

Labor Market Flows and Development^{*}

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Abstract

We build a new cross-country dataset of harmonized rotating panel labor force surveys covering thirteen countries with widely varying average income. We document that poor countries experience flows between labor force states 2–3 times higher than in rich countries. We label higher transition rates in poor countries *churn*, because it seems to involve cycling among labor states rather than climbing a job ladder. This characterization draws on three key findings: (1) half of employment in poor countries is in apparently undesirable self-employed work; (2) half of the remainder is in explicitly temporary wage work; (3) poor countries have steeper tenure-wage profiles but lower tenure. We use accounting decompositions to provide suggestive evidence on the characteristics of people and firms that may explain these facts. Firm characteristics, particularly firm size, play a central role: poor countries have few large firms, which generally employ workers for longer spells rather than temporary work.

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1 Introduction

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

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

We document that our data agree with a number of standard cross-sectional labor force statistics, such as the employment to population ratio and unemployment rate by development status. We then turn to our main contribution, which is to document new facts about labor market dynamics, by which we mean the flows between states such as unemployment and employment. Our key finding is that transition rates between any two states are substantially higher in poor countries, typically by a factor of 2–3. For example, the

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

employment exit rate is 15 percent per quarter in our poorest countries but only 5 percent in the richest. Job finding rates are also higher in poor countries, although this pattern is partially obfuscated by the fact that unemployment and inactivity (not in the labor force) are less distinct states in poor countries than in rich ones.²

It is useful to contrast our results with those from an existing literature that documents labor market dynamics among rich countries. That literature finds large variation in labor market flows among rich countries and ties this variation to the underlying labor market institutions. In particular, rigid labor market institutions in many European countries are found to inhibit the efficient reallocation of labor (Ljungqvist and Sargent, 1998; Jung and Kuhn, 2014; Krause and Uhlig, 2012). By contrast, our goal is to look at countries representing a much wider range of development and to capture the underlying relationship between labor market flows and development. Still, it is an open question whether these higher labor market flows suggest more efficient reallocation of labor in poorer countries.

We provide three findings that suggest it is not, and which lead us to label these flows *churn* in poorer countries. First, we emphasize the central role of self-employment, which accounts for half of all employment in our poor countries. An existing literature argues that most of this self-employment in poor countries is subsistence self-employment that functions as a substitute to missing unemployment insurance.³ We provide new and related evidence by showing that higher job finding rates in poor countries are accounted for largely by higher transitions of workers who are not in the labor force and do not want jobs to self-employment. Further, self-employment is less persistent in poor countries; for example, the exit rate to wage work is similar for self-employment and unemployment. Second, we find an important role for explicitly temporary wage work. One-quarter of the labor force (half of all wage workers) work in jobs with defined, short durations. Not surprisingly, these jobs have much higher exit rates.

The third finding that suggests interpreting labor market flows as churn draws on wage and tenure data for a subset of countries. We use these data to document average tenure rates and tenure-wage profiles for these countries. We find lower average and median tenure in poorer countries, consistent with higher employment exit rates documented above. More strikingly, we find no consistent pattern in tenure-wage profiles between poor and rich countries. These findings contrast sharply with the finding of Lagakos et al. (forthcoming)

²We follow the spirit of Flinn and Heckman (1983), who suggest that unemployment and not in the labor force are distinct states only if they have different job finding hazards. We do not observe the entire hazard so we compare job finding rates, which we find are more similar (but not the same) in poorer countries.

³See Albrecht et al. (2009), Schoar (2010), and Poschke (2013).

that experience-wage profiles are consistently flatter in poorer countries. Our findings suggest that flat experience-wage profiles are driven by low tenure and a failure to climb the job ladder rather than low within-job wage growth.

Our second contribution is to provide suggestive evidence on the sources of cross-country differences in labor market flows. To do so, we utilize accounting decompositions, which allow us to ask what characteristics of people or firms are both predictive of job finding and employment exit and correlated with development. These decompositions are related to our first contribution because they help us identify the characteristics of individuals and firms that are associated with the elements we have identified so far, such as self-employment and temporary wage work.

We find that none of these characteristics account for much of cross-country differences in job finding rates. On the other hand, we find a large role for firm size in accounting for cross-country differences in employment exit rates. This fact is attributable to the fact that there are large gaps in exit rates by firm size that are relatively constant across development but large differences in the firm size distribution by country.⁴ For example, firms with 1–5 workers have an average exit rate of 15 percent, against only 6 percent for firms with 11 or more workers. Most workers in poor countries work in the former, while most workers in rich country work in the latter. This finding has a straightforward relationship to our findings above: large firms are much less likely to offer temporary work.

Our emphasis on type of employment and firm size ties in with two existing literatures. The first uses experimental variation to measure the impact of changing job search and hiring practices. For example, [Blattman and Dercon \(forthcoming\)](#) alters directly the jobs of workers to measure the impact on wages and health; [Groh et al. \(2016\)](#) subsidizes employers to hire certain workers to see if they move faster up the job ladder; and [Franklin \(forthcoming\)](#) and [Abebe et al. \(2017\)](#) reduce frictions to job search to see if workers find better jobs. The second literature attributes the lack of large firms in poor countries to distortions that inefficiently reduce the size of firms ([Guner et al., 2008](#)). In a companion paper we show that our labor market findings provide a natural amplification mechanism that increases the impact of such firm size distortions ([Donovan et al., 2018](#)).

The structure of our paper is as follows. In Section 2 we outline the data, our harmonization

⁴It is well-known that workers at large firms earn higher wages and have more stables in the United States; see for example [Oi and Idson \(1999\)](#). We extend this finding and show that similar patterns hold in all countries in our data. A recent literature has documented the absence of large firms in poor countries ([Hsieh and Olken, 2014](#); [Bento and Restuccia, 2017](#)). Our contribution here is to tie the absence of large firms to labor market outcomes.

procedures, and the basic facts. In Section 3 we construct and compare labor market flows across countries. In Section 4 we provide three pieces of evidence on why higher flows in poor countries should be thought of as churn. Section 5 provides the accounting results that attribute an important role to firm characteristics, while Section 6 concludes.

2 Data

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

We focus on countries that utilize a rotating panel design; typically this means that each household is followed for two consecutive quarters and half of the sample is rolled over each quarter.⁵ Finally, we focus further on countries where consistent individual identifiers are available to us over time. This restriction eliminates the Canadian and European Labor Force Surveys because identifiers are re-anonymized each quarter to prevent matching of people over time. The European Union does publish some aggregate labor force statistics including quarterly transition rates. We incorporate these in figures when possible to facilitate comparison with the existing literature that focuses mostly on the United States and European Union.

We were able to identify thirteen countries with labor force surveys meeting these criteria. The countries are listed in Table 1. The duration of data availability varies widely, ranging from three years in Nicaragua and Paraguay to 38 years in the United States. Our countries cover a wide range of development, with Palestine and Nicaragua having purchasing power parity adjusted GDP per capita around \$4,000 and the United States over \$50,000 in recent years (Feenstra et al., 2015).

We use the identifiers to match people for two consecutive quarters. We follow the standard protocol from the United States of checking the validity of these matches by requiring that they be unique and that they agree on age, sex, and (in the United States only) race,

⁵The United States Current Population Survey (CPS) is an outlier in this and several other dimensions. Nonetheless we can mimic 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 ^a
Argentina	2003 – 2017	671	12,500 – 20,200
Brazil	2002 – 2015	2,208	8,500 – 14,900
Chile	2010 – 2017	1,664	19,000 – 21,600
Costa Rica	2010 – 2017	299	12,600 – 14,200
Ecuador	2007 – 2015	184	8,000 – 11,000
Mexico	1994 – 2017	15,714	10,900 – 15,900
Nicaragua	2013 – 2015	194	4,200 – 4,500
Palestine	2000 – 2015	558	3,700 – 4,300
Paraguay	2013 – 2015	18	8,100 – 8,300
Peru	2003 – 2017	236	5,400 – 11,000
South Africa	2008 – 2017	1,050	11,400 – 12,100
UK	1997 – 2017	3,514	30,900 – 40,200
US	1979 – 2017	6,325	29,500 – 52,300
Total		32,633	

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

following [Madrian and Lefgren \(2000\)](#). These checks have little effect in most countries but do lead us to discard matches in the United States, particularly in earlier years. Most countries provide weights for the matched sample that correct for attrition. In the United States we adjust the provided cross-sectional weights for attrition so that our sample of matched observations agrees with the unmatched cross-section on key dimensions. Our approach follows the literature closely; see Appendix A.1 for details. Finally, we restrict our attention to the largest possible sample that we can get consistently for all countries, which turns out to be the urban population aged 16–65. Table 1 shows the number of observations per country, where an observation is a person matched for two consecutive quarters. Altogether, we have over 32 million observations.

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

We de-seasonalize the quarterly data and aggregate to the country-year level. We then merge with purchasing power parity-adjusted GDP per capita from Penn World Tables (which is only available annually).⁶ Figure 1 shows the employment to population ratio and unemployment rate from our data plotted against development, where again each observation is a country-year. The results from our dataset are plotted in blue circles; we have also added the published figures for European Union countries, shown with yellow diamonds. There is substantial variation among countries but little evidence of any relationship with development for these standard labor market indicators, in line with existing work.⁷ One exception is Palestine, which is the poor country outlier in both figures. The Palestinian labor market is subject to a number of unusual frictions that likely do not carry over to other countries, so we exclude them from all regressions and fit lines throughout the paper (Amodio et al., 2017; Mansour, 2010).

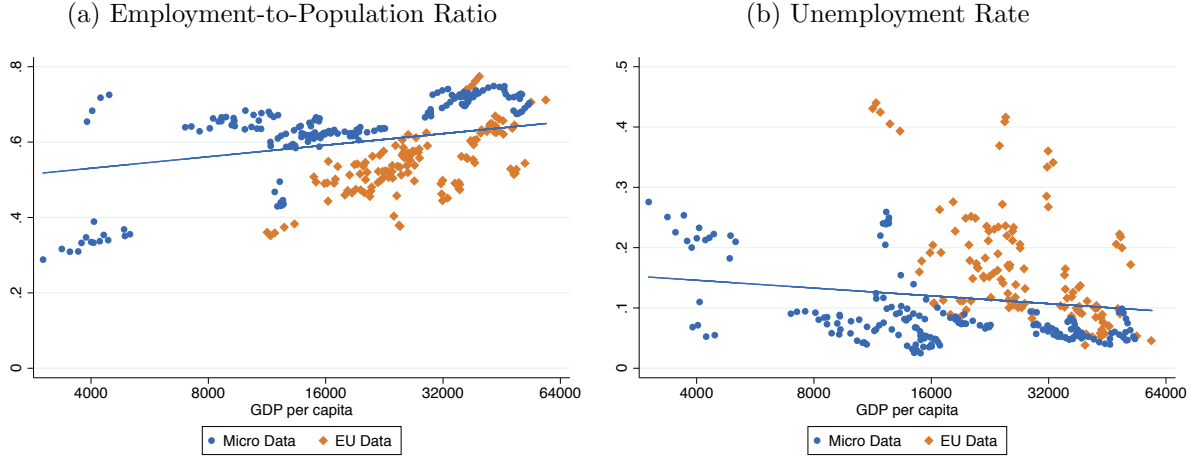
At some points we break these labor force statuses down further. For the employed, we distinguish between wage and salaried workers (who work for someone else) and the self-employed, where the latter includes employers and unpaid family workers. For the unemployed we harmonize categorical responses on the duration of the unemployment spell. Finally, for people who are inactive we can distinguish consistently between those who want a job (but are not available or not looking) and those who do not want a job.

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

⁶Penn World Tables 9.0 stops in 2014. We use the growth rate of PPP GDP per capita from 2014–2016 from World Development Indicators to extend the data when possible.

⁷See Bick et al. (2018) and Feng et al. (2017). Note that they find much higher employment to population ratios and much lower unemployment in the poorest countries, which are absent from our sample.

Figure 1: Cross-Sectional Employment Statistics



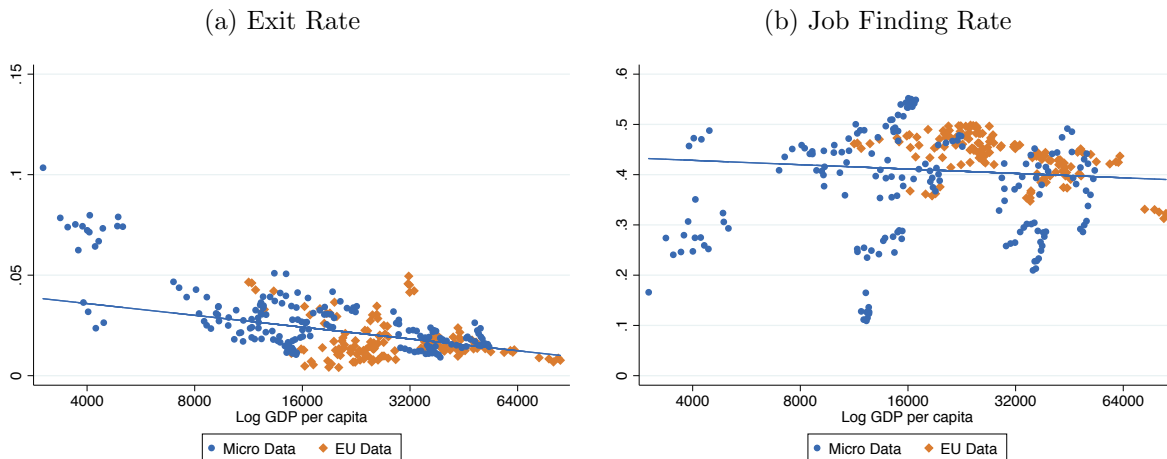
For firms, we focus on size and industry. Our measure of firm size is number of employees in the firm. Most surveys were careful to distinguish firm from establishment, but in some poorer countries the distinction was not so clearly made. The rarity of multi-establishment firms in poor countries makes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

Finally, we harmonize several characteristics of the job. We know the worker’s occupation, again aggregated into a hybrid 1/2-digit occupation coding scheme following [Minnesota Population Center \(2014\)](#). In many countries we have information on (observed) tenure, that is, how long a worker has been with his or her current employer. It is measured in years in most countries although some allow workers to report in months for short spells. And 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.

3 Aggregate Labor Market Flows and Development

In this section we develop our main results on the patterns between labor market flows and development. Before turning to the results, we first lay out some definitions and notation. We decompose the population into the three standard groups of employed, unemployed, and inactive, denoted by E , U , and N . We denote by T_{ij} the quarterly transition rate from i to j , meaning the share of people in i at quarter t who are in j at quarter $t + 1$. As in the previous section we de-seasonalize the quarterly data, aggregate to the country-year level, and merge with PPP GDP per capita. Note that since we only observe people at a quarterly frequency we may miss some transitions due to time aggregation (Shimer, 2012). Standard corrections to produce the implied hazard rates would not affect the underlying trends of interest.

Figure 2: Quarterly Transitions



In line with much of the literature we start by looking at flows between unemployment and employment, disregarding for the moment movements in and out of the labor force. Figure 2 plots the job finding rate and the employment exit rate against PPP GDP per capita.⁸ The transition rates we constructed from microdata are shown in blue circles, with each mark denoting a country-year observation. We have also added the published transition rates for European Union countries from Eurostat, which are again marked with yellow diamonds.

⁸We follow Shimer (2012) in using the term exit rate rather than separation rate because some workers who experience separation will move to another job and this is not included in our measure.

The key message of this figure is that labor market flows are negatively correlated with development. The trend for the employment exit rate is pronounced: poor countries have exit rates roughly two times higher than rich countries, 4 percent compared to 2 percent (Figure 2a). The trend for the job finding rate is weaker, with the unemployed in poor countries finding jobs at only a modestly higher rate than the unemployed in rich countries (Figure 2b). The main goal of the paper is to understand the source and implications of these negative trends between labor market flows and development. First, however, we need to deal with an apparent discrepancy. The fact that poor countries have much higher employment exit rates and only modestly higher job finding rates would seem to suggest that they have higher unemployment rates. Nonetheless, we showed in the last section that unemployment is uncorrelated with development (Figure 1b). It turns out that this discrepancy results from the fact that we have followed the literature and ignored flows in and out of the labor force. We now add this additional information.

3.1 Inactivity

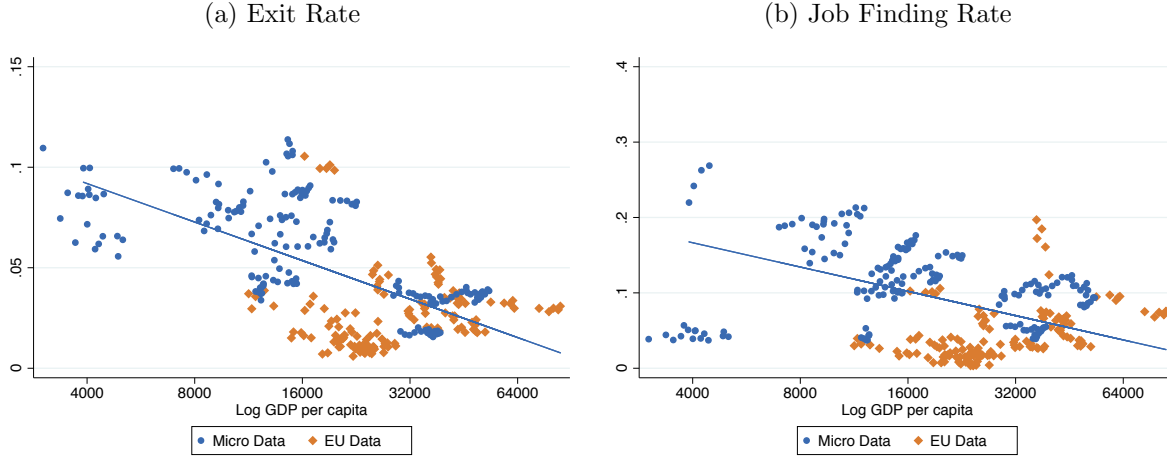
Conventional analyses of labor market flows abstract from movements in and out of the labor force, at least initially. Recent work by [Elsby et al. \(2015\)](#) shows that this is not innocuous for studying cyclical variation in labor market outcomes such as the unemployment rate. Here we show that workers who are out of the labor force play an even larger role in understanding the cross-country patterns in labor market dynamics.

We start with the basic data. Figure 3 shows the quarterly flows between employment and inactivity. Figure 3a shows that the exit rate from employment to inactivity displays a similar downward trend as the exit rate from employment to unemployment. Figure 3b shows that higher exit rates in poor countries are balanced by higher job finding rates from inactivity. For example, while about 10 percent of Americans who are inactive in a quarter transition to employment in the subsequent quarter, roughly 25 percent of Nicaraguans do so. A different way to look at the same trend is that job finding is higher in poor countries, driven almost entirely by a higher job finding rate from inactivity.

These flows help explain why unemployment rates vary little by development. While poor countries have higher exit rates from employment, they also have higher job finding rates from inactivity. The job finding rate from inactivity in poor countries is more than half the job finding rate from unemployment.

This finding recalls the literature that debates whether unemployment and inactivity are

Figure 3: Quarterly Transitions Between Employment and Inactivity

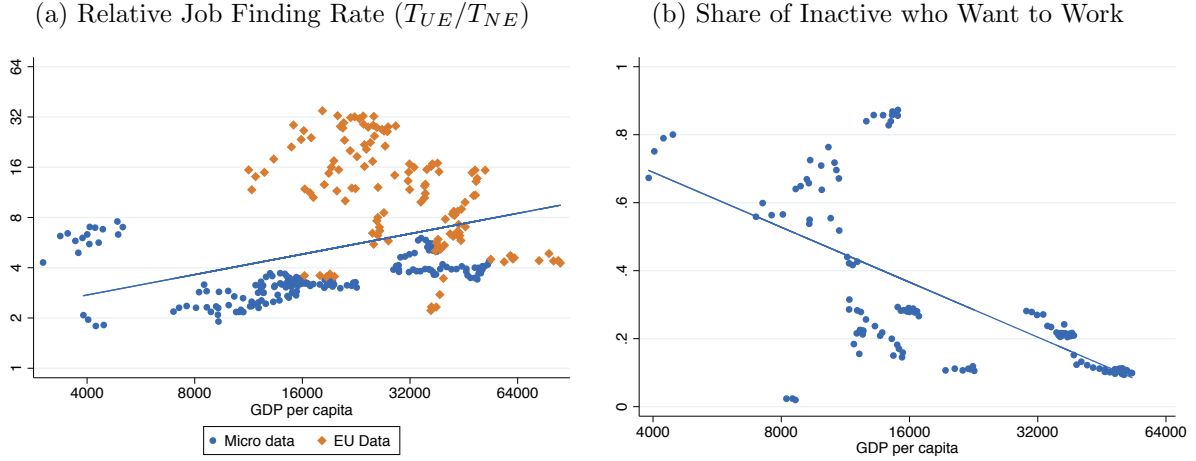


distinct, well-measured labor force statuses. [Abowd and Zellner \(1985\)](#) cites unpublished Census estimates that 10 percent of unemployed workers in the United States are misclassified (the other two statuses are estimated at only 1 percent). The concern within rich countries is strongest for people who are not eligible for unemployment insurance, such as the young ([Clark and Summers, 1982](#); [Ellwood, 1982](#)). This debate has a natural carry-over to our context given that most of the poorer countries either do not offer unemployment insurance or offer much less generous unemployment insurance benefits.

[Flinn and Heckman \(1983\)](#) propose a test of whether unemployment and inactivity are distinct states, based on comparing the job-finding hazards for each. The idea is that if people who have been inactive for six months are as likely to find work as people who have been unemployed for six months, then there is little difference between these two states. Although our data do not allow us to construct the entire job finding hazard, we can construct the relative job finding rate, T_{UE}/T_{NE} . We plot this relative job finding rate against GDP per capita in Figure 4a. The unemployed are more likely to find work than the inactive 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 the proportion grows to around a factor of 4. Flows are also modestly higher between unemployment and inactivity in poor countries, consistent with the view that they are less distinct (not shown).

We use the microdata to investigate why so many workers transition between inactivity and

Figure 4: Inactivity and Development



employment in poor countries. Recall that people without a job have to satisfy a three-part test to be classified as unemployed: 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. We find large cross-country variation in the fraction of people counted as out of the labor force because they do not want a job. We plot this fraction against development in Figure 4b. In rich countries, three-quarters or more of people who are classified as inactive simply do not want a job; the share classified as inactive because they are not available or not searching is small. By contrast, most people who are classified as inactive in poor countries want a job. It is not surprising that they exhibit higher job finding rates.

To summarize, we find higher rates of labor market flows in poor countries. The pattern for the job finding rate is less clear because it does not manifest itself in the classic flows directly from unemployment to employment.

Broadly, we describe these for the rest of the paper as a higher employment exit rate and a higher job finding rate. For much of the remainder of the paper we pool unemployment and inactivity and study the exit rate (to either) or the job finding rate (from either). Once we do this, the underlying pattern is clear: higher job finding rates and higher exit rates in poor countries.

The latter is perhaps less clear in the data. The point of this subsection is to show that unemployment and inactivity are less distinct concepts in poor countries, and that the higher job finding rate happens because more workers who are classified as inactive in poor

countries want and eventually find jobs.

It is useful to contrast our results with those from an existing literature that documents and explains large variation in labor market dynamics among rich countries ([Ljungqvist and Sargent, 1998](#); [Jung and Kuhn, 2014](#); [Krause and Uhlig, 2012](#)). This existing work has generally emphasized the role of labor market institutions in generating variation in labor market dynamics. By expanding our sample to include much poorer countries, we make it possible to observe the underlying relationship between labor market flows and development. This expanded sample is important, because among rich countries the trends are obfuscated by labor market institutions and often go in the opposite direction. For example, the U.S. is richer and generally has higher rates of labor market flows than most European countries.

A second important contribution of the existing literature has been to emphasize that labor market institutions that lower labor force transition rates often hinder the efficient reallocation of labor. This finding raises an important question for us: are the higher rates of labor market transitions in poor countries indicative of faster climbing up the job ladder or more efficient labor reallocation? We provide some evidence against this hypothesis in the next section.

4 Labor Market Flows and Churn

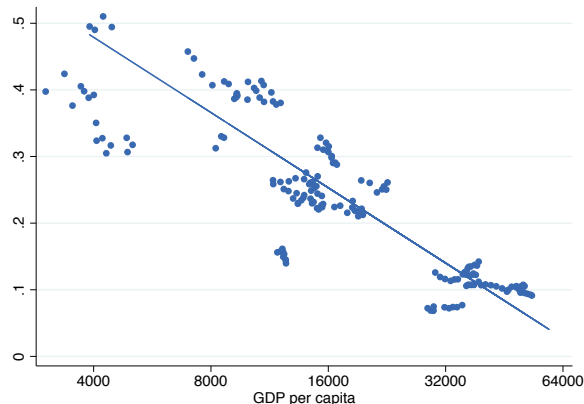
In this section we document three key findings that suggest that higher transition rates in poor countries represent *churn* of people cycling among similar employment states rather than an efficient reallocation of labor. First, we show that half of employment in poor countries is in self-employed work that people enter reluctantly and exit rapidly. Second, we show that half of the remainder of employment in poor countries is in explicitly temporary wage work. Finally, we show for a subset of countries with wage and tenure data that the flat experience-wage profiles documented elsewhere are accounted for by short job tenures rather than flat tenure-wage profiles ([Lagakos et al., forthcoming](#)).

4.1 Self-Employment

Our first piece of evidence draws on the importance of self-employment in poor country labor markets. The self-employed are workers who work for themselves (including unpaid family workers; with or without employees). It is well-known that self-employment is strongly

negatively correlated with development ([Gollin, 2002](#)). We confirm this finding in our data as well. Figure 5 shows the share of workers who are self-employed against development; the figure ranges from half in the poorest countries to 10–15 percent in the richest countries.

Figure 5: Share of Self-Employment in Total Employment



Not surprisingly, self-employment plays a central role in labor market flows. Figure 6 gives the job-finding rate and employment exit rate separately for self-employed and wage and salary workers. Figure 6a shows that the entire cross-country difference in the job finding rate can be attributed to a higher rate of finding self-employed work in poor countries. Figure 6b shows that the self-employed are more likely to exit work than are wage workers. The high exit rate from self-employment, multiplied by the prevalence of self-employment in poor countries, accounts for much of the of cross-country differences in the employment exit rate.

Self-employment accounts for much of the higher labor market flows in poor countries. This fact does not by itself imply that labor market flows are churn. Self-employment could well represent a step up a job ladder or an efficient reallocation of labor. However, a growing literature suggests otherwise. [Poschke \(2013\)](#) utilizes data from the Global Entrepreneurship Monitor survey, which asks standardized questions to self-employed workers around the world. He shows that half of workers in poor countries reply that they are self-employed because they have no better choices for work rather than because they have a business opportunity; the corresponding figure in rich countries is 20 percent. This evidence has given rise to a literature that models these necessity or subsistence entrepreneurs as using self-employment as a substitute to missing unemployment insurance ([Albrecht et al., 2009](#); [Schoar, 2010](#); [Poschke, 2013](#)).

Figure 6: Self-Employment and Labor Market Flows

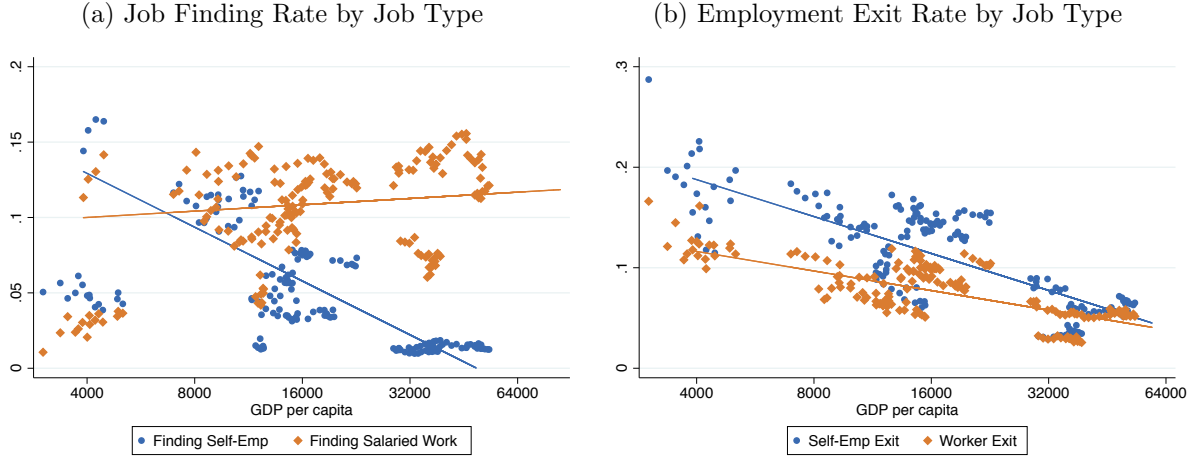
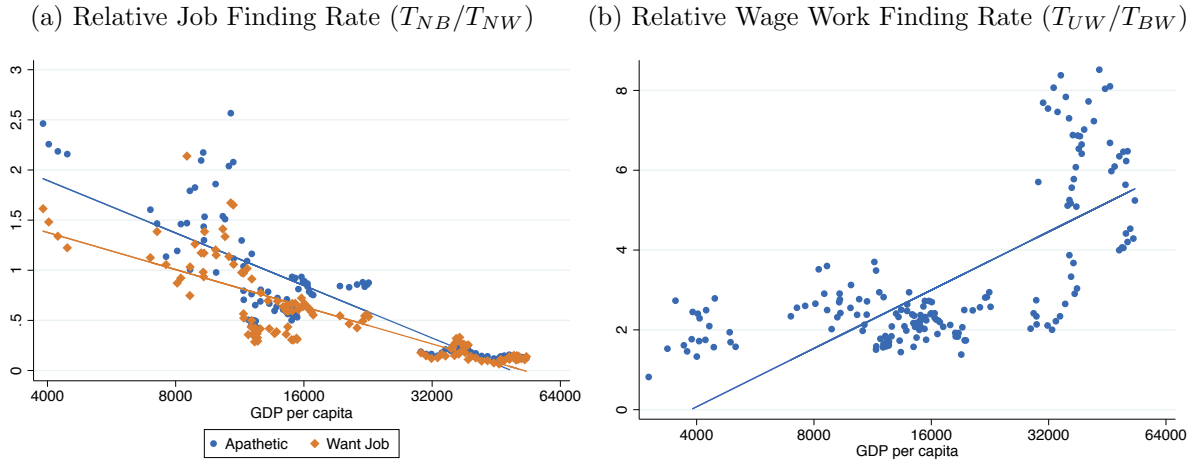


Figure 7: Relative Job Finding Rates



Our data enable us to bring new evidence to bear on this subject. Rather than drawing inferences from workers' stated reasons for being self-employed, we draw inferences from their preferences revealed through their labor market flows. A stark but useful way to understand our approach is to imagine a model where anyone can choose to be self-employed, meaning that there is no need to find self-employment and no exogenous destruction of self-employed jobs. In this case, labor market flows into and out of self-employment contain information about which labor market states and types of employment are preferable to

self-employment.

We apply this approach first to the job finding margin, asking: what kinds of people enter self-employment? We find that people who were previously inactive are disproportionately likely to enter self-employment, particularly in poor countries. We show this result in Figure 7a, which plots the rate at which the inactive find self-employment relative to the rate at which they find wage work. Within the inactive, we distinguish between those who reported that they want a job and those who reported that they did not. The inactive in rich countries move mostly to wage work, but in poor countries they are more likely to move into self-employment. This trend is magnified if we focus on the subset of the inactive who report not wanting a job, who are twice as likely to move into self-employment as wage work in the poorest countries.

We then apply this revealed preference approach to the employment exit margin, asking which labor market states people leave self-employment for. As noted above in Figure 6b, the self-employed are more likely to exit employment altogether, as compared to wage workers. This finding is already suggestive. A related fact is that the self-employed are also likely to exit to wage work in poor countries. Figure 7b plots this rate relative to the rate at which the unemployed find wage work. In rich countries the unemployed are 4–8 times as likely to find wage work, but in the poor countries they are only twice as likely to find wage work. We used similar evidence in Section 3.1 to show that unemployment and not in the labor force are less distinct in poor countries; this finding suggests further that unemployment and self-employment are also less distinct.

Put together, these findings offer further support for the hypothesis that self-employment works differently in poor and rich countries. Self-employment in rich countries is a persistent, intentional state; few people enter it, but those who do have low exit rates to non-employment or wage work. Self-employment in poor countries is closer to unemployment. Entry and exit patterns show that many self-employed workers have marginal labor force attachment and that the self-employed are likely to be simultaneously looking for wage work. These findings suggest that self-employment is not a step up a job ladder or an efficient reallocation of labor. Given the central role of self-employment for poor country labor markets and cross-country differences in labor market transitions, this is our first evidence for the churn hypothesis.

4.2 Temporary Work

Although self-employment is important in poor countries, it still accounts for only half of all employment. A second key piece of evidence in favor of the churn hypothesis is that wage and salary work also appears to be quite different in poor than in rich countries. One clear indicator of this fact is the central role that temporary jobs play in poor countries: jobs with a limited, short duration defined in advance. This category includes seasonal work, jobs with a pre-defined end date, and jobs that involve completing a specific task.

Figure 8: Entry and Exit by Job Type

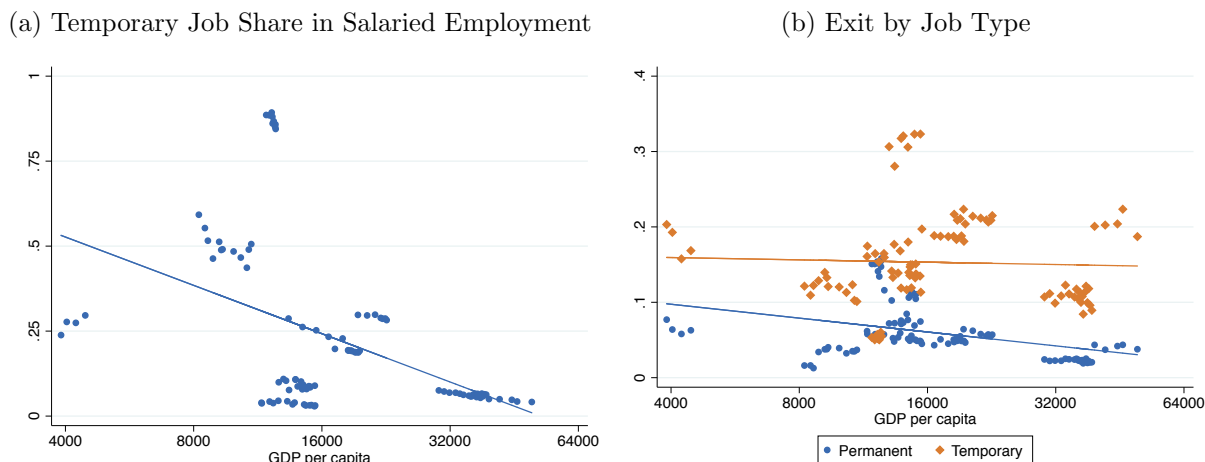


Figure 8a plots the share of wage and salary jobs that are explicitly temporary against development. Temporary jobs are extremely rare in rich countries, typically accounting for 1–2 percent of all jobs. In poor countries they are generally much more important, although there are pronounced differences between countries. Almost all jobs in Palestine and South Africa are temporary, but the figure is also 25–50 percent in other poor countries such as Nicaragua.

Not surprisingly, temporary jobs are associated with higher labor market flows. In Figure 8b we show the employment exit rate separately for wage and salary workers who are working temporary or “permanent” (non-temporary) jobs. Workers are about twice as likely to exit temporary jobs as permanent ones. The employment exit rate for permanent workers does not vary strongly with average income, suggesting that much of the higher employment exit rate in poor countries is accounted for by the large number of temporary jobs.

Altogether, about three-fourths of employment in our poor countries is in apparently undesirable self-employment or explicitly temporary wage work. These findings suggest that many workers may be experiencing labor market churn. In the next section we offer further evidence on this point by drawing on wages.

4.3 Returns to Experience and Tenure

Recent work has documented that life-cycle wage profiles are flatter in poor than in rich countries (Lagakos et al., forthcoming). We find a similar pattern among the ten countries for which we have wage data. Throughout this section we focus on wage and salary workers, because wage data are generally not available or not reliable for the self-employed. We follow the literature closely, estimating a wage equation of the form:

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

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

Figures 9a and 9b plot the estimated returns to 10 – 19 and 20+ years of experience (as compared to the omitted category of 0 – 1 years) against GDP p.c. We find a pattern very similar to Lagakos et al. (forthcoming), with poorer countries having 20–40 percentage point lower returns to experience. Lower life-cycle wage growth suggests important cross-country differences in labor market dynamics, but the mechanism is not clear.

We add to this literature by distinguishing between returns to experience and returns to observed tenure, meaning the length of time the worker has been with their current job. An existing literature suggest that returns to tenure can be informative about accumulation of job-specific human capital or the dynamics of worker selection among jobs. Figure 10c shows that average tenure is shorter poor countries, 4–6 years versus 6–8 years in rich countries, consistent with the higher rates of labor market flows. This finding suggests that

⁹Lagakos et al. (forthcoming) also consider allowing for cohort effects but generally find a small role for them empirically.

Figure 9: Wage Returns to Experience



one possible explanation for the low returns to experience is low accumulation of job-specific human capital.

To investigate the relative importance of returns to experience and returns to tenure, we estimate an augmented Mincer wage equation:

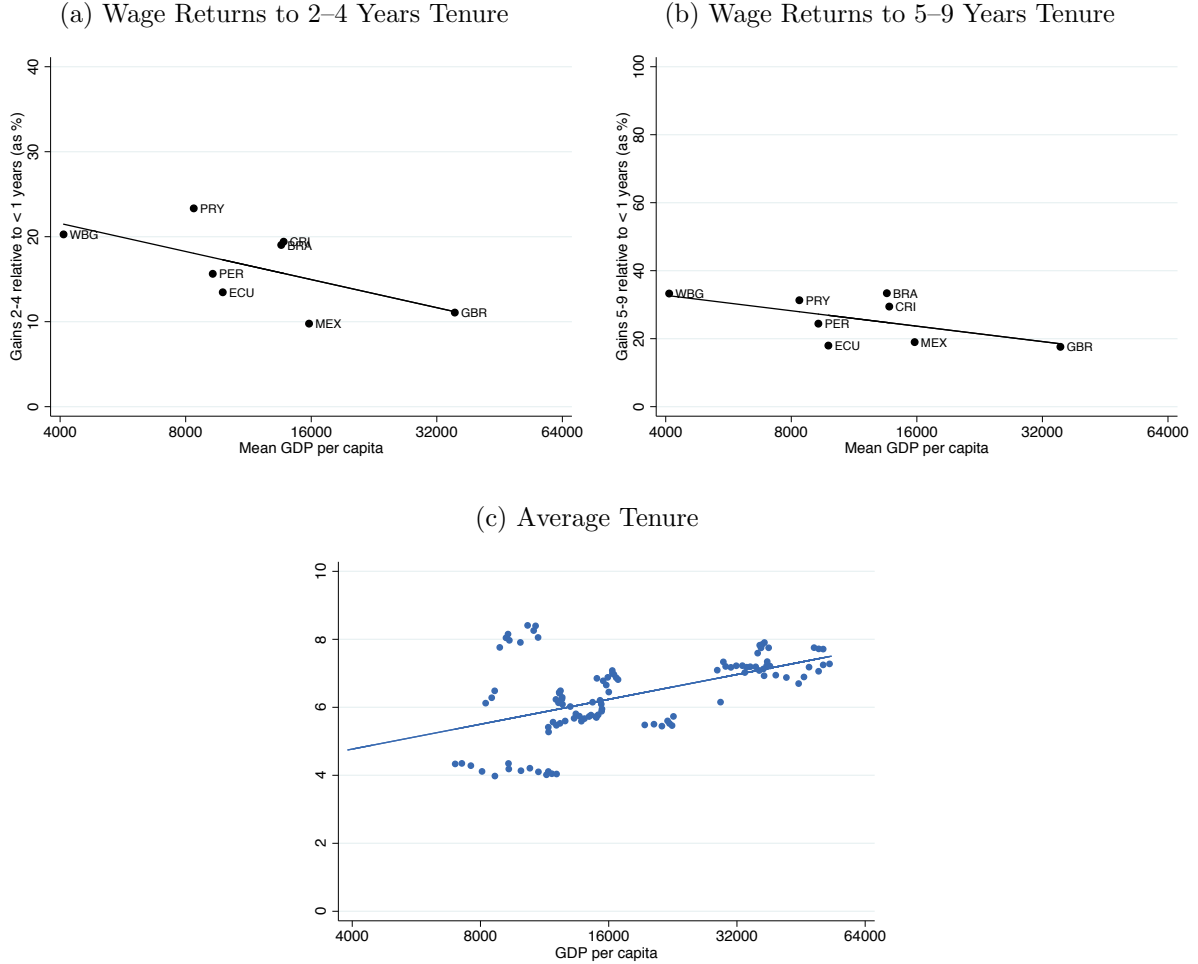
$$\log(w_{it}) = \alpha + \sum_{x \in X} \phi_x D_{it}^x + \sum_{\tau \in T} \psi_\tau D_{it}^\tau + \theta s_{it} + \gamma t + \varepsilon_{it} \quad (2)$$

where D_{it}^τ is a dummy variable that takes the value of one if a worker is in tenure group $\tau \in T = \{1, 2-4, 5-9, 10-19, 20+\}$, with < 1 years of tenure serving as the omitted reference group. We focus on shorter durations of tenure since mean and median tenure is much lower than mean and median experience.

Figures 10a and 10b show the estimated wage returns to 2–4 and 5–9 years of tenure (as compared to less than one year of tenure) plotted against GDP per capita. Unlike for experience, 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: returns to tenure are the same or higher in poorer countries. Finally, we note that this joint estimation that controls for returns to tenure does not overturn the result in Figure 9 of higher returns to experience in rich countries.

[Topel \(1991\)](#) notes that returns to tenure jointly measure the accumulation of job-specific human capital and selection of heterogeneous workers into different tenure spells. In prin-

Figure 10: Wage Returns to Tenure and Average Tenure



ciple, the cross-country variation in returns to tenure could be driven by differential accumulation of job-specific human capital or differential selection. The patterns for returns to experience are useful for distinguishing between the two. If our patterns are driven by differential accumulation of job-specific human capital, then controlling for low tenure and high returns to tenure in poor countries should reduce the gap in estimated returns to experience. As noted above, we find that it does not.

These findings point to differential selection of workers. What that means here is that more able workers are more likely to achieve higher tenure; and that this force is stronger in poorer countries, pushing up the estimated returns to tenure, while less able workers are more likely to exit employment. The fact that much of labor market transitions can be

attributed to less able workers moving between jobs again suggests that labor market flows in poor countries are churn rather than than workers climbing a job ladder.

4.4 Summary of Findings

Poorer countries have higher labor market flows. We offered three pieces of evidence to suggest that these flows should be thought of as churn. First, self-employment plays a central role in poor countries. Half of all workers are self-employed and job finding into self-employment accounts for all of the higher job finding rate. Yet self-employed workers' transitions suggest that self-employment is an undesirable state closer in spirit to unemployment than to wage work. Second, half of wage and salary employment is explicitly temporary, with high exit rates. Third, tenure-wage profiles in poor countries are similar to those in rich countries, but workers in poor countries have lower tenure and lower life-cycle wage growth. Put together, these findings suggest that workers in poor countries are churning through undesirable labor market states and marginal attachment to the labor market, rather than transitioning up a job ladder or being efficiently reallocated between jobs. We now investigate some of the proximate sources of churn that might help guide theories of these transitions.

5 Accounting for Churn

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

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

$$T_{ct} = \alpha_1 + \beta_1 \log(y_{ct}) + \nu_{1ct}$$

where T_{ct} is one of the labor market transitions in country c and year t . y is GDP per capita, and ε is a mean zero error term. Our goal is to investigate the sources of β_1 . This approach differs somewhat from the usual accounting approach, which attempts to account

for the total variation in the outcome of interest. Our view is that much of this variation is generated by important alternative forces such as labor market institutions or cyclical fluctuations that are less relevant for us. We want to focus on why poor and rich country labor markets behave differently.

In order to do our accounting we construct counterfactual labor market flows that fix the composition of people, firms, or jobs 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 w_{gct} , then our counterfactual transition rate is

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

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

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

$$\hat{T}_{ct} = \alpha_2 + \beta_2 \log(y_{ct}) + \nu_{2ct}.$$

We say that accounting for group G is important if it substantially attenuates the estimated relationship between flows and development, e.g., if $\beta_2 < \beta_1$. Formally, we say that group G accounts for

$$share = 1 - \beta_1/\beta_2$$

of the overall flows-development trend accounted for. We consider the importance of the characteristics of people, firms, and jobs in turn.

5.1 Accounting for Demographics

We begin with the characteristics of people. We have harmonized age, gender, and education (see Section 2 for details). We consider the full interaction between these characteristics, generating $6 \times 2 \times 7 = 84$ bins of worker characteristics. We also explore aggregating characteristics so that there are three age groups and two education groups, giving us

$3 \times 2 \times 2 = 12$ coarser bins of worker characteristics.¹⁰

Table 2: Counterfactual Regressions for Demographics

	Detailed Classification			Broad Classification		
	Data	Counterfactual	Share	Data	Counterfactual	Share
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Exit Rate:</i>						
Log GDP p.c.	-0.037 (0.003)***	-0.024 (0.003)***	35%	-0.037 (0.003)***	-0.025 (0.003)***	32%
<i>Job Finding Rate:</i>						
Log GDP p.c.	-0.043 (0.006)***	-0.044 (0.003)***	-2%	-0.043 (0.006)***	-0.047 (0.006)***	-9%
N	159	159		159	159	
Countries	12	12		12	12	
Country F.E.	N	N		N	N	
Year F.E.	N	N		N	N	

Table notes: Classification 1 includes 84 bins, while Classification 2 includes 12. Odd columns are the observed exit rates from the sample used in each classification, while even columns are the counterfactual exit rates that hold demographics fixed. Each row is the coefficient on log GDP p.c. regressed on the listed transition rate. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As one would expect, demographics differ widely between poor and rich countries. Detailed figures are available in Appendix C.1, but poorer countries are systematically younger and less educated than are richer countries. There are also noticeable differences between demographic groups in their labor market flows. Nonetheless, the interactions between the two turn out to be too small to account for much of the cross-country differences in flows.

This point is demonstrated in Table 2. Column (1) shows the estimated coefficient β_1 from regressing either the employment exit rate or the job finding rate on GDP per capita. Both rates are strongly negative, in line with the figures in Section 3. Column (2) replaces actual transition rates with the counterfactual transition rates that hold the population composition by demographic groups fixed. Doing so reduces the exit rate somewhat but does little to the job finding rate. This finding indicates that the exit rate can be partially accounted for by cross-country differences in demographic shares. Column (3) shows that by our proposed metric, 35% ($= 1 - \frac{-0.024}{-0.037}$) of the exit rate is accounted for, and essentially none of the job finding rate.

¹⁰The age bins are then young (16–29), middle-aged (30–49), and old (50–65) and education is less than high school graduate versus high school graduate or more.

Columns (4)–(6) repeat this exercise using our coarser bins. Doing so does not change the findings much, suggesting that simple broad groupings of age and education categories suffices. Overall, the data suggest a modest role for demographic differences, and only in accounting for exit rates.

5.2 Firm Characteristics: Size, Informality, and Sector

We now turn to firm characteristics. We focus on exit rates. Workers in most of our countries are asked questions about the size (measured in number of employees), formal status, and sector or industry of their employer (again, see Section 2 for details). These characteristics turn out to account for a large portion of churn, so we consider them each individually and in more detail than we did with demographics.

5.2.1 Firm Size

We start with firm size, measured as the number of employees in the firm. We can consistently classify firms in most countries into small (1–5 employees), medium (6–10), and large (11 or more). Figure 11 gives the basic facts that indicate firm size is likely to account for a large share of the exit rate pattern. Figure 11a shows that there are large differences in firm size by country. A small and stable share of workers, about ten percent, work for medium firms. However, while two-thirds of workers in rich countries work in large firms, two-thirds of workers in poor countries work in small firms.

These findings matter because they are paired with large and stable differences in exit rate by firm size, shown in Figure 11b. Workers in large firms are about half as likely as workers in small firms to exit employment in a quarter. After controlling even for these three crude firm size bins, we find little remaining relationship between exit rates and development.

The accounting results reported in Table 3 confirm an important role for firm size. Columns (1) and (2) show the results from regression the actual and counterfactual, fixed firm size share transition rates on development. Holding the firm size composition fixed reduces the estimated coefficient on development by two-thirds (column (3)).

As discussed in Section 2, one tradeoff we face is that between detail and country inclusion. Our baseline results include three bins but force us to exclude the United Kingdom, which does not have enough detail for small firms. We experiment with a second classification that includes only two firm size bins: 1–10 and 11 or more. This coarse scheme allows

Figure 11: Firm Size and Exit Rates

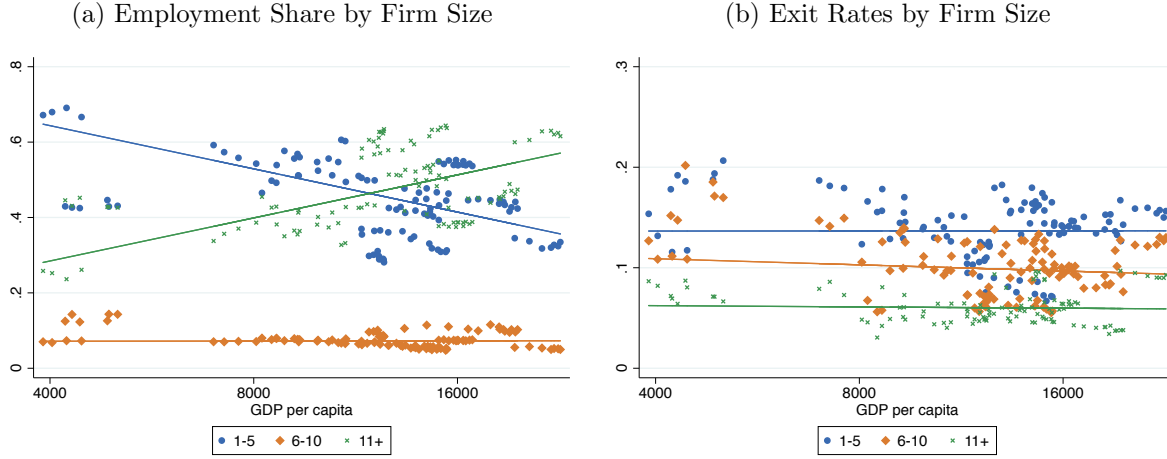


Table 3: Counterfactual Firm Size Exit Regressions

	Detailed Classification			Broad Classification		
	Data (1)	Counterfactual (2)	Share (3)	Data (4)	Counterfactual (5)	Share (6)
Log GDP p.c.	-0.0489 (0.007)***	-0.0162 (0.006)***	67%	-0.021 (0.013)***	-0.009 (0.007)	57%
N	107	107		100	100	
Countries	11	11		10	10	
Country F.E.	N	N		N	N	
Year F.E.	N	N		N	N	
R^2	0.302	0.072		0.210	0.019	

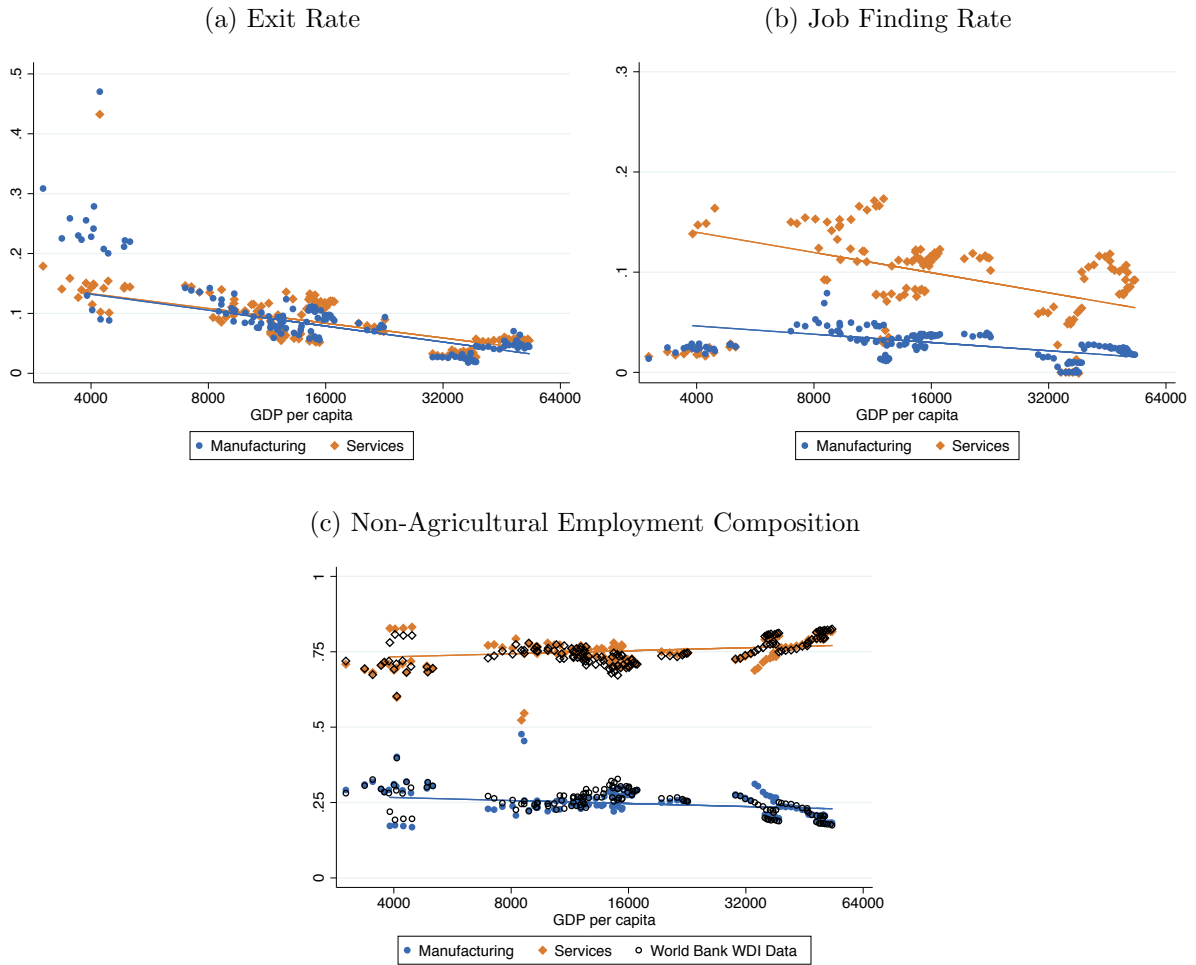
Table notes: Classification 1 is: 0-1, 2-5, 6-10, 11+, and drops the U.K.. Classification 2 is: 0-10, 11+. Odd columns are the observed exit rates from the sample used in each classification, while even columns are the counterfactual exit rates that hold firm size fixed. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

us to include every country with firm size information. Even using just these two bins again reduces the correlation between development and flows substantially, by 57 percent (columns (4)–(6)).

5.2.2 Sectors

Figure 12 plots the share of non-agricultural employment in the two broad categories of manufacturing and services. As a check of data reliability, we also include the shares provided by the World Bank World Development Indicators ([World Bank, 2018](#)). First, as expected, Figure B4a shows that richer countries have a larger share of employment in services. Moreover, our estimated shares track the WDI numbers well. However, Figure B4b shows almost no difference between manufacturing and service exit rates within a country. While both are higher in poor countries, there is no differential effect. Thus, the divide between manufacturing and services cannot explain the aggregate exit rate.

Figure 12: Transition Rates by Sector



To test this in more detail, we consider a more detailed sectoral breakdown. Many countries have individual sector characterizations that vary with country-specific updates, so we use country-specific crosswalks and those provided by IPUMS to harmonize sectoral definitions. Thus, our data maps to the 16 sectors IPUMS-International provides (15 sectors plus missing).¹¹ Costa Rica and Paraguay do not provide sufficient information to map to IPUMS sectors, so we also include a coarse manufacturing/services divide that includes all of our data. Our accounting results are in Table 4.

Table 4: Counterfactual Sectoral Exit Regressions

	Detailed Classification			Broad Classification		
	Data	Counterfactual	Share	Data	Counterfactual	Share
	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP p.c.	-0.032 (0.003)***	-0.0269 (0.003)***	16%	-0.037 (0.003)***	-0.037 (0.003)***	0%
N	137	137		161	161	
Countries	10	10		12	12	
Country F.E.	N	N		N	N	
Year F.E.	N	N		N	N	
R^2	0.402	0.323		0.531	0.521	

Table notes: Classification 1 are the 15 IPUMS sectors, while Classification 2 is manufacturing and services. Odd columns are the observed exit rates from the sample used in each classification, while even columns are the counterfactual exit rates created by equation (??). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As one can see from columns one and two of Table 4, differences in sectoral employment shares account for only about 16 percent of the relationship between exit rates and income. We account for none of the relationship with the coarser classification, which is to be expected in light of Figure B4b.

5.3 Occupations

Occupation is unavailable for the self-employed. We therefore consider the impact of these differences on in flows from salaried work to non-employment (T_{WM}). Occupation codes are

¹¹Specifically, we do the following. We use country-year-specific crosswalks to convert country sectoral codes to a specific ISIC revision. We then create a crosswalk between each ISIC revision and the IPUMS coding scheme. Some countries can be directly mapped directly from their coding scheme to IPUMS if the labor force survey uses the same level of sectoral detail as the census and includes the proper years, though there are few of these countries. The 15 sectors are those in the IPUMS variable *indgen*.

constructed similarly to sectoral codes. We use country-year crosswalks to map to specific ISCO revisions, then map those to the ten-occupation classification used in IPUMS. This requires us to drop Costa Rica, who like with sectors, provides aggregated occupation information that cannot be mapped to the IPUMS classification.

Table 5: Counterfactual Occupation Exit Regressions

	Occupation	
	Data	Counterfactual
	(1)	(2)
Log GDP p.c.	-0.024 (0.003)***	-0.016 (0.003)***
N	150	150
Countries	11	11
Country F.E.	N	N
Year F.E.	N	N
R^2	0.312	0.201

Table notes: *Occupation* is the 10 IPUMS occupation codes plus unknown occupation. Odd columns are the observed exit rates from the sample used in each classification, while even columns are the counterfactual exit rates created by equation (??). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 show that both occupation plays some role in accounting for exit rates of salaried employment, accounting for a third of the exit rate.

6 Conclusion

We build a new cross-country dataset of harmonized rotating panel labor force surveys covering thirteen countries with widely varying average income. We use this dataset to document that poor countries experience flows between labor states 2–3 times higher than in rich countries, although this fact is somewhat obfuscated by the finding that unemployment and inactivity are more closely related in poor than in rich countries.

We use our data to provide evidence that these higher transition rates in poor countries represent *churn* rather than the climbing of a job ladder or an efficient reallocation of labor

between jobs. This characterization draws on three key findings: (1) half of employment in poor countries is in apparently undesirable self-employed work; (2) half of the remainder is in explicitly temporary wage work; (3) poor countries have steeper tenure-wage profiles but lower tenure.

Finally, we use accounting decompositions to provide suggestive evidence on the characteristics of people and firms that may explain these facts. Firm characteristics, particularly firm size, play a central role: poor countries have few large firms, which generally employ workers for longer spells rather than temporary work. These findings suggest important dynamic interactions between workers and firms. We provide one theory of this interaction in a companion paper where we show that our labor market findings provide a natural amplification mechanism that increases the impact of such firm size distortions ([Donovan et al., 2018](#)).

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A Data Details

A.1 Longitudinal Weights

We use the sampling weights provided with the data whenever we study cross-sectional moments. However, these weights are not sufficient when constructing longitudinal moments such as the job finding rate. The underlying problem is what is called *margin error* in this literature, or the failure to match workers with complete information across periods. This failure could arise because of attrition, temporary absence from the sample, inability to create a unique match, or nonresponse to the relevant outcomes in either period. If we drop all such observations and use standard 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. We follow Fujita and Ramey (2009). The basic idea is to re-weight the provided cross-sectional weights w_i so that the values of key cross-sectional moments are the same whether we use the matched or the unmatched sample. In practice we focus on the labor force that is employed in each quarter. We choose a time-invariant multiplier v_j for each transition type $j \in \{EE, EN, NE, NN\}$ to minimize the weighted sum of squares between the quarterly employment to population ratio constructed with w_i on the unmatched sample and the quarterly employment to population ratio constructed with $v_j w_i$ on the matched sample. Our general finding is that we need to increase the weight on workers who undergo transitions, consistent with the literature in the U.S. This is likely due to the fact that workers who do not change employment status are more stable, more likely to live at the same address, and more likely to be included in the sample twice.

A related problem much discussed in the literature is *classification error*: if workers misreport their labor force status then we impute spurious transitions over time when none exist. Since our goal is to compare transition rates across countries, we are particularly concerned that classification error might vary by country. The existing approaches to this problem in the literature use information from reinterview surveys from the U.S. to estimate the likelihood of such errors, but this is not helpful for the question of whether workers in some countries misreport more often than in others (Abowd and Zellner, 1985; Poterba and Summers, 1986). Further, we are not aware of such studies outside the U.S. We plan to conduct sensitivity analysis around this point in the future.

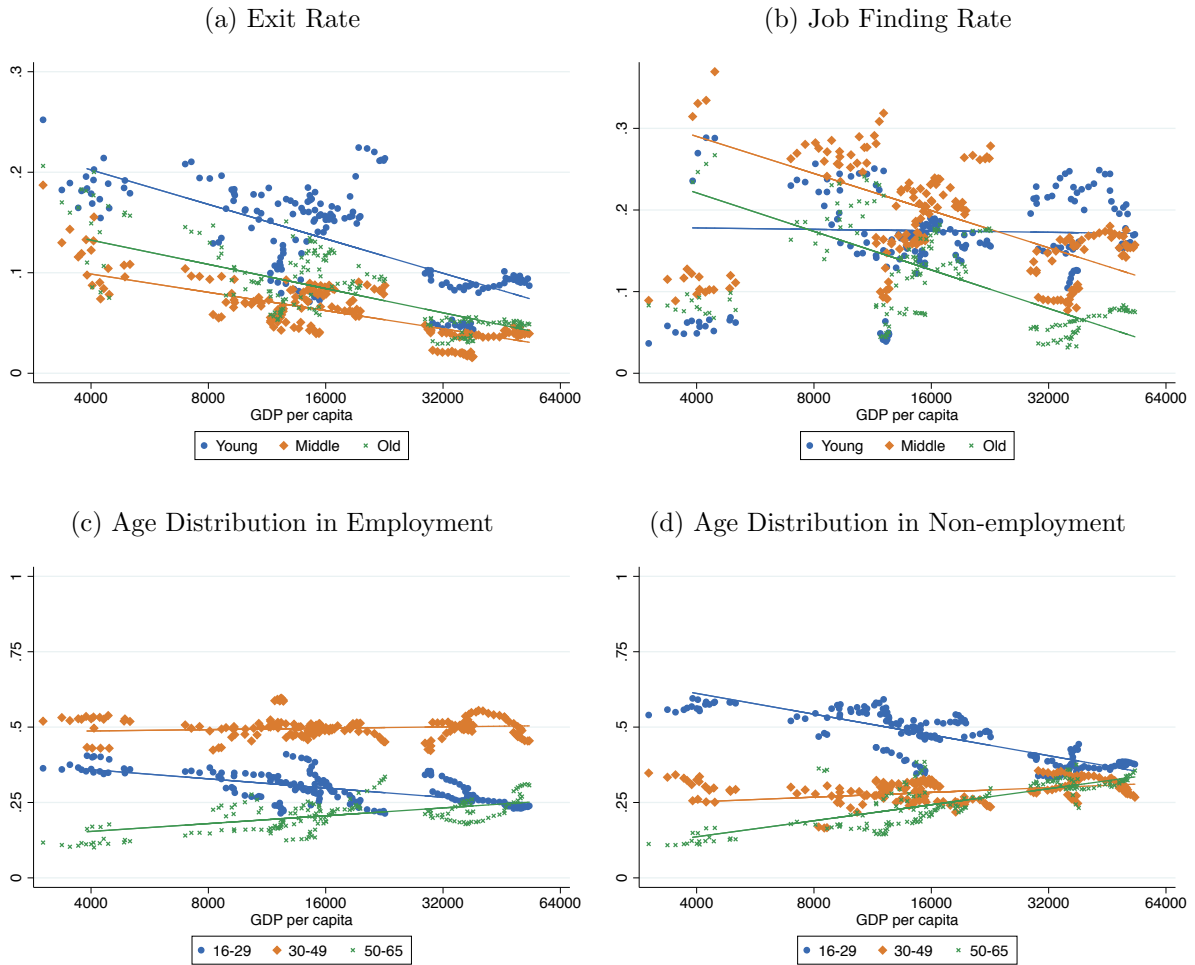
B All Exit Accounting Results

Table 6: Exit Accounting Regressions

	Data $\hat{\beta}_1$	Counterfactual $\hat{\beta}_2$	Share	Data R^2	Counterfactual R^2	Obs.	Countries
Demographics (detailed)	-0.037 (0.003)***	-0.024 (0.003)***	0.35	0.520	0.250	159	12
Demographics (broad)	-0.037 (0.003)***	-0.025 (0.003)***	0.32	0.520	0.269	159	12
Firm Size (detailed)	-0.021 (0.007)***	-0.001 (0.006)	0.95	0.421	0.001	103	10
Firm Size (broad)	-0.049 (0.007)***	-0.016 (0.006)***	0.67	0.302	0.072	107	11
Sectors (detailed)	-0.032 (0.003)***	-0.027 (0.003)***	0.16	0.402	0.342	137	11
Sectors (broad)	-0.038 (0.003)***	-0.037 (0.003)***	0.03	0.568	0.552	161	12
Informality	-0.019 (0.011)*	0.015 (0.013)	1.79	0.056	0.024	55	7
Informality [†]	-0.087 (0.012)***	0.033 (0.008)***	1.38	0.405	0.177	76	9
Temporary [†]	-0.030 (0.004)***	-0.022 (0.005)***	0.27	0.371	0.156	102	11
Occupation [†]	-0.024 (0.003)***	-0.016 (0.003)***	0.33	0.320	0.201	150	12

Table notes: All regressions are computed without country or year fixed effects, with a dependent variable of exit from employment to non-employment. Palestine is not included in any regression. Those marked with [†] have a dependent variable of exit from salaried work only, because the variable is unavailable for self-employed. We run informality regressions on both, as the sample size is quite small. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure B1: Transition Rates by Age



C Additional Results

C.1 Further Results on Demographics

C.1.1 Age

C.1.2 Gender

Figure B2 shows exit and job finding rates by gender. Note that there are indeed important differences in exit rates by gender, as women in poor countries are nearly twice as likely to exit in poor countries, while men and women exit at about the same rates in rich countries

(Figure B2a). As one can see from Figure B2c, however, there is little variation in gender employment shares. Therefore, while there are indeed large differences across genders, female employment differences can explain little of the aggregate variation.

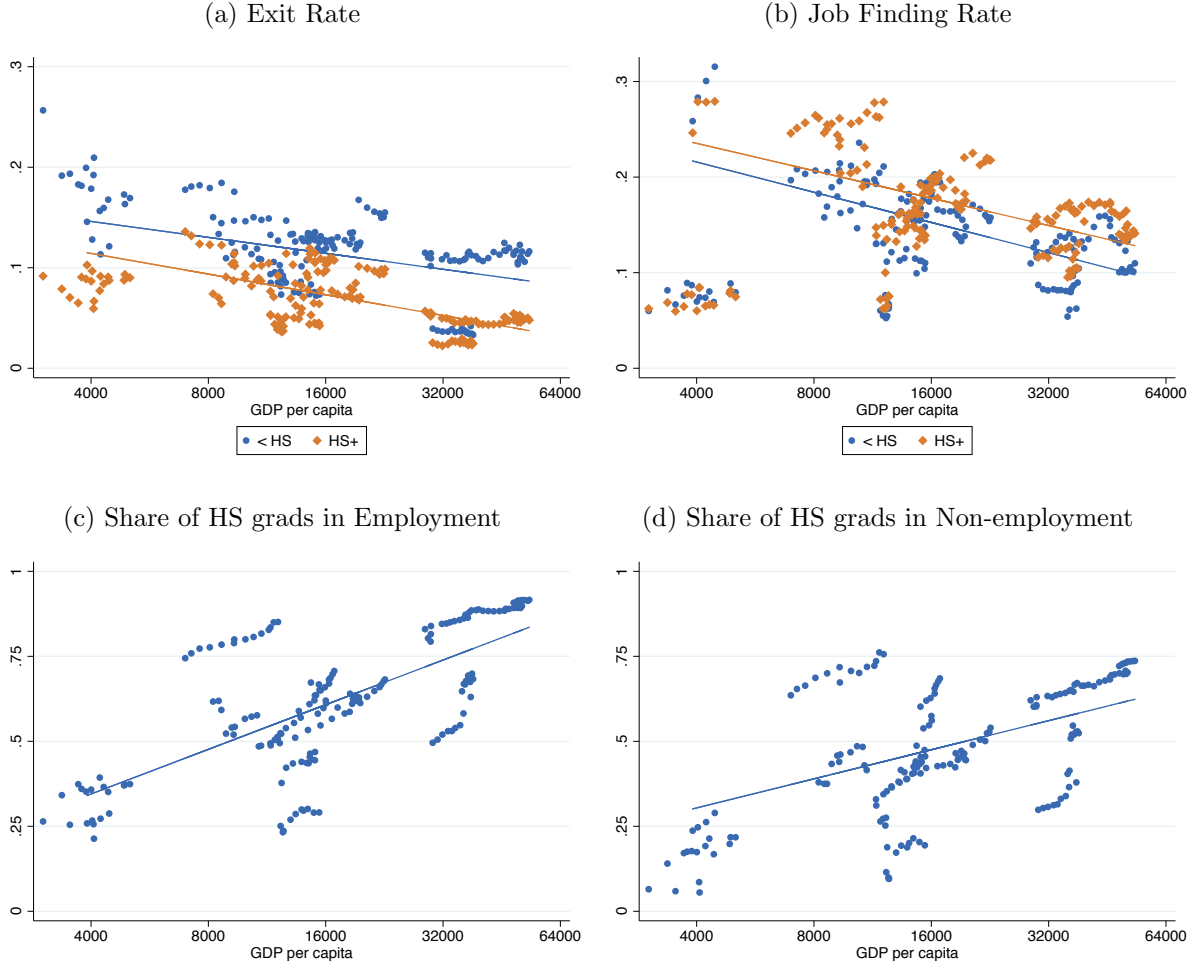
Figure B2: Transition Rates by Gender



C.1.3 Education

Figure B3 shows exit and job finding rates by high school education. As expected, more highly educated individuals are more likely to be employed and less-likely to exit.

Figure B3: Transition Rates by Education

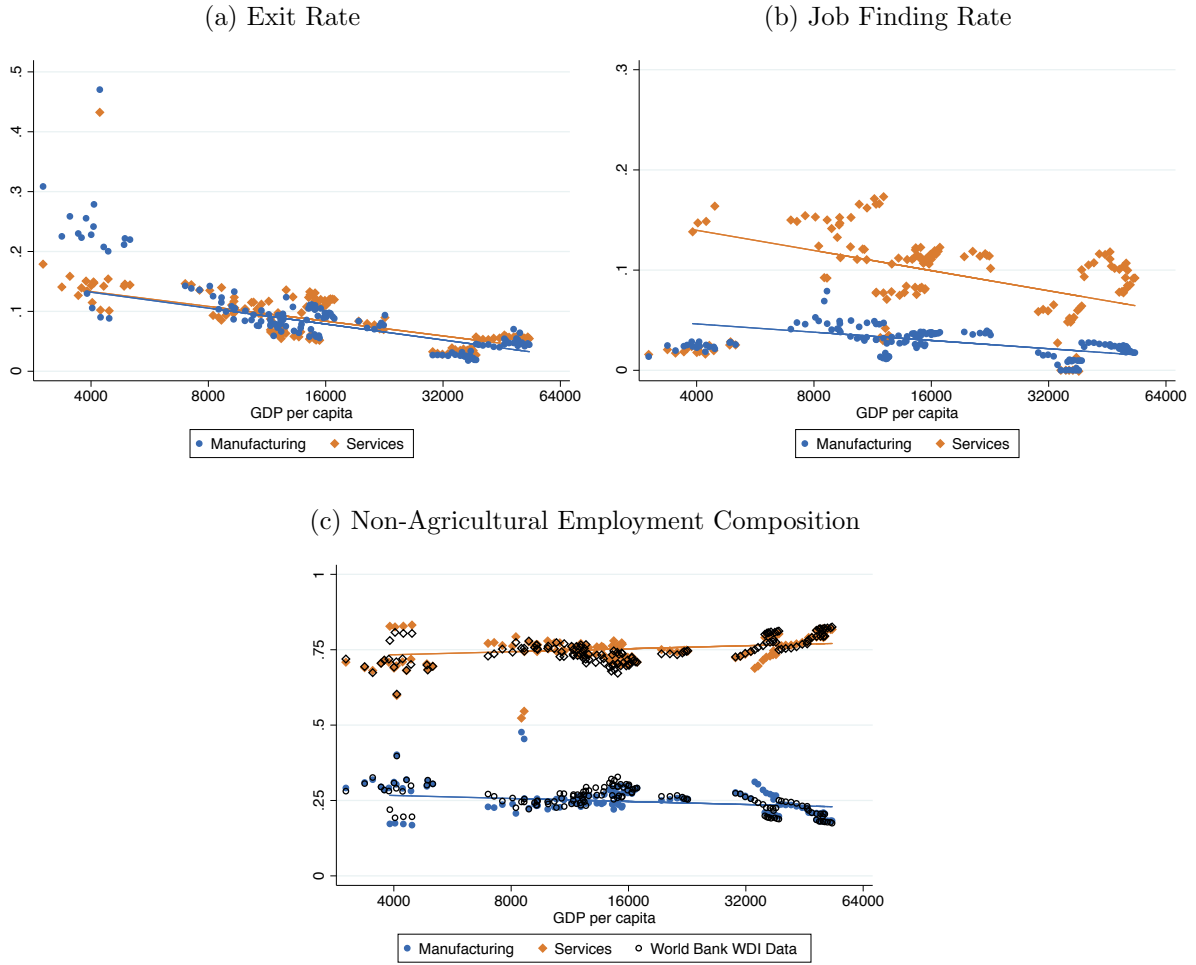


C.2 Further Results on Job and Occupation Characteristics

C.2.1 Sector

Figure B4 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 B4c shows the share of non-agricultural employment in services and manufacturing. As expected, richer countries have more employment in services. Note that we also plot aggregated data from the World Bank World Development Indicators, and find that our measures constructed from micro data line up quite well.

Figure B4: Transition Rates by Sector



C.2.2 Formality

We also consider formality. In some countries, formality is not defined for the self-employed (Argentina, Chile) or for any employment state (Peru, U.K., U.S.A.). We consider both formality by all employed, and also only in salaried work to include more countries.

Figure B5: Transition Rates by Formality, Salaried Work Only



Figure B6: Transition Rates by Formality, All Employment

