labor market flows, higher returns to tenure, but lower returns to experience. In this section we show that a simple theory can fit these facts. The theory is based on the idea that a match between a worker and a firm can be an experience good or an inspection good (Jovanovic, 1979; Menzio and Shi, 2011). When a match is an inspection good, the worker and the firm know the quality in advance of production. On the other hand, when a match is an experience good, the

worker and the firm learn about the quality only through production. We show in this section that these two models generate very different implications for hiring, employment exit hazards, and returns to tenure. The setup of the model and many of the results are close to those of [Menzio and Shi \(2011\)](#).

To preview the model results, we find that rich countries' labor markets resemble more the inspection model, while poor countries' labor markets resemble more the experience model. Although this finding is interesting, it is somewhat abstract. In the next section we use accounting decompositions to try to discover the observable characteristics of workers, firms, and jobs that account for the cross-country differences in labor market flows. We find a consistently large role for skill. Less skilled workers – those with less education, or who work in elementary or manual occupations – consistently have higher rates of labor market transitions as well as steeper tenure-wage profiles in all countries. Further, workers in poor countries are on average much less educated and much more likely to work in low-skilled jobs. Hence, we have in mind an underlying model where firms find that they are less able or have less need to invest in pre-match screening of unskilled workers.

4.1 Environment

Consider a meeting between an unemployed worker and a vacancy. The two are jointly considering whether to form a match and produce. They draw a match-specific productivity x from distribution $F(x)$ that has mean μ . However, the productivity is not observed. Instead, following [Menzio and Shi \(2011\)](#), the worker and the firm draw a signal s which is equal to x with probability p and is an i.i.d. draw from F with probability $1 - p$. p indexes the quality of the signal. In the limit cases, $p = 1$ corresponds to matches as inspection goods, whose quality can be determined perfectly in advance, while $p = 0$ corresponds to matches as experience goods, whose quality can only be learned through production.

Workers and firms decide whether to form a match after observing this signal. They have outside options of receiving flow unemployment benefits b and holding open the vacancy 0 , respectively. Each is risk-neutral. We assume throughout that $\mu > b$, so that the average meeting is profitable. What matters is that the pair agree to form a match if expected surplus exceeds the outside option, which occurs if $ps + (1 - p)\mu \geq b$. It follows that the probability that a meeting leads to a match is given by:

$$\pi = 1 - F\left(\frac{b - (1 - p)\mu}{p}\right). \quad (2)$$

Variation in the match formation rate is the first prediction of interest, because it can help us understand variation in the job finding rate.⁸

Workers and firms who form a match produce in the same period. After production, but before the next period, they face two potential shocks. First, with probability δ the match is exogenously destroyed. Second, with probability λ match productivity is revealed to the worker and the firm. In some cases, this revelation will be favorable and the two will continue to produce. However, some matches will be revealed to have negative surplus. While the past losses are sunk, the worker and the firm can at least agree endogenously to end the match going forward. The probability that a match generates negative surplus is given by:

$$\begin{aligned} p \left[F(b) - F\left(\frac{b - (1-p)\mu}{p}\right) \right] + (1-p)F(b) \\ = F(b) - pF\left(\frac{b - (1-p)\mu}{p}\right). \end{aligned}$$

The first expression has two terms, which capture the probability of a negative surplus match given an accurate and an inaccurate signal, respectively. The second expression shows that this is the same as the probability that a meeting has a low productivity draw, minus the probability that the signal is accurate and low enough that the worker and the firm do not form the match.

For matches that are retained, this process repeats in subsequent periods. A match with t periods of tenure results in production, then it is exogenously destroyed with probability δ and, if productivity has not yet been revealed, it is revealed with probability λ . These assumptions imply that the probability that a match with tenure t is destroyed before $t+1$ is given by

$$d_t = \delta + (1-\lambda)^{t-1}\lambda \left[F(b) - pF\left(\frac{b - (1-p)\mu}{p}\right) \right]. \quad (3)$$

This expression captures the two sources of match destruction: matches can be destroyed exogenously; and they can be destroyed endogenously if they generate negative surplus, they have not previously received a learning shock, and they receive a learning shock in the current period. This expression for the employment exit hazard is the second prediction of

⁸An alternative approach is to vary the rate at which workers and firms meet, either by exogenously varying match quality or endogenously increasing the vacancy posting rate (Mortensen and Pissarides, 1994).

interest.

The third prediction that we are interested in is the wage-tenure profile. To derive this, we need to specify a wage-setting rule. We assume that workers and firms engage in Nash bargaining with equal weights in each period of a match. When match productivity is unknown, they split the expected surplus; if productivity is learned, they bargain over actual surplus. This implies that wages for a newly-formed match are given by:

$$w_0 = p\mathbb{E}\left(x|x > \frac{b - (1-p)\mu}{p}\right) + (1-p)\mu + b.$$

Finally, consider a cohort of matches all formed at the same date. As tenure accumulates for this cohort, a growing share of matches have their productivity revealed. Matches that survive this revelation have higher average productivity and hence pay higher average wages. This implies that the mean wage for jobs with tenure level t is given by:

$$w_t = (1-\lambda)^t \left[p\mathbb{E}\left(x|x > \frac{b - (1-p)\mu}{p}\right) + (1-p)\mu \right] + [1 - (1-\lambda)^t] \mathbb{E}(x|x > b) + b$$

It is straightforward to show that this expression implies that the returns to t years of tenure (as compared to 0 years, in line with our empirical results above) is:

$$r_t = [1 - (1-\lambda)^t] \left(\frac{\mathbb{E}(x|x > b)}{p\mathbb{E}\left(x|x > \frac{b - (1-p)\mu}{p}\right) + (1-p)\mu} - 1 \right). \quad (4)$$

4.2 Model Predictions

We now discuss the model's main predictions, which are the comparative statics of the match formation π , the employment exit hazard d_t and the returns to tenure r_t with respect to the precision of the initial signal p and the rate of learning λ . We start with three extreme cases to build a common underlying intuition: in the inspection model fewer matches are formed and employment exits and wages vary little with tenure (because more information is known ex ante and less is revealed with tenure). On the other hand, in the experience model more matches are formed and employment exits and wages vary more with tenure (because less information is known ex ante and more revealed with tenure).

A first useful case is $p = 1$, the inspection model. In this case the value of λ is irrelevant because match productivity is known perfectly upon meeting. Using the expressions above

shows that $\pi = F(b)$ matches are formed, the employment exit hazard is constant at $d_t = \delta$, and there are no returns to tenure ($r_t = 0$). The accumulation of tenure reveals no new information. All workers are paid a constant wage and matches continue production until they are exogenously destroyed, which occurs at rate δ .

The polar opposite case is $p = \lambda = 0$, in which case match productivity is never known or learned. This case yields higher rates of match formation $\pi = 1$ but the same tenure predictions of $d_t = \delta$ and $r_t = 0$. Once again, the insight is that the accumulation of tenure reveals no new information. All workers are paid a constant wage and matches continue production until they are exogenously destroyed, which occurs at rate δ .

Finally, a third useful case is $p = 0, \lambda = 1$. This is a simple model of experience goods: although match quality cannot be known in advanced, it is learned perfectly through a single period of production. This case implies $\pi = 1, d_1 = \delta + F(b)$ and $r_1 = \mathbb{E}(x|x > b)/\mu - 1$. Thus, although $F(b)$ negative surplus matches are formed, they are all discarded after one period (with $d_t = \delta$ for $t > 1$). This same force causes the observed wages to rise substantially with one period of tenure (wages plateau at this level $r_t = r_1$ for $t > 1$).

These forces can be generalized as comparative statics.

Proposition 1 *Assume $\mu > b$. Then the share of meetings that lead to matches is decreasing in p . The employment exit hazard is decreasing in p for all tenure levels t and decreasing in λ for all tenure levels $t < 1/\lambda$. The returns to tenure are increasing in p and λ .*

The proof involves straightforward differentiation of the above conditions. The only result that requires extra comment is the effect of λ on employment exit hazards. Intuitively, a higher probability of learning match productivity increases the job destruction rate at short horizons because it allows matches with negative surplus to be identified more quickly. At sufficiently long horizons it actually implies a lower employment exit hazard simply because eventually most bad matches have already been identified. Another way to make the same point is that the cumulative employment exit hazard is strictly increasing in λ at all horizons.

This result offers a simple way to interpret the data. The flows and tenure results for poorer countries are consistent with the experience model (low p and high λ). The flows and tenure results for richer countries are consistent more with the inspection model (high p). A next natural question is what characteristics of workers, firms, and jobs in poor countries make pre-match screening versus post-match learning possible or optimal. In the next section we

provide some accounting results to help guide this discussion.

5 Decomposing the Empirical Results

In this section we exploit the rich set of worker, firm, and job characteristics that we have harmonized across countries to perform accounting results. We show that the results point towards a persistent role for skill in accounting for a large share of cross-country labor market flows. These results suggest that skill may be a useful place to start when pursuing microfoundations for why matches in poorer countries feature less screening.

5.1 Accounting For Exit Rates

Our database includes harmonized characteristics of demographics (such as age), skills (such as education), firms (such as firm size), and jobs (such as formality). In this section we investigate which of these characteristics can help account for cross-country differences in labor market flows. Our goal is not to identify causal forces but rather to identify the important proximate sources of differences in labor market flows that may connect to the theory of the last section.

Our specific goal is to identify the factors that account for the relationship between labor market flows and development. That is, we estimate regressions of the form

$$T_{ijct} = \alpha_1 + \beta_1 \log(y_{ct}) + \nu_{ijct}$$

where T_{ijct} is the rate of labor market transitions between i and j in country c in year t . y is GDP per capita and ν is a mean zero error term. Our goal is to investigate the sources of the estimated $\hat{\beta}_1$. This approach differs somewhat from the usual accounting approach, which attempts to account for the total variation in the outcome of interest. Our view is that much of this variation is generated by important alternative forces such as labor market institutions or cyclical fluctuations that are less relevant for us. We want to focus on why poor and rich country labor markets behave differently.

In order to do our accounting we construct counterfactual labor market flows that fix the composition of people, firms, or job types at a common level, isolating only the variation in flows by type. If we decompose the overall transition rate T_{ijct} into the transition rate by group $g \in G$, T_{ijgct} , and the share of group g in the relevant population w_{gct} , then our

counterfactual transition rate is

$$\tilde{T}_{ijct} = \sum_{g \in G} \bar{w}_g T_{ijgct}$$

where \bar{w}_g is the average share for group g in our cross-country sample.

We then estimate the relationship between this counterfactual, fixed-share flows and development:

$$\tilde{T}_{ijct} = \alpha_2 + \beta_2 \log(y_{ct}) + \zeta_{ijct}.$$

We say that accounting for group G is important if it substantially attenuates the estimated relationship between flows and development, e.g., if $\hat{\beta}_2 < \hat{\beta}_1$. Formally, we say that group G accounts for

$$share = 1 - \hat{\beta}_1 / \hat{\beta}_2$$

of the overall flows-development trend accounted for.

Throughout we focus solely on accounting for the simple exit rate T_{EN} from any employment to any non-employment. We view this statistic as more straightforward to work with than the job finding rate because job finding rates may naturally vary with the prevalence of different types of vacancies (e.g., at firms of different sizes, or in different industries). Rather than work with these complicated objects (or try to normalize away such differences), we work with the employment exit rate. Nonetheless it is of course true that in steady state there is a relationship between the exit rate, the job finding rate, and the stocks of workers who are employed and non-employed, so many of our results carry over to decompositions of the job finding rate. We now turn to the results.

Accounting Results Table 3 summarizes our accounting results, ranked from smallest to largest in their ability to account for aggregate exit rates. We include demographics, firm and job characteristics, and skills as separate panels.

The first row of Panel A shows that sex accounts for very little of cross-country differences in labor market flows. The way to read this row is that the estimated semi-elasticity of employment exit rates with respect to GDP per capita is -0.030 . We replace each country's age distribution with the sample average age distribution and construct a counterfactual exit rate. The semi-elasticity of the counterfactual exit rate with respect to GDP per capita

Table 3: Exit Accounting Regressions

	Data $\hat{\beta}_1$	Counterfactual $\hat{\beta}_2$	Share	Obs.	Countries	Bins
<i>Panel A: Worker Characteristics</i>						
Sex	-0.030 (0.002)	-0.031 (0.003)	-0.02	174	13	2
Age	-0.030 (0.002)	-0.027 (0.002)	0.10	174	13	6
<i>Panel B: Firm and Job Characteristics</i>						
Sector	-0.030 (0.002)	-0.028 (0.003)	0.08	149	11	15
Establishment Size	-0.022 (0.004)	-0.017 (0.002)	0.20	113	11	2
Informality	-0.026 (0.003)	-0.022 (0.003)	0.16	142	12	2
<i>Panel C: Skills</i>						
Education	-0.030 (0.002)	-0.018 (0.002)	0.40	174	12	7
Occupation	-0.025 (0.003)	-0.019 (0.002)	0.23	160	12	11

Table notes: All regressions are computed without country or year fixed effects, with a dependent variable of exit from employment to non-employment. The number of observations varies due to data limitations for some countries and/or years. All coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ are significant at one percent.

is nearly as large in absolute value, -0.031 . This implies that the age distribution actually makes the income-exit relationship result stronger. The remaining rows of the table can be read similarly, with the corresponding detailed figures for each available in Appendix B. The second row shows that age accounts for slightly more of this trend, around 10 percent. Panel B shows the results of accounting for firm and job characteristics, which include sector (industry), establishment size, and informality. The first row accounts for industry. We harmonize industry in 12 of 13 countries to the 1.5 digit level.⁹ The sectoral composition

⁹Specifically, we do the following. We use country-year-specific crosswalks to convert country sectoral codes to a specific ISIC revision. We then create a crosswalk between each ISIC revision and the IPUMS coding scheme. Some countries' codes can be directly mapped to IPUMS if the labor force survey uses the same level of sectoral detail as the census and includes the proper years, though there are few of these countries. The 15 sectors are those in the IPUMS variable *indgen*. For all countries, we can harmonize

accounts for little of the relationship.

The next row accounts for establishment size. Establishment size is binned in most countries, with the bins used varying widely. If we want to cover all countries with establishment size data we can distinguish only firms with ten or fewer employees versus those with more than ten. Even this crude coding scheme accounts for 20 percent of the cross-country variation, behind only education and occupation.¹⁰ Finally, the last row of Panel B accounts for informality. In most of our countries workers are asked explicitly if they are employed on an informal basis. Of course this question is not asked in our rich countries and so no firms are recognized as informal per se. We take the stand that there are no informal firms in rich countries. Note that this creates a large difference in the prevalence of informal and formal firms between poor and rich countries. Nonetheless informality accounts for only 16 percent, which is probably best viewed as an upper bound on the importance of informality.

The most promising characteristics are in Panel C, which covers proxies for skill. Education is measured using the seven Barro-Lee categories (none, some primary, primary complete, and so on). It accounts for fully 40 percent of the relationship between income and exit rates. Less educated workers are more likely to exit and are also a much higher share of employment in poor countries. Occupation is measured at the 1-digit level, at which point it proxies for worker skills. It accounts 23 percent of the relationship. There is some overlap between education and occupation, but when combined they account for 55 percent of the relationship between income and exit rates. In the next section, we consider these factors in more detail, tying them to the theory developed in Section 4.

5.2 The Importance of Skill

The last section shows that skill accounts for the largest share of the trend relationship for labor market flows. Our last goal is to make a firmer connection of skills to the stylized model of matches as experience and inspection goods. In particular, we want to suggest that viewing matches with unskilled workers as experience goods and those with skilled workers as inspection goods offers a plausible starting point for understanding our findings. To do so, we repeat our main empirical facts, dividing the sample in each country into two skill groups: workers with less than secondary (high school) completed versus those with

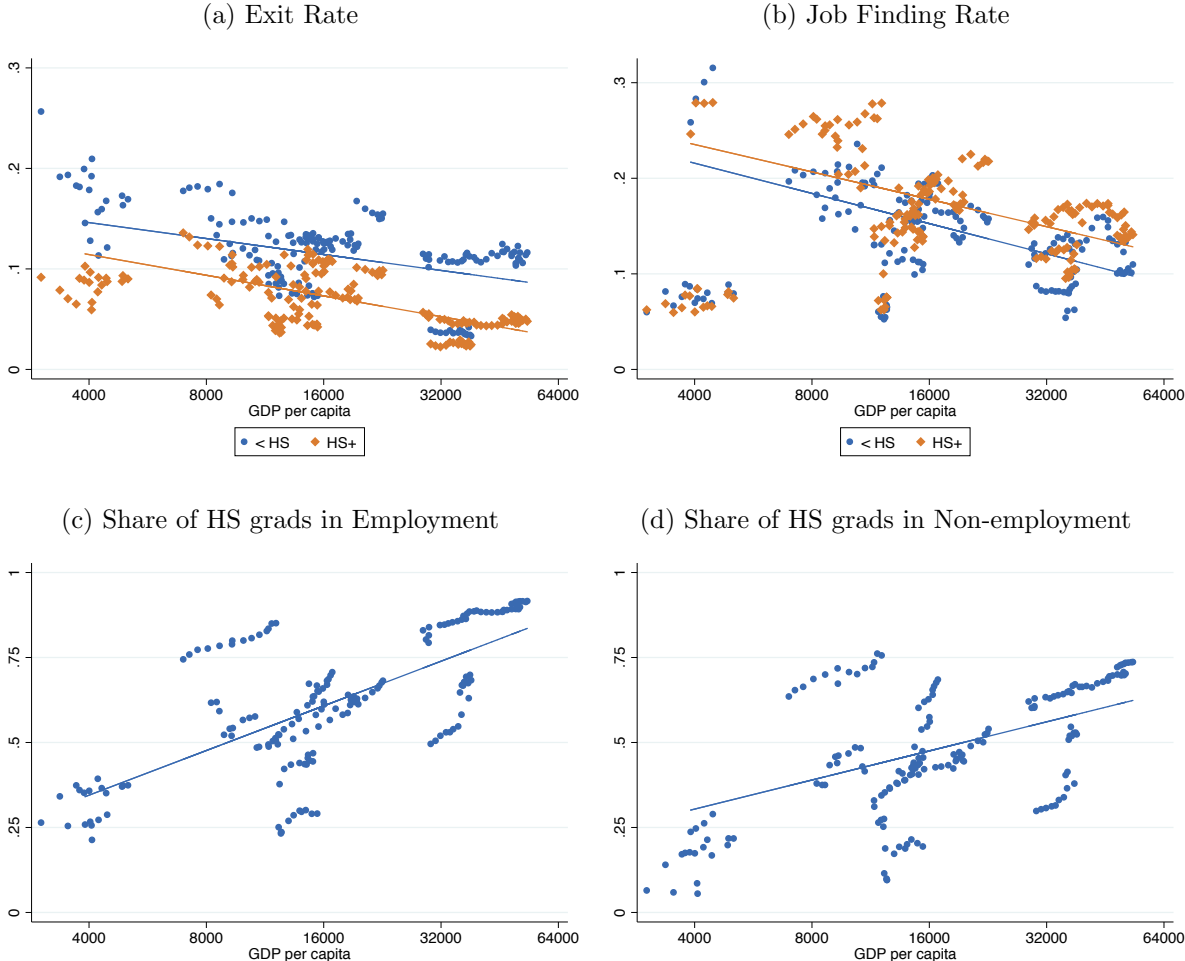
broad a manufacturing-services decomposition, and the results do not change.

¹⁰Note that we cannot measure exit rates by establishment size in the United States because the question is only asked to workers during their second quarter in the sample (in the outgoing rotation group). Also, we can drop countries and provide slightly more detailed bins, and the results do not change.

at least secondary completed. We focus on education because it is the single variable that accounts for the largest share of the results.

We start by showing the accounting results separately for these two groups in Figure 5. As one would expect from Table 3, more educated workers are more likely to find jobs and less likely to exit in all countries. Further, there are large cross-country gaps in the share of high school graduates in the labor force. These two patterns help visualize why education is important in accounting for the trends in labor market flows.

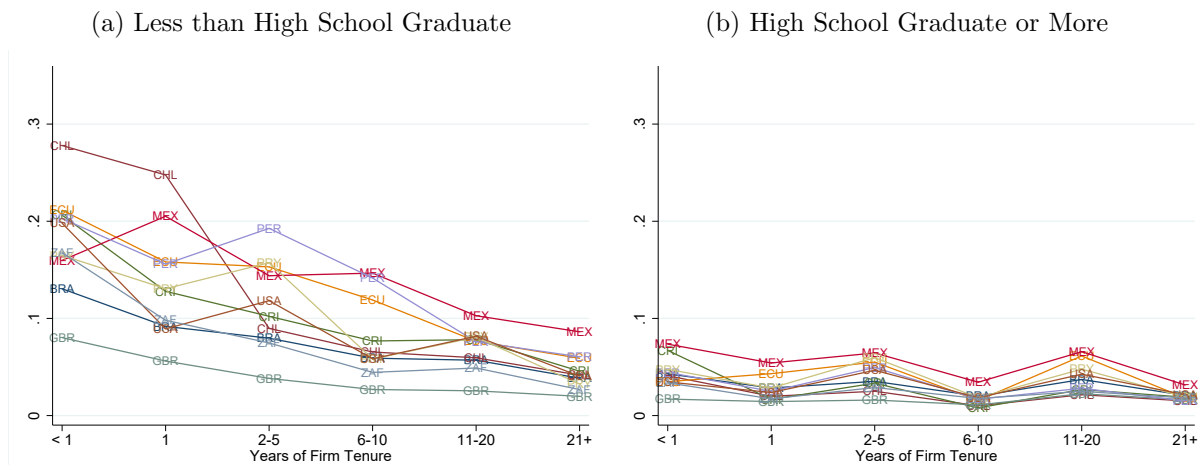
Figure 5: Transition Rates by Education



In addition to labor market flows, our model makes additional predictions that we exploit. Most importantly, tenure hazards of unskilled workers should be steeper if matches with unskilled workers are more experience goods. In Figure 6 we compare the tenure hazards for

workers in our two education groups for all countries for which we have the data. We can see indeed the employment exit hazard is much steeper for less educated workers, whereas it is almost flat for highly educated workers. Put differently, almost all of the higher employment exit rate for less educated workers occurs at low levels of tenure.

Figure 6: Tenure Hazard by Education



These findings suggest that matches with unskilled workers may generally be experience goods. This could arise if, for example, firms find it more difficult to inspect unskilled workers, perhaps because education reveals valuable information about a worker’s type. Alternatively, it could be that firms find it less valuable to inspect unskilled workers. Returning to our theory, it could be that unskilled workers are generally employed in jobs where productivity is rapidly revealed (high λ), whereas educated, white-collar workers work in teams that make it difficult to learn a worker’s specific productivity. Our results suggest that theories along these lines can help explain cross-country differences in labor market dynamics.

6 Conclusion

We build a new cross-country dataset of harmonized rotating panel labor force surveys covering thirteen countries with widely varying average income. We use this dataset to document two main new facts. First, poor country labor markets are characterized by flows between labor states 2–3 times higher than in rich countries. Second, observed employment

exit hazards and tenure wage profiles are steeper in poor countries.

We constructed a simple theory of matches as experience goods in the footsteps of [Menzio and Shi \(2011\)](#) can rationalize these findings. The main idea is that workers and firms have less precise ex ante information about match productivity, so they both start and destroy more matches (as productivity is learned). Employment exit hazards are steeper in poor countries because unproductive matches are more likely to be started but then subsequently identified and endogenously destroyed. Wage-tenure profiles are steeper for the same reason.

We provide suggestive evidence on how to microfound this model by showing that skill plays an important role. Less skilled workers have higher labor market flows and steeper tenure hazards everywhere. Further, poor countries have much larger shares of less skilled workers. These two findings jointly account for more than half of the cross-country differences in labor market flows. They suggest that a model of why less skilled workers are harder to inspect or easier to learn about through experience is a promising avenue for future research.

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A Data Details

A.1 Longitudinal Weights

All of our countries provide sample weights so that cross-sectional moments are representative of the population of interest (typically urban populations age 16–65). We use these original sampling weights when constructing cross-sectional moments. However, these weights are not sufficient when constructing longitudinal moments such as the job finding rate. The underlying problem is what is called *margin error* in this literature, or the failure to match workers with complete information across periods. This failure could arise because of attrition, temporary absence from the sample, inability to create a unique match, or nonresponse to the relevant outcomes in either period. If we drop all such observations and use the cross-sectional weights, then we are assuming that these variables are *missing at random*, while substantial evidence suggests that attrition is correlated with labor market transitions (Abowd and Zellner, 1985; Bleakley et al., 1999; Fujita and Ramey, 2009). No country provides weights that correct for this problem.

Multiple solutions to this approach have been proposed in the literature (see, for example, Bleakley et al. (1999) or Fujita and Ramey (2009)). We choose to post-stratify our weights so that our population distribution in the matched sample matches that of the unmatched sample along dimensions of interest. For example, it could be that unemployed people are more likely to move and drop out of our sample, leading then to be underrepresented in the longitudinally matched sample relative to the unmatched sample. Post-stratification adjusts upward the weight of unemployed workers remaining in the longitudinal sample such that the implied unemployment rate matches the cross-section.

An important question with post-stratification is which dimensions to use in re-weighting the data. Adding more dimensions, and fitting joint distributions rather than just marginals, allows for a better match of longitudinal and cross-sectional data and reduces concern about attrition bias. On the other hand, adding too many factors generates practical problems as cell sizes become small and the adjustments to the original weights large. At the extreme, post-stratification breaks down in cases where the unmatched sample has observations in a cell but the matched sample does not.

Our compromise is to implement a two-step procedure. In principle, we want to match the full joint distribution of employment status (wage workers, self-employed, unemployed, and inactive), age (in 10-year bins), sex, and education for each country-year. Post-stratifying

Table A1: Matching and Weights

Country	Share Unmatched (%)	Weight Correlation
Argentina		
Brazil		
Chile		
Costa Rica		
Ecuador		
Mexico		
Nicaragua		
Palestine		
Paraguay		
Peru		
South Africa		
UK		
US	11–16	0.96–0.99

Table notes: Share unmatched is the share of observations that cannot be uniquely matched (ranges refer to variation across years within the country). Weight correlation is the correlation between the original cross-sectional weights and post-stratified weights.

on employment status is important so that we fit cross-sectional moments such as the unemployment rate. Post-stratifying on age and sex is important given the large differences in moments such as the job-finding rate by age and sex. Finally, we post-stratify on education given that we find it is one of the most important factors in accounting for cross-country differences. We fit the joint distribution because of important interaction effects, for example, between gender and education.

In practice, when we implement the first step we often find many cells with few or no observations. In a second step, we aggregate categories to keep a minimum number of observations per cell. Most commonly we have to aggregate education categories somewhat. For example, the United States has few workers with no or primary schooling, so we aggregate all categories with some secondary or less together to ensure sufficient cell sizes. For some countries the underlying sample is small and so we have to pool multiple years. For example, Paraguay has only about 6,000 households per year; by pooling all three available years, we increase cell counts to reasonable levels.

Table A1 summarizes the impact of re-weighting. The second column displays for each

country the range of observations that remain unmatched. The third column displays the range of the correlation between the cross-sectional and post-stratified, longitudinal weights. For most countries matching works well and only small adjustments are needed.

A related but distinct problem frequently discussed in the literature is *classification error*: workers may misreport their labor force status, leading us to impute spurious transitions over time when none exist. [Abowd and Zellner \(1985\)](#) and [Poterba and Summers \(1986\)](#) draw on reinterview surveys from the Current Population Survey in the United States to estimate misclassification rates. By far the most common misclassification is labeling unemployed workers as inactive. Our results suggest that this problem could well be worse in poorer countries, where the two states are even less distinct. However, we pool them for all of our main results, so this form of misclassification does not affect us.

The other forms of misclassification are found to be less common in the United States. Four percent of the unemployed are misclassified as employed in the U.S.; the other rates are all less than two percent. It is possible that other forms of misclassification could be more common in poorer countries. We are not aware of any studies or estimates on this issue. We could apply the corrections of [Abowd and Zellner \(1985\)](#) and [Poterba and Summers \(1986\)](#) to all countries. Doing so would affect the levels but not the cross-country trends in labor market flows that we are interested in, so we do not pursue it here.

B Further Results

B.1 Aggregate Labor Market Statistics

Figure B1 plots two standard labor market indicators, the employment-to-population ratio and the unemployment rate, against development (PPP GDP per capita). As stated in the text, there is little evidence of a trend in either, particularly after excluding Palestine.

Figure B2 shows the trends in two important types of employment arrangements with development. First, figure B2a shows the variation in the share of employment that is self-employment. The self-employed are workers who work for themselves, including employers and unpaid family workers. It is well-known that self-employment is strongly negatively correlated with development ([Gollin, 2002](#)). We confirm this finding in our data as well: the figure ranges from 50 percent in the poorest countries to 10–15 percent in the richest countries.

Figure B1: Cross-Sectional Employment Statistics

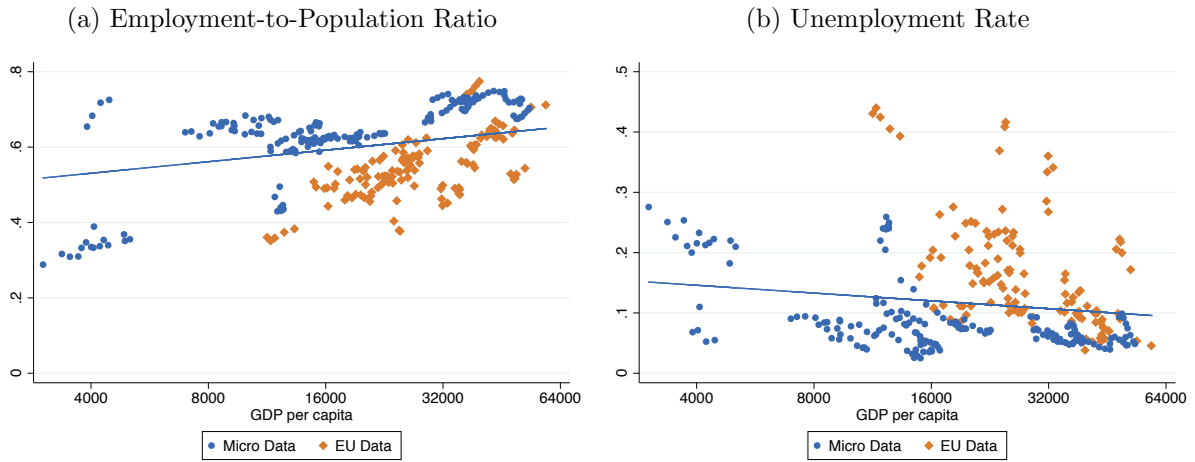
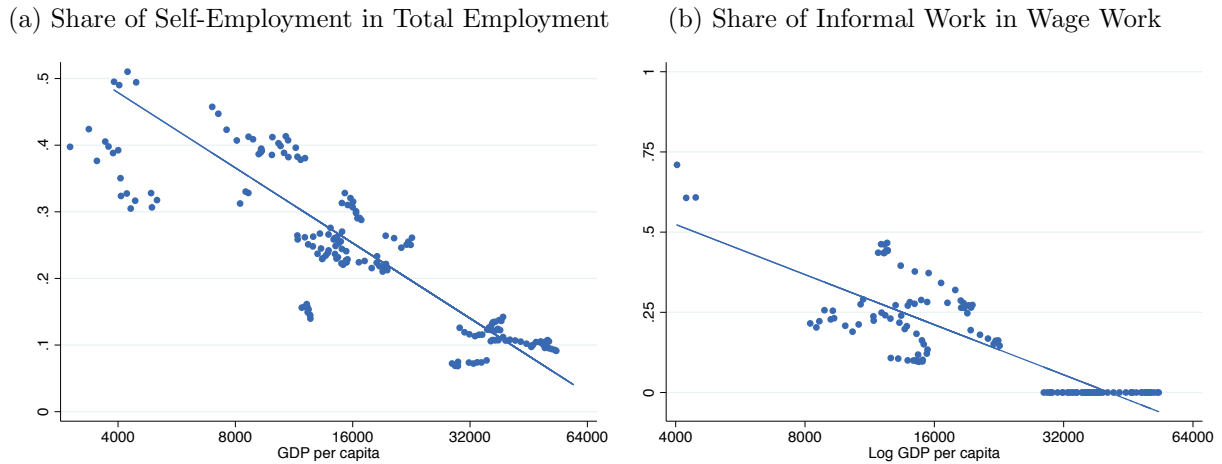


Figure B2: Types of Employment

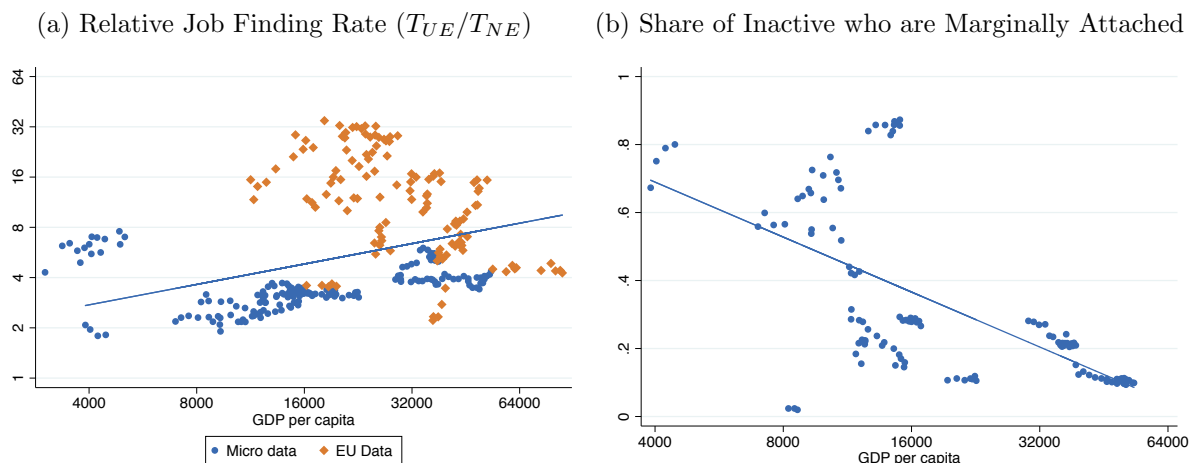


A second important feature is the prevalence of informal work in poorer countries. In most countries informality is defined (typically on the basis of payments into social insurance programs) and recorded in the data. We focus on informality among wage and salary workers in salaried work to include more countries. Figure B10d shows that informal work is common in poor countries (up to half of wage work) but rare in rich countries (a trivial share of wage work in the U.K.; the U.S. does not include any questions about it).

B.2 Unemployment and Inactivity

Conventional analyses of labor market focus on movements between employment and unemployment and abstract from inactivity, at least initially. The underlying logic is that for rich countries there is generally a fairly clear distinction between those who want work and those who do not.¹¹ There are some exceptions. For example, within the United States there is concern that for people who are not eligible for unemployment insurance, such as the young, the distinction may not be so clear (Clark and Summers, 1982; Ellwood, 1982). We find that this idea extends naturally to poor countries, where unemployment and inactivity appear to be close substitutes. This leads us to pool the two into a single “not employed” state in our baseline analysis.

Figure B3: Inactivity and Development



We formalize this idea by following in the footsteps of Flinn and Heckman (1983), who propose a test of whether unemployment and inactivity are distinct states based on comparing the job-finding hazards for each. The idea is that if people who have been inactive for six months are as likely to find work as people who have been unemployed for six months, then there is little difference between these two states. Although our data do not allow us to construct the entire job finding hazard, we can construct the relative job finding rate, T_{UE}/T_{NE} . We plot this relative job finding rate against GDP per capita in Figure B3a. The unemployed are more likely to find work than the inactive in all countries. However,

¹¹Although recent work by Elsbey et al. (2015) shows that this is not innocuous for studying cyclical variation in labor market outcomes such as the unemployment rate.

there is a strong positive trend in development. In the poorest countries the unemployed are only twice as likely to find a job; in the richest in our sample the proportion grows to around a factor of 4. The figures for European countries (included in yellow) are much higher still. Flows are also modestly higher between unemployment and inactivity in poor countries, consistent with the view that they are less distinct (not shown).

We use the microdata to investigate why so many workers transition between inactivity and employment in poor countries. We find large cross-country variation in the fraction of people who would in the U.S. be described as marginally attached to the labor force, meaning that they are classified as inactive but may be interested in a job. We categorize workers as marginally attached or not based on their response to a question asking why they are not searching for work. Broadly, answers implying an inability to find work (wrong skills, too young or old, no work currently available, etc.) are coded as marginal attachment, while answers implying the respondent is physically unable to work (sick, disabled) or has another use of time (school, retirement, caring for the household or family) are coded as no attachment.¹² Figure B3b shows the fraction of inactive workers who are marginally attached to the labor force against GDP per capita. While 75 percent of the inactive in poor countries are marginally attached to the labor force, only 10 percent in rich countries are.

B.3 Detailed Transition Rates

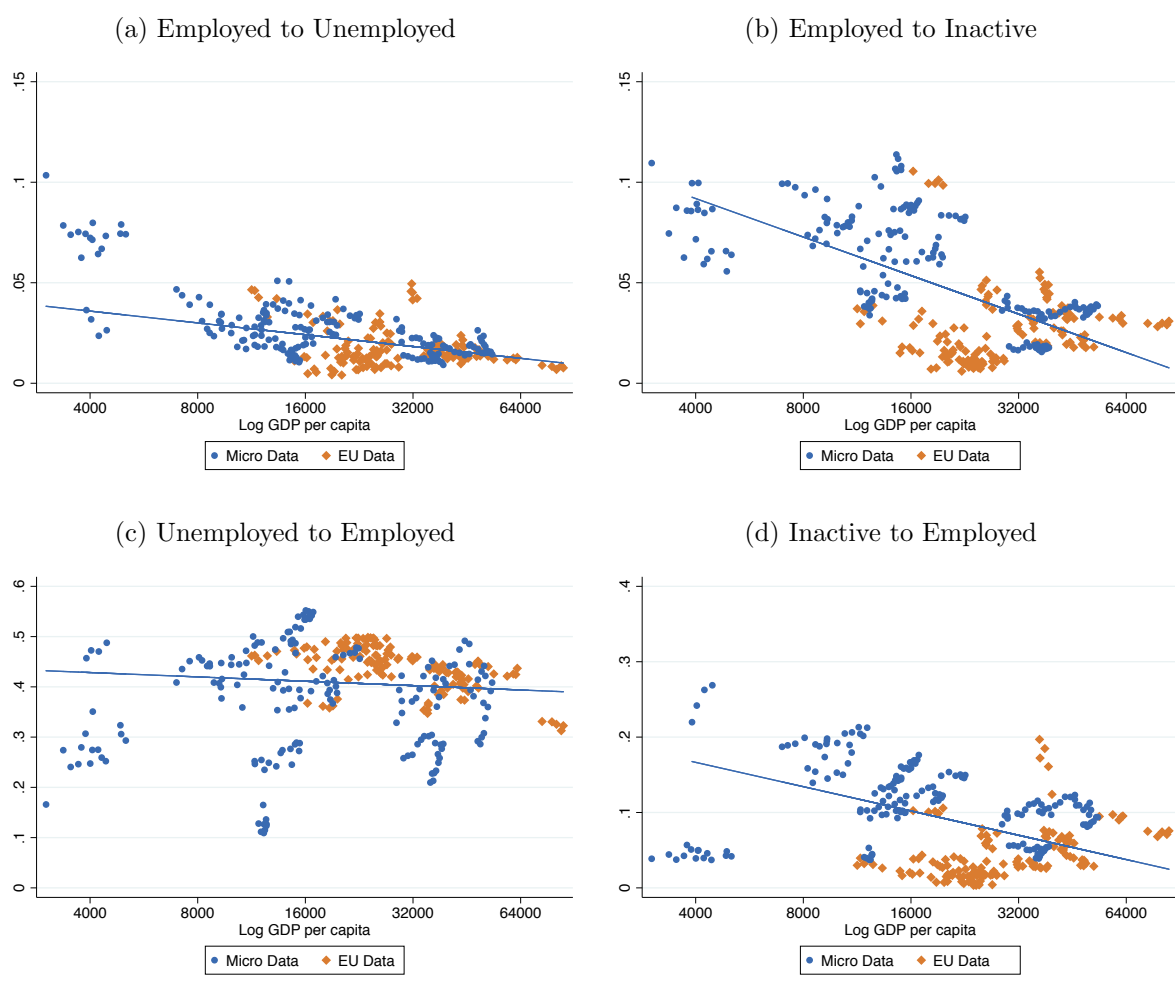
In this appendix we show detailed transition rates, distinguishing between unemployment and inactivity. Figure B4 shows the quarterly flows, plotted against PPP GDP per capita. Each of the underlying flows has a strong negative trend except for the job finding rate from unemployment, which has a trend that is statistically indistinguishable from 0. The trends into and out of inactivity are stronger than those into and out of unemployment.

B.4 Self-Employment

A growing literature suggests that self-employment fulfills different roles in poor and rich countries. For example, [Poschke \(2013\)](#) utilizes data from the Global Entrepreneurship Monitor survey, which asks standardized questions to self-employed workers around the world. He shows that half of workers in poor countries reply that they are self-employed

¹²For a subset of countries we can utilize instead a direct question about whether the respondent “wants to work”; similar results apply.

Figure B4: Detailed Quarterly Transitions



because they have no better choices for work rather than because they have a business opportunity; the corresponding figure in rich countries is 20 percent. This evidence has given rise to a literature that models these necessity or subsistence entrepreneurs as using self-employment as a substitute to missing unemployment insurance (Albrecht et al., 2009; Schoar, 2010; Poschke, 2013).

Our data enable us to bring new evidence to bear on this subject. Rather than drawing inferences from workers' stated reasons for being self-employed, we draw inferences from their labor flows. In particular, we apply the same logic as the Flinn-Heckman test in the last section and study the difference in the rate at which the non-employed and the self-employed find wage work.

Figure B5: Self-Employment and Labor Market Flows

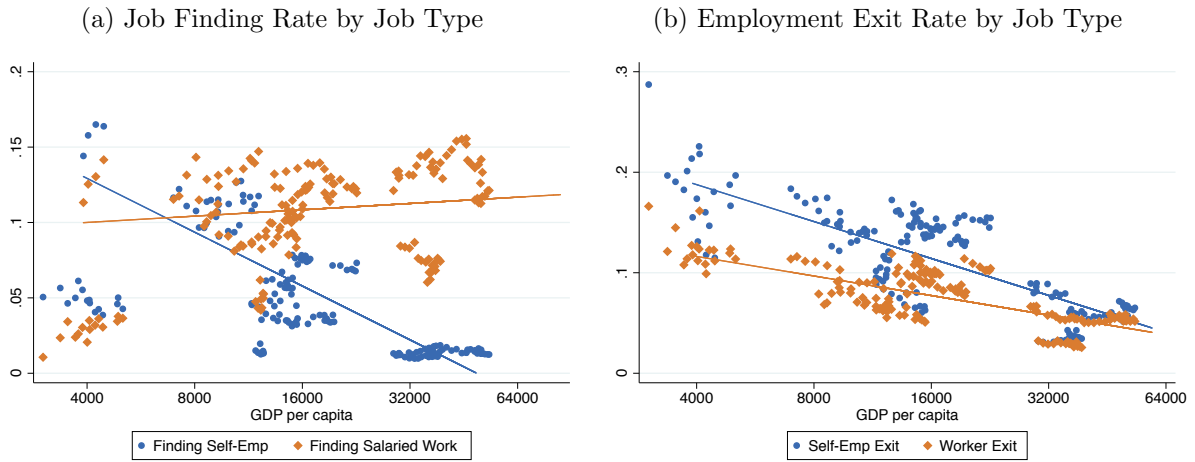


Figure B6: Relative Wage Work Finding Rate (T_{NW}/T_{BW})

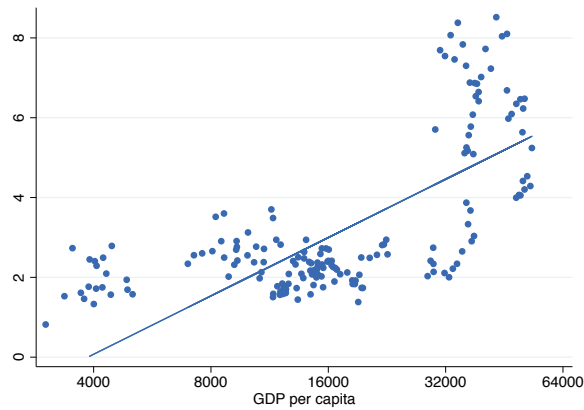


Figure B6 plots the ratio of flows from non-employment to wage work T_{NW} to the flows from self-employment to wage work T_{BW} against development. Poor countries have values around 2, meaning that people who are not in the labor force are around twice as likely to find wage work as are the self-employed; that figure is much higher (4–8 times as likely) in rich countries, despite the fact that overall flows from non-employment are much lower in rich countries. This finding offers further support to the idea that self-employment functions as a substitute for unemployment in poor countries, which in turn implies that the high flows into and out of self-employment are unlikely to constitute an efficient reallocation of

labor.

B.5 Estimated Returns to Experience

Figure B7 plots the estimated returns to experience from equation (1) against GDP per capita. As discussed in the text, the returns to experience are higher for more developed countries. This holds both for 10–19 years of experience and 20 or more years of experience (as compared to 0–4 years) and confirms the previous findings of [Lagakos et al. \(2018\)](#).

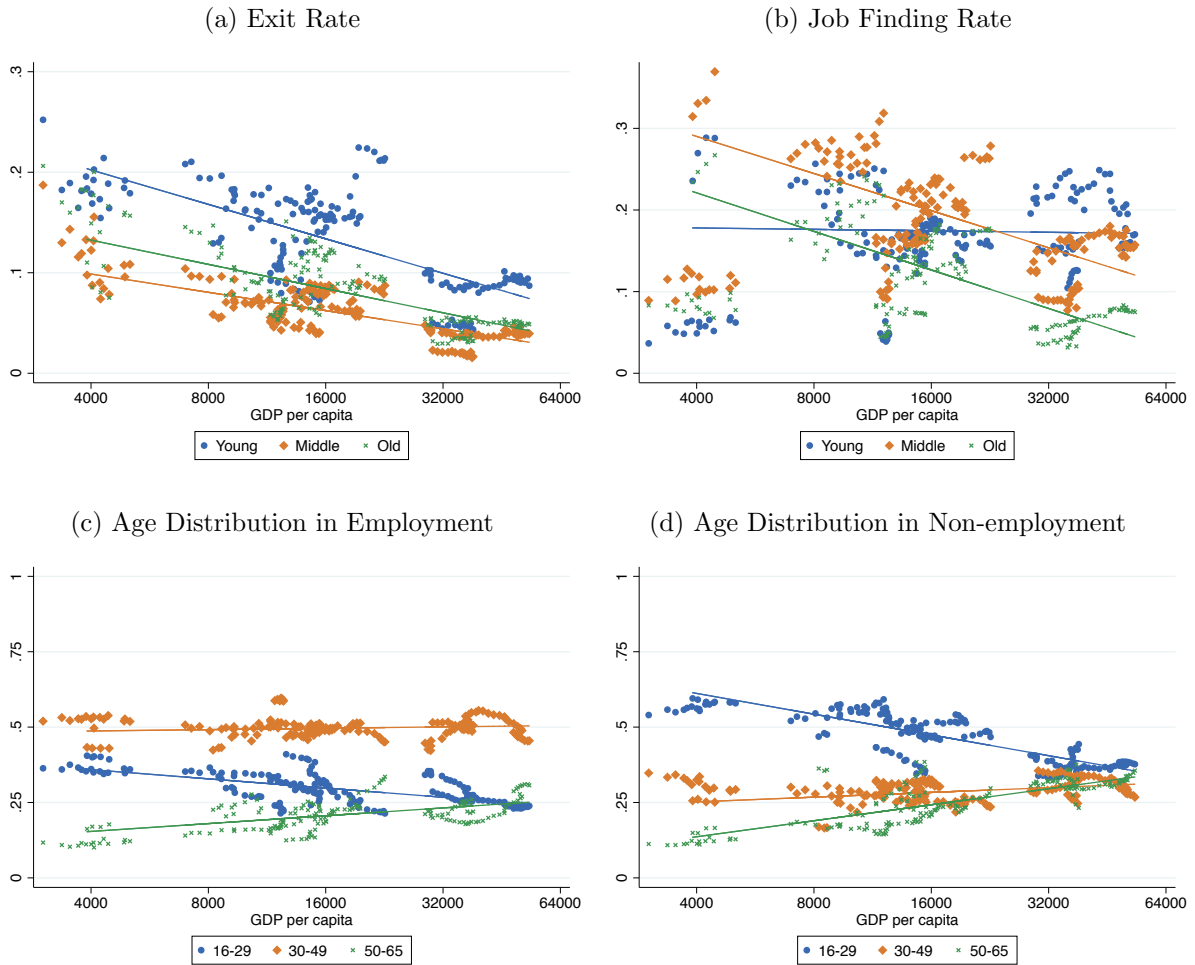
Figure B7: Wage Returns to Experience



B.6 Detailed Accounting Results: Age

Figure B8 provides detailed information on the role of age in accounting for labor market flows. For visual clarity we divide the population into three groups, young (16–29 years of age), middle-aged (30–49 years) and old (50–65 years). Figures B8a and B8b show the exit rate and job finding rate by age category against GDP per capita. Figures B8c and B8d show the age distribution of employment and non-employment against GDP per capita. Although there are large differences in transition rates by age category, the population shares do not differ enough by age to account for much of labor market transitions.

Figure B8: Transition Rates by Age



B.7 Detailed Accounting Results: Gender

Figure B9 shows exit and job finding rates by gender. Note that there are indeed important differences in exit rates by gender, as women in poor countries are nearly twice as likely to exit in poor countries, while men and women exit at about the same rates in rich countries (Figure B9a). As one can see from Figure B9c, however, there is little variation in gender employment shares. Therefore, while there are indeed large differences across genders, female employment differences can explain little of the aggregate variation.

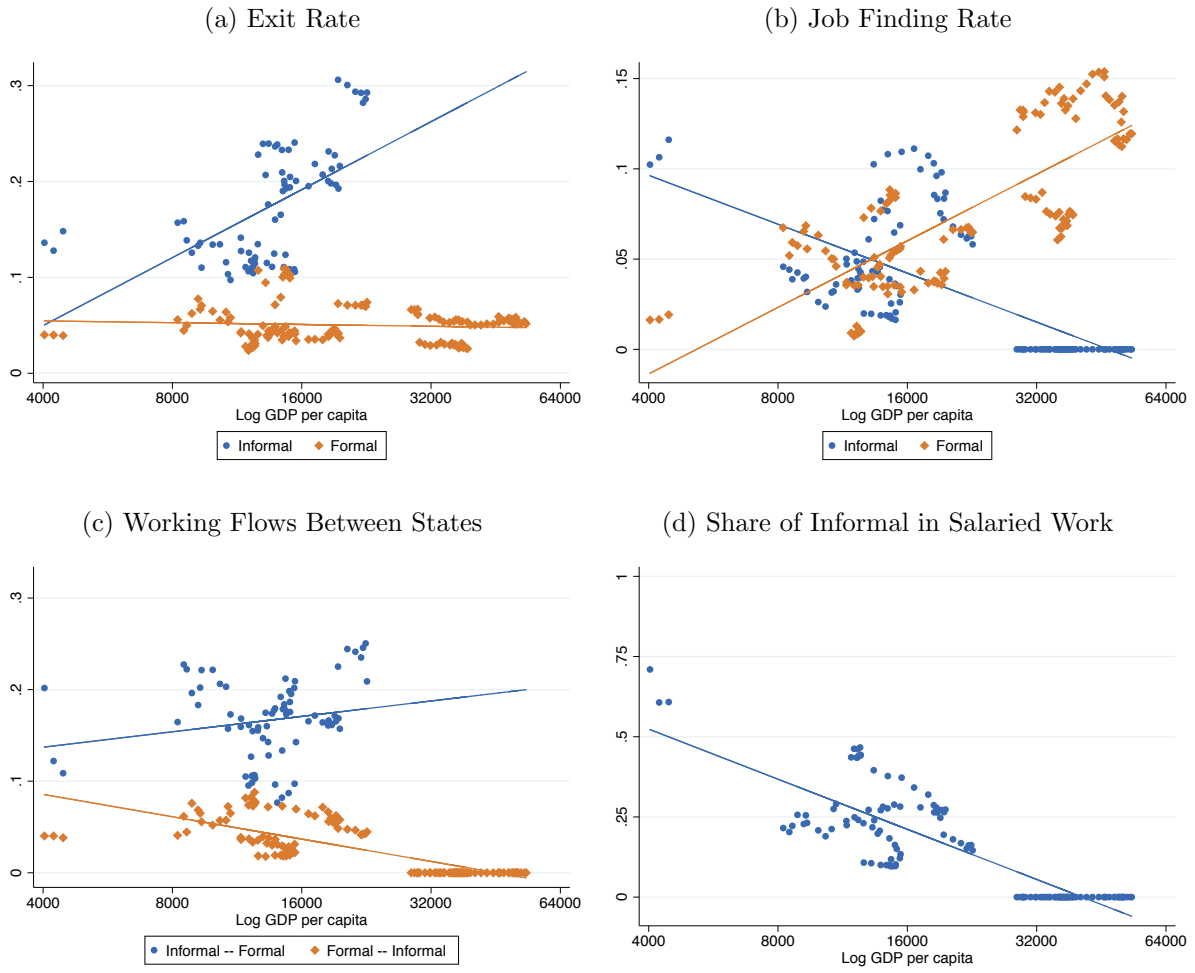
Figure B9: Transition Rates by Gender



B.8 Detailed Accounting Results: Informality

Figure B10 breaks down accounting results for formal and informal wage work. Figures B10a and ?? show exit rates and job finding rates from and to formal versus informal wage work. Workers are much more likely to exit from informal work, although the gap is smaller in poorer countries. Figure B10c shows transitions between states and is suggestive of a job ladder: workers are more likely to move from informal to formal work than vice versa. Finally, figure ?? repeats the share of informal workers by country, which declines from one-half to almost none in rich countries.

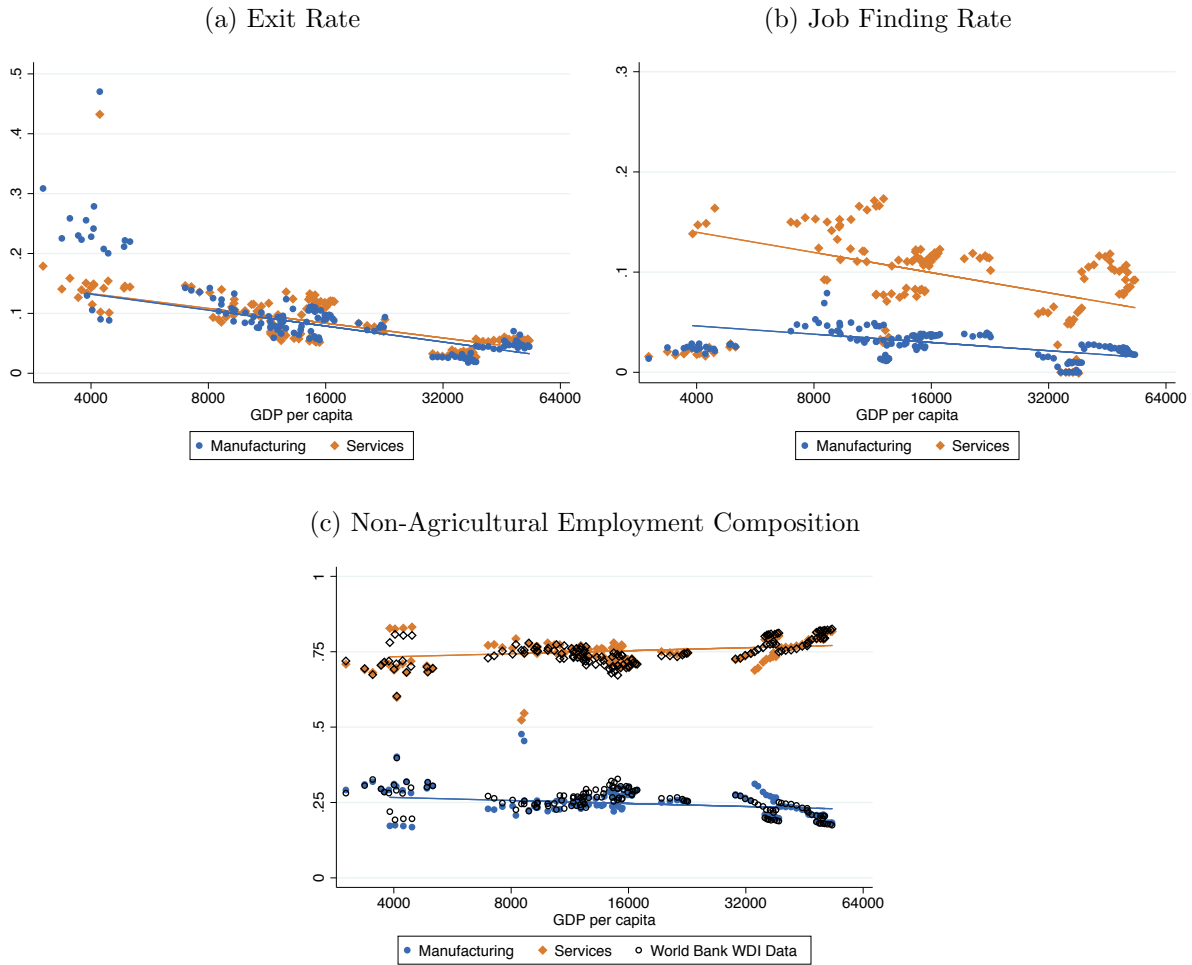
Figure B10: Transition Rates by Formality, Salaried Work Only



B.9 Detailed Accounting Results: Sector

Figure B11 breaks down exit and finding rates by broad non-agricultural sectors. Interestingly, there is almost no difference in exit rates across these sectors, which echo the more detailed results in the main text. Figure B11c shows the share of non-agricultural employment in services and manufacturing. As expected, richer countries have more employment in services. Note that we also plot aggregated data from the World Bank World Development Indicators, and find that our measures constructed from micro data line up quite well.

Figure B11: Transition Rates by Sector



B.10 Detailed Accounting Results: Firm Size

Figure B11 breaks down exit rates and employment shares by firm size, focusing on a harmonized grouping of firms into small (1–5 workers), medium (6–10 workers) and large firms (11 or more workers). Figure B12a shows that exit rates are higher for workers in small firms and lowest for workers in large firms in all countries. Figure B12b shows that poorer countries have more employment in small firms and less in large firms. We do not show the job finding rate because it is dominated by the fact that poorer countries have more small firms (and so workers find work in small firms at a higher rate).

Figure B12: Transition Rates by Firm Size

