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 40 countries across a wide range of development. We document that labor market transition rates (the job-finding rate, employment exit rate, and job-to-job transition rate) are 2–3 times higher in poor as compared to the richest countries. We use accounting approaches to show that cross-country differences in labor market institutions or the composition of workers or firms account for at most half of this trend. Much of the difference can be attributed to workers with low levels of job tenure, who are particularly likely to exit employment or switch jobs in poor countries. These results are consistent with theories that feature a more important role for endogenous separation and selection of matches into long tenure in poor countries. Such theories also rationalize our new and otherwise puzzling finding that returns to tenure are higher in poor countries.

JEL Classification Codes: O1, J6

Keywords: job flows, job-finding rate, separation rate, selection

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1 Introduction

A common view in the development policy literature is that the poor functioning of labor markets hinders economic growth (e.g. World Bank, 2013). This view appears to be grounded in the fact that employment in poor countries is concentrated in activities that have become much less common in rich countries, such as self-employment, informal employment, or wage work at small firms (Gollin, 2008; La Porta and Shleifer, 2014; Hsieh and Klenow, 2009). Research on this topic has been limited by the absence of systematic evidence on how poor and rich country labor markets compare along other dimensions. A notable absence is information on labor market flows, which both provide information on labor market dynamism and function as the central empirical ingredient needed to extend search and matching theory to developing countries.[1]

We provide this evidence and take a first step towards interpreting it through the lens of existing theory. To do so, we build a new dataset of harmonized rotating panel labor force surveys, which ask detailed questions about the same worker's labor force status in multiple periods. These surveys allow us to capture how labor market dynamics – the process of finding a job, losing a job, or switching between jobs – vary with development.[2] Our data set consists of harmonized microdata from rotating panel labor force surveys from 40 countries. All of the surveys allow us to follow a representative sample of people for two consecutive quarters and to measure their quarterly transition rates among labor market statuses. The countries span a broad range of development, with purchasing power parity (PPP-) adjusted GDP per capita ranging from around \$4,000 (Nicaragua, India, Palestine, Philippines) to more than \$50,000 (Ireland, United States). The underlying microdata are rich and typically include information on labor force status, demographics, worker skills, firm characteristics, and job characteristics.

We use the original responses to labor force questions to construct consistent measures of four labor force statuses across countries: wage work, self-employment, unemployment, and inactivity. Each status is more persistent in richer countries. At a quarterly frequency, the gap in persistence between the richest and poorest countries is 15–25 percentage points. It follows that labor market flows – transitions between statuses – must generally decline with development. We find that this is true for most of the possible flows between detailed

[1]The last major review article on labor markets in developing countries dates back twenty years and focuses primarily on rural, agricultural labor markets (Behrman, 1999). Subsequent work has shown important differences in cross-sectional moments such as hours worked or unemployment but not dynamics (Bick et al., 2018; Feng et al., 2018).

[2]Elsewhere, we use this data set to study heterogeneous responses of labor markets to shocks (Donovan et al., 2019).

labor market statuses, plus the job-to-job transition rate.

Our goal is to relate these findings to the search and matching literature. The heart of this literature is a matching function that gives the job finding rate as a function of the number of job seekers and vacancies. Empirically, the set of job seekers is typically equated to the pool of unemployed people. We suspect that this mapping may not be appropriate in our context, which includes poorer countries with different labor market institutions and little or no unemployment insurance. These differences raise the question of whether there is a meaningful distinction between unemployment and inactivity.

To help address this concern, we implement a simplified version of the Flinn and Heckman (1983) test for whether unemployment and inactivity are distinct. We show that while the unemployed are five times more likely to find a job than the inactive in rich countries, they are only twice as likely to do so in poor countries. Thus, the distinction between unemployment and inactivity is blurrier in poorer countries. We provide corroborating evidence by showing that a much higher share of inactive people in poor countries are marginally attached to the labor force. A similar comparison suggests that self-employment and unemployment are less distinct in poor countries as well, consistent with other recent work documenting that the self-employed in poor countries are more likely to be "subsistence entrepreneurs" (Schoar, 2010; Poschke, 2013).

Since the interpretation of labor market statuses varies systematically with development, there is no obvious solution for how to map search theory to cross-country evidence. Our preferred approach is to pool unemployment and inactivity into a single category of non-employment and to pool self-employment and wage work into a single category of employment. When we view the data from this perspective, we find that three key transition rates are 2–3 times higher in poorer countries: the employment exit rate (from any employment to non-employment); the job finding rate (from non-employment to any employment); and the job-to-job transition rate (from self-employment to wage work, or between wage jobs). However, we consider other approaches, including the standard one, and show that there is a negative relationship between flows and GDP per capita in all of them.

We consider this finding through the lens of the simplest textbook search and matching theory (Pissarides, 1985; Mortensen and Pissarides, 1994). The main endogenous margin in this model is that more profitable matches induces firms to post more vacancies, which raises the job finding rate. However, we find that matches are if anything less profitable in poor countries. This result highlights that our findings are not obvious from the perspective of standard theory. We pursue two avenues for trying to understand the trend between labor market flows and development.

First, we explore whether the relationship between labor market flows and development can be accounted for by labor market institutions or differences in the compositions of workers and firms based on observable characteristics. Our interest in labor market institutions is motivated by a literature that shows they explain differences in flows among rich countries (Ljungqvist and Sargent, 1998; Krause and Uhlig, 2012; Jung and Kuhn, 2014; Engbom, 2017). We find that measures of labor market institutions correlate with flows in our sample, but that controlling for them does not overturn the negative relationship between labor market flows and development. We then use shift-share accounting methods to explore whether they can be accounted for by differences in the compositions of workers and firms based on observable characteristics, motivated by a literature that has documented important differences in flows by some of these characteristics such as informality or education (Maloney, 1999; Wolcott, 2019). We find that even interactions of multiple characteristics account for at most half of the relationship between labor market flows and development.

We therefore turn to search and matching theories that can explain why otherwise similar workers and firms behave differently in poor and rich countries. A useful result that helps narrow our focus is that much of the cross-country variation in employment exit rates is concentrated among workers with short tenure spells (one year or less). By contrast, there is little variation in exit rates among workers with five or more years of tenure. This result is consistent with evidence on the importance of the decline in short job spells over time in the United States (Mercan, 2017; Pries and Rogerson, 2019). It motivates us to focus on theories in which tenure plays an important role, notably workhorse models of labor market turnover developed in Jovanovic (1979) and built into general equilibrium search models by Moscarini (2005) and Menzio and Shi (2011). This class of models features endogenous separation that generates selection of which matches reach high tenure. They can explain our patterns if there is more endogenous separation and more selection of matches in poorer countries.

This class of models also generate an additional implication: returns to tenure should be *higher* in poorer countries. We estimate returns to tenure in our data and validate this prediction. This finding is surprising given that we re-confirm the finding in the literature that the return to experience is *lower* in poor countries (Lagakos et al., 2018). The result therefore provides a sharp test of the selection model, while also narrowing the set of possible explanations for the flatter life-cycle wage profiles observed in poor countries. Taken together, these results suggest that search theories that emphasize endogenous separation and selection are a promising avenue for understanding labor market dynamics in poor versus rich countries. We do not take a stand on which form of selection (learning and separation, climbing the job ladder, etc.) is most promising. We do use our data to provide some suggestive evidence on why there might be more selection of matches in poorer countries.

There are two important caveats to our database and the types of results we can provide. First, we are not aware of any country with GDP per capita less than $2,800 that has implemented a rotating panel labor force survey. Thus, our results do not cover the very poorest countries in the world, including much of sub-Saharan Africa. We have explored alternative cross-sectional data sources that allow us to back out the implied flows from retrospective data, but even this type of evidence is rare. Second, about one-fourth of our samples cover only urban areas. We choose to focus only on urban areas for our benchmark results. We show in the Appendix that the results appear if anything stronger in rural areas when we have both types of data. Additional data sources on the poorest, primarily rural countries would be valuable, particularly given evidence that some labor market patterns diverge in these countries (Bick et al., 2018; Feng et al., 2018).

Our work relates most closely to two existing literatures. The first is the large literature on search and matching and job-to-job flows. Most existing theoretical and empirical work is aimed at understanding rich countries.[3] We are aware of three main exceptions. Three recent papers have extended the search and matching framework to allow for self-employment or informal employment, which we also find to be an important part of cross-country differences (Albrecht et al., 2009; Poschke, 2018; Bobba et al., 2018). Martellini and Menzio (2019) provide a model that accounts for the long-run (non-)trends in job finding rates in the United States in the face of large presumed gains in matching efficiency. Finally, Rud and Trapeznikova (2018) provide the only other facts on labor market dynamics in poorer countries by looking at flows between self-employment and wage work using lower-frequency data for six sub-Saharan African countries. They develop a dual economy model with labor market frictions to interpret their findings. One goal of our work is to provide a broader set of facts to make this type of analysis easier for future researchers.

Second, our work relates to a large and growing literature on labor market policies and labor market dynamics in development economics. Groh et al. (2016) subsidizes employers to hire certain workers to see if they move faster up the job ladder, while Franklin (2018) lowers search costs via transport subsidies. Closer in spirit to our findings, Abebe et al. (2019) and Bassi and Nansamba (2019) show that allowing workers to signal skills has a

[3] See Rogerson et al. (2005) for a recent review of work in search and matching or Elsby et al. (2013) for recent cross-country work on flows among (relatively developed) OECD countries.

positive impact of labor market outcomes, and Carranza et al. (2019) study information frictions from both the worker and firm perspective. These experiments are often motivated by an understanding of the specific context of a particular labor market. Our goal is to offer a broader snapshot to help set this work into perspective.

The structure of our paper is as follows. Section 2 outlines the data, our harmonization procedures, and the basic facts. Section 3 includes construction of labor market statuses and comparison of labor market dynamics across countries. Section 4 provides the accounting results. Section 5 provides results on tenure and theories of endogenous separation and selection. Section 6 concludes.

2 Data Description and Harmonization

The empirical results of this paper build on a new harmonized dataset constructed from the microdata of the rotating panel labor force surveys of 40 countries around the world. Our goal was for our dataset to be as comprehensive as possible. We identified the official labor force survey for all countries, meaning the survey used to generate officially reported labor force indicators such as the unemployment rate. We identified 60 countries that have utilized a rotating panel design, which includes households for multiple periods. Many countries experiment with different designs; we attempt to identify any cases where a country utilized a rotating panel design even briefly.

We restrict our attention to the subset of countries that satisfy two additional criteria. First, we require that the country provide the original microdata with consistent identifiers so that we can match respondents over time. This restriction rules out countries that treat the microdata as confidential or that only release anonymized versions without individual identifiers. Second, we require that the data allow us to match people for two consecutive quarters. This allows us to focus on using the largest possible comparable subset of surveys, including designs where households are followed for exactly two quarters or more complicated designs that include such tracking.[4]

Our final dataset contains microdata from 40 countries. The European Union Labour Force Survey includes 15 countries with usable identifiers. Labor force surveys for the remaining countries are collected individually; see Appendix A.1 for further details as well as countries that have appropriate data that we were not able to use.

[4]For 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.

Table 1: Sample Overview

Country	Years Covered	Obs. (Thousands)	PPP GDP per capita
Albania	2012–2013	37	10,400 – 10,500
Argentina	2003–2018	765	13,400 – 19,800
Bolivia	2015–2018	247	6,400 – 7,000
Brazil	2002–2017	7,323	11,600 – 15,500
Chile	2010–2018	1,983	19,400 – 22,900
Costa Rica	2010–2018	352	12,900 – 15,700
Cyprus	2005–2018	226	29,900 – 36,000
Czech Republic	2005–2010	591	25,800 – 29,400
Denmark	2007–2018	266	43,400 – 47,700
Dominican Republic	2016–2017	52	14,500 – 15,000
Ecuador	2007–2017	258	8,800 – 10,900
Egypt, Arab Rep.	2008–2012	205	9,500 – 10,000
Estonia	2005–2018	75	22,200 – 31,000
France	2003–2017	3,070	35,300 – 39,000
Georgia	2009–2016	141	6,500 – 9,300
Greece	2005–2018	1,400	23,700 – 32,100
Guyana	2017–2017	2	7,400 – 7,400
Hungary	2005–2018	1,461	22,200 – 28,200
Iceland	2005–2018	58	40,100 – 48,600
India	2017–2018	190	6,500 – 6,900
Ireland	2007–2018	732	42,900 – 70,400
Italy	2005–2018	1,793	33,900 – 38,600
Latvia	2007–2018	79	18,300 – 26,400
Lithuania	2005–2018	187	18,500 – 31,100
Malta	2009–2018	49	27,500 – 38,100
Mexico	1995–2017	15,400	13,500 – 17,900
Nicaragua	2009–2012	194	3,900 – 4,400
Palestine	2000–2015	558	2,800 – 4,600
Paraguay	2010–2017	45	9,700 – 11,800
Peru	2003–2018	248	6,900 – 12,800
Philippines	1988–2003	1,989	3,800 – 4,400
Romania	2005–2018	817	14,400 – 24,500
Slovak Republic	2005–2018	572	20,000 – 31,300
Slovenia	2010–2018	113	27,600 – 32,700
South Africa	2008–2018	1,228	11,800 – 12,400
Spain	2000–2018	6,843	30,000 – 35,100
Sweden	2005–2018	1,562	40,900 – 47,200
Switzerland	2010–2017	373	55,900 – 58,000
United Kingdom	1997–2017	3,591	30,300 – 39,900
United States	1979–2019	9,083	36,300 – 55,700
Total:			
40 countries	**484 country-years**	**64,161**	**2,800 – 70,400**

[a] *Table notes:* Range of PPP GDP per capita World Bank (2019), rounded to the nearest one hundred dollars. An observation is an individual surveyed in two consecutive quarters.

In most countries we have household and person identifiers. In these countries, we use the identifiers to match people for two consecutive quarters. We follow the standard protocol of including only matches that are unique and have consistent responses on age, gender, and (in the United States only) race (Madrian and Lefgren, 2000). The share of possible matches that fail these tests is generally low. In a few countries we have household but not person identifiers. For these countries we match on household identifiers, age, sex, and education. We keep only observations with unique, exact matches on these three variables.

All of our countries sample dwellings (physical addresses) and interview whoever inhabits those dwellings at the appropriate times. Thus, households that move dwellings between quarters cannot be matched. This fact has the potential to bias our estimates to the extent that moving (or other forms of non-response) is correlated with outcomes of interest, such as finding a job. We follow the typical approach in the literature of adjusting the provided sample weights so that the matched sample agrees with the unmatched sample along important dimensions (Bleakley et al., 1999; Fujita and Ramey, 2009). In particular, we rake the weights so that the matched and unmatched samples have the same density by education-labor force status and age-gender. See Appendix A.3 for details. The adjusted weights are generally similar to the provided weights, measured using the correlation between the two (Table A4) or the fact that standard moments are fairly similar regardless of which weight is used (Figure A1).

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 focus throughout on the urban population aged 16–65. Our main results of interest are even stronger when we focus on the three-quarters of samples that include both urban and rural areas; see Appendix A.5.[5] We focus attention on workers aged 16–65 to mitigate concerns about cross-country differences in labor market institutions such as child labor laws or retirement policies.

Table 1 identifies the countries that are covered and basic summary information. Altogether, we have about 64 million observations spanning 476 country-years. The duration of data availability varies widely, ranging from two quarters of the newly-formed Guyanese Labor Force Survey to 41 years in the United States. We merge our data with annual PPP GDP per capita from the World Development Indicators when discussing development trends (World Bank, 2019). Our countries cover a wide range of development, with Nicaragua, India, Palestine, and the Philippines having PPP GDP per capita around

[5]See also Jeong (2019) for RCT-level evidence of frictional labor markets in rural Tanzanian village economies.

$3,000–6,000 and the United States and Ireland over $50,000 in recent years. We lack data on the very poorest countries, where the cost of such panel surveys is generally prohibitive. We can infer dynamics from retrospective questions on employment history for a few such countries but are not able to form reliable estimates of the patterns there; see Appendix C for further details.

2.1 Harmonization

We harmonize 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. The employed include those who work for someone else (wage and salary workers) and the self-employed, which in turn includes employers, own-account workers, and unpaid family workers who work 15 or more hours per week. Most surveys, including especially those in poorer countries, include a battery of questions designed to insure that they capture people who are engaged in self-employment. For example, it is typical to have separate questions about whether the respondent raises crops or livestock for own consumption, operates a small business, or produces small handcrafts, rather than a single question asking whether he or she is self-employed.

Those who are not employed are categorized either as unemployed or inactive (out of 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.

Most of our measures of labor flows are derived as changes in labor force status between quarters. The lone exception is the job-to-job transition rate among wage workers. This is available in fewer countries because it generally has to be inferred using reported tenure on the job: we define a job-to-job transition as a case where a worker reports working a wage job at time t and then reports working a wage job with tenure less than three months at time $t+1$.[6] We can only do this for the subset of countries that ask questions about tenure

[6] The 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).

and allow workers to report tenure duration in weeks or months for short spells.

We also harmonize a number of the characteristics of people and firms that might help explain 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. Age is coded either in years or bins of years. We work with ten-year age bins (16–25, 26–35, and so on). Gender is straightforward.

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- and two-digit level following the International Standard Classification of Occupations (ISCO)-08 standards. Most countries use ISCO occupational schemes directly or adapt their own schemes from the ISCO, which makes harmonization somewhat easier. In some cases we do have to build extensive crosswalks. The first digit of the ISCO-08 codes largely captures skill level. For example, group 1 consists of managers, group 2 of professionals, group 5 of services and sales workers, and group 9 of elementary occupations, with a clear ranking of typical skill between broad groups.

The main characteristics of the firm are firm 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 establishment 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). We categorize industry using a hybrid 1/2-digit industry coding scheme with 15 possible codes suggested by Minnesota Population Center (2014), which maps well into our data.

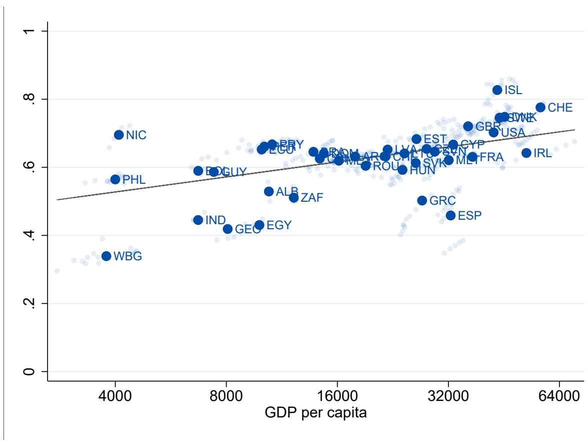
We harmonize three job (match) characteristics. As mentioned above, we have information on tenure. Second, we know whether wage workers are employed on a formal or informal basis in many countries. A formal job is one where the employer makes payments into social programs (such as pensions) on the worker's behalf. This test is not clearly defined, and the question often not asked, for the self-employed. 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.

2.2 Basic Cross-Sectional Facts

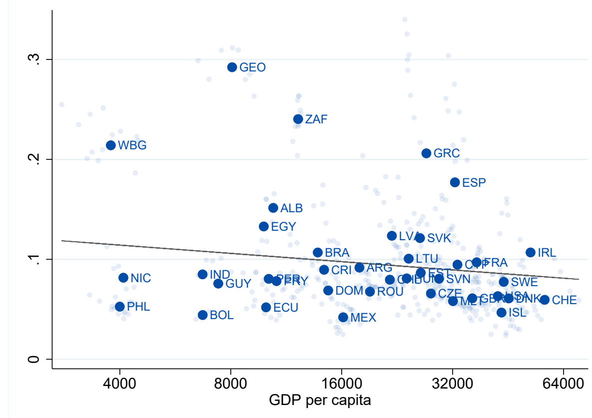
Before proceeding to the baseline analysis, we overview cross-sectional facts that do not use the panel data. Doing so allows us to show that our data generally line up with existing results when possible. It also allows us to highlight some important differences in labor markets by development that will be of interest in what follows.

Figure 1: Cross-Sectional Labor Force Facts

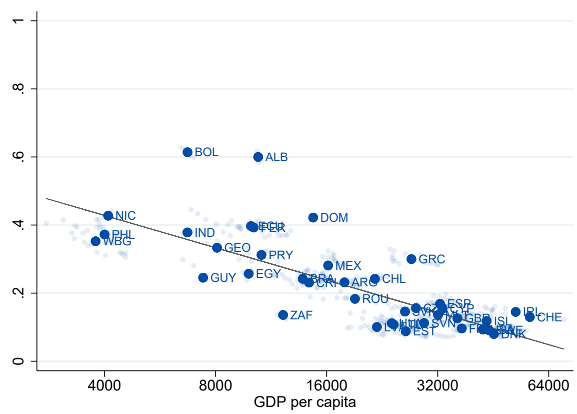
(a) Employment-to-Population Ratio



(b) Unemployment Rate



(c) Self-Employment as a Share of Employment



We start by constructing two standard labor market indicators, the employment to population ratio and the unemployment rate. They are plotted in Figures 1a and 1b. These figures adopt the common format we use throughout the paper, so some explanation is in order. First, we always plot outcomes of interest against PPP GDP per capita using a log-scale. Each observation is a country-year pair constructed as discussed above. We also compute and plot the average observation for each country, labeled with the standard 3-digit country codes. Given the clustering by country, this label often helps distinguish within from between country patterns. Finally, we include in all scatter plots a best fit line of a regression of the data points against log PPP GDP per capita.

Turning to the results, 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., 2018). One difference is that existing work finds much higher employment to population ratios and much lower unemployment rates in the very poorest countries; we have no such countries in our sample.

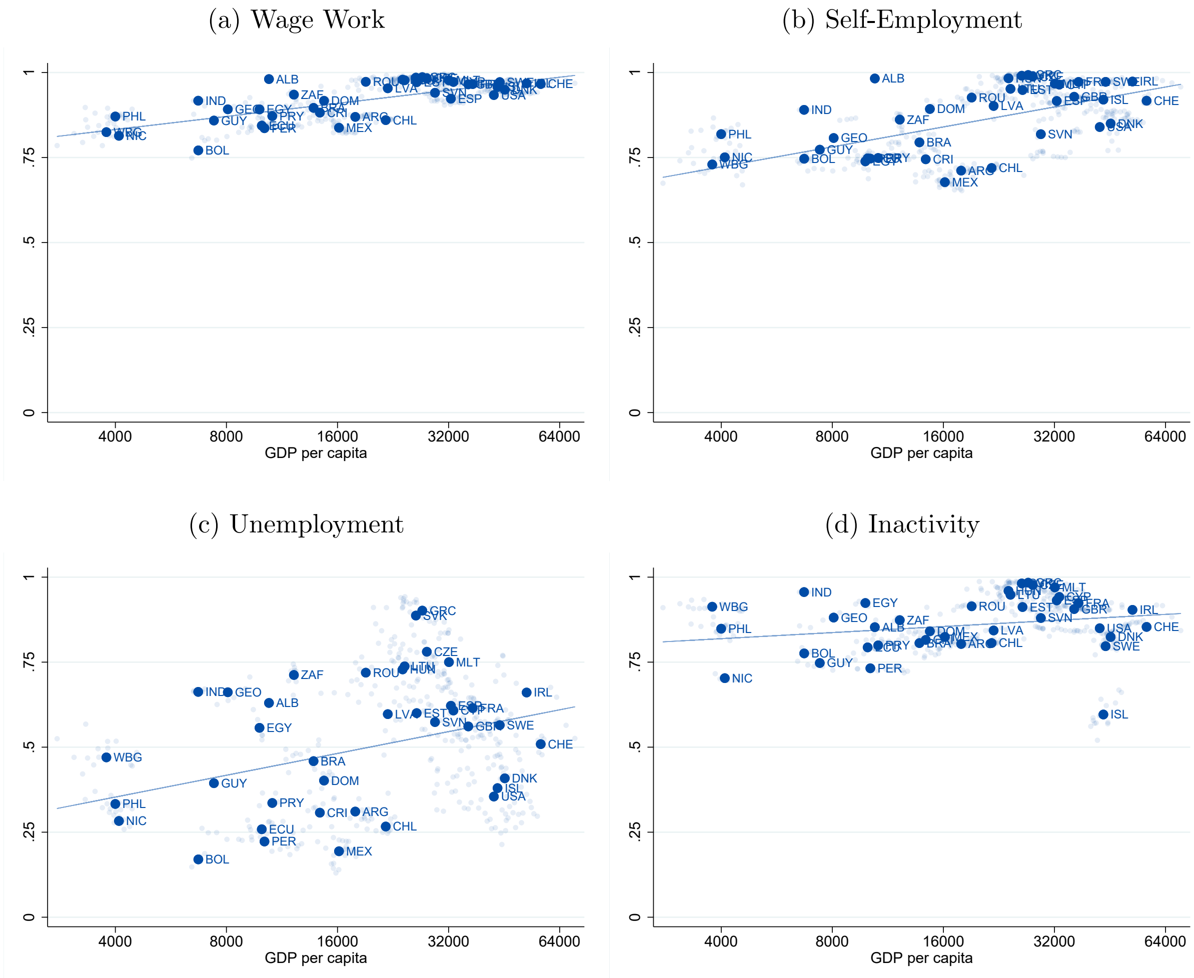
Finally, Figure 1c shows the share of self-employment in total employment by country. This share shows a strong negative trend with development, consistent with the literature (Gollin, 2008). In existing work focused on rich countries it is common to group the self-employed with wage workers, which is likely innocuous given their low share in the employment pool. Since they are a larger share of employment in poor countries we preserve the distinction between the two for our exploratory flows analysis, which we turn to now.

3 Labor Market Flows and Persistence of Labor Force Status

We now study labor force dynamics: the average quarterly persistence of labor force status and the average quarterly transition rates between statuses by country-year. As discussed above, we include inactivity and maintain the distinction between wage work and self-employment in this exploratory analysis. Persistence and transitions are defined throughout by comparing the reported status in two consecutive quarters. We generally do not observe and abstract from workers who have transitions within the quarter (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 2 shows the quarterly persistence of each status. The main feature of this figure is that persistence is strongly correlated with development. These differences are large: the estimated regression lines suggest that labor force status is 15–25 percentage points more persistent in the richest as compared to the poorest countries. Figure B1 in Appendix B.1 shows the detailed quarterly transition rates, e.g., from wage work to unemployment and so on. Nine out of the twelve underlying flows are less common in richer countries. The

Figure 2: Quarterly Probability of Remaining in Same Status

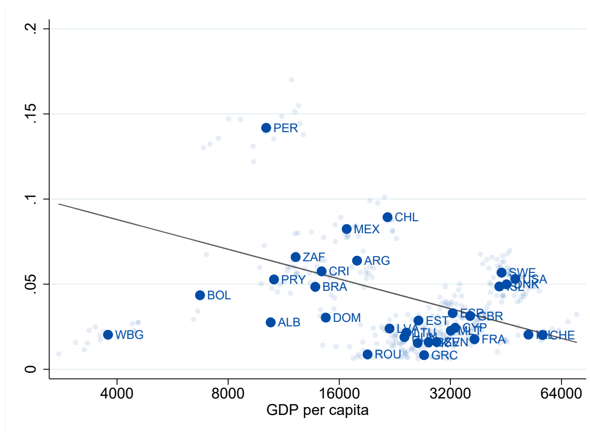


(a) Wage Work (b) Self-Employment (c) Unemployment (d) Inactivity

most prominent exception is the transition rate from unemployment to wage work, which is higher in rich countries. This is perhaps to be expected given the much higher share of wage employment in rich countries.

Employment persistence includes two underlying categories: workers who remain in the exact same job; and workers who make intervening job-to-job transitions. One form of job-to-job transition involves moving between self-employment and wage work, which is already shown in Figure B1. For a subset of countries we can also measure the transitions between wage work jobs, which is shown in Figure 3. There is again a strong negative trend with development: while workers in poorer countries have a 25 percent chance of switching between wage jobs in a quarter, workers in rich countries have roughly a 5 percent chance of doing so. This finding is consistent with Figure B1. Labor force status is more persistent, and flows are lower, in richer countries.

Figure 3: Quarterly Job-to-Job Transition Rates (Wage Work)



Our next goal is to aggregate these findings to the standard flows familiar from search and matching literature. The heart of this literature is a matching function that governs the job finding rate as a function of the number of job seekers and vacancies. Empirically, the set of job seekers is typically equated to the pool of unemployed people. We suspect that this mapping may not be appropriate in our context, which includes poorer countries with different labor market institutions. For example, several of our countries do not offer unemployment insurance, raising questions of whether there is a meaningful distinction between unemployment and inactivity. Additionally, Figures 1 and B1 show that much of employment in poorer countries is self-employment and that flows into and out of self-employment look quite different in those countries. We re-examine both unemployment and self-employment.

3.1 Unemployment and Inactivity

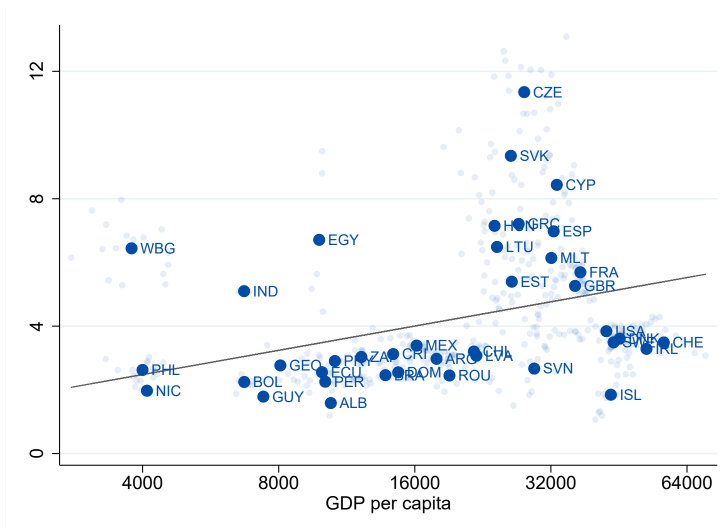
Conventional analyses of labor markets focus on movements between employment and unemployment and abstract from inactivity, at least initially.[7] The underlying logic is that for rich countries there is generally a fairly clear distinction between those who want work and those who do not. However, our sample includes poorer countries where assistance programs for the unemployed are less generous or absent. This absence raises the concern that unemployment and inactivity may not be clearly differentiated for all workers,

[7]There are exceptions; Elsby et al. (2015) show that cyclical variation in labor market outcomes such as the unemployment rate are affected by movements in and out of the labor force.

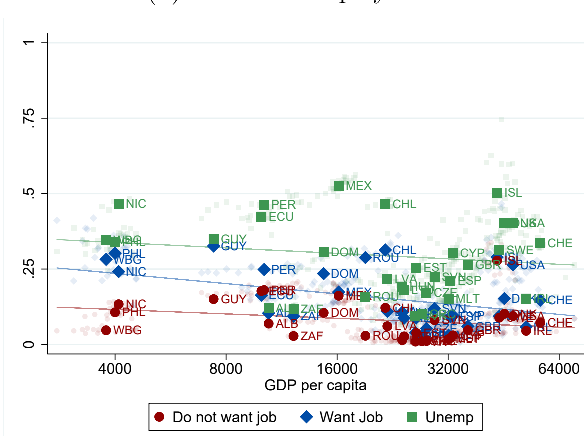
recalling an older literature on whether they are distinct for workers who are ineligible for unemployment insurance in rich countries, such as the young (Clark and Summers, 1982; Ellwood, 1982).

Figure 4: Inactivity and Development

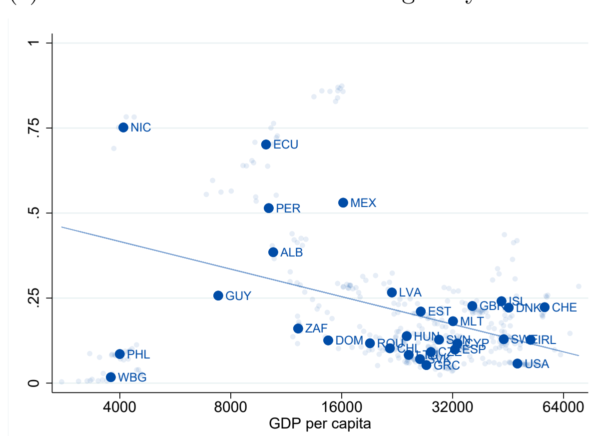
(a) Relative Job-Finding Rate (Unemployed/Inactive)



(b) Flows to Employment



(c) Share of Inactive who are Marginally Attached



We conduct a simple test of whether unemployment and inactivity are distinct states in the spirit of Flinn and Heckman (1983). They propose that the two states are distinct only to the extent that they have different job-finding hazards. 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 no meaningful behavioral difference between the two. Although our data do not allow us to construct the entire job finding hazard, we can construct the relative quarterly job finding rates. We plot these rates against GDP per capita in Figure 4a. The unemployed are more likely to move to employment in all countries. However, 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 4–12.

We use the microdata to investigate why so many workers transition between inactivity and employment in poor countries. Figure 4b unpacks the job finding rate of inactive workers coded based on self-reported reason for not seeking work. We code workers who report being unable to find suitable work (wrong skills, too young or old, no work currently available, etc.) as marginally attached, while those who are unable to work or uninterested in work (sick, disabled, in school, retired, caring for the household or family) are coded as no attachment.[8] As expected, the marginally attached are more likely to move to employment across all countries, but there is no correlation with development. There is, however, large cross-country variation in the fraction of people who are marginally attached to the labor force, shown in Figure 4c. While 75 percent of the inactive in poor countries are marginally attached to the labor force, only 10 percent in rich countries are. These results indicate that unemployment and inactivity are less distinct in poor countries.

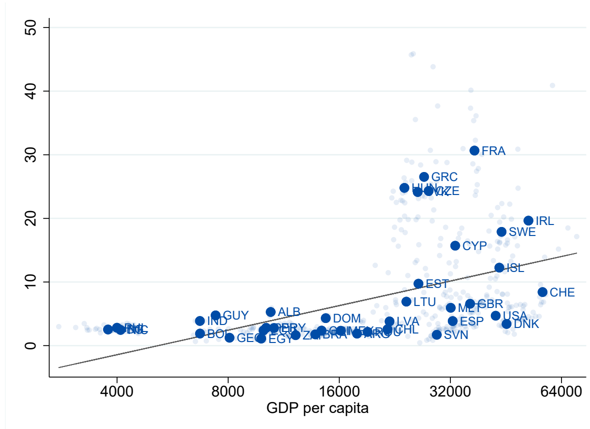
3.2 Self-Employment

The central role of self-employment in poor country labor markets suggests that it, too, is worth re-examining, particularly in light of a growing literature suggesting that self-employment fulfills different roles in poor and rich countries. For example, Poschke (2013) shows that 50 percent of workers in poor countries reply that they are self-employed because they have no better choices for work rather than because they have a business opportunity, whereas the corresponding figure for rich countries is 20 percent. This evidence has given rise to a literature that models self-employment in poor countries as being a closer substitute for missing unemployment insurance than for wage work (Albrecht et al., 2009; Schoar, 2010; Poschke, 2018).

Our data enable us to bring new evidence to bear on this subject. We apply the same logic as the Flinn-Heckman test in the last section and study the difference in the rate at which the unemployed and the self-employed find wage work. Figure 5 plots the ratio of the transition rate from unemployment to wage work to the transition rate from self-employment to wage work against GDP per capita. Poor countries have values around 2,

[8] For a subset of countries we can utilize instead a direct question about whether the respondent "wants to work"; similar results apply.

Figure 5: Relative Wage Work Finding Rate (Unemployed/Self-Employed)



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 an order of magnitude higher in many rich countries. Even ignoring observations where the ratio exceeds 10 yields a strong, positive relationship. This finding offers further support that self-employment is more of a search technology in poorer countries.

3.3 Aggregating Flows

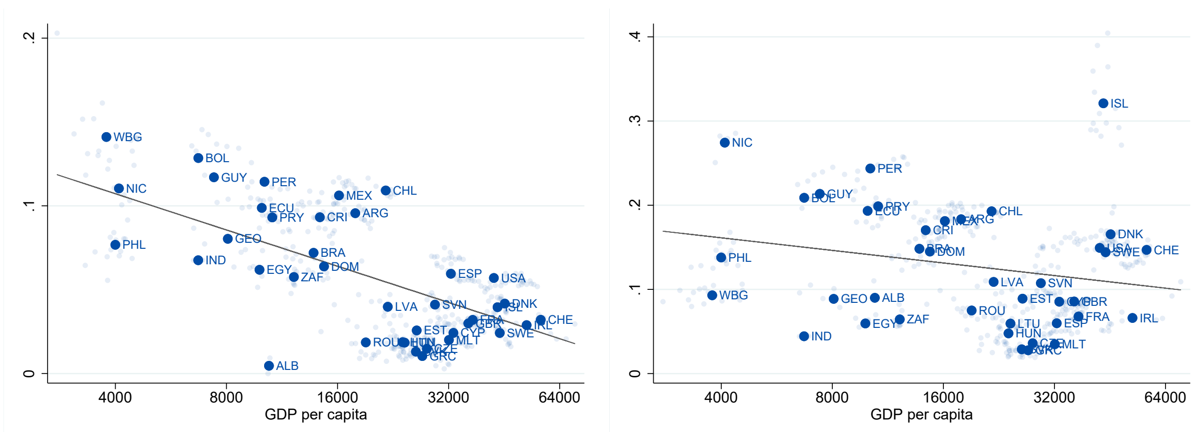
We now return to the goal of aggregating flows to arrive at the familiar job-finding rate, separation rate, and job-to-job transition rates. The results of the last two subsections show that the interpretation of labor market status varies systematically with development, implying that there is no obvious solution for how to map search theory to cross-country evidence. Our approach is to consider multiple possible aggregations. For each, we find that the three canonical measures of labor market transitions are flat or decline with development. Intuitively, this result arises because almost all of the underlying detailed flows decline systematically with development (Figure B1). Thus, the interpretation of labor market status matters quantitatively but not qualitatively.

We start with our preferred benchmark, which pools wage work and self-employment into employment (e) and pools unemployment and inactivity into non-employment (n). We include self-employment in employment because it is most consistent with national accounts data: it ensures that our workers are precisely those who spend time producing GDP as measured in the national accounts. We pool the inactive with the unemployed because the two statuses are apparently less distinct in poor countries.

Figure 6 shows our baseline result. 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 higher than those in rich countries, and job finding rates nearly twice as high.

Figure 6: Quarterly Transition Rates

(a) Employment Exit Rate (b) Job Finding Rate



We have considered two alternative groupings that yield qualitatively similar results. First, we explored excluding the inactive, which yields the conventional mapping of the model to the data. Similar results apply.[9] Second, we have explored treating the self-employed as unemployed, which then implies that only wage workers are employed. Doing so has little effect on rich countries (where few people are anyway self-employed), but changes results substantially for poor countries. For example, it implies the unemployment rate is over fifty percent in some countries. The resulting labor market flows decline with development, although the effect is very strong for the employment exit rate and almost non-existent for the job finding rate. Details, including figures, are available in Appendix B.2.

Finally, we note that it is important to have a broad set of countries to find this pattern. Table 2 provides the regression estimates from Figure 6, and also re-runs the same regressions using only E.U. countries (including the U.K.), Switzerland, and the United States.

[9] Note that this is equivalent to an intermediate case where we construct the pool of "job-seekers" as the unemployed plus the inactive weighted by the country-specific relative job-finding rate.

Indeed, for our full sample, this correlation is negative and statistically significant. However, if we focus on the subsample of rich countries (similar to what is commonly studied in the literature), we find a *positive* relationship between labor market flows and development. These countries span a fairly narrow range of development and have large differences in labor market institutions, suggesting caution is required when attempting to extrapolate broader questions of economic growth from analyses conducted among rich countries.

Table 2: Labor Market Turnover and Income

	Rich Countries		All Countries	
	Exit Rate	JFR	Exit Rate	JFR
Log GDP per capita	0.018	0.106	-0.031	-0.022
	(0.003)***	(0.012)***	(0.002)***	(0.005)***
Sample Average	0.033	0.103	0.054	0.124
Obs.	273	273	445	445
R^2	0.113	0.229	0.358	0.040

Table Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Palestine not included, but results do not change if included.

3.4 Search and Matching Theory

The flows between detailed states (Figure B1), our preferred aggregation into standard flows (Figure 6), and plausible alternative aggregations (Appendix B.2) all imply that labor force status persistence increases and labor market flows decrease with development. The goal of the rest of the paper is to identify possible sources and implications of this trend.

Given that we have constructed the standard flows familiar from search theory, we consider whether the textbook version of this theory provides an obvious explanation for our patterns. We start with the simplest version of the model from Pissarides (1985) to fix ideas. This theory features endogenous match formation but exogenous match destruction, so we focus only on whether it can help us understand cross-country variation in the job finding rate.

The heart of the theory is the matching function $m(n, v)$ that gives the number of matches formed in a period as a function of the number of non-employed people n and the number of vacancies v. Following standard practice, we assume that this matching function is Cobb-Douglas, $m(n, v) = Mn^{\eta}v^{1-\eta}$. The job finding rate is then the share of non-employed people who find a job in each period, $m(n,v)/n = M\theta^{1-\eta}$, where $\theta \equiv v/n$ is the market tightness (from the perspective of firms). The parameters M and η are exogenous. The model then has one margin to generate variation in the job finding rate, which is through market tightness.

All non-employed people are assumed to search for jobs, so variation in market tightness comes from the incentives of firms to post vacancies. The model is set in continuous time, with firms discounting future flows at rate r. Firms pay a flow cost κ to hold a vacancy open and receive flow payoff $x - w$ from a filled position, where x is the value of output and w is the equilibrium wage. This leads to two value functions for a filled job and a vacancy, J and V respectively,

$$rJ = x - w + \delta(V - J) \tag{1}$$

$$rV = -\kappa + M\theta^{-\eta}(J - V). \tag{2}$$

Firms can enter freely, meaning that the value of posting a vacancy in equilibrium is $V = 0$. This assumption makes it possible to re-arrange the value functions to yield an expression for the job finding rate:

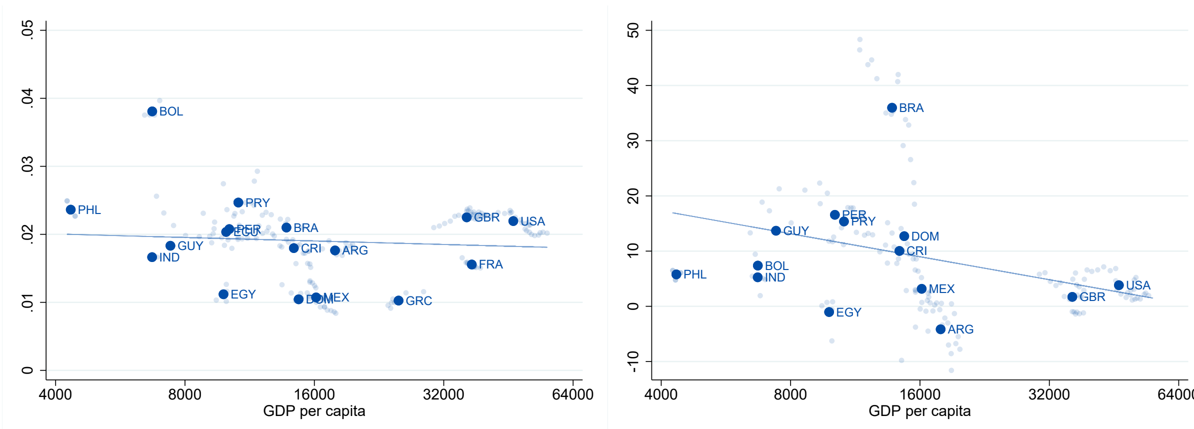
$$\begin{aligned}\text{job finding rate} = M\theta^{1-\eta} &= M^{1/\eta}\kappa^{1-1/\eta}\left[\frac{x-w}{r+\delta}\right]^{(1-\eta)/\eta} \\ = M\theta^{1-\eta} &= M^{1/\eta}\hat{\kappa}^{1-1/\eta}\left[\frac{1-\hat{w}}{r+\delta}\right]^{(1-\eta)/\eta}.\end{aligned} \tag{3}$$

Equation (3) follows after normalizing through by the flow value of output, with $\hat{\kappa} = \kappa/x$ and $\hat{w} = w/x$. It links firms' willingness to post vacancies to match profitability, which depends on wages (relative to output), discount rates, and separation rates.

We explore whether these factors are systematically lower for poor countries, which could explain higher job finding rates there. We divide average wages in our data by average GDP per worker (our proxy for x) and plot against development in Figure 7a. There is no strong trend. The separation rate consists of the employment exit rate plus the job-to-job transition rate. We have documented that both of these flows are higher in poor countries, which tends to make matches less profitable there. Finally, we assume that firms discount future profits using the interest rate, consistent with standard arbitrage arguments. We plot the real interest rate from World Development Indicators against development in Figure 7b. Interest rates are higher in poor countries, which implies that firms should discount future profits at a higher rate and hence implies matches are less profitable, not more.[10]

Figure 7: Components of Match Profitability

(a) Wages/GDP per worker (b) Interest Rate (Percent)



Altogether, the textbook search and matching theory emphasizes the link from firm profitability to their willingness to post vacancies to the job finding rate. Observable indicators suggest matches should be, if anything, less profitable in poor countries; through the lens of the model, this should lead to a lower job finding rate. Thus, the theory is left to appeal to unobservably lower vacancy posting costs $\hat{\kappa}$ or unobservably higher efficiency of the match technology M.[11]

In the next two sections we consider two parallel tracks to understanding the relationship between labor market flows and development. In Section 4, we consider whether they can be accounted for by differences in labor market institutions or the composition of workers and firms by country. In Section 5, we consider whether other search and matching theories can explain these results as arising from different behaviors of workers and firms by country.[12]

[10]The exact series is FR.INR.RINR. To the extent that firms in poor countries may not have access to credit at these interest rates, they would discount future profits even more, strengthening the result.

[11]Standard logic implies that $\hat{\kappa}$ should be falling with development if it represents physical resources (software for filtering resumes) or constant if it represents worker time (interviewing candidates) – not rising, as would be required here (Bollard et al., 2016). Martellini and Menzio (2019) provide a theory where the efficiency of the match technology varies endogenously over time.

[12]The model of Mortensen and Pissarides (1994) with endogenous separation provides one comparative static consistent with higher job finding and exit rates: higher dispersion of match quality. However, this model has predictions for tenure hazards and tenure-wage profiles at odds with the data that we document in Section 5.

4 Accounting for Flows

In this section we explore whether the relationship between labor market flows and development can be accounted for by forces previously considered in the literature. We start by considering whether it can be explained by labor market institutions, motivated by a literature that uses these factors to explain differences in flows among rich countries (Ljungqvist and Sargent, 1998; Krause and Uhlig, 2012; Jung and Kuhn, 2014; Engbom, 2017). We then use shift-share accounting exercises to investigate whether the observable characteristics of workers or firms contribute to these trends. Although some of the factors we consider show some promise, in the end we conclude that at least half of the trend remains unaccounted for.

A third candidate that we do not consider here is that the trend may be explained by a negative correlation between overall economic volatility and development (Lucas, Jr., 1988; Koren and Tenreyro, 2007). Our data do not allow us to address this candidate directly because our surveys sample workers and so lack detailed firm-level data. The current frontier work suggests that firm exit rates among developing countries are positively correlated with GDP p.c. (and higher than small firm death rates in the United States) (McKenzie and Paffhausen, 2019).[13] This finding would imply that economic volatility is also unlikely to explain our trends, although further work in this area would be beneficial.

4.1 Accounting for Labor Market Institutions

We start by accounting for labor market institutions, by which we mean broadly the set of regulations, rules, and norms that affect employment relations in a country. Our measures of institutions come from the World Bank's Doing Business Survey, which has an extensive annex that measures a wide variety of labor market institutions for countries around the world. As with other Doing Business Survey indices, their index specifies a particular case of interest: the institutions governing employment of a cashier at a supermarket in the retail sector. The data are available from 2014–2018, although the exact indicators available vary by year.

We investigate the relationship between labor market flows and development after con-

[13] They find that a one log point increase in GDP p.c. is correlated with a 5.2 percentage point higher annualized firm death rate. See their paper for an extensive discussion of why previous work generally fails to capture the relevant set of firms in developing countries.

trolling for labor market institutions using the regression

$$T_{ct} = \beta \log(y_{ct}) + \psi z_{ct} + \gamma_t + \varepsilon_{ct}, \tag{4}$$

where T_{ct} is a measure of flows in country c in year t, y_{ct} is GDP per capita, and z_{ct} is one of the various measures of labor market regulations and institutions provided. We also include year fixed effects γ_t. Our main question of interest is whether controlling for labor market institutions substantially estimates the estimate of β.

Table 3 shows the results. We focus in the main text on the employment exit rate, but results for the job finding rate are similar and can be found in Appendix D. The first column confirms that the exit rate declines with income. We then proceed to introduce various labor market indicators. We control for the extent of severance pay requirements; paid leave requirements; the existence of labor courts for resolving labor disputes; whether fixed-term contracts are legal or prohibited; the minimum wage, expressed as a ratio of value added per worker; and the duration of a probationary period for new workers. Finally, in column (8) we use principal component analysis to extract the common factor among all the measures of institutions.

There are two main results of interest. First, regulations and institutions do affect exit, consistent with the existing literature. Most of the estimates are statistically significant at conventional levels. The second finding is that the strong negative relationship between labor market flows and development is affected only modestly by controlling for labor market regulations and remains statistically significant throughout. Even controlling for the bundle of labor market institutions produced by principal component analysis reduces the coefficient by only a little more than half. Thus, while labor market institutions are an important determinant of cross-country variation in labor market flows, they do not explain the trend relationship between labor market flows and development.

4.2 Accounting for Worker and Firm Characteristics

In this section we exploit the rich set of worker and firm characteristics that we have harmonized across countries to decompose the trend in labor market flows using shift-share accounting results. As is standard, we acknowledge that these results capture only the proximate or direct impact of observable characteristics. They cannot capture spillovers or general equilibrium effects. For example, if the presence of an informal sector alters the behavior of workers or firms in the formal sector, this is not captured by accounting for the share of workers in the informal sector. However, we view this as a promising introductory

Table 3: Employment Exit Rates and Labor Market Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita	-0.039	-0.027	-0.040	-0.037	-0.039	-0.036	-0.040	-0.022
	(0.004)***	(0.005)***	(0.004)***	(0.005)***	(0.005)***	(0.005)***	(0.004)***	(0.007)***
Severance pay		0.009						
(weeks of salary)		(0.002)***						
Annual paid leave required			-0.016					
(days of work)			(0.003)***					
Existence of labor court				0.015				
				(0.008)*				
Legal to have fixed-term					1.133e-4			
contracts for permanent work?					(0.005)			
Min Wage/VA per worker						0.021		
						(0.015)		
Probationary period							1.656e-4	
(months)							(1.051e-4)	
1st principal component								0.010
								(0.002)***
Sample Average	0.051	0.051	0.051	0.051	0.051	0.052	0.049	0.048
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	125	125	125	83	125	97	115	48
R^2	0.407	0.476	0.498	0.423	0.407	0.422	0.474	0.629
coeff, GDP per capita	-0.039	-0.039	-0.039	-0.038	-0.039	-0.039	-0.041	-0.040"
(no institutions)	(0.004)***	(0.004)***	(0.004)***	(0.005)***	(0.004)***	(0.005)***	(0.004)***	(0.006)***
R^2 (no institutions)	0.407	0.407	0.407	0.394	0.407	0.408	0.461	0.487

Table notes: All regulations are taken from the World Bank Doing Business Survey. Severance and annual paid leave are measured as inverse hyperbolic sines, to approximate a log specification while allowing zeros. The row labeled "coeff, GDP per capita (no institutions)" is the coefficient from the regression of exit on log GDP per capita in the restricted sample without including any labor market indicators. "R^2 (no institutions)" is the associated R^2.

analysis to evaluating whether the trend in labor market flows is about different workers and firms or different behaviors.

Our benchmark estimate of the trend relationship between labor market flows and development is a regression of the form:

$$T_{ct} = \alpha + \beta \log(y_{ct}) + \varepsilon_{ct}.$$

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_{ct} into the transition rate by group $g \in G$, T_{gct}, and the share of group g in the relevant population ω_{gct}, then our counterfactual transition rate is

$$\tilde{T}_{ct} = \sum_{g \in G} \bar{\omega}_g T_{gct}$$

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

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

$$\tilde{T}_{ct} = \tilde{\alpha} + \tilde{\beta}\log(y_{ct}) + \tilde{\varepsilon}_{ct}.$$

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

$$share = 1 - \frac{\tilde{\beta}}{\beta}$$

of the overall flows-development trend.

We focus on accounting for the trend relationship between the employment exit rate and development. The exit rate is the most straightforward to use for accounting purposes because it allows us to observe both worker and firm characteristics for each match. By contrast, we can provide fewer accounting results for job-finding rates or job-to-job transition rates because we only observe the number of workers of various types and not the number of vacancies. We provide the smaller subset of job-finding rate accounting results that do not suffer from this problem in Appendix D.

Table 4 summarizes our accounting results. The columns give the results for total employment or for wage workers alone. The main reason for studying wage employment is that the self-employed in most countries do not provide information on their sector/industry or formal status, so we can provide these accounting results only for wage workers. When we can compute results for the self-employed they are generally in line with those for other workers.

We start with Panel A, which considers each factor in isolation. These accounting results are small: any single worker or firm characteristic accounts for less than one-quarter of the development trend. The largest share goes to occupation and then age and informality. Gender actually accounts for a negative share.

Small accounting results can be generated in one of two ways: if the groups have similar transition rates, or if countries vary little in the employment share by group. Figure 8 shows how we arrive at small results for the case of gender. Figure 8a shows that there are large differences in employment exit rates by gender; women have higher employment exit rates in almost all countries. However, Figure 8b shows that there is little cross-country

Table 4: Accounting for Employment Exit Rates

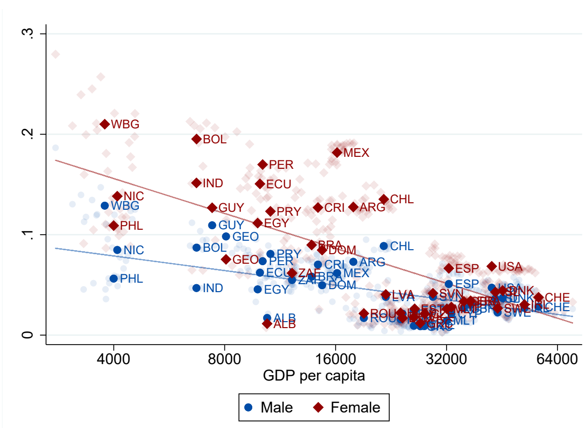
	Share Accounted for (%)	
Panel A: One Factor	Total Employment	Wage Employment
Age	8.5	16.7
Gender	-5.0	-6.9
Education	9.8	11.0
Sectors	n/a	3.6
Occupation	n/a	17.5
Informality	n/a	26.3
Establishment Size	22.4	10.7
Panel B: Multiple Factors		
Establishment Size + Edu	22.8	17.8
Establishment Size + Age	30.5	25.4
Occupation + Establishment Size	n/a	29.9
Occupation + Edu	n/a	32.9
Occupation + Age	n/a	29.6
Occupation + Sector	n/a	24.8
Age + Edu + Gender	14.8	26.6
Occupation + Establishment Size + Education + Age	n/a	51.4

Table notes: All figures capture the share of the exit rate-development relationship accounted for by the worker or firm characteristics given in the rows. The share accounted for is constructed as explained in the text. Columns give the corresponding figure for total employment or wage employment; n/a indicates that the figure cannot be computed.

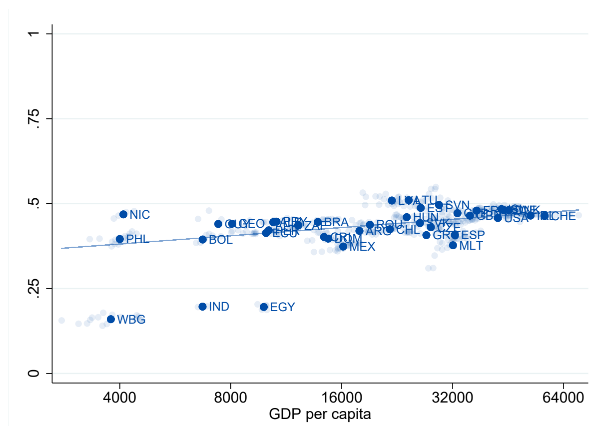
variation in the employment share of women, with that variation going in the wrong way: poor countries tend to have lower employment shares of women, who have the higher exit rate. We provide similar detailed figures for other characteristics in Appendix D to give further intuition for our results.

Figure 8: Accounting for Gender

(a) Exit Rate by Gender



(b) Employment Share of Women



Panel B of Table 4 considers interactions of factors and their ability to account for the trend in labor market flows. Broadly, the findings are consistent with a small role for observable characteristics. Two factors account for at most 30 percent; accounting for interactions of three or four terms can push the figure up to at most 55 percent. We conclude that the trend in labor market flows likely contains a substantial behavioral component. We now turn to search theory to help rationalize what this component might be.

5 Tenure and Selection

In this section we consider whether other search and matching theories can explain the trend relationship between labor market flows and development as arising from different behaviors of workers and firms by country. First, we provide an additional empirical result that helps narrow our search. Two recent papers have documented that much of the decline in turnover over time in the United States is accounted for by a reduction in very short employment spells (Mercan, 2017; Pries and Rogerson, 2019). We show that the same is true in our cross-country context. To do so, we construct the probability that a worker transitions to non-employment or to a new job as a function of tenure in all countries for which we have the data. We group workers into four tenure bins for visual clarity: those on the job for less than six months; six to twelve months; one to five years; and five years or more.

Figure 9: Transition Rates by Job Tenure

(a) Transition to Non-Employment (b) Transition to New Job

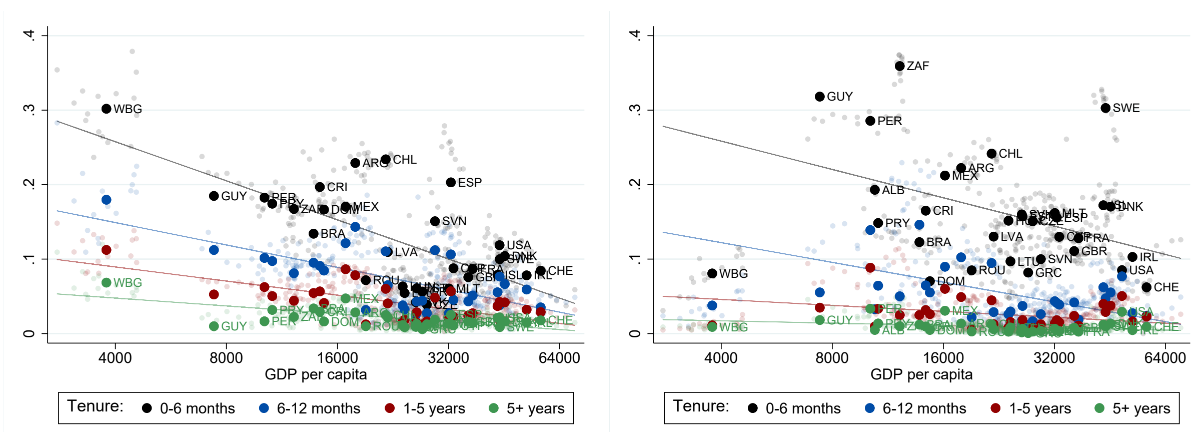


Figure 9a shows the results for transitions to non-employment and Figure 9b shows the results for transitions to a new job. In both cases there is an important role for tenure. Much of the trend in labor market flows is accounted for by workers on the job for less than a year. By contrast there is a much weaker trend in transition rates for workers with more than a year of tenure and essentially none for workers with more than five years of tenure, who are unlikely to switch jobs or transition to non-employment in any country.

These results are quantitatively important. If we re-do our accounting results using tenure bins, we find that tenure accounts for 36–40 percent of the development trend, depending on the number of bins used. This figure is nearly twice as important as any other single factor considered in Table 4. Of course, tenure is an endogenous feature of a match, not an exogenous characteristic of workers or firms. Still, the importance of this endogenous feature when evaluated using our accounting metrics suggests that we focus on models with endogenous separation and meaningful tenure predictions.

5.1 Theories of Tenure and Selection

Two classes of search and matching theory make endogenous predictions about tenure. In learning models, workers and firms are imperfectly informed about match productivity, but learn more by producing (Jovanovic, 1979, 1984; Menzio and Shi, 2011). If they learn that a match is unproductive they endogenously (jointly) choose to separate. In job ladder models, workers receive outside employment offers (Burdett and Mortensen, 1998). Attractive offers induce workers to quit their current job and move. Although the setups and mechanisms are different, both models emphasize endogenous separation, which generates selection. Transition hazards are informative about the rate and amount of post-match selection. Both theories predict that the same selection forces should affect wages, providing an additional testable implication. We present simplified versions of both models to highlight the central mechanisms.

5.1.1 Learning

Our version of the learning model draws on Menzio and Shi (2011), although the predictions of interest hold also in the original model of Jovanovic (1979). We consider a match between an unemployed person and a vacancy, potentially generated by the matching function from Section 3.4. Upon meeting, the pair draw a match-specific productivity x from distribution $F(x)$ that has mean μ. However, productivity is unknown to both. Instead, the worker and the firm draw a signal s that is equal to x with probability p and is an independent draw from F with probability $1 - p$; p indexes the quality of the signal. In the limit case

$p = 1$, matches are said to be *inspection goods*, whose quality can be determined perfectly in advance. In the limit case $p = 0$, matches are said to be *experience goods*, whose quality can only be learned through production.

The worker and the firm are both risk-neutral and they have outside options b and 0, respectively. They first decide whether or not to engage in production. If they do so, they produce x. They produce if joint expected surplus exceeds the combined outside option b. Each period of production reveals true match quality with probability λ. Matches that are revealed to have negative surplus ($x < b$) lead to endogenous separation. Matches are also exogenously destroyed with probability δ.

This simple model yields three useful insights. First, it allows for the possibility that some matches (with sufficiently low match quality signals) endogenously do not produce. Thus, this framework allows a second margin that affects the job finding rate, which is the share of matches that lead to production. In the model, this is the share of matches that generate expected surplus above the outside option, which is given by

$$1 - F\left(\frac{b - (1-p)\mu}{p}\right). \tag{5}$$

The share is decreasing in b and p, under the assumption that $\mu > b$ (the average match surplus exceeds the outside option). The higher job finding rate in poor countries could thus be explained by less precise ex-ante signals about match quality or by worse outside options for workers.

Second, this model generates declining tenure hazards, consistent with the data. Define the share of matches that engage in production despite having (unobserved) match productivity below the reservation level as

$$\nu \equiv (1-p)F(b) + p\left[F(b) - F\left(\frac{b-(1-p)\mu}{p}\right)\right]$$

This is the share of matches that will endogenously separate after receiving the λ shock. The two terms capture type-1 and type-2 errors, respectively: the probability of using an inaccurate signal from a bad match, plus the probability of failing to reject a marginally bad match because of signal imprecision.

Given this, the probability that a match is destroyed after achieving tenure τ is given by:

$$d_\tau = \delta + (1-\lambda)^{\tau-1}\lambda\nu. \tag{6}$$

The probability is strictly declining in tenure if $\lambda > 0$ and $p < 1$, consistent with the data in all countries. It is also decreasing in p. Again, the initially higher but declining hazard in poor countries is consistent with less precise ex-ante signals about match quality. The interaction with b cannot be signed without assumptions on the distribution F.

The underlying intuition for these results is that they reflect selection. If matches are inspection goods ($p = 1$), then all selection happens ex ante. Since signals are fully revealing, only matches with $s = x > b$ lead to production. Nothing is learned ex post, so all job destruction is exogenous. For $p < 1$, matches have an experience good component. Matches with signals marginally below the cutoff ($\frac{b-(1-p)\mu}{p} \leq s < b$) engage in production, so there is less ex-ante selection and a higher job finding rate. After matches are formed, experience yields information about match quality. Lower p implies higher ν and hence more ex-post selection. As tenure increases the share of matches that have not yet had match quality revealed declines and so does the rate of ex-post selection.

This selection process is also central for generating our third insight, which concerns the wage-tenure profile. To derive this prediction, we need to specify a wage-setting rule, taking care to ensure that it is consistent with our assumption that all matches with expected match quality above b lead to production. One analytically convenient wage rule that does so is to assume that workers and firms split the surplus equally in each period. Surplus depends on match quality if it is known and expected match quality if not. Then average wages for matches with known and unknown quality are given by:

$$\begin{aligned} w^k &= \frac{\mathbb{E}(x|x > b)}{2} - \frac{b}{2} \\ w^u &= \frac{\left[p\mathbb{E}\left(x|x > \frac{b-(1-p)\mu}{p}\right) + (1-p)\mu\right]}{2} - \frac{b}{2}. \end{aligned}$$

Note that $w^k \geq w^u$, with strict equality if $p < 1$.

With this notation we can characterize the wage tenure profile. For example, log-wages of a worker with tenure τ relative to a new worker with no tenure is given by:

$$\log(w_\tau) - \log(w_0) = \log\left[(1-\lambda)^\tau + (1-(1-\lambda)^\tau)\frac{w^k}{w^u}\right]. \tag{7}$$

The right-hand side can be captured by a Mincer regression and would typically be called the return to tenure, although in this model it is purely driven by selection rather than human capital accumulation. Wages are an increasing and concave function of tenure for $0 < \lambda < 1$ and $p < 1$. More importantly, the return to tenure is decreasing in p. This implies that if poor country labor markets are characterized by less ex-ante selection and more ex-post selection, we should expect them to have higher measured returns to tenure. We show that this indeed holds in the data in Section 5.2. First we consider a second model of endogenous separation that turns out to yield similar predictions, which is the job ladder model.

5.1.2 Job Ladder

We work with a simplified version of the job ladder model with two discrete types of jobs: low-wage jobs and high-wage jobs paying $w_L < w_H$, respectively.[14] The supply of vacancies of each type is exogenous and fixed, with π denoting the share of low-wage vacancies. The unemployed have an outside option b drawn from a distribution with cdf B and support $[\underline{b}, \overline{b}]$ satisfying $\underline{b} \leq w_L \leq \overline{b} < w_H$.

Unemployed people who meet a randomly chosen vacancy decide whether to accept. After production in each period, matches are subject to two shocks. First, they can be destroyed exogenously with probability δ. Second, workers can receive outside offers. These offers generate endogenous separation in a manner similar to learning in the previous model, so we use the notation λ to denote the probability of receiving an outside offer to emphasize the commonality. Workers who receive an offer from a higher-paying job switch. Workers who receive an offer from a job that pays the same as their existing job are indifferent and are assumed to remain with their current employer. Clearly, given this simple setup, workers switch jobs if they can ascend the one rung up the job ladder, from the low-paying to the high-paying job.

This simple model yields three insights that parallel those of the learning model. First, it allows for the possibility that some matches (between low-wage firms and high opportunity cost workers) can endogenously not lead to production. This share of matches that leads to production is given by $\pi B(w_L)+1-\pi$, which is decreasing with outside options, summarized here by $B(w_L)$, the share of workers whose outside option is worse than the low-wage job.

Second, this model again generates declining tenure hazards, consistent with the data. In steady state, the share of low-wage matches among all matches with tenure level τ is

[14] Burdett and Mortensen (1998) show how to get wage heterogeneity in equilibrium even with ex-ante identical firms and workers. We take wage heterogeneity as a fundamental as in Ridder and Berg (2003). We focus on two discrete types for clarity of exposition, but they show that the key results go through in a model with a continuum of types.

given by

$$\ell_\tau = \frac{[1-\lambda(1-\pi)]^\tau}{[1-\lambda(1-\pi)]^\tau + \frac{1-\pi}{\pi B(w_L)} + \frac{\lambda(1-\pi)(1-\delta)}{1-(1-\delta)[1-\lambda(1-\pi)]}}.$$

The numerator captures the mass of low-wage matches that have not received a high-wage outside offer, which declines with tenure if $\lambda >$ and $0 < \pi < 1$.[15]

Given this, the probability that a match is destroyed after achieving tenure τ is given by

$$d_\tau = \delta + \ell_\tau \lambda(1-\pi).$$

The probability is strictly declining in tenure if $\lambda > 0$ and $0 < \pi < 1$. The initial level depends on the rate of arrival of outside offers and the initial share of workers in low-wage jobs, which in turn depends on outside options through $B(w_L)$.

As with the learning model, these results reflect selection via endogenous separation. The unemployed initially match with both low-wage and high-wage jobs. As tenure increases and outside offers accumulate, a growing share of the workers who initially worked low-wage jobs will have received a high-wage outside offer. Hence, tenure implies a growing share of workers with high-wage jobs.

This selection process once again has implications for the wage-tenure profile. We again characterize the log-wages of a worker with tenure τ relative to a new worker

$$\log(w_\tau) - \log(w_0) = \log\left[\frac{\ell_\tau w_L + (1-\ell_\tau)w_H}{\ell_0 w_L + (1-\ell_0)w_H}\right],$$

which is positive and concave if $\lambda > 0$ and $0 < \pi < 1$. There is an interaction in this model between the share of workers who initially accept low-wage jobs due to low outside opportunities (higher $B(w_L)$) and the rate at which workers receive outside offers λ.

5.2 Wage-Tenure Profiles

Both of our theories emphasize an interaction between tenure and selection: separation from unproductive matches in learning models; separating from low-paying jobs in job ladder models. An additional prediction of these models is that if selection is an important

[15] The two terms in the denominator capture the initial ratio of high-wage to low-wage jobs. The first term is the ratio among those who enter from unemployment, while the second term captures the additional effect of low-wage workers who transition to high-wage jobs and reset their tenure to 0.

factor in labor market flows, then the returns to tenure should be higher in poorer countries. We now document that this is indeed the case.

We focus on wage and salary workers, because wage data are generally not available or not reliable for the self-employed.[16] 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 al. (2018). We pool all available years for each country and regress:

$$\log(w_{it}) = \alpha + \phi_x + \xi_\tau + \rho_{edu} + \gamma_t + \varepsilon_{it}. \tag{8}$$

w_{it} is the hourly wage of individual i observed at time t. The vector ϕ_x consists of dummies for potential experience groups $\{2-4, 5-9, 10-19, 20+, ...\}$, with $0-1$ years of experience serving as the omitted reference group, where potential experience is constructed as age minus expected years of schooling minus six. The vector ξ_τ consists of dummies for tenure group $\{1, 2-4, 5-9, 10-19, 20+\}$, with < 1 years of tenure serving as the omitted reference group. The vector ρ_{edu} is a set of dummies for the seven Barro-Lee education categories and γ_t is still year dummies.[17] ε_{it} is a mean-zero error term.

Figures 10a and 10b show the estimated percentage wage difference between workers with 1 or 2–4 years of tenure, as compared to less than one year of tenure, plotted against GDP per capita. As our theories predict, the 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. This finding offers further support for a central role of endogenous separation and selection interacting with development.

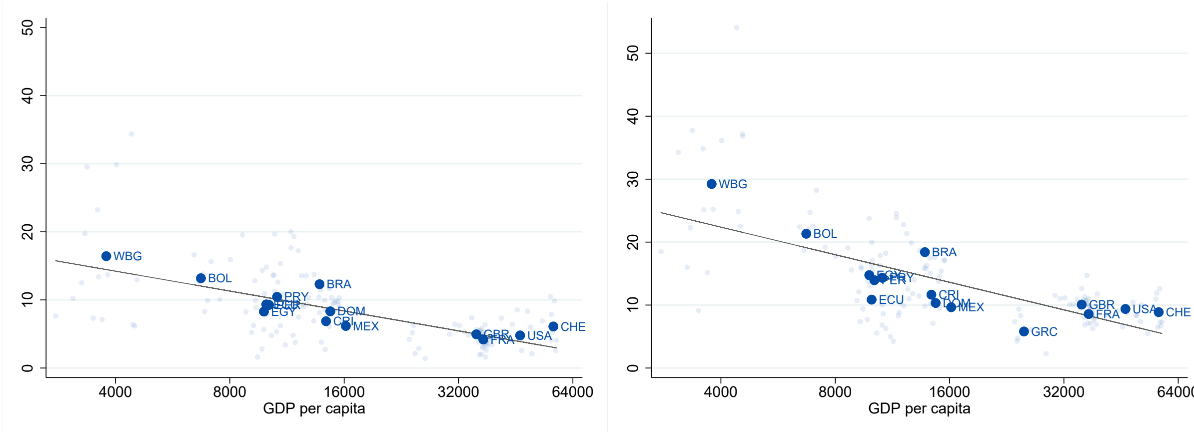
This finding is particularly surprising because recent work has shown that the returns to experience are *positively* correlated with development: workers wages' rise less quickly with experience in poor as compared to rich countries (Lagakos et al., 2018). Our specification allows us to estimate the returns to experience jointly with returns to tenure in our data. Figure 11 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. Overall, we conclude that the negative relationship between returns to tenure and development is surprising in light of other facts and thus points strongly

[16] The E.U. Labour Force Survey does not report wages, only wage deciles. Hence, our sample is smaller in this section than above.

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

Figure 10: Tenure-Wage Profiles

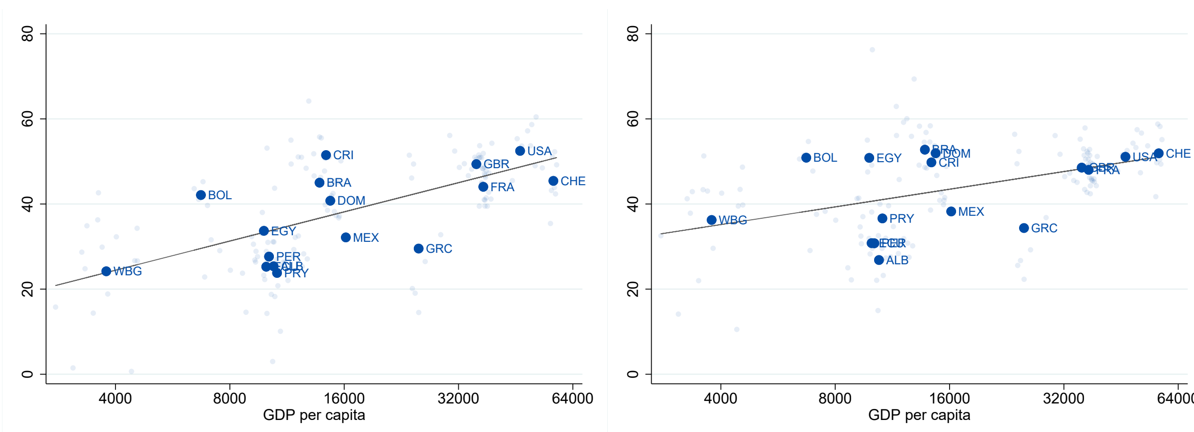
(a) Wage Returns to 1–2 Years of Tenure (b) Wage Returns to 2–5 Years Tenure



towards a role for models with endogenous separation and selection in understanding the trend relationship between labor market flows and development. It also rules out search and matching frictions as a candidate explanation for lower life-cycle wage growth in poor countries.

Figure 11: Experience-Wage Profiles

(a) Wage Returns to 10–19 Years Experience (b) Wage Returns to 20+ Years Experience



5.3 Discussion: Selection and Development

Our goal here is to show that theories with endogenous separation and selection of which matches survive to different tenure lengths are promising theories for understanding our findings. We provide simple versions of two such theories in the literature, the learning and job ladder models, but other theories with similar mechanisms might also explain our findings.[18] Given that our data is derived from individual-level surveys and is restricted to short panels, we are limited in our ability to discriminate between these models. With that caveat noted, we use this section to discuss what our evidence tells us about different microfoundations for endogenous separation and selection.

Imprecise Information Our theories suggest possible mechanisms. The learning model can explain the data if ex-ante signals of match quality are simply less precise in poor countries. The role of imperfect information about match quality has a substantial history in studies of the U.S. labor market, including both theoretical (Jovanovic, 1979; Moscarini, 2005; Menzio and Shi, 2011) and empirical (Altonji and Pierret, 2001; Kahn and Lange, 2014; Craig, 2019). Thus, our results take a widely accepted mechanism and shows that it extends to a cross-country context.

Moreover, recent randomized controlled trials highlight the importance of similar theories in the context of developing countries, including Abebe et al. (2019) in Ethiopia, Bassi and Nansamba (2019) in Uganda, and Carranza et al. (2019) in South Africa. Our results therefore additionally provide some aggregate, cross-country evidence in favor of such interventions.

Job Ladder and Self-Employment The job ladder model can rationalize these same findings if worse outside options in poor countries make workers more willing to accept-low wage jobs instead of waiting for a high-wage offer (e.g., $B(w_L)$ falls with development). Traditional calibrations of search and matching models tie the outside option b at least in part to unemployment insurance, which is lower or absent altogether in poor countries (Feng et al., 2018). One possibility would be to think of low-wage employment in poor countries as consisting in part of subsistence entrepreneurship. Doing so also helps rationalize why the share of subsistence entrepreneurship in total entrepreneurship is higher in poor countries

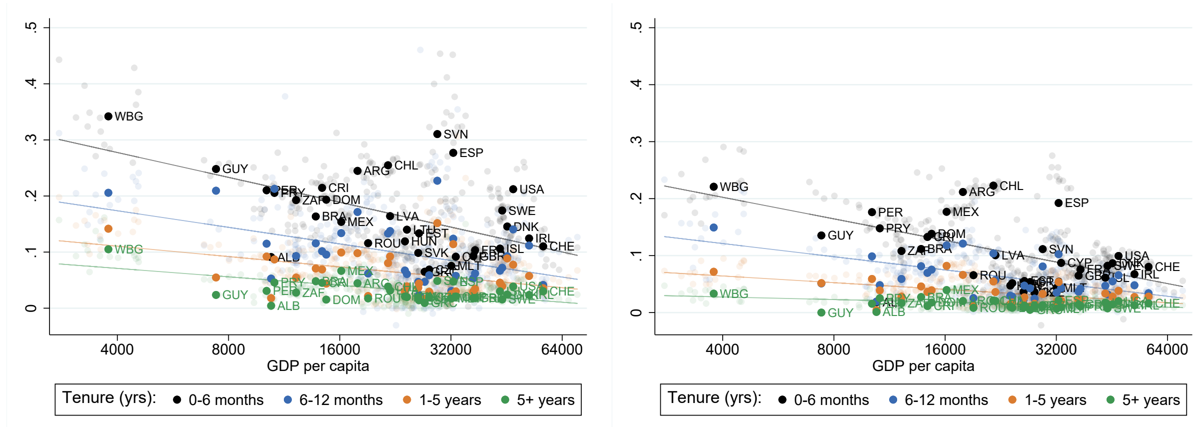
[18] The simplest example of this is that we rely on match-specific uncertainty, which could come from uncertainty on the part of workers or firms. Our lack of firm data prevents a deeper investigation of this. However, it simultaneously highlights the strong complementarity between cross-country empirical work and RCTs like Carranza et al. (2019), who randomize information interventions from both the worker and firm side to study the underlying forces at work.

(Schoar, 2010; Poschke, 2013). In this case, subsistence entrepreneurship is a substitute for missing unemployment insurance and also an extra, lower rung on the job ladder.

Composition A slightly more subtle possibility is that the aggregate differences we highlight are generated by underlying compositional differences across countries. For example, Arcidiacano et al. (2010) documents that firms are better informed about more educated workers' abilities in the United States. If this is true worldwide, then the low education levels in poor countries provide one explanation for less aggregate ex-ante information about match quality. For evidence on this hypothesis, we consider results on tenure hazards by education level in poor countries, shown in Figure 12. While there are differences in exit hazards between the two groups those differences are small. We find similar results when comparing for example the most and least skilled occupations. These findings reinforce the conclusion from Section 4.2 that observable characteristics seem to be unable to account for a large share of our cross-country findings.

Figure 12: Transition Rate to Non-Employment, by Tenure and Education

(a) Less than High School (b) High School or More



Establishment-Level Shocks A final possibility is that unobservable differences on the firm side generate the results. Koren and Tenreyro (2007), for example, highlight higher volatility in developing countries. To the extent that this volatility manifests itself in a higher variance of match productivities, this could explain the results without variation in signal precision. The intuition remains identical to that of Section 5.1. A given signal still provides less information about match quality in poor countries, but does so by allowing the distribution of potential (true) match productivities to vary instead of the signal precision.

A related but likely less important factor is firm exit. McKenzie and Paffhausen (2019), for example, shows that exit is positively correlated with GDP per capita in a sample of developing countries. Moreover, to the extent exit is correlated with firm size, our accounting results in Section 4 suggest this is an unlikely culprit.

We discuss these results to highlight the extent to which our data, despite the undertaking to collect it, invites future work on the issue. To study the exact mechanism that drives the results, one would need even *more* sophisticated data. This suggests a potentially important role for matched employer-employee data, as Cornwell et al. (2019) and Morchio and Moser (2019) conduct with Brazilian data, or more theory-motivated randomized controlled trials as highlighted above. We view this as an important direction for future work.

6 Conclusion

We build a new cross-country dataset of harmonized rotating panel labor force surveys covering 40 countries with widely varying average income. We use this dataset to document that labor market transition rates are 2–3 times higher in poor as compared to the richest countries. This finding holds for conventional aggregated flows (e.g., the job finding rate) as well as most flows between detailed states (e.g., flows from inactivity to self-employment).

We pursue two avenues to understand why labor market flows vary systematically development. First, we show that labor market institutions, worker characteristics, and firm characteristics go some way toward accounting for the trend, but that at least one-half remains unaccounted for.

Second, we consider theories where otherwise similar workers and firms in rich and poor countries behave differently. We document an important role for tenure: much of the high employment exit rates in poor countries are concentrated among workers with short employment tenures (one year or less). By contrast, there is almost no variation for workers with five or more years of tenure. We interpret these findings through the lens of theories where tenure is the result of endogenous separation. The theories provide several possible rationalizations for more ex-post selection, including worse ex-ante information about match quality, more frequent outside offers, and worse outside options for workers. More ex-post selection of workers rationalizes the new and otherwise puzzling fact that returns to tenure are higher in poorer countries.

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Table of Contents for Appendix

A Data Construction Details

A.1 Data Sources

We are aware of a large number of countries that have instituted a rotating panel labor force survey for at least some years (many countries switch between rotating and non-rotating designs). All European Union countries have labor force surveys with such a design, organized and collected under the European Union Labour Force Survey. Additionally, at least 35 other countries have instituted a rotating panel labor force survey at some point. At least basic information for most countries' labor force surveys can be found under the name given at the website of the International Labour Organization at https://www.ilo.org/surveydata/index.php/home.

We have been able to clarify with the national statistical agencies of most countries the conditions (if any) under which they will make the microdata with individual identifiers available for research purposes. Table A1 shows the samples included in our dataset. It lists for each country the name of the underlying dataset (with preference for the English name, if in common usage) and a brief description of how we acquired the data. Available online indicates that the data can be easily accessed online. In some cases it can simply be downloaded, but we also include countries that have a short and minimal registration or application process. Application required indicates that data can be accessed under somewhat stronger conditions. This typically includes submitting a formal application and research proposal to the relevant national statistical agency. It might also include assurances or plans to protect and not disseminate the data or a fee. Personal correspondence indicates that the data were acquired through direct communication with the national statistical office.

The European Union Labour Force Survey is a complicated case. Eurostat does not make the data with longitudinal identifiers available to researchers. However, roughly half of EU countries use consistent household and person identifiers within each year, which makes it possible to match people over time within a calendar year.[19] For France and the United Kingdom we are also able to access microdata with longitudinal identifiers directly from the national statistical office. We use these data instead so that we can also match individuals across calendar years and because they include additional information about certain variables of interest.

[19] We thank Nik Engbom for bringing this point to our attention. We were able to confirm that these identifiers are consistent for some countries with Eurostat. We determined which countries could be matched in this way through experimentation; the relevant countries have extremely high rates of agreement over time on age and sex, while others do not.

Table A1: Rotating Panel Labor Force Surveys – Included

Country	Name[a]	How Acquired[b]
Albania	Labour Force Survey	Available online
Argentina	Encuesta de Hogares y Empleo	Available online
Bolivia	Continuous Employment Survey	Available online
Brazil	Continuous National Household Sample Survey (PNAD)[c]	Available online
Chile	National Employment Survey (ENE)	Available online
Costa Rica	Continuous Employment Survey (ECE)	Available online
Cyprus	European Union Labor Force Survey	Application required
Czech Republic	European Union Labor Force Survey	Application required
Denmark	European Union Labor Force Survey	Application required
Dominican Republic	Mercado de Trabajo Encuesta Continua (ENCFT)	Personal correspondence
Ecuador	Encuesta de Empleo	Available online
Egypt, Arab Rep.	Labour Force Sample Survey	Application required
Estonia	European Union Labor Force Survey	Application required
France	Enquete Emploi en Continu	Application required
Georgia	Monitoring of Household Survey	Available online
Greece	Labor Force Survey	Application required
Guyana	Labor Force Survey	Available online
Hungary	European Union Labor Force Survey	Application required
Iceland	European Union Labor Force Survey	Application required
India	Periodic Labor Force Surveys	Available online
Ireland	European Union Labor Force Survey	Application required
Italy	European Union Labor Force Survey	Application required
Latvia	European Union Labor Force Survey	Application required
Lithuania	European Union Labor Force Survey	Application required
Malta	European Union Labor Force Survey	Application required
Mexico	Encuesta Nacional de Empleo	Available online
Nicaragua	Encuestas de Hogares	Personal correspondence
Palestine	Labor Force Survey	Application required
Paraguay	Encuesta Permanente de Hogares Continua	Available online
Peru	Encuesta National de Hogares	Available online
Philippines	Labour Force Survey	Application required
Romania	European Union Labor Force Survey	Application required
Slovak Republic	European Union Labor Force Survey	Application required
Slovenia	European Union Labor Force Survey	Application required
South Africa	Quarterly Labour Force Survey	Available online
Spain	Encuesta de Poblacion Activa	Application required
Sweden	European Union Labor Force Survey	Application required
Switzerland		
United Kingdom	Labour Force Survey	Available online
United States	Current Population Survey	Available online

[a] Name of dataset, in English if the national statistical office designates such a name.
[b] Brief description of how data were acquired. See text for details.
[c] Data for 2002–2011 come from the Brazilian Monthly Employment Survey (PME), which samples six urban areas in Brazil. Patterns of interest are similar to those from urban areas for more recent data so we keep both.

Table A2: Rotating Panel Labor Force Surveys – Excluded

Country	Name[a]	Status[b]
Armenia	Labour Force Survey	Wrong rotation scheme
Australia	Labour Force Survey	Restricted access
Bangladesh	Labour Force Survey	Confidential
Canada	Labour Force Survey	Restricted access
Indonesia	National Labor Force Survey (Sakernas)	Only alternating quarters released
Israel	Labour Force Survey	Restricted access
Japan	Labour Force Survey	Wrong rotation scheme
Korea	Economically Active Population Survey	Restricted access
New Zealand	Household Labour Force Survey	Confidential
Nigeria	Household Labour Force Survey	No response
Russia	Labor Force Survey	Wrong rotation scheme
Saudi Arabia	Labor Force Survey	Confidential
Taiwan	Manpower Survey	Wrong rotation scheme
Thailand	Labour Force Survey	Restricted access
Turkey	Household Labour Force Survey	Confidential

[a] Name of dataset, in English if the national statistical office designates such a name.
[b] Brief description of why data cannot be acquired or are not useful for our purposes. See text for details.

A number of countries appear to have rotating panel labor force surveys that we cannot access or that are not useful for our research design. One prominent example is the remaining countries in the European Union Labour Force Survey that randomize identifiers across quarters within a year. Table A2 gives the remaining countries we are aware of, again with the name of the survey and the reason why the data are not included.

Restricted access indicates data that are available under one or more of three restrictive conditions: researchers have to be citizens/nationals of the country; they have to be affiliated with a university or research institute of the country; or they have to travel to a secure location in the country. Confidential indicates that data are not available to researchers, to the best of our knowledge. Wrong rotation scheme indicates that the workers can be matched, but at a different frequency, typically monthly or annually. Indonesia operates a quarterly rotating panel labor force survey but only makes semi-annual data available, which for our purposes is the same as the wrong rotation scheme. Finally, no response indicates that the country appears to collect the appropriate data, but we were unable to find the data or secure a response from the national statistical agency despite numerous attempts to do so.

A.2 Variable Availability

Not all countries include all requisite data. For example, the E.U. LFS does not inlucde earnings (only earnings deciles), thus eliminating its use in some parts of the paper. The table below specifies which countries include which data.

Table A3: Variable Availability by Sample

Country	Employment Status	Age	Education	Gender	JJ Flows	Marginally Attached	Sector	Occupation	Formality	Establishment Size	Tenure	Earnings	Hours	Rural
Albania	x	x	x	x	x		x	x	x	x	x	x	x	
Argentina	x	x	x	x	x	x	x	x	x	x	x	x	x	
Bolivia	x	x	x	x	x	x	x	x	x	x	x	x	x	
Brazil	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Chile	x	x	x	x	x	x	x	x			x		x	x
Costa Rica	x	x	x	x	x				x	x	x	x	x	x
Cyprus	x	x	x	x	x	x	x	x		x	x		x	x
Czech Republic	x	x	x	x	x	x	x	x		x	x		x	x
Denmark	x	x	x	x	x	x	x	x		x	x		x	x
Dominican Republic	x	x	x	x	x	x	x	x	x	x	x	x	x	
Ecuador	x	x	x	x		x	x	x	x	x	x	x	x	
Egypt, Arab Rep.	x	x	x	x			x	x	x	x	x	x	x	x
Estonia	x	x	x	x	x	x	x	x		x	x		x	x
France	x	x	x	x	x		x	x		x	x	x	x	x
Georgia	x	x	x	x	x		x	x	x			x	x	
Greece	x	x	x	x	x	x	x	x		x	x	x	x	x
Guyana	x	x	x	x		x	x	x	x	x	x	x	x	x
Hungary	x	x	x	x	x	x	x	x		x	x		x	x
Iceland	x	x	x	x	x	x	x	x		x	x		x	x
India	x	x	x	x		x	x	x	x			x	x	
Ireland	x	x	x	x	x	x	x	x		x	x		x	x
Italy	x	x	x	x	x	x	x	x		x	x		x	x
Latvia	x	x	x	x	x	x	x	x		x	x		x	x
Lithuania	x	x	x	x	x	x	x	x		x	x		x	x
Malta	x	x	x	x	x	x	x	x		x	x		x	x
Mexico	x	x	x	x	x	x	x	x	x	x	x	x	x	
Nicaragua	x	x	x	x		x	x	x		x			x	x
Palestine	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Paraguay	x	x	x	x	x	x		x	x	x	x	x	x	
Peru	x	x	x	x	x	x	x	x		x	x	x	x	
Philippines	x	x	x	x		x	x	x				x	x	x
Romania	x	x	x	x	x	x	x	x		x	x		x	x
Slovak Republic	x	x	x	x	x	x	x	x		x	x		x	x
Slovenia	x	x	x	x	x	x	x	x		x	x		x	x
South Africa	x	x	x	x	x	x	x	x		x	x		x	
Spain	x	x	x	x	x	x	x	x		x	x		x	x
Sweden	x	x	x	x	x	x	x	x	x	x	x		x	x
Switzerland	x	x	x	x	x	x	x	x	x	x	x	x	x	x
United Kingdom	x	x	x	x	x	x	x	x		x	x	x	x	
United States	x	x	x	x	x	x	x	x		x	x	x	x	x

[a] x = variable included for at least one year.

A.3 Longitudinal Weights

All of our countries provide sample weights so that cross-sectional moments are representative of the population of interest (typically the labor force). 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 the 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 at 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 we have the same distribution in the matched and unmatched samples along dimensions of interest. For example, if unemployed people are more likely to move to find work and drop out of the sample, then they will be underrepresented in the longitudinally matched sample relative to the unmatched sample. Post-stratification increases 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 become 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.

We focus on four dimensions that are available in all countries and are important for understanding labor force dynamics: labor force status (wage workers, self-employed, unemployed, and inactive), age (in 10-year bins), gender, and education (Barro-Lee categories). Post-stratifying on labor force status is important so that we fit cross-sectional moments such as the unemployment rate. After that, we focus on demographics and education because we find that they are observable factors that account for a lot of variation in labor force status and labor force flows.

We cannot fit the full joint distribution of these characteristics. Our compromise is to rake the weights so that the matched and unmatched samples for each country-year have the same density by education-labor force status cells and age-gender cells. We focus on these dimensions because they are available and comparable across all countries and because matching them is important for the overall results. In some cases we have to aggregate categories slightly before raking. For example, the number of unemployed workers with tertiary education in poorer countries or primary education in rich countries can be quite small; in such cases, we might merge tertiary with secondary degrees.

Table A4 shows the impact of re-weighting by comparing the original and adjusted weights. The two are highly correlated for all countries. The median absolute deviation is generally small, on the order of 2-7 percent. Another way to make the same point is to compare key moments constructed in the sample using the original versus longitudinal weights. Figure A1 reproduces some of the main figures in the text, but compares the raw versus adjusted data. Re-weighting has a visible effect on the unemployment rate (Figure A1b) but a negligible effect on the employment-to-population ratio or the implied flows.

A second problem frequently discuss 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 these two groups into non-employment for all of our main results, so this form of misclassification does not affect our results.

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.

A.4 Comparison of E.U. Micro Data versus Reported Flows

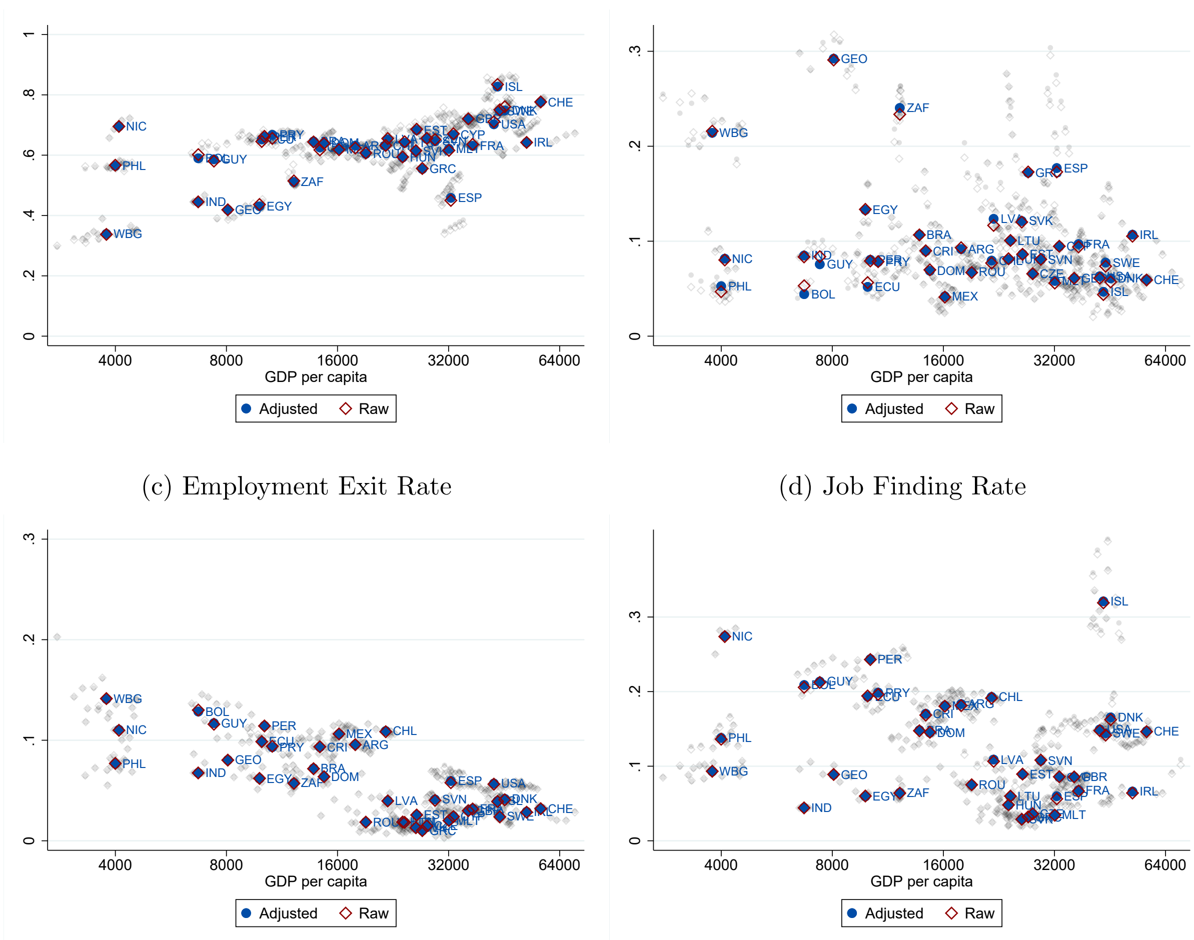
The E.U. reports flow data directly. It differs from our reported figures in a number of ways. First, they report flows among the population aged 15 – 74, while we cut at 65 to remain

Table A4: Impact of Re-Weighting

Country	Weight Correlation	Median Absolute Change
Albania	0.997	0.038
Argentina	0.998	0.031
Bolivia	0.893	0.200
Brazil	0.999	0.024
Chile	0.999	0.027
Costa Rica	0.998	0.038
Cyprus	0.991	0.025
Czech Republic	0.999	0.008
Denmark	0.989	0.049
Dominican Republic	0.999	0.011
Ecuador	0.978	0.063
Egypt, Arab Rep.	0.981	0.041
Estonia	0.996	0.026
France	0.998	0.026
Georgia	0.999	0.013
Greece	0.999	0.010
Guyana	0.972	0.069
Hungary	1.000	0.009
Iceland	0.946	0.041
India	1.000	0.004
Ireland	0.990	0.035
Italy	0.999	0.014
Latvia	0.996	0.035
Lithuania	0.998	0.023
Malta	0.989	0.040
Mexico	1.000	0.020
Nicaragua	0.997	0.020
Palestine	0.998	0.015
Paraguay	0.990	0.040
Peru	0.994	0.038
Philippines	0.993	0.044
Romania	0.999	0.011
Slovak Republic	0.998	0.009
Slovenia	0.998	0.025
South Africa	0.994	0.036
Spain	0.997	0.031
Sweden	0.997	0.025
Switzerland	0.999	0.012
United Kingdom	1.000	0.000
United States	0.995	0.042

Table notes: Weight correlation is the correlation between the original cross-sectional weights and post-stratified weights. Median absolute change is the median of the absolute log deviation between cross-sectional weights and post-stratified weights

Figure A1: Labor Market Facts (Adjusted vs Raw Data)



(a) Employment-to-Population Ratio (b) Unemployment Rate (c) Employment Exit Rate (d) Job Finding Rate

consistent across various countries. Second, while the E.U. uses a similar raking procedure to adjust weights, it differs in that they use only age group, sex, and labor status. We additionally include education.[20] The figures below show how our data differ from theirs, in both stocks and flows.

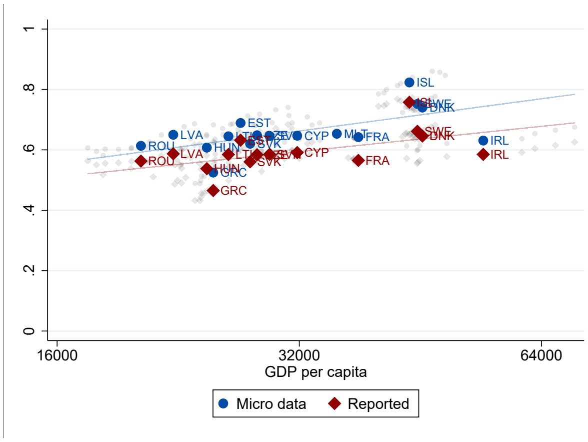
A.5 Urban-Rural

Our baseline analysis focuses on urban labor markets because half of our surveys do not sample rural labor markets. In this appendix we use the other half of the surveys to

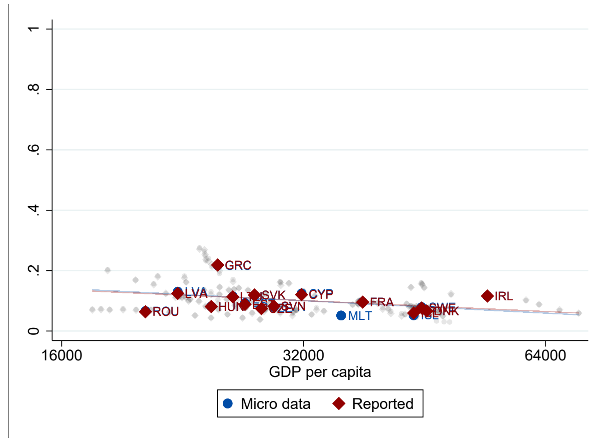
[20]More details of the E.U. procedure are available online at https://ec.europa.eu/eurostat/statistics-explained/index.php/Labour_market_flow_statistics_in_the_EU.

Figure A2: Stocks

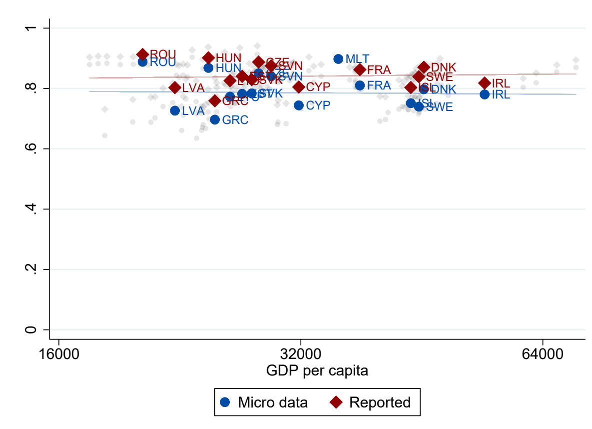
(a) Employed Population Share



(b) Unemployment Rate



(c) Inactive Share of Non-Employed

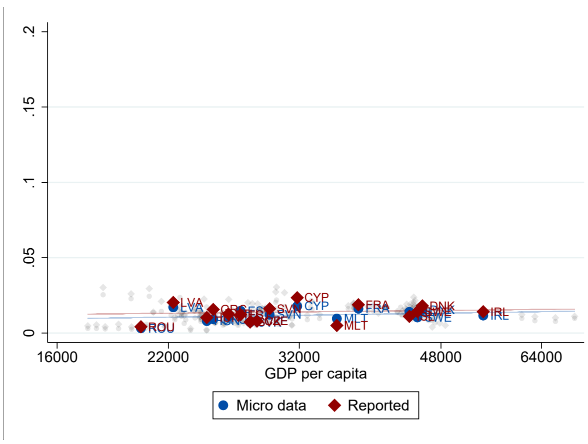


investigate differences between rural and urban labor markets.

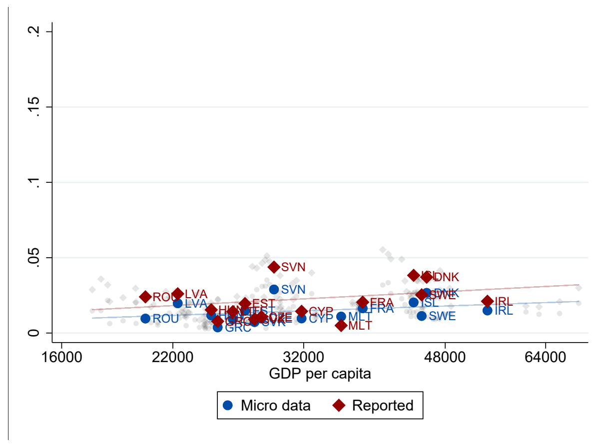
Figure A4 plots employment exit rates and job finding rates against GDP per capita separately for rural and urban workers. Transition rates are similar for the two types of workers in the richest countries, but elsewhere rural workers systematically have higher transition rates. Poorer countries also have systematically higher rural population shares. Put together, these findings imply that the relationship between labor market flows and development is probably stronger than what we estimate using only urban workers. For this sample of countries, the estimated coefficient from a regression of flows on PPP GDP per capita is 36 percent higher for employment exit rates in rural relative to urban areas and 34 percent higher for job finding rates.

Figure A3: Flows

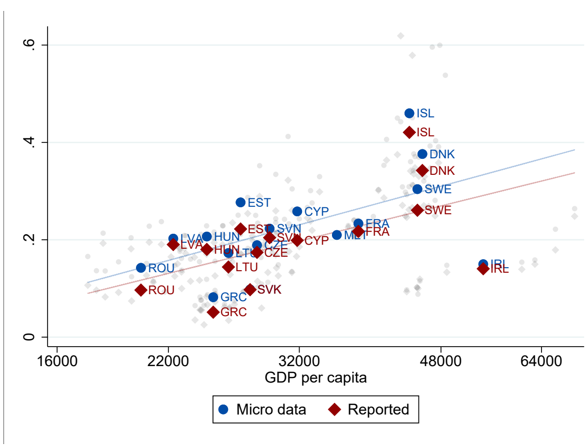
(a) $E-U$ flows



(b) $E-N$ flows



(c) $U-E$ flows



(d) $N-E$ flows

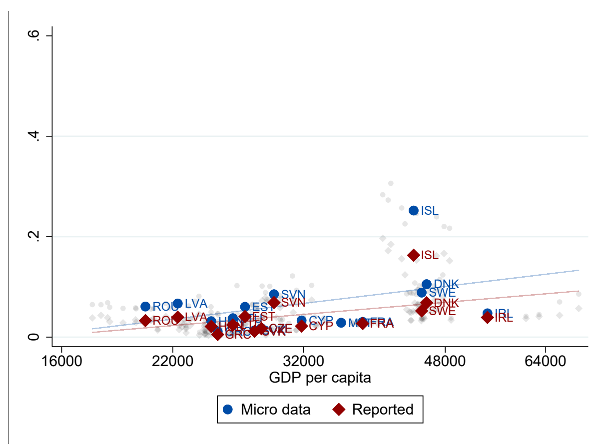
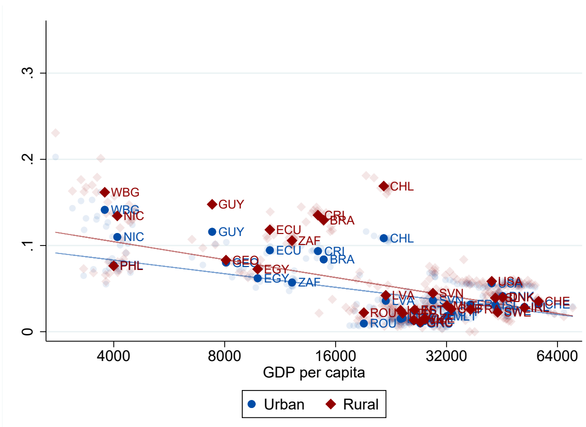
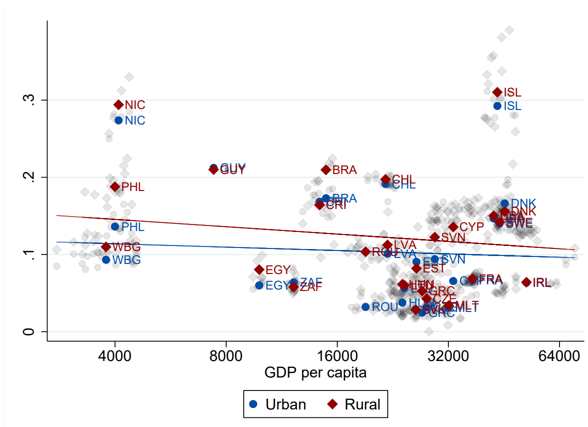


Figure A4: Quarterly Transition Rates: Rural versus Urban Workers

(a) Employment Exit Rate



(b) Job Finding Rate



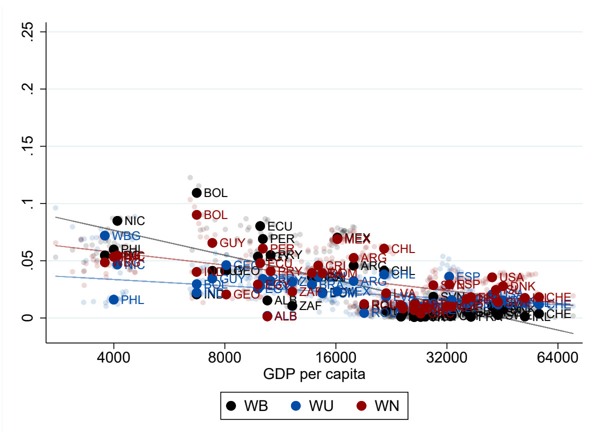
B Additional Results on Stocks and Flows

B.1 Detailed Transition Rates

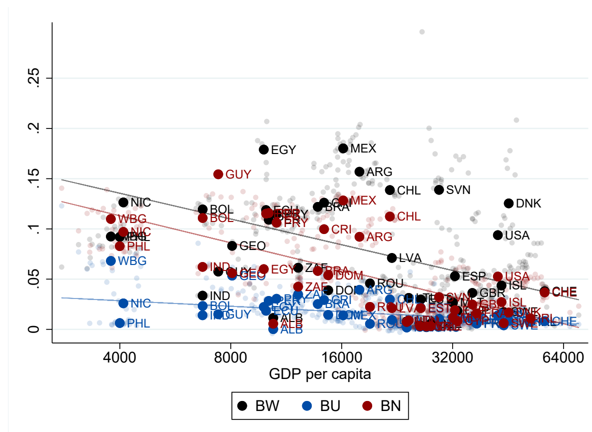
Figure B1 shows the detailed transition rates between states. Recall that W denotes wage work, B denotes self-employment, U denotes unemployment, and N denotes inactivity. Estimated regression lines of transition rates against log GDP per capita are included in all figures. The trend is negative for eleven of the twelve transitions, with the transition from unemployment to wage work the exception.

Figure B1: Detailed Quarterly Transition Rates

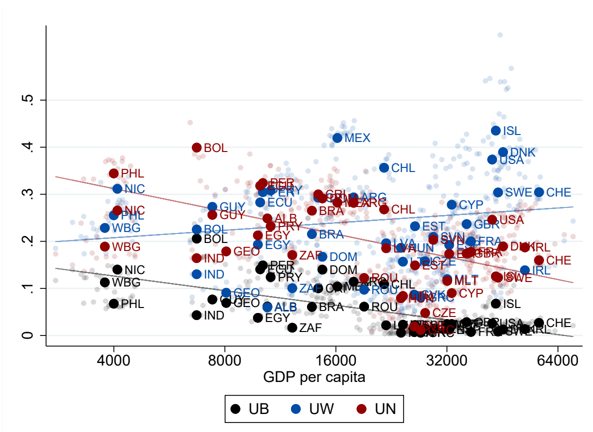
(a) From Wage Work



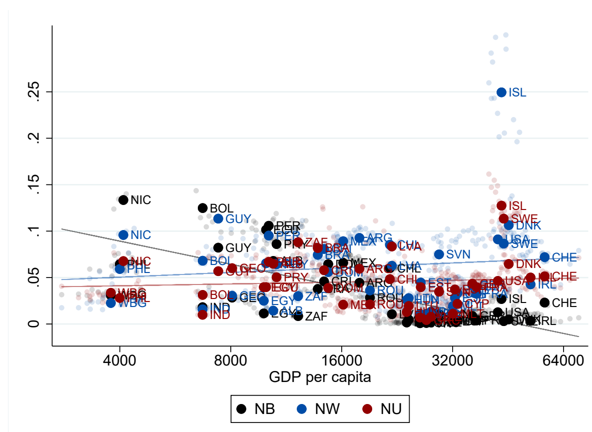
(b) From Self-Employment



(c) From Unemployment



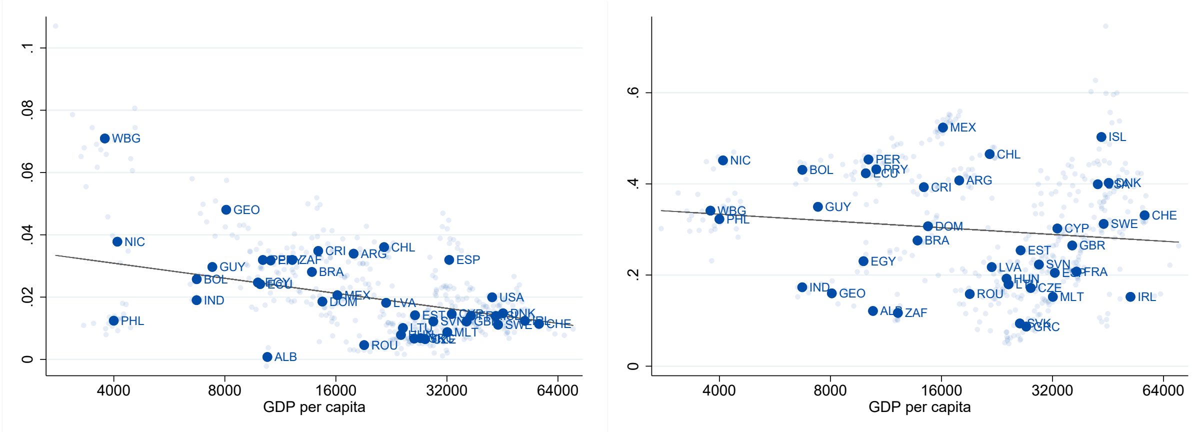
(d) From Inactivity



B.2 Alternative Aggregations of Labor Market States

Figure B2: Labor Market Results: Excluding Inactivity

(a) Employment Exit Rate (b) Job Finding Rate



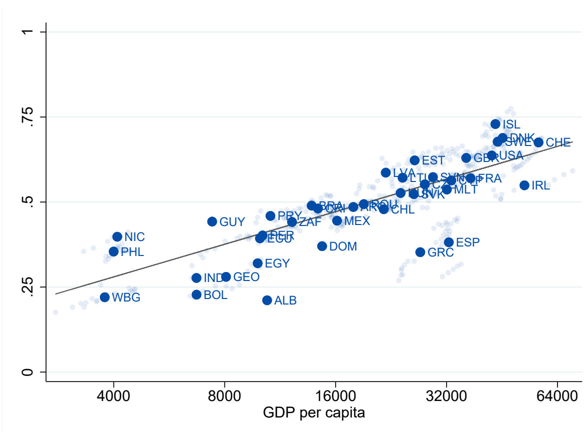
Our baseline approach in the paper is to include self-employment in employment for the purposes of constructing standard measures such as the employment exit and job finding rates. We do so under the rationale that the self-employed evidently spend time producing output which is included in GDP and hence they should be counted as employed. Nonetheless, the evidence that suggests that self-employment is a closer substitute for unemployment in poorer countries leads us to explore the results that would arise if the self-employed were included in non-employment instead.

Figure B3 shows the results. Figures B3a and B3b show that this change has dramatic implications for standard labor market indicators in poor countries, which follows from the fact that one-third to one-half of the population is self-employed in our poorest countries. Re-classifying these workers as unemployed lowers the employment-to-population ratio and raises the unemployment rate dramatically in poor countries.

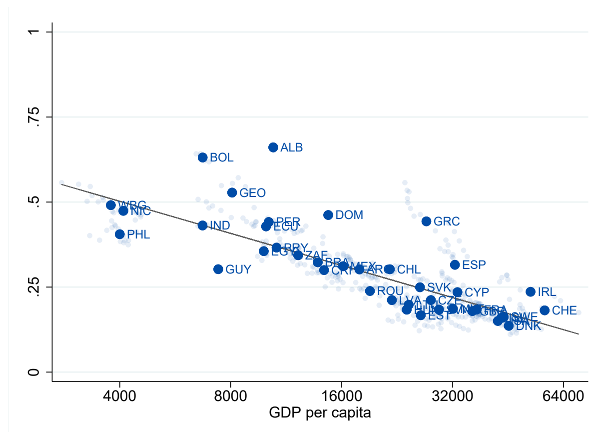
Figures B3c and B3d show the implied flows. Here, the employment exit rate is the share of wage workers that leave wage work per quarter, while the job finding rate is the share of the population without wage work that finds wage work per quarter. Both decline with development, although the trend for the job finding rate is no longer significant.

Figure B3: Labor Market Results: Self-Employment Included in Unemployment

(a) Employment-to-Population Ratio

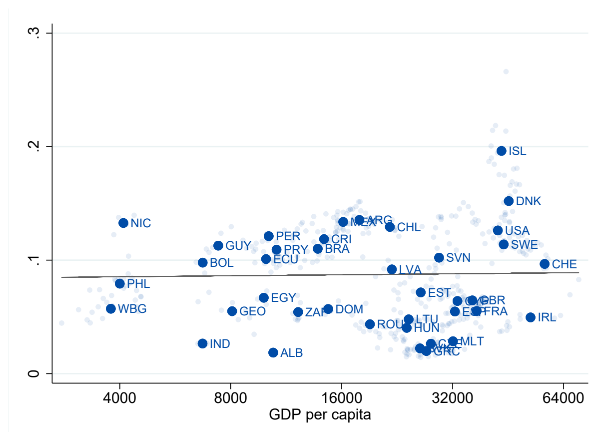


(b) Unemployment Rate



(c) Employment Exit Rate

(d) Job Finding Rate

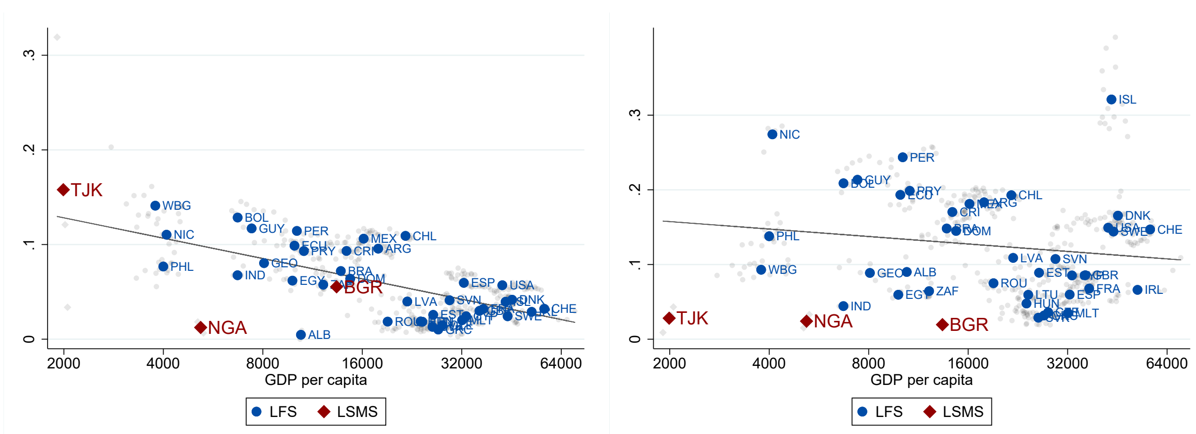


C Inclusion of Other Data

As we note in the text, we are missing nearly all Sub-Saharan African countries. Thus, we are unable to answer whether or not these same patterns hold when we include the poorest countries in the world. To attempt to study this question, we turned to the Living Standard Measurement Surveys (LSMS) released by the World Bank. These are cross-sectional surveys, but some include labor market modules that include the length of employment (which, in principal, could be used to back out a job finding rate) or the length of non-employment (for the employment exit rate). Unfortunately, only a small set of the 121 surveys include the proper questions, and even when they do, most do not properly map to our measure of the job finding rate or exit rate.[21] However, four surveys include retrospective monthly panels of labor market indicators.[22] They are Bulgaria-2007, Nigeria-2010, Nigeria-2012, and Tajikistan-2009. We include them below.

Figure C1: Flows

(a) Employment Exit (b) Job Finding Rate



Overall, the employment exit rates (Figure C1a) seem to line up with our data. The job finding rates (Figure C1b) are quite low, though the rationale for this result is difficult to come by. Feng et al. (2018) and Bick et al. (2018) highlight how including such countries

[21] For example, the Ghanian survey asks "How many years or months have you been doing this work, all together?" thus including the entire length of any E–U–E flows in the same occupation/job. This makes this question inconsistent with the definition of a job finding rate. The Serbian survey asks "When did you cease to perform your last job?" but only records years, thus making it impossible to measure an employment exit moment at the frequency required.

[22] We considered all country-surveys available on the LSMS website (121 surveys, available here: https://microdata.worldbank.org/index.php/catalog/lsms). These four had documented retrospective panels.

may change the overall shape of cross-sectional labor market patterns. Given the extra cost in collecting (even short) panel data, however, labor force surveys are unfortunately unavailable in such countries. We view this as an important question for future work.

D Additional Accounting Results

This section provides results on the ability of labor market institutions and worker characteristics to account for job finding rates and job-to-job transition rates.

D.1 Accounting for Job-Finding Rates

Table D1 recreates the results in the main text, except replacing the employment exit rate with the job finding rate. Column one shows the relationship between GDP per capita and the JFR for years 2014 – 2018 (the only years the regulation data is available).

Table D1: Job Finding Rates and Labor Market Institutions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita	-0.022	-0.032	-0.023	-0.020	-0.033	-0.018	-0.027	-0.013
	(0.011)**	(0.013)**	(0.011)**	(0.014)	(0.012)***	(0.014)	(0.012)**	(0.024)
Severance pay		-0.008						
(weeks of salary)		(0.006)						
Annual paid leave required			-0.017					
(days of work)			(0.009)*					
Existence of labor court				0.006				
				(0.020)				
Legal to have fixed-term					-0.024			
contracts for permanent work?					(0.013)*			
Min Wage/VA per worker						0.029		
						(0.037)		
Probationary period							-1.942e-3	
(months)							(2.840e-3)	
1st principal component								0.009
								(0.008)
Sample Average	0.130	0.130	0.130	0.128	0.130	0.130	0.129	0.125
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	128	128	128	82	128	101	118	48
R^2	0.035	0.045	0.063	0.030	0.060	0.043	0.053	0.073
coeff, log GDP per capita	-0.022	-0.022	-0.022	-0.021	-0.022	-0.023	-0.023	-0.029"
(no institutions)	(0.011)**	(0.011)**	(0.011)**	(0.014)	(0.011)*	(0.012)*	(0.011)**	(0.018)
R^2 (no institutions)	0.035	0.035	0.035	0.023	0.035	0.037	0.049	0.051

Table notes: All regulations are taken from the World Bank Doing Business Survey. Severance and annual paid leave are measured as inverse hyperbolic sines, to approximate a log specification while allowing zeros. The last two rows are the estimated coefficient and R^2 of the regression of the JFR on log GDP per capita on whatever sample is used in that column.

Table D2: Accounting for Job Finding Rates

	Share Accounted for (%)	
	Total Employment	Wage Employment
Age	28.0	-58.2
Gender	-17.5	24.1
Education	-8.5	24.5
Age + Edu + Gender	-28.7	22.6

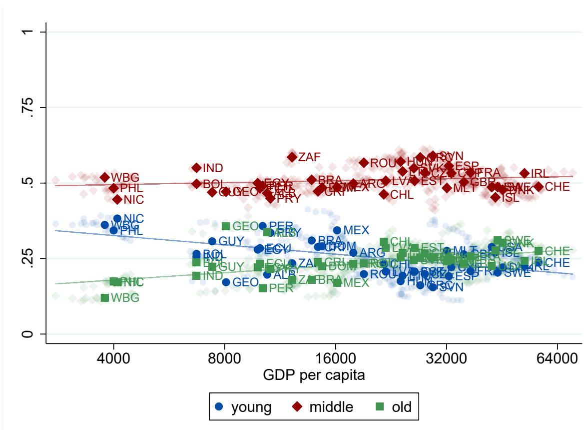
Table notes: All figures capture the share of the JFR-development relationship accounted for by the characteristics given in the rows. The share accounted for is constructed as explained in the text. Columns give the corresponding figure for total employment or wage employment; n/a indicates that the figure cannot be computed.

D.2 Detailed Accounting Results: Age

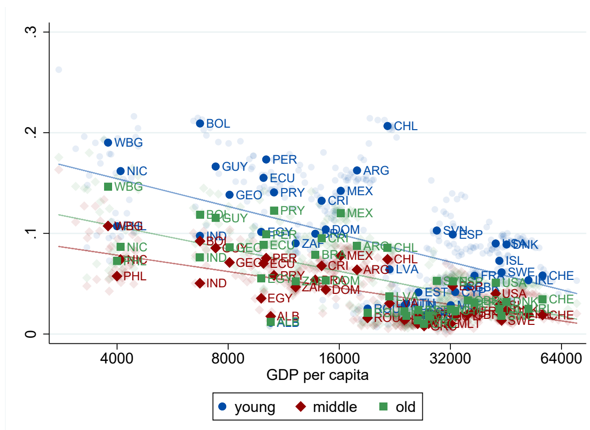
Figure D1 provides detailed information on the role of age in accounting for labor market flows. For visual clarity we divide the population into three groups, young (16–29 years of age), middle-aged (30–49 years) and old (50–65 years). Figures D1b and D1a show the exit rate and employment share by GDP 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 D1: Accounting for Age

(a) Employment Share by Age



(b) Exit Rate by Age



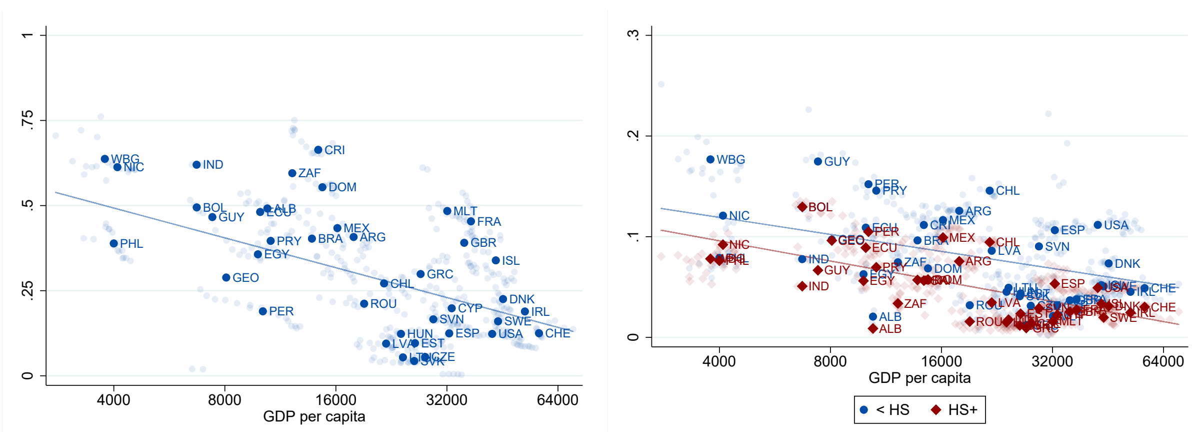
D.3 Detailed Accounting Results: Education

Figure D2 provides detailed information on the role of education in accounting for labor market flows. We focus on a simple split of the workforce into those with less than a high school degree versus those with a high school degree or more. This split accounts for the highest share of the trend relationship between exit rates and flows, because there is both large variation in the employment share by education (Figure D2a) and a large level difference in the exit rate conditional on education that seems to hold in most countries (Figure D2b).

Figure D2: Accounting for Education

(a) Employment Share, <HS

(b) Exit Rate by Education



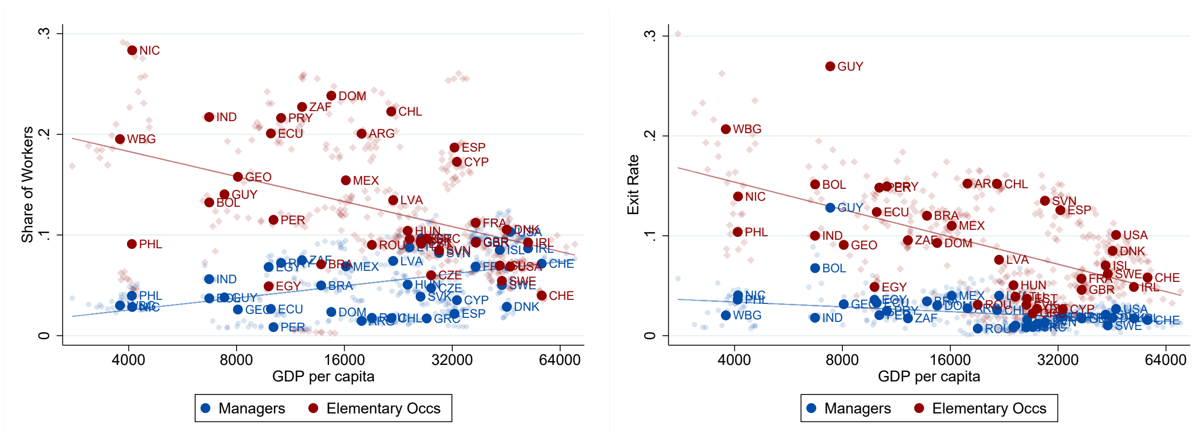
D.4 Detailed Accounting Results: Occupations

Figure D3 provides detailed information on the role of occupation in accounting for labor market flows. For visual clarity we focus on the two extreme ends of the occupational distribution: managers (the most skilled category in ISCO) and elementary workers (the least skilled). There are clear differences in the employment shares of these occupations between poor and rich countries (Figure D3a) and large differences in exit rates (Figure D3b). Overall, occupation accounts for somewhat less of the overall picture than education because the other occupations (ISCO 1-digit groups 2–8) offer a less clear pattern than the extremes.

Figure D3: Accounting for Occupation

(a) Employment Share, Select Occupations

(b) Exit Rate, Select Occupations



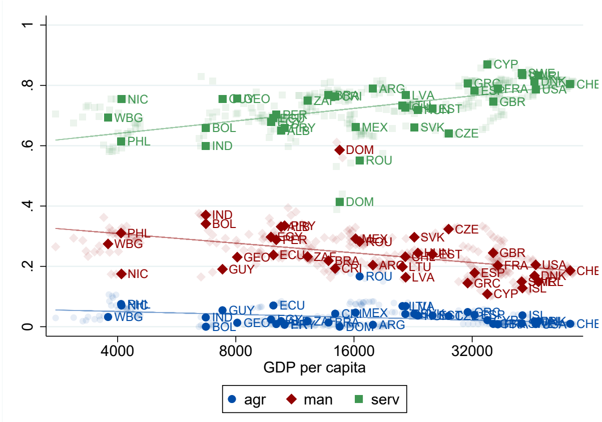
D.5 Detailed Accounting Results: Sectors

Figure D4 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 D4a shows the share of employment in services and manufacturing. As expected, richer countries have more employment in services.[23]

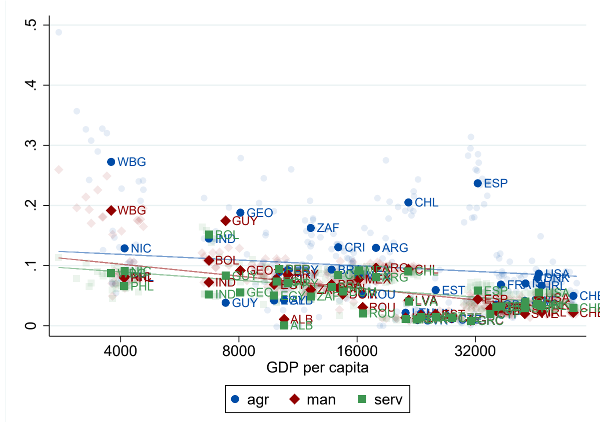
[23] There is a small amount of agriculture even urban areas here. The sampling unit is a dwelling, so some urban workers may still work in agriculture.

Figure D4: Accounting for Sectors

(a) Employment Share by Sector



(b) Exit Rate by Sector

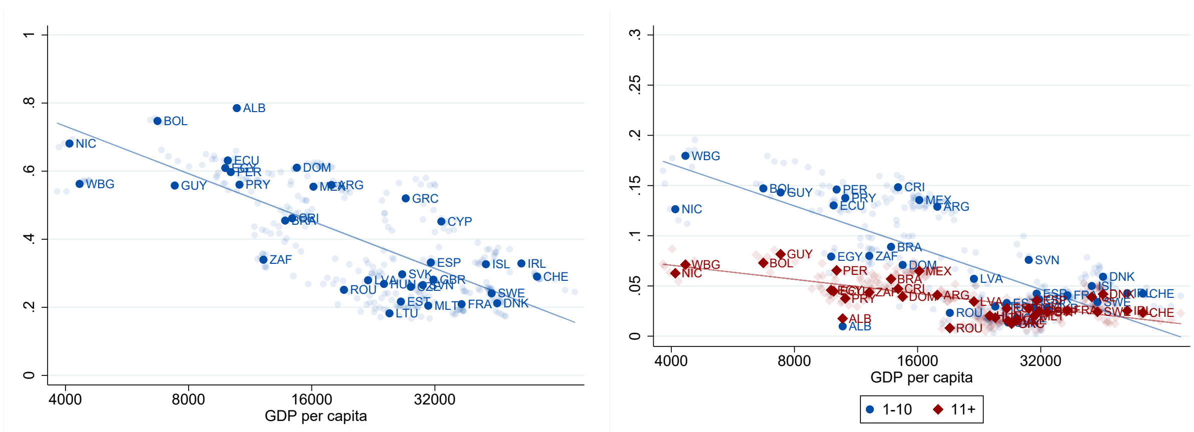


D.6 Detailed Accounting Results: Establishment Size

Figure D5 breaks down exit rates and employment shares by establishment size. Chile explicitly asks about workers in the firm within the entire country, and we drop them from the analysis. As mentioned in the text, countries generally bin establishment size. We use the bin that maximizes sample size, which is a coarse decomposition of $1-10$ workers and 11+ workers. Figure D5b shows that exit rates are higher for workers in small firms and lowest for workers in large firms in all countries. Figure D5a 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 D5: Accounting for Establishment Size

(a) Employment Share by Establishment Size　　(b) Exit Rate by Establishment Size



D.7 Detailed Accounting Results: Informality

Figure D6 breaks down accounting results for formal and informal wage work. Figures D6b shows exit rates for formal and informal workers. Workers are much more likely to exit from informal work, although the gap is smaller in poorer countries. Figure D6a repeats the share of informal workers by country, which declines from one-half to none in rich countries (the latter, by assumption).

Figure D6: Accounting for Informal Employment (Wage Work)

(a) Employment Share, Informal Workers

(b) Exit Rate by Formality