Wage employment, unemployment and self-employment across countries*

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Abstract

Poor countries have low wage employment and high self-employment. This paper shows that they also have high unemployment relative to wage employment, and that self-employment increases with this ratio. To understand the sources of these patterns, I build a search and matching model with choice between job search and self-employment and with learning about matches, and calibrate it to match all transition rates between wage employment, unemployment and self-employment as well as separation hazards by job duration, separately for all 37 countries with available data. Quantitative analysis of the model shows that labor market frictions affect self-employment as much as unemployment. Labor market frictions also reduce aggregate output, not only by raising unemployment, but also by worsening the average quality of both wage employment matches and active self-employment projects.

Keywords: wage employment, unemployment, self-employment, labor market frictions, occupational choice, productivity

JEL codes: O11, E24, J64, L26

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1. Introduction

Labor markets in poor countries differ fundamentally from those in richer ones. A central distinguishing feature consists in their very low levels of wage employment, and high self-employment. For instance, in urban areas of countries with GDP per capita below $5,000 (in 2017 int. $), the self-employment rate on average exceeds the wage employment rate (45 vs 43%). In the United States, in contrast, own-account workers make up only about 5% of employment, and wage and salary workers account for about 85% of the labor force.

These differences matter. Indeed, the creation of wage jobs has been identified as a key development challenge, and the employment rate is part of the United Nations Millennium Development Goals (United Nations, 2010). But why is wage employment so low, and self-employment so high, in developing countries?

The existing literature on the topic has mostly focussed on differences in technology, barriers to job creation and firm growth, and the implications of regulation for firm size.[1] In essence, the argument typically is that productivity or wages in wage employment are low in poor countries, while self-employment is comparatively unregulated and easily accessible. As a consequence, many workers enter self-employment.

This paper proposes a different explanation. I argue that low levels of wage employment and high levels of self-employment cannot be understood without taking frictions in labor markets into account. This argument is motivated by the generally high levels of unemployment relative to wage employment in poor countries that I document in this paper. The proposed new mechanism is as follows: As labor market frictions make jobs in wage employment less attractive or hard to find, they not only cause high unemployment relative to wage employment, but also make self-employment relatively more attractive. Variation in labor market frictions across countries then implies both a negative relationship between wage employment and self-employment and a positive relationship between the unemployment to wage employment ratio and self-employment across countries.

The first contribution of this paper is to establish new facts on labor market stocks and

[1]See e.g. Gollin (2007), Restuccia and Rogerson (2008), Buera et al. (2015), and Poschke (2018).

flows across countries. I establish two new facts using harmonized census data provided by IPUMS International (Minnesota Population Center, 2017), covering 53 countries ranging in income per capita from Ethiopia to the United States. First, because the unemployment rate does not vary systematically with income per capita but poor countries have low wage employment, the ratio of unemployment to unemployment plus wage employment, which I call the "*UN* ratio", is much higher in poor countries. On average, it decreases by two and a half percentage points (pp) every time income per capita doubles. As a result, it is almost 10pp larger in the poorest compared to the richest countries. Second, in urban areas, self-employment is particularly high in countries with a high *UN* ratio, even after controlling for GDP per capita. An increase in the *UN* ratio by 1pp is associated with an increase in self-employment by around 1.3pp, or 0.7pp when controlling for GDP per capita. Most poor countries have a high *UN* ratio and high self-employment. I label this combination HUHS. Next, I turn to cross-country data on labor market flows collected and provided by Donovan et al. (2023, hereafter DLS). These data reveal that HUHS countries have much higher job destruction rates, but no higher job finding rates. They also have high flows in and out of self-employment.

To understand the determinants of these differences in flows and stocks, I build a model of frictional labor markets with self-employment, the second contribution of this paper. The model is conceived to be the simplest extension of the Diamond-Mortensen-Pissarides (DMP) search and matching model with endogenous job destruction that can generate flows across *all three* observable labor market states of wage employment, unemployment, and self-employment as well as a job separation hazard that decreases with tenure. Matching flows allows understanding the sources of differences in stocks. The separation hazard is stressed by both DLS and a recent microeconometric literature discussed in more detail below as an important feature of labor markets in poor countries.

To achieve this, I extend the DMP model in four ways. First and foremost, the unemployed choose between searching for a job or entering self-employment. Then, a reduction in the attractiveness of search raises entry. Second, the self-employed differ in productivity. As a result, worse projects are acceptable when the alternative is less attractive, and labor market frictions affect mean self-employment output. Third, to match the decreasing job separation hazard, matches involve screening and learning. If screening is weak, many new matches will turn out to be unsuitable, implying a high destruction rate at low job tenures. Destruction at higher tenures, in contrast, is caused by productivity shocks. This device allows distinguishing differences in shocks from those in screening. Fourth, the model allows for transitions between wage employment and self-employment, which are empirically significant. The possibility of "on the job" (OTJ) search by the self-employed makes some low-productivity self-employment projects worthwhile that otherwise would not be.

The model endogenously generates all the flows among wage employment, unemployment, and self-employment (except for self-employment exit, which is exogenous) and a decreasing exit hazard from wage employment. It also implies reservation productivities for wage and self-employment, which determine mean output in each activity and, in combination with the rates of unemployment and self-employment, aggregate output.

To understand data patterns, I calibrate the model to match all flow rates among wage employment, unemployment, and self-employment as well as the job separation hazard in all the 37 countries in DLS's data. The structural analysis of the determinants of all these moments for such a large number of countries is novel and the third contribution of the paper. Inspecting calibration results reveals that the combination of a high UN ratio and high self-employment in HUHS countries is driven by a combination of parameters: Matches in HUHS countries are only somewhat more costly to create than in the mean country. But they face a low rate of screening and frequent productivity shocks, leading to a high destruction rate. Because self-employment entry is cheap, many individuals opt for that alternative. Heterogeneity in all of these dimensions is required for a good fit of the calibration.

Counterfactual model analysis highlights the connection between unemployment and self-employment. I find that a greater arrival rate of productivity shocks not only raises unemployment, as is standard in DMP models, but increases self-employment by just as much. Higher vacancy posting costs even raise self-employment more than unemployment. These changes in self-employment relative to the UN ratio are quantitatively close to the regression coefficients around 1 found in IPUMS data. These effects vary across countries: High self-employment attenuates the effect of labor market frictions on unemployment, while a high UN ratio amplifies their effect on self-employment. As a result, in HUHS countries, labor market frictions affect the self-employment rate much more strongly than the unemployment rate.

The counterfactual analysis also reveals that labor market frictions have effects on output that go beyond that of higher unemployment. A greater shock arrival rate and higher vacancy posting costs both reduce the average quality of matches, since a lower value of search and more frequent shocks reduce the reservation match productivity. In addition, a lower value of search – the outside option to self-employment – reduces the average productivity of self-employment. These selection effects account for one to two thirds of the aggregate output effect of labor market frictions.

Related literature. Apart from the literature on self-employment cited above, this paper is most closely related to the part of the literature on labor market search that takes into account the option of self-employment. Early papers are Fonseca et al. (2001) and Rissman (2003), who study the effect of entry costs and unemployment insurance in OECD countries, as do Bradley (2016) and Galindo da Fonseca (2022) more recently. Albrecht et al. (2009), Margolis et al. (2012) and Narita (2020) analyze job search and self-employment (sometimes called an informal or traditional sector) in individual poorer countries, with a focus on policy reforms. Rud and Trapeznikova (2021) analyze the interplay of job search and wage inequality in several Sub-Saharan African countries. Feng et al. (2018) study the effect of skill biased technology on patterns in unemployment across countries at the national level. Only the last two consider more than a single country. Except for Narita's (2020) detailed study of Brazil, none of these papers allow for the full set of flows across unemployment, wage employment and self-employment. In addition, most assume exogenous job destruction, and none allow for a role of information frictions or a decreasing job loss hazard.

My findings – a low rate of screening, more frequent match productivity shocks, and a low cost of self-employment entry in HUHS countries, combined with a slightly higher cost of vacancy creation – echo mechanisms that have been studied in the literature in isolation for individual countries.

The idea that matches are experience goods has a long tradition (see e.g. Jovanovic, 1984; Pries and Rogerson, 2005, 2022). Screening is likely to be even harder where education levels are low and skill certification less common. Indeed, Bassi and Nansamba (2022), Carranza et al. (2019) and Abel et al. (2020) find that providing references or certifying worker skills improves matching outcomes. Blattman and Dercon's (2018) observation that manufacturing firms in Ethiopia do not face a shortage of job applicants, but experience high rates of quits and turnover also suggests obstacles to screening. More frequent firm-level productivity shocks are consistent with a more uncertain and volatile economic environment in poor countries, as amply documented by Koren and Tenreyro (2007), Ahir, Bloom and Furceri (2022) and others.

A lower cost of self-employment entry can arise from scarce enforcement of regulation on such firms (see e.g. the review Ulyssea, 2020). In addition, own-account workers in poor countries perform less skill-intensive activities with lower setup costs compared to those in richer countries (Gindling and Newhouse, 2012; Shi, 2023). A greater vacancy posting cost may simply be due to hiring and firing costs faced by firms (Créchet, 2023), which have been documented for some HUHS countries. In my setting, it can also reflect search costs for workers or matching frictions, which Franklin (2018), Abebe et al. (2021a,b), Beam (2016) and Banerjee and Chiplunkar (2018) document in individual countries. Lagakos et al.'s (2018) finding of flatter experience-wage profiles in poorer countries is also consistent with more severe search frictions. A common theme in these studies are information frictions in matching, which may result in quick separations and high churn. This is in line with the steep employment exit hazards that Donovan et al. (2023) observe in poor countries.

Compared to this rich recent literature, the present paper is the first one to quantitatively analyze the full matrix of flows as well as the separation hazard in a cross-section of countries.

The next section documents the joint relationship of wage employment, self-employment, unemployment and GDP per capita across countries. Section 3 presents the model. Section 4 describes the calibration, and Section 5 presents counterfactual similation results.

2. Wage employment, unemployment and self-employment across countries: Evidence

This section presents evidence on the relationship between wage employment, self-employment and unemployment across the income distribution of countries.

2.1. Data sources and measurement

I use two main data sources: census data for a large number of countries from IPUMS (IPUMS International, Minnesota Population Center (2017)), and data on labor market flows for 37 countries from Donovan et al. (2023, hereafter DLS).

IPUMS. IPUMS provides access to micro data from almost 200 censuses collected in more than 60 economies. This allows computing measures of wage employment, self-employment and unemployment for many countries not only for the aggregate economy, but also for subgroups, like urban residents. My main sample consists of urban residents of both sexes aged 20 to 65, from countries with a population of at least one million. Income per capita throughout is in 2017 international US dollars, converted at PPP, from the World Bank's World Development Indicators, available from 1990 onwards for most countries.

My definitions of wage employment, self-employment and unemployment follow those in the UN System of National Accounts. The wage-employed receive remuneration for their labor. The self-employed include both employers and own-account workers, which I distinguish where possible. The unemployed do not currently work, but are available and actively searching for work. In the IPUMS data, I use the harmonized variables EMPSTAT and CLASSWK to identify individuals as either self-employed, wage or salary workers, unpaid workers, or other, according to their main job.

The only concern regarding comparability comes from the fact that the reference period for job search varies across censuses, and occasionally is not specified. Therefore, I group the censuses into quality tiers, in a way similar to Feng et al. (2018).[2] Results shown below

[2]Like Feng et al. (2018), I assign the top quality tier where the reference period for EMPSTAT is clearly specified as the past week, the second tier if it is the last four weeks, and the third tier otherwise.

are generally similar when restricting the analysis to the top tier, apart from occasionally lower statistical significance due to lower sample size.

Because many rural workers in poor countries work in agriculture, with non-agricultural self-employment rather than wage employment as the main alternative (see e.g. Alvarez-Cuadrado et al., 2019), my main analysis uses data for urban areas. This also ensures consistency with DLS's data. I report results for the entire country where informative.

My IPUMS analysis sample consists of 100 censuses covering urban areas in 53 countries, of which 35 with average GDP per capita across censuses below $10,000. At the country level, there is information for an additional 13 countries. For robustness, I also consult aggregate measures of unemployment and self-employment from the ILO. An important disadvantage of this source is that only country-level measures are available.

DLS. The IPUMS data do not contain any information on labor market flows. For this, I turn to data from the large scale harmonization and measurement exercise of DLS. DLS have used data from rotating panel labor force surveys for many countries to measure flow rates between wage employment, self-employment, unemployment, and out of the labor force as well as exit hazards from wage employment to unemployment by job tenure. These data are available for 433 surveys from 37 countries with a population over one million. Unfortunately, only two of these countries have average GDP per capita below $10,000. Hence, my analysis of stocks draws on IPUMS data with their more complete country coverage, while I use DLS's data for measures of labor market flows.

2.2. The distribution of labor force status and development

Figure 1 depicts the prevalence of different types of labor force status in urban areas by country log income per capita. The figure shows, for each country, cumulative shares. For any country, the lowest marker (triangles) shows the unemployment rate u, the difference between the black dot and the triangle shows the share of wage/salary workers n, and the difference between the grey dot at the top and the black dot shows the self-employed rate e. The difference between the grey dot and one gives the fraction of "other". This is negligible, so I ignore it in the following. I also exclude unpaid workers, who account for a very small share of the urban labor force even in the poorest countries. For each set of points, I plot a line of best fit for an OLS regression on log GDP per capita. The shading of areas clearly highlights the prevalence of different employment statuses by GDP per capita.

[Figure 1 about here.]

It is immediate from the figure that wage employment is much less common in poor countries. Wage employment rates range from about 40% in urban areas of the poorest countries to over 80% in the richest ones. The self-employment rate, in contrast, is much higher in poor countries, at almost 50% compared to only 10% in rich countries, echoing the well-known finding of Gollin (2007). The urban unemployment rate is quite variable but does not vary systematically with development, in line with Caselli (2005) and DLS.

[Table 1 about here.]

Regression results using country averages are reported in Table 1. They are similar when censuses are pooled (see Table A.1 in the Appendix). The unemployment rate does not vary systematically with log income per capita in urban areas, whereas the wage employment rate and the self-employment rate vary symmetrically: the self-employment rate declines by 0.13 percentage points (pp) for each 1% increase in income per capita, and the wage employment rate increases by roughly the same amount. The middle panel of the table and Figure A.1 show that at the country level, the patterns are similar for wage employment and self-employment, whereas the unemployment rate increases slightly with log GDP per capita. The bottom panel shows that the difference between urban and national results cannot be attributed to differences in the sample. Table A.2 shows that results are essentially identical when only information from countries in the top tier of data comparability is used.

[Table 2 about here.]

The top panel of Table 2 shows that the overall pattern in self-employment is driven by own-account workers, who on average account for 88% of the self-employed. The fraction of employers is actually higher in richer countries.

The UN ratio. Figure 1 clearly shows the importance of self-employment in poor economies. It also shows that the unemployment rate $u/(u+n+e)$ does not vary with income per capita in urban areas. This invariance hides a systematic relationship: the denominator of the unemployment rate contains many wage employees and few self-employed in rich countries, but few wage employees and a large number of self-employed individuals in poor countries. That is, the reason why the unemployment rate is not higher in poor countries despite low n consists in high e. In fact, higher e systematically reduces u unless *all* the additional self-employed would be wage-employed otherwise.

Because of the influence of self-employment, the unemployment rate provides a count of the unemployed, but does not accurately reflect the consequences of job destruction or the incidence of failed job search. An alternative measure of unemployment is the "*UN* ratio" $u/(u+n)$. This is of course identical to u in a world without self-employment. Since the *UN* ratio differs from u only in its denominator, it has a similar order of magnitude. While u has a median of 8.4% (10th percentile: 4.3%, 90th percentile: 20.4%) in the IPUMS data, the *UN* ratio has a median of 12.3% (10th percentile: 6.2%, 90th percentile: 28.8%).[3]

Since u does not vary systematically with GDP per capita, but poor countries have systematically lower wage employment, it is clear from Figure 1 that the *UN* ratio attains systematically higher values in these countries. This is corroborated by the regression coefficients in the last column of Table 1, which are economically and statistically significant. The *UN* ratio declines by 2.5 pp as country income per capita doubles.[4]

2.3. Self-employment and unemployment

Less attractive job search could be expected to affect occupational choice, pushing the unemployed away from job search and encouraging own-account work. High self-employment in poor countries may thus at least partly be due to lower attractiveness of job search.

[3] The unemployment to wage employment rate u/n has similar properties and implies similar results.

[4] Table A.3 in the Appendix shows that this finding is not due to differences in demographics, since it holds within age group, both in urban areas and for the entire country. The relationship is slightly stronger when a narrow measure of the unemployment rate is used, both for urban areas and for the entire country (not shown). Finally, Table A.4 in the Appendix shows that the relationships between the e, u, the *UN* ratio and GDP per capita are similar in ILO data.

[Figure 2 about here.]

Figure 2a shows the bivariate relationship between the self-employment rate and the *UN* ratio. It is clear that there is a positive relationship between the two variables for almost the entire range of the *UN* ratio. (The relationship flattens above the 90th percentile of the *UN* ratio due to the influence of a few censuses. Figure A.2a shows the full range and includes country labels.) A non-linear (locally weighted) regression, shown as a dashed line, produces almost exactly the same fit. The relationship is also present at the level of the entire country (Figure A.2b). The relationship is economically and statistically significant, with a regression coefficient of 1.31 (middle panel of Table 2).

Up to the 90th percentile of the *UN* ratio, the relationship is robust to also controlling for log GDP per capita (bottom panel of Table 2). An increase in the *UN* ratio by 1pp, at a constant level of GDP per capita, is associated with an increase in the self-employment rate by 0.7pp, due to an increase in the fraction of own-account workers by 0.8pp.[5]

Figure 2b shows self-employment rates and *UN* ratios from DLS data. Here, too, there is a positive relationship between the two, although it is attenuated due to differences in country coverage. The regression line has a slope of 0.61, with a standard error of 0.28.

Patterns by (UN,SE)-quadrant. To ease comparisons across data sets, I divide the (*UN*,SE)-space in Figure 2 into four quadrants, with a vertical line at a *UN* ratio of 0.1 and a horizontal line at a self-employment (SE) rate of 0.2.[6] Refer to the top right quadrant as HUHS (high *UN* ratio, high self-employment), the bottom right ones as HULS, (high *UN* ratio, low self-employment) etc. The combination of the mean *UN* ratio and mean self-employment rate in each quadrant is indicated by a red triangle.

[5]Results are similar in pooled data (Table A.5). When only using data in the top data comparability tier, point estimates are very similar but standard errors grow due to the smaller sample size (Table A.6). At the level of the entire country, the inclusion of GDP per capita in the regression leads to an insignificant coefficient on the *UN* ratio (Table A.7, and Table A.8 using ILO data). This is in line with the predominance of subsistence agriculture and generally small role of wage employment in rural areas of poor countries.

[6]10% is close to the mean *UN* ratio in the sample (10.6%), and slightly above the median of 8.4%. A self-employment rate of 20% is only the 28th percentile of the self-employment rate in the IPUMS data, but close to the median in DLS's data. Strictly speaking, these dividing lines are arbitrary. But they generate a division of the sample into "high" and "low" *UN* ratio and self-employment that is useful. Results below do not hinge on precise dividing lines.

Table 3 describes each quadrant in more detail. Quadrant LULS contains only a small share of countries in the IPUMS sample, but accounts for 80% of countries with GDP per capita above \$25,000. The DLS data similarly indicate that many rich countries are in this quadrant. Quadrant HUHS accounts for the bulk of the IPUMS sample (44% of countries). It is dominated by poor countries, with mean GDP per capita in the quadrant below \$5,000, and contains 60% of countries with mean GDP per capita below \$10,000. While the DLS data contain few poor countries, all but one of them lie in this quadrant. HULS contains predominantly rich and middle income countries, in both data sets. LUHS contains poor and middle income countries. It accounts for almost 30% of poor countries in IPUMS. Summarizing, most rich countries are in quadrant LULS. In contrast, almost all poor countries have high self-employment, in most cases combined with a high *UN* ratio, putting them into HUHS or (less frequently) into LUHS.

[Table 3 about here.]

While the quantitative analysis covers all countries in the DLS data, I highlight one "focus" country from each quadrant for concreteness. These are large countries that are present in both data sets: the USA (LULS), Brazil (HUHS), Mexico (LUHS) and South Africa (HULS). Apart from the US, these are all middle income countries. (No poor country is present in both data sets.) They are labelled in Figure 2.

2.4. Flows

The quantitative analysis will match flows in each country. As DLS have shown, labor market flows differ with GDP per capita. In a nutshell, apart from the job (wage employment) finding rate of the unemployed, labor market flow rates are higher in poor countries. For an extensive set of figures documenting this, refer to DLS or Figure A.3.

Table 3 shows flows and stocks by quadrant. (See Table A.9 and Figure A.3 for the focus countries.) By definition, they differ in *UN* ratio and in self-employment. What differences in flows lead to this? HUHS countries only have a slightly lower job finding rate ($P(UW)$) than LULS countries, but a job destruction rate ($P(WU)$) that is almost three times as large.

They also have a four times higher self-employment exit rate. All these forces contribute to higher unemployment in HUHS countries. An almost six times larger self-employment entry rate from unemployment more than counterbalances the high self-employment exit rate, and implies a high level of self-employment.

The bottom part of each panel of Table 3 shows job separation hazards, or exit hazards from wage employment into unemployment, by job tenure. It shows that both the short term and the long term separation hazards are significantly higher in HUHS than in LULS. The absolute difference is larger for short tenures, and the relative one for high tenures.[7]

HULS countries combine a low job finding rate with a high destruction rate, in particular early in matches, leading to high unemployment. Because their self-employment entry rate is comparable to that in LULS countries, the self-employment rate is similarly low. LUHS countries, in contrast, combine a high job finding rate (which leads to low unemployment despite a fairly high destruction rate) with high self-employment entry.

Summarizing the analysis in this section, the comparison of urban labor markets of countries at different stages of development reveals four regularities: Labor markets in poor countries feature (1) systematically lower wage employment and higher self-employment rates, and (2) higher rates of unemployment relative to wage employment (a higher *UN* ratio). In addition, (3) self-employment is higher in countries with a high *UN* ratio, even conditional on GDP per capita. (4) In terms of flows, countries with a high *UN* ratio and high self-employment stand out for their high rate of job destruction, at both short and long tenures, and their high self-employment entry and exit rates.

3. A model of frictional labor markets with endogenous entry into self-employment

The second objective of this paper is to develop a simple model that can account for key features of labor markets not just in advanced economies, but for a broad cross section of

[7]Note that the US is very different from the average LULS country, with job finding and destruction rates that are about twice as large (see Table A.9 and Figure A.3). This implies that HUHS countries are more different from the US in terms of job finding rates, but less so in terms of destruction rates. Differences to the US in the latter are almost entirely due to separations in jobs that are less than half a year old.

countries. In particular, the model is designed to generate flows across *all three* observable labor market states of wage employment, unemployment, and self-employment.

I base the model on a version of the Diamond-Mortensen-Pissarides (DMP) model of random search and matching with endogenous job destruction, close to Pissarides (2000, Chapter 2). Compared to a standard DMP model, I extend the model in four ways. First, the unemployed can choose whether to search for a job or enter self-employment, at a cost. This generates a flow from unemployment to self-employment. Second, not only matches but also self-employment opportunities differ in productivity, implying that there are selection effects. Third, some matches will eventually turn out to be "unsuitable". This may be learned at entry or later, implying that "screened" and "unscreened" matches coexist. This allows the model to match decreasing employment exit hazards by job tenure and their variation across countries. Fourth, the wage employed and the self-employed occasionally receive opportunities (which they may accept or reject) to switch to the other working state. This generates flows between wage employment and self-employment.

As a result, the model is able to replicate the full flow matrix across wage employment, unemployment, and self-employment, as well as the employment exit hazard. The calibration exercise in the next section then reveals which parameter values are required to generate the observed flow matrices and exit hazards in the 37 countries in the DLS data.

3.1. States, flows and the labor market

Time is discrete. The economy consists of a measure one of ex ante homogeneous individuals. They value the present value of income, applying a discount factor β.

An individual can be in exactly one of four states: unemployment (U), screened (W^s) or unscreened (W^u) wage employment in an employer firm, or self-employment (E). In the data, only W, the union of W^s and W^u, is observed. Let the measures of the four states be u, n^s, n^u and e. Any period, an individual in state A can flow to any state A', $A, A' \in \{U, W^s, W^u, E\}$ (with one exception). Let $P(AA')$ be the flow rate from A to A'.

Job search and matching. The unemployed can choose whether to search for wage employment or to enter self-employment. Job seekers enter a frictional labor market, where they search for vacancies posted by employers at a per period cost k_v. The number of matches per period is given by a standard Cobb-Douglas matching function. Let labor market tightness be θ. Then, as usual, the job finding probability for a searcher is $\theta q(\theta)$, which increases in θ. The vacancy filling probability for a firm is $q(\theta)$, with $q'(\theta) < 0$.

Wage employment and screening. Output is produced in firm-worker matches, which are the combination of a firm and one worker. Each match has specific productivity y. New matches produce output y_0 per period. Every period, a new match productivity y is drawn from a distribution $\tilde{G}(y)$ with probability λ. Let $G(y) \equiv 1 - \tilde{G}(y)$. When this occurs, the worker and the firm may decide to dissolve the match. As shown below, it is optimal to do so if productivity is lower than a reservation productivity level R.

Regardless of y, a fraction π of new matches is "suitable", and a fraction $1 - \pi$ is not. When a worker and a firm meet, they screen for suitability, and learn it with probability p_0 (the screening rate). With probability $1 - p_0$, screening is inconclusive. Then suitability of a match is revealed in each future period with probability p_1. At any time, the match is dissolved if it is found to be unsuitable. In the following, I refer to screening status as s(creened) and u(nscreened), and use the generic index $i = s, u$.

A fraction $p_0\pi/(p_0\pi + 1 - p_0)$ of new matches is "screened" and suitable. This fraction increases every period with learning, and eventually goes to 1. Almost all old matches are screened, so that their destruction only reflects productivity shocks. In contrast, the separation rate for the youngest matches mostly depends on the screening rate p_0, which determines how many new matches remain unscreened and thus at risk of dissolution. The learning rate p_1 determines the rate of decline of the hazard function. This structure is inspired by the models of learning about match productivity of Jovanovic (1979), Moscarini (2005), Pries and Rogerson (2005) and Menzio and Shi (2011) and the model in DLS. Uncertainty about match suitability rather than productivity makes the problem more tractable. Lack of suitability of a match can be interpreted as a host of match attributes that are only learned over time, like personal incompatibilities or low medium to long-term productivity.

Self-employment. All entrants into self-employment draw a permanent level of per-period output z from a distribution $\tilde{H}(z)$. Let $H(z) \equiv 1 - \tilde{H}(z)$. As shown below, they return to unemployment if z is below a reservation productivity $\bar{z}$.

Unemployed agents may enter self-employment by paying a startup cost k_f. This cost is common across agents. It increases in the aggregate entry rate from unemployment e_{in}, with $k_f = \bar{k}_f e_{\text{in}}^{\varepsilon}$.

The wage employed receive a self-employment "opportunity" with probability χ per period. In this case, they may enter self-employment costlessly. Whether this opportunity is accepted depends on match productivity y and screening status i. Define $\chi^i(y) = \chi$ if it is optimal to accept the opportunity, and zero otherwise.[8]

The active self-employed face a probability δ per period of having to exit to unemployment.[9] In addition, they engage in on the job search, and find a match with probability $\zeta\theta q$. After learning the outcome of screening, they decide whether to accept the job. Let $d^i(z) = 1$ if it is optimal to accept a job of type i. With search by both the unemployed and the self-employed, tightness is $\theta = v/(u + \zeta e)$.

[8] Given that all entrants take a draw from the same productivity distribution, in equilibrium, the wage employed only enter self-employment if they face a lower entry cost. Economically, this can be interpreted as a lower cost of finding clients, thanks to relationships that persist from the previous wage job. In practice, the level of the entry cost for the wage employed and χ cannot be identified separately from the aggregate flow data provided by DLS. So I normalize the entry cost of the wage employed to zero.

[9] An alternative would be to model self-employment exit as endogenous in response to productivity shocks, just as job destruction. Given the lower value of the outside option of job search in HUHS countries, the self-employed in these countries would have a lower exit threshold. This would imply that even larger differences in δ between HUHS and LULS countries would be required to match the difference in self-employment exit shown in Table 3.

Flows. The outcomes of these choices imply a transition matrix of labor market states $\mathbf{P}$, with generic element $P(AA')$:

$$
\begin{aligned}
P(UW^s) &= (1-e_{\text{in}})\theta q p_0 \pi & P(UW^u) &= (1-e_{\text{in}})\theta q(1-p_0) \\
P(UE) &= e_{\text{in}} H(\bar{z}) & & \\
P(W^s W^u) &= 0 & P(W^s(y)E) &= \chi^s(y)G(\bar{z}) \\
P(W^s(y)U) &= (1-\chi^s(y))\lambda G(R^s) + \chi^s(y)(1-G(\bar{z})) & & \qquad (1) \\
P(W^u W^s) &= (1-\chi^u(y))(1-\lambda)p_1\pi & P(W^u(y)E) &= \chi^u(y)G(\bar{z}) \\
P(W^u(y)U) &= (1-\chi^u(y))[\lambda G(R^u) + (1-\lambda)p_1(1-\pi)] + \chi^u(y)(1-G(\bar{z})) & & \\
P(E(z)W^s) &= (1-\delta)\zeta\theta q p_0 \pi d^s(z) & P(E(z)W^u) &= (1-\delta)\zeta\theta q(1-p_1)d^u(z) \\
P(EU) &= \delta & &
\end{aligned}
$$

Apart from $P(EU) = \delta$, all these flow rates are endogenous. They depend on market tightness, which depends on vacancy posting and the choice of job search versus self-employment entry, as well as on several reservation productivities. Flows between wage employment and self-employment also depend on the productivity in the origin state, so that aggregate flow rates between these states depend on distributions.

Stocks and the modified Beveridge curve. It is instructive to derive the Beveridge curve for a simplified version of this dynamic system. Consider the case where $p_0 = 1$ and $\pi = 1$ (so all matches are screened with positive result), and $\chi = \zeta = 0$ (so there are no flows between wage employment and self-employment). Then steady state unemployment is

$$u = \frac{\lambda G(R)}{\theta q + \lambda G(R) + e_{\text{in}}(H(\bar{z})/\delta - \theta q)}. \qquad \text{(MBC)}$$

This is the usual Beveridge curve, modified for the presence of self-employment. How this affects u depends on the rate of successful entry $H(\bar{z})$ and the self-employment exit rate δ compared to the rate of successful job search, θq. Since e_{in} is an equilibrium object, the presence of attractive self-employment opportunities tends to reduce u.

3.2. Agents' problems, value functions, and occupational choice

Unemployment, self-employment entry and search. The unemployed choose between job search and self-employment entry, so the value of unemployment is $U = \max(S, Q - k_f)$, where S is the value of search, Q the expected value of entry, and k_f the equilibrium entry cost. With free self-employment entry, in equilibrium

$$S = Q - k_f = U \quad \text{and} \quad k_f = Q - U \tag{OC}$$

The value of search is

$$S = b + \beta\theta q \left[p_0 \pi W^s(y_0) + (1 - p_0)W^u(y_0)\right] + \beta(1 - \theta q + \theta q p_0(1 - \pi))U, \tag{2}$$

where b is the flow value of unemployment. The possibility of a match being unsuitable reduces the probability of successfully finding a job.

Workers. Employed workers receive a wage w per period. Wage determination is discussed below. Given the flows just described, the value of a screened job to a worker is

$$W^s(y) = w^s(y) + \beta(1 - \chi^s(y))[(1 - \lambda)W^s(y) + \lambda E(\max(W^s(y'), U))] + \beta\chi^s(y)Q. \tag{3}$$

With probability λ, a productivity shock arrives, which results in separation if $W^s(y') < U$. The value of an unscreened job to a worker is

$$\begin{aligned} W^u(y) = w^u(y) + \beta(1 - \chi^u(y))\{&p_1\pi[(1 - \lambda)W^s(y) + \lambda E(\max(W^s(y'), U))] \\ &+ (1 - p_1)[(1 - \lambda)W^u(y) + \lambda E(\max(W^u(y'), U))] + p_1(1 - \pi)U\} + \beta\chi^u(y)Q. \end{aligned} \tag{4}$$

Unscreened workers not only face productivity shocks, but also the possibility of a positive screening outcome, converting their match into a screened one, or a negative outcome, resulting in unemployment. A worker of any type may receive an opportunity to enter self-employment costlessly with probability χ per period. This yields Q, so it is optimal to accept if $Q > W^i(y)$, which is the case if y is below the threshold y^i_Q at which $W^i(y) = Q$. Thus, $\chi^i(y) = \chi$ for $y < y^i_Q$ and 0 otherwise.

Jobs. Firms maximize the present value of profits. They are ex ante homogeneous. The value of a filled screened job to a firm is

$$J^s(y) = y - w^s(y) + \beta(1 - \chi^s(y))[(1-\lambda)J^s(y) + \lambda E(\max(J^s(y'), 0))]. \tag{5}$$

The match is subject to productivity shocks, and may be dissolved if it yields negative value at the new productivity level y'. It also dissolves if workers receive and accept a self-employment opportunity. The value of an unscreened job to a firm, given in equation (B.1) in the Appendix, is similar but lower because the match might turn out to be unsuitable.

Firms can post vacancies at a cost k_v to hire a worker. The value of a vacancy is

$$V = -k_v + \beta q\left[p_0 \pi J^s(y_0) + (1 - p_0)J^u(y_0)\right] \tag{6}$$

The vacancy is filled with probability q, and may result in a screened or an unscreened match. Free entry (until $V = 0$) then yields the typical free entry condition

$$\frac{k_v}{q} = \beta\left[p_0 \pi J^s(y_0) + (1 - p_0)J^u(y_0)\right]. \tag{JC}$$

Wages. Wages are determined by Nash bargaining. The worker's bargaining weight is η. This implies a sharing rule

$$(1 - \eta)(W^i(y) - U) = \eta J^i(y) \tag{7}$$

for all $i = s, u$ and y. Using the value functions, this implies that the wage is

$$w(y) = \eta y + (1 - \eta)[(1 - \beta)U - \beta\chi^i(y)k_f] \tag{8}$$

for both screened and unscreened matches. This expression is standard, except for the last term, which captures the fact that the contribution of self-employment opportunities to match surplus (worth $k_f = Q - U$) is shared between the firm and the worker, so that its presence reduces the wage. Screened and unscreened wages are identical for given productivity apart from $\chi^i(y)$ because the matches only differ in the separation rate. This affects both shares of the surplus in the same way, leaving the wage unaffected.

Job destruction. With this wage function, the value of a screened match becomes

$$J^s(y) = \frac{1}{1-\beta(1-\lambda)(1-\chi^s(y))}\{(1-\eta)[y-(1-\beta)U+\beta\chi^s(y)k_f] \\ +\beta\lambda(1-\chi^s(y))E[\max(J^s(y'),0)]\}\,. \tag{9}$$

This is a piecewise linear function of y. (Piecewise because of $\chi^s(y)$.)

It is only optimal to operate matches that generate non-negative surplus. Given the sharing rule, workers and firms agree that the worst match to operate generates $J^i(R^i) = 0$. This implies that the reservation productivity for a screened match is implicitly defined as

$$R^s = (1-\beta)U - \beta\chi k_f - \frac{\beta\lambda(1-\chi)}{1-\eta}G(R^s)E(J^s(y')|y' > R^s). \tag{JD}$$

The potential opportunity of self-employment entry adds to match value and thus reduces the reservation productivity. Note that for $y = R$, accepting a self-employment opportunity is always optimal because in an equilibrium with entry, $Q > U = W(R)$. Hence, $\chi(R) = \chi$. R^u is given in equation (B.2) in the Appendix.

Self-employment. The value of ongoing self-employment with productivity z is

$$F(z) = z + \beta\{(1-\delta)[(1-\zeta\theta q+\zeta\theta q p_0(1-\pi))F(z) + \zeta\theta q(p_0\pi\max(W^s(y_0),F(z)) \\ + (1-p_0)\max(W^u(y_0),F(z)))] + \delta U\} \tag{10}$$

Self-employment income z flows until exit or a switch to wage employment occurs. The latter arises with probability $\zeta\theta q$, if a new match is preferable to self-employment. Since match value is independent of z, switching is optimal if $z < z^i_W$, where z^i_W is z s.t. $F(z) = W^i(y_0)$. Thus $d^i(z) = 1$ if $z < z^i_W$.

Self-employment entrants draw their productivity z. Hence, the value of entry is

$$Q = E(\max(F(z),U)). \tag{11}$$

For low productivity draws, it is preferable to return to unemployment. The reservation self-employment productivity is $\bar{z} \equiv \{z|F(z) = U\}$.

3.3. Equilibrium

A stationary equilibrium consists in value functions $W^i(y), J^i(y), F(z)$, values U, S, Q, V, a transition matrix $\mathbf{P}$, distributions $n^i(y), e(z)$, a mass u, thresholds $R^i, \bar{z}, z_W^i, y_Q^i$, policy functions $\chi^i(y), d^i(z)$ and numbers θ, k_f and e_{in}, for $i = s, u$, such that individuals and firms behave optimally.

The key equilibrium objects are U, R^i and k_f. The wage employment side of the model is standard, apart from the role of k_f. The job creation and destruction conditions, depicted in Figure 3a for a fixed value of k_f, are familiar: A higher outside option U raises the reservation productivity R (JD), and a higher reservation productivity reduces vacancy posting and thus the value of unemployment (JC). These conditions determine equilibrium U and R^i, and thus also θ and $w(y)$, for given k_f.[10]

Self-employment entry and flows between wage and self-employment are new in this model. Figure 3b shows how equilibrium k_f and thus self-employment entry is determined. First, due to $\chi > 0$, greater k_f raises the value of wage employment, and thus also U, as it shifts both JC and JD right in Figure 3a. This is captured by the line labelled $U(k_f)$. For empirically plausible χ (the graph is drawn using US parameter values), this effect is weak. Second, given a productivity distribution of self-employment, greater U makes entry less attractive, implying lower willingness to pay k_f. This is captured by the downward-sloping line labelled OC. The intersection of the two lines determines equilibrium k_f and U.

[Figure 3 about here.]

Comparative statics of the model now include changes in self-employment and their feedback to unemployment on top of those familiar from DMP. For example, consider an increase in the shock arrival rate λ. This reduces job creation (JC shifts left) and the reservation productivity (JD shifts down), due to a greater option value. R unambiguously decreases. It can be shown that generally, the first shift dominates, and θ and U decline. Despite lower job destruction, the effect of lower hiring dominates, and unemployment increases.[11]

[10] It is convenient here to show U instead of θ on the axis. The figure also ignores screening, for simplicity.

[11] This holds if the match productivity distribution is log concave, as required for a downward-sloping Beveridge curve in models with endogenous job destruction (Flinn and Heckman, 1983; Pissarides, 2000).

These changes shift the $U(k_f)$ line left in Figure 3b. Q only falls slightly via OTJ search of the self-employed, so equilibrium U falls and k_f rises. Self-employment entry increases, mitigating the increase in unemployment. Finally, lower R implies a lower average quality of matches, while lower U implies lower $\bar{z}$, and thus lower average quality of self-employment. These forces reduce aggregate output beyond the decline due to higher unemployment. All these changes are similar for an increase in the vacancy posting cost k_v.

4. Calibration

This section describes how the model is calibrated separately for all 37 countries from the DLS data set with available data for all flows and job separation hazards.

4.1. Calibration procedure

The calibration requires setting parameter values for 18 parameters for each country. Two of these allow for normalizations. I then proceed by setting five to values commonly used in the literature, and calibrate a further three using information from the United States. The remaining eight parameters are calibrated to match each country's flow matrix across labor market states and the hazard function for transitions from wage employment to unemployment. These target moments are shown in Figure A.3 in the Appendix. As a result, the model replicates labor market flows in all 37 countries exactly.

Externally set parameters, functional forms and normalizations. The model time period is set to one month. I set the discount factor β such that $1/\beta^{12} - 1$ equals 4%. I assume that the distribution of self-employment output z is Pareto with minimum z_m and tail index k. I normalize the productivity in new matches, y_0, to one and assume that the distribution of productivity shocks is uniform $[0, 1]$. I set the elasticities of the matching function and the bargaining weight η to 0.5, following Petrongolo and Pissarides (2001).

As is typical in search and matching models, matching function productivity A and the vacancy posting cost k_v cannot be identified separately without direct information on the cost of hiring, on tightness or on the number of vacancies. Such information is only available for a few, rich countries. I therefore normalize A to one. This implies that a high calibrated value of k_v can result from either truly high costs of hiring or from low matching efficiency. Exercises varying k_v should be thus interpreted as varying either of these. Their results do not depend on the true nature of k_v.[12]

As in Pries and Rogerson (2022), π is not identified by the model. I set it to 0.5. The same is true for ε, the elasticity of entry costs with respect to the entry rate. In the benchmark analysis, I set it to 1, so that a doubling of entry implies a doubling of entry costs. Section 5.4 discusses sensitivity to these choices.

Common, internally calibrated parameters. Each country's labor market flows and exit hazards from wage employment idenfity eight country-specific parameters. This leaves three parameters to calibrate: the flow value of unemployment b, the tail index of the distribution of self-employment output k, and the relative job offer rate for the self-employed, ζ. There is not enough country-specific information in the DLS data to identify these for each country. I therefore calibrate them to the US, and assume that they take the same value in other countries. In Section 5.4, I explore the effects of lower b in poor countries.

In setting the flow value of unemployment b, I follow Hall and Milgrom (2008) and Gregory et al. (2021) who argue that on average, the sum of unemployment benefits and the value of leisure amount to about 65% of wage earnings. The tail index of self-employment output, k, is the main determinant of mean self-employment income. The relative job offer rate for the self-employed, ζ, affects the reservation self-employment productivity and thus lower-tail self-employment income, because OTJ search is valuable. I thus set k and ζ to match the ratio of the mean and the tenth percentile of hourly self-employment income to the corresponding wage moments. These moments are 1.24 and 0.67 for full time workers (annual hours > 1800) in the American Community Survey (Ruggles et al., 2023, waves for 2006, 2011, 2016 and 2019, accessed via IPUMS USA).

[12]Higher k_v also has the same effects that taxes on the revenue of employers would have. However, calibrated k_v is not correlated with effective marginal tax rates from the OECD (Hanappi, 2018), which are available for 32 countries in the DLS data, including 8 HUHS ones.

Country-specific parameters. Given these parameter values, I set the values of the remaining eight parameters, namely the vacancy posting cost k_v, the shock arrival rate λ, the screening rate p_0, the learning rate p_1, the arrival rate of self-employment opportunities χ, the scale of entry costs $\bar{k}_f$, the minimum self-employment productivity z_m, and the self-employment exit rate δ, to exactly match the flow matrix across labor market states and the exit hazard from wage employment to unemployment.

To do so for 37 countries, it is not efficient to search over the entire space of eight parameters for each country. Instead, I integrate calibration and model solution, taking advantage of the fact that in several cases, model equilibrium values combined with data moments directly imply parameters. For example, the reservation productivity for screened matches, R^s, combined with the empirical separation rate for high-tenure matches directly implies λ. So, once R^s is known, search over λ is not required. Similarly, once λ and the reservation productivities R^s and R^u are known, p_0 and p_1 imply the shape of the employment exit hazard to unemployment at shorter durations, and can be found by simulation without knowing further parameters. The only parameters requiring a full model solution are χ and z_m. They mostly affect $P(WB)$ and $P(BW)$, which depend on distributions and therefore require full model simulation. Appendix C describes the algorithms for model solution and calibration in detail.

4.2. Calibration results

Table 4 shows calibration results for the core parameters k_v, λ, p_0 and $\bar{k}_f$ together with median target moments. In addition, it shows δ. It shows the median across all countries, the median in each quadrant, and results for the four focus countries. Patterns are similar for means, but the mean is affected by a small number of outliers, in particular for $\bar{k}_f$ and k_v. Table A.10 in the Appendix shows all calibrated parameters, for all countries. Figure 4 shows the key parameters for all countries, graphing each against the most closely associated moment.[13]

[13]The remaining parameters δ, p_1, χ and z_m also differ significantly across countries. For space reasons, I focus the discussion on the parameters controlling the four model aspects that are most often used in the

[Table 4 about here.]

[Figure 4 about here.]

In general, calibrated parameters align closely with differences in target moments across countries. Table 3 showed lower job finding rates in HUHS and HULS compared to LU countries. In the model, this is reflected in higher vacancy posting costs k_v in these countries.[14] Higher destruction rates at long tenures in HUHS and LUHS countries translate into a higher shock arrival rate λ. A high separation rate for new matches in HUHS implies a low rate of screening, p_0. High self-employment entry from unemployment in LUHS and HUHS countries implies lower entry costs $\bar{k}_f$. High self-employment exit in HUHS countries implies high δ. The same patterns are visible when comparing parameters and moments across all countries, as shown in Figure 4.

There are salient differences in parameters across quadrants. The mostly rich LULS countries have low vacancy posting costs, low shock arrival rates, and high screening rates, which lead to a low *UN* ratio. They also have high self-employment entry costs, implying low self-employment. The mostly poor HUHS countries are different from them in almost every way: they overall have much higher shock arrival rates and lower screening rates which, combined with somewhat higher vacancy posting costs, imply their high *UN* ratios. In addition, they have low entry costs, which further contribute to high self-employment, despite high self-employment exit.

The other two quadrants fall in between. LUHS countries similarly have low vacancy posting costs and high screening rates. While they have high shock arrival rates, as evidenced by their high separation rates for long-tenure matches, their low vacancy posting cost compensates for this, keeping their *UN* ratio low. Their high self-employment rates despite low labor market frictions reflect very low self-employment entry costs. HULS countries have similarly low shock arrival rates and high entry costs as LULS countries, but lower screening rates and very high vacancy posting costs, causing their higher *UN* ratio.

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literature. More detailed analysis of further aspects, in particular transitions between wage employment and self-employment and worker heterogeneity, is a promising avenue for future work.

[14] To the extent that revenue taxes are higher in rich countries, the true gap in k_v is understated.

Figure 4 reveals that there is substantial heterogeneity within quadrants. Among HUHS countries, dispersion of λ and k_v is large. What unites them is their overall low levels of the screening rate p_0 and mostly low entry costs $\bar{k}_f$.

4.3. Simpler calibrations fit less well

The model has many channels and parameters. To explore whether all of these are required, I implement a set of simpler calibrations, where one parameter is set to a common value across countries, while the remaining ones are re-calibrated to minimize the sum of squared deviations for all eight target flow moments.[15]

These simpler calibrations result in a significantly worse fit in some dimensions, as shown in Table A.11. For example, setting k_v to its cross-country median in all countries implies a median deviation of the job finding rate from the data moment of 35%. Doing the same for λ or k_f leads to a median deviation of the separation rate and the self-employment entry rate from their targets by 22% and 77%, respectively.

[Figure 5 about here.]

Re-calibrating the country-specific parameters somewhat attenuates the deviations of these model flows from the data. At the same time, it implies a worse fit in additional dimensions. Consider an example. Setting k_v to its cross-country median implies too low job finding rates in countries with low benchmark k_v. This can be alleviated by a lower λ, which increases the value of vacancies and thus vacancy posting.[16] But this comes at the cost of too low job destruction, as shown by its negative deviations from target at low values of k_v in the left panel of Figure 5. The reverse occurs in countries with high benchmark k_v.

The right panel shows that in some countries, an additional channel operates: in some countries with a low scale of the entry cost $\bar{k}_f$ (squares), the re-calibration implies self-employment entry significantly above the target value. This helps to raise the job finding rate towards its target via a smaller pool of searchers.

[15] I thank a referee for suggesting these simulations.

[16] In many cases, this results in a new λ of zero. Job destruction is nonetheless positive because of destruction of new matches.

This exercise clearly illustrates the importance of an integrated treatment of worker flows across unemployment, wage employment, and self employment.

5. The effect of labor market frictions

How do labor market frictions affect unemployment, self-employment and aggregate output? Panel A of Figure 6 shows the effect of an increase in λ or k_v on the UN ratio and self-employment for all 37 countries, starting again from the benchmark calibration. Figure A.4 shows the effect of a reduction in p_0 or an increase in $\bar{k}_f$. The upper panel of Table 5 shows the mean effect across countries. The figures show the effect of changing each parameter by the same proportion everywhere, as a result of changing its log by one tenth of the standard deviation of the log across countries.[17,18]

[Figure 6 about here.]

[Table 5 about here.]

5.1. The effect of λ and k_v on unemployment and self-employment

It is clear that labor market frictions increase unemployment. An increase in $\ln \lambda$ by a tenth of a standard deviation (s.d.) raises the UN ratio and the unemployment rate by 0.16 and 0.22 percentage points, respectively. An increase in $\ln k_v$ by 0.1 s.d. raises the UN ratio and the unemployment rate by 0.3 and 0.2 percentage points, respectively. Put differently, in response to a 0.1 s.d. change in $\ln \lambda$ ($\ln k_v$), unemployment and the UN ratio change on average by 0.34 (0.41) and 0.33 (0.45) times as many standard deviations. The elasticity of u and the UN ratio with respect to λ (k_v) is around two thirds (0.4).

The frictions also raise self-employment. For k_v, this is immediately obvious from the fact that almost all points in Figure 6 lie above the 45 degree line. An increase in k_v by

[17] This implies an increase in λ (k_v) [$\bar{k}_f$] of about 6% (11.8%) [19%] (not percentage points). Because p_0 is calibrated to be zero in two countries, I increase it by 0.1 standard deviations of its level, or 2.25pp. Appropriately standardized effects are similar for larger but not extreme changes in frictions.

[18] This exercise reveals the effect of specific individual frictions. In the data, countries may differ in several dimensions simultaneously, as shown in Tables 3 and 4 above. These tables also give an indication of the effect of pertinent *joint* differences in parameters.

0.1 s.d. raises the self-employment rate by 0.5pp on average. For λ, the changes in the self-employment rate and the *UN* ratio are quantitatively similar. In response to a 0.1 s.d. change in λ (k_v), the self-employment rate changes on average by 0.19 (0.43) times as many standard deviations. Its elasticity with respect to λ (k_v) is around a quarter. It is lower than that for u because the self-employment rate generally is greater than the unemployment rate.

On average, the effect of λ or k_v on the level of self-employment is 1 to 1.7 times as large as that on the *UN* ratio. The relationship is similar across countries: Regression coefficients for a median regression of the change in self-employment on the change in the *UN* ratio are 1.32 (SE: 0.15) and 1.2 (0.19) for changes in λ and k_v, respectively. OLS regression coefficients are similar, but estimated less precisely. These numbers are very close to the coefficient of 1.31 from the analogous regression in IPUMS data (see Figure 2).

Heterogeneous effects. Figure 6 and Table A.12 show that the effect of increases in λ or k_v differs across quadrants. Both have a larger effect on unemployment in countries with a high *UN* ratio (HUHS and HULS). But high self-employment attenuates the effect of labor market frictions on unemployment, whereas a high *UN* ratio amplifies their effect on self-employment. As a result, in HUHS countries, labor market frictions affect the self-employment rate much more strongly than the unemployment rate.

To save space, I do not report in detail how the frictions interact, except to highlight that greater λ affects the *UN* ratio and self-employment more in countries with high k_v. Conversely, greater k_v affects the *UN* ratio more in countries with high λ. Its effect on self-employment is larger and that on *UN* ratio smaller in countries with low $\bar{k}_f$.

5.2. The effect of frictions on selection, output and wages

The lower two panels of Table 5 show the effect of higher λ or k_v on core model variables and on aggregate outcomes. These mirror the discussion in Section 3.3. The decline in self-employment income is larger than the decline in wages. Aggregate output declines because of these distributional changes plus the increase in unemployment. The penultimate column of the bottom panel of Table 5 reports the change in output due to selection only, computed using the changes in mean y and z, but benchmark values of u and the self-employment rate. Selection accounts for one to two thirds of the output decline.

Panel B of Figure 6 shows how an increase in λ or k_v affects wage employment and self-employment output across countries. Almost all points lie below the 45 degree line, indicating a greater decline in mean z. For an increase in k_v, both mean y and mean z fall most in HUHS countries, and least in LULS countries. The same holds for aggregate output (see Table A.12). Changes in response to greater λ align less closely with quadrants.

5.3. The effect of entry costs

Table 5 and Figure A.4b show that changes in the scale of entry costs, $\bar{k}_f$, have very different effects from those of λ and k_v. They reduce self-employment substantially, by about half a percentage point on average. Wage employment cannot absorb all of this, and so u (the UN ratio) increases, by 0.14pp (0.13pp) on average.

Table A.12 shows that this effect on unemployment is particularly large in countries with high self-employment. These findings illustrate that not only do labor market frictions affect self-employment, but that self-employment also affects unemployment.

5.4. Sensitivity

The calibration assumed common values for ε, π and b across countries. ε and π were not identified but set exogenously. How do their choices affect results?

The elasticity of entry costs, ε, only affects counterfactual results. Table A.13 shows results for ε of 0.5 instead of 1, implying a slower increase in entry costs with the entry rate. Here, increases in frictions raise self-employment more, so that u increases less. Hence, the relative change in self-employment is larger than in the benchmark. Output falls less.

The probability that a match is suitable, π, also affects the calibration. Greater π raises the value of vacancy posting and implies less destruction of young matches. Matching the job finding rate then requires higher k_v. Matching the separation rate for young matches requires lower p_0. In this case, fewer young matches are destroyed because they are unsuitable, and more because of failed screening at hiring. The lower bound of zero on p_0 implies an upper bound of 0.68 on π in the average HUHS country. Other parameters do not change. Counterfactuals with respect to λ, k_v and $\bar{k}_f$ are unaffected.

Assuming lower b in poorer countries also affects the calibration. Lower b reduces U, which reduces the reservation productivity. Maintaining the rate of destruction of screened matches then requires slightly higher λ. Lower b also increases match surplus and thus hiring. Hence, greater k_v is required to match the job finding rate. Other parameters do not change appreciably. This alternative thus implies greater differences in λ and k_v between HUHS and LULS countries than the benchmark.[19] It also implies smaller changes in u and larger ones in self-employment in counterfactuals varying λ or k_v.

6. Conclusion

This paper has documented that because poor countries have high self-employment and low wage employment rates, they face high unemployment relative to wage employment (the "*UN* ratio"). Across countries, self-employment increases with the *UN* ratio. Most countries with a high *UN* ratio and high self-employment are poor. A novel model of unemployment and self-employment with uncertainty about match suitability allows matching all flows between unemployment, wage employment and self-employment as well as the exit hazard from wage employment in the data. Applying this model to data from 37 countries revealed that labor market frictions affect self-employment as much as the *UN* ratio. They also reduce output by worsening selection of active matches and self-employment enterprises. Matches in countries with a high *UN* ratio and high self-employment on average are less well screened initially and suffer more frequent shocks subsequently, leading to more separations and a higher *UN* ratio. These factors, combined with low entry costs, lead to high self-employment.

Across individual countries, the sources of a high *UN* ratio and high self-employment can differ even if these statistics are similar. The framework in this paper can be used to diagnose these sources for any country, given data on flows and the employment exit hazard.

[19] Matching median flows among HUHS countries requires 0.02pts larger λ and 20 larger k_v if b is set 20% lower. It also requires 30% lower $\bar{k}_f$.

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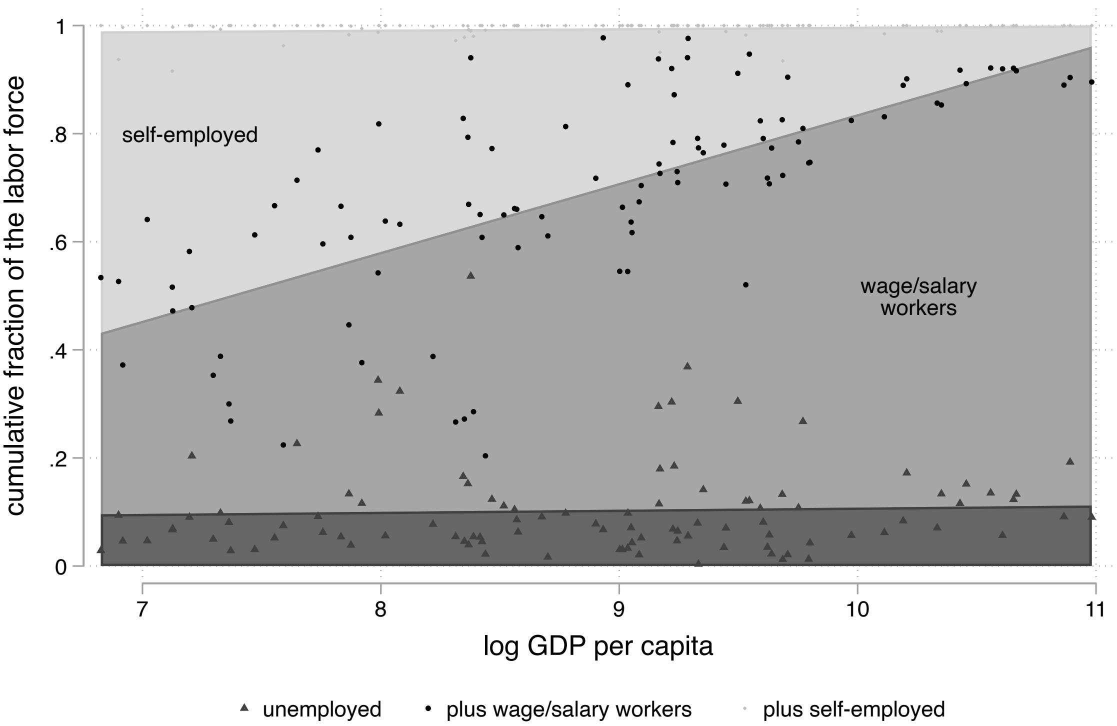
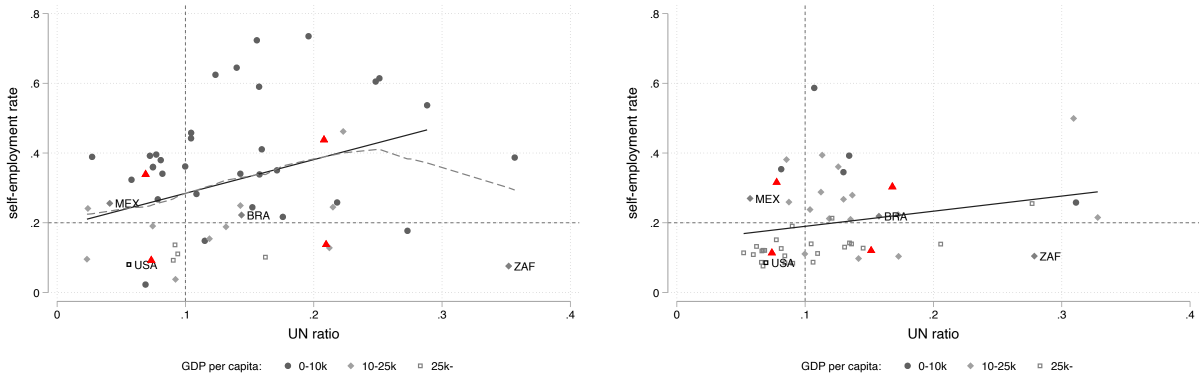


Figure 1: Composition of the labor force and development

Sources: GDP per capita: WDI. Employment status: IPUMS International. 100 censuses covering 53 countries over the years 1990 to 2011. Data for urban areas. Bottom area: unemployment rate.

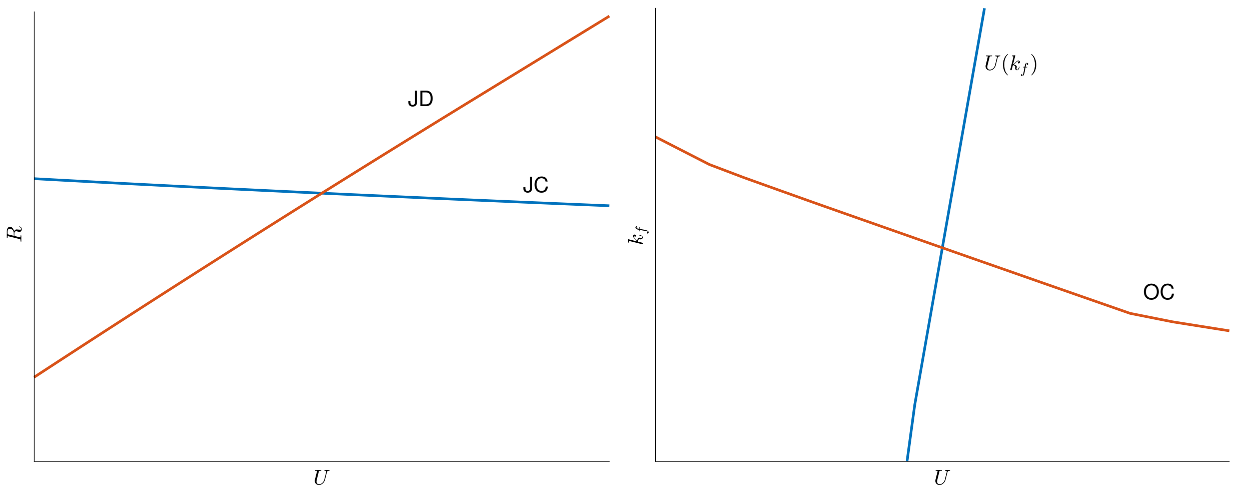


(a) IPUMS data

(b) DLS data

Figure 2: The self-employment rate versus the UN ratio $u/(u+n)$

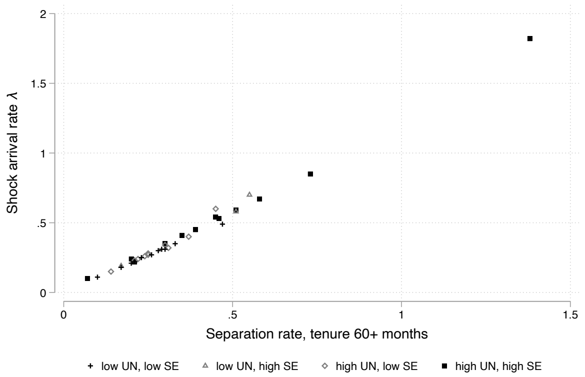
Notes: Left figure: The solid line shows the fit from an OLS regression. The regression coefficient is 1.31, standard error 0.38. (The regression excludes observations of UN ratio above the 90th percentile of the variable (0.31).) The broken line shows the fit of a locally weighted regression. The figure excludes three observations with UN ratios above 0.4. Figure A.2 in the Appendix shows the full range and data for the entire country. Right figure: The regression coefficient is 0.61, standard error 0.28. The vertical line at a UN ratio of 0.1 and the horizontal line at a self-employment rate of 0.2 are drawn to divide countries into four sets, differing in their levels of the UN ratio and the self-employment rate.



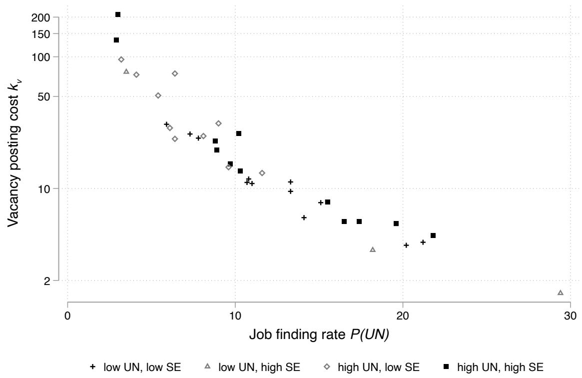
(a) Job creation (JC) and destruction (JD)

(b) Self-employment entry

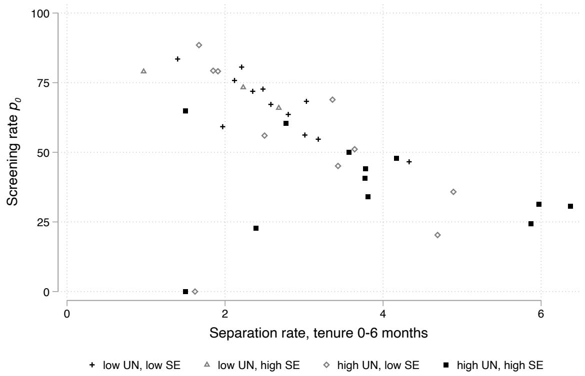
Figure 3: Equilibrium in the search model with self-employment



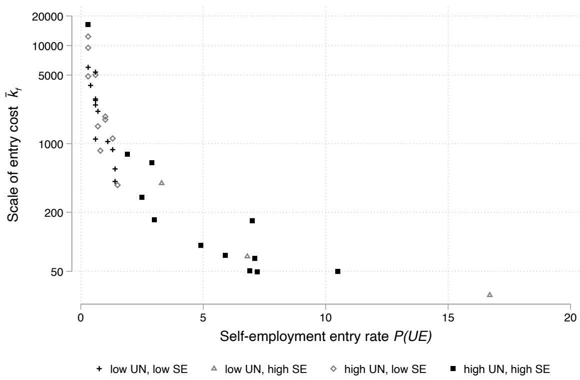
(a) The shock arrival rate λ and the separation rate (60+ months)



(b) The vacancy posting cost k_v and the job finding rate

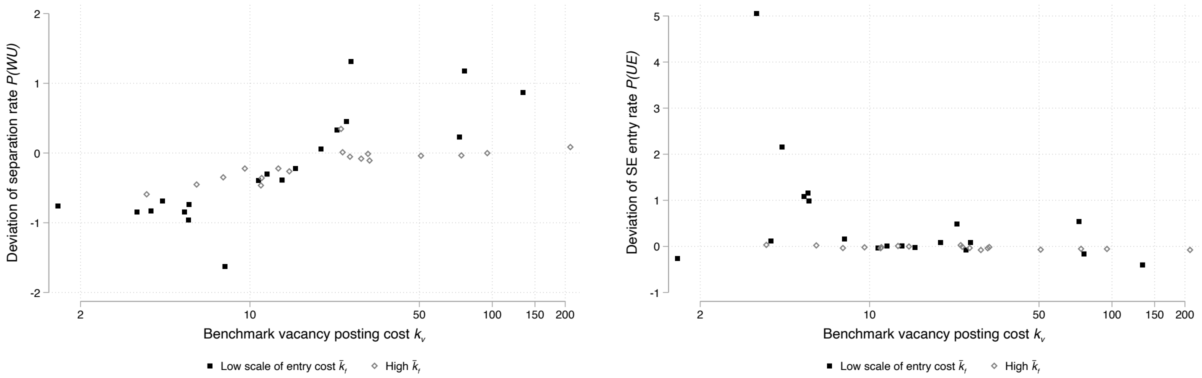


(c) The screening rate p_0 and the separation rate (0-6 months)



(d) The scale of fixed costs $\bar{k}_f$ and the SE entry rate

Figure 4: Calibrated model parameters versus data moments



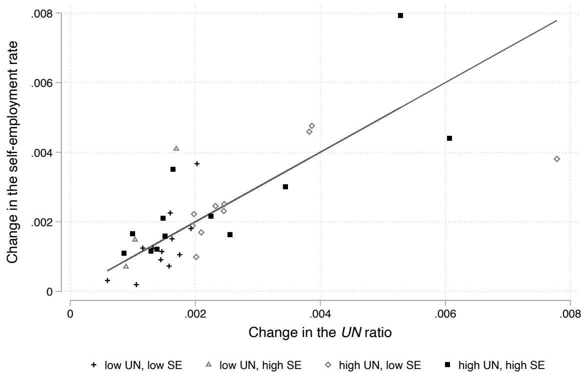
(a) Deviation of the separation rate $P(NU)$

(b) Deviation of the self-employment entry rate $P(UE)$

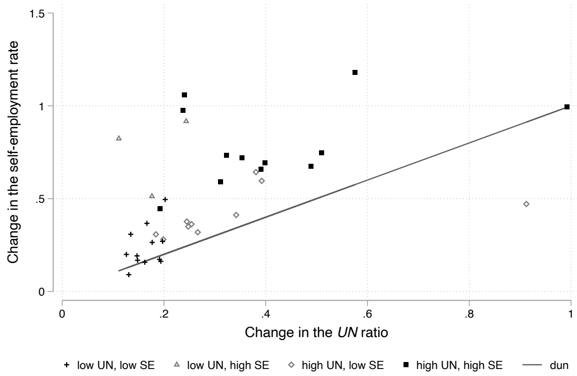
Figure 5: Deviations of model flows from data when the vacancy posting cost k_v is set equal across countries

Notes: The figures show percentage point deviations of selected model flows from their data counterparts when the vacancy posting cost k_v is set to its cross-country median of 14.5 in all countries. The remaining parameters are re-calibrated to minimize the sum of squared deviations from target moments.

Panel A: The effect of frictions on the UN ratio and self-employment

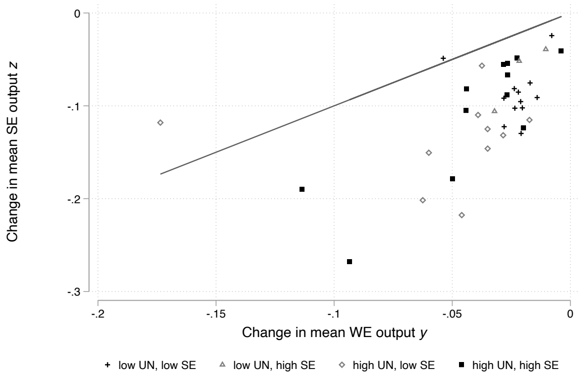


(a) An increase in the shock arrival rate λ

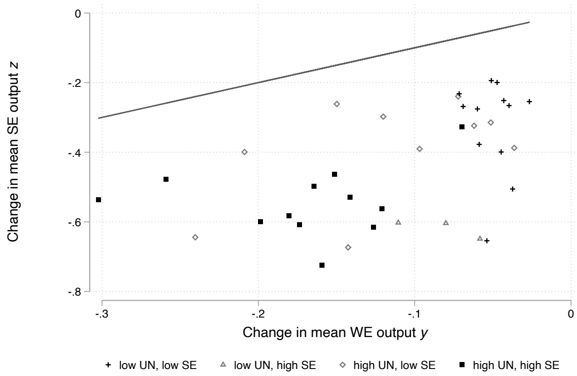


(b) An increase in the vacancy posting cost k_v

Panel B: The effect of frictions on output



(c) An increase in the shock arrival rate λ



(d) An increase in the vacancy posting cost k_v

Figure 6: The effect of changing labor market frictions and entry costs on the UN ratio and on self-employment across countries.

Notes: Each figure in the top panel shows the effect of changing a parameter by one tenth of its standard deviation across the 37 countries on the UN ratio and the self-employment rate, in percentage points, and a 45 degree line. Each figure in the bottom panel shows the effect on mean wage employment output (y) and self-employment output (z), in percent, and a 45 degree line. Regression coefficients for a median regression of the change in self-employment on the change in the UN ratio (regression line not shown in the figure) are 1.2 (SE: 0.19) and 1.32 (0.15). OLS regression coefficients are similar, but the regressions are noisier.

List of Tables

Table 1: Composition of the labor force and development

dependent variable:	wage employment rate	self-employment rate	unemployment rate	*UN* ratio
Urban areas:				
log GDP per capita	0.138***	-0.134***	0.005	-0.035**
	(0.018)	(0.018)	(0.010)	(0.016)
R^2	0.547	0.531	0.005	0.084
observations	100	100	111	100
countries	53	53	59	53
Entire country, all countries:				
log GDP per capita	0.181***	-0.187***	0.015**	-0.035***
	(0.013)	(0.015)	(0.007)	(0.013)
R^2	0.746	0.721	0.067	0.104
observations	137	137	151	137
countries	66	66	73	66
Entire country, sample from top panel:				
log GDP per capita	0.201***	-0.214***	0.018*	-0.036**
	(0.017)	(0.019)	(0.010)	(0.017)
R^2	0.724	0.716	0.061	0.077
observations	100	100	100	100
countries	53	53	53	53

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita, using time averages of country data (between regression). Constant not reported. Data sources as in Figure 1. Results for a regression using pooled data are similar and are shown in Table A.1.

Table 2: The relationship between self-employment, income per capita, and the *UN* ratio

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
Self-employment and income per capita:			
log GDP per capita	-0.134***	-0.148***	0.013***
	(0.018)	(0.019)	(0.003)
R^2	0.531	0.565	0.275
observations	100	94	94
countries	53	49	49
Self-employment and the UN ratio:			
UN ratio	1.321***	1.427***	0.019
	(0.381)	(0.438)	(0.062)
R^2	0.207	0.206	0.002
observations	89	83	83
countries	48	43	43
Self-employment and the UN ratio, controlling for GDP per capita:			
UN ratio	0.709**	0.772**	0.088
	(0.295)	(0.317)	(0.055)
log GDP per capita	-0.117***	-0.133***	0.014***
	(0.018)	(0.020)	(0.003)
R^2	0.584	0.630	0.300
observations	89	83	83
countries	48	43	43

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita and/or the *UN* ratio, using time averages of data for urban areas (between regression). Constant not reported. Standard errors in parentheses. Data sources as in Figure 1. Results for a regression using pooled data are similar (Table A.5).

Table 3: Labor market stocks and flows by quadrant

	Low UN ratio, low self-employment (LULS)			**High UN ratio, low self-employment (HULS)**		
Share of countries (IPUMS)	15.3			17		
Mean GDP per capita	23.3			14.6		
Transition matrix from \to	*U*	*W*	*E*	*U*	*W*	*E*
U	87.3	11.9	0.8	91.7	7.5	0.9
W	0.44	99.4	0.18	0.8	99.0	0.2
E	0.26	1.6	98.2	0.7	1.1	98.2
Stocks	6.6	82.1	11.3	13.3	74.7	12.0
UN ratio	7.4			15.2		
Probability of separation by job tenure	0-6 mths	7-12 mths	5+ yrs	0-6 mths	7-12 mths	5+ yrs
	2.5	1.4	0.24	3.7	2.2	0.34
	Low UN ratio, high self-employment (LUHS)			**High UN ratio, high self-employment (HUHS)**		
Share of countries (IPUMS)	23.7			44.1		
Mean GDP per capita	7.1			4.9		
Transition matrix from \to	*U*	*W*	*E*	*U*	*W*	*E*
U	79.7	14.7	5.7	84.5	10.8	4.6
W	0.80	97.1	2.10	1.3	97.2	1.5
E	0.50	4.1	95.4	1.1	3.4	95.5
Stocks	5.3	63.1	31.6	11.8	57.9	30.3
UN ratio	7.7			16.9		
Probability of separation by job tenure	0-6 mths	7-12 mths	5+ yrs	0-6 mths	7-12 mths	5+ years
	1.9	1.3	0.40	3.6	2.2	0.48

Notes: The table shows means of each variable for all countries in a quadrant. All variables in %, except GDP per capita (PPP) in thousands of 2017 int. $. Quadrant definitions: A *UN* ratio (self-employment rate) below 0.1 (0.2) is classified as low. Sources: Stocks and flows: DLS. Monthly transition rates implied by the quarterly rates reported by DLS. Country shares and GDP per capita: IPUMS and WDI data. Flows and stocks for individual countries are shown in Figures A.2a and A.3 in the Appendix, and in Table A.9 for the focus countries.

Table 4: Calibration results: key parameter values and target moments, quadrant medians and focus countries

Panel A. Common parameters									
Common parameters, externally calibrated:	β	η	μ	π	ε				
	$1.04^{-1/12}$	0.5	0.5	0.5	1				
Common parameters, calibrated to US data:	b	k_z	ζ						
	0.625	4.6	1.45						
Panel B. Country-specific parameters									
	Parameters					Moments			
	k_v	λ	p_0	$\bar{k}_f$	δ	P_{UW}	$P_{WU,60+}$	$P_{WU,0-6}$	P_{UE}
Median, all countries:									
	14.5	0.31	56.2	868.7	0.35	10.2	0.29	2.8	1.3
Quadrant medians:									
high UW, high SE	13.6	0.53	40.7	91.7	1.3	10.3	0.42	3.8	5.4
high UW, low SE	31.2	0.28	51.1	1886.0	0.3	6.4	0.25	2.9	0.8
low UW, high SE	3.4	0.58	73.3	70.9	0.5	18.2	0.51	2.2	6.8
low UW, low SE	11.1	0.25	68.3	2135.5	0.2	12.2	0.25	2.5	0.6
Focus countries:									
BRA	15.4	0.54	50.0	168.1	1.3	9.7	0.45	3.57	3.0
ZAF	73.1	0.6	35.8	849.1	1.5	4.1	0.45	4.89	0.8
MEX	1.6	0.58	73.3	70.9	0.7	29.4	0.51	2.23	6.8
USA	3.9	0.49	54.7	411.9	0.7	21.2	0.47	3.18	1.4

Notes: All entries in percent, except for k_v and $\bar{k}_f$. Recall that $\bar{k}_f$ is not the equilibrium entry cost, but the scale parameter. See Table A.10 in the Appendix for results for all countries and for additional parameters. Model frequency: monthly.

Table 5: The effect of frictions on unemployment, self-employment, selection, output and wages

Change	Effect on ...					
	u		UN ratio		self-employment rate	
	(pp)	(ela.)	(pp)	(ela.)	(pp)	(ela.)
λ	0.16	0.62	0.22	0.67	0.22	0.23
k_v	0.20	0.38	0.30	0.44	0.51	0.24
p_0	0.03	0.32	0.04	0.28	-0.07	-0.24
$\bar{k}_f$	0.14	0.15	0.13	0.11	-0.57	-0.18

Change	Effect on ... (in %)		
	θ	R_s	R_u
λ	-0.43	-0.18	-0.17
k_v	-11.8	-0.60	-0.60
p_0	0.05	0.03	0.03
$\bar{k}_f$	0	0	0

Change	Effect on ... (in %)					(ela.)
	mean y	mean w	mean z	aggregate output	agg. output (constant u, e)	aggregate output
λ	-0.04	-0.1	-0.11	-0.17	-0.05	-3.0
k_v	-0.11	-0.33	-0.44	-0.29	-0.19	-2.6
p_0	-0.09	-0.03	0.21	-0.08	-0.03	-3.6
$\bar{k}_f$	-0.01	0	0	-0.27	0.00	-1.5

Notes: The table shows the mean effect across the 37 countries of raising k_v, λ or $\bar{k}_f$ by 0.1 standard deviations, or reducing p_0 by the same amount. The top panel shows changes in outcomes in percentage points, as well as as elasticities. The lower two panels show percent changes.

Appendix – For Online Publication

Appendix A. Additional Tables and Figures

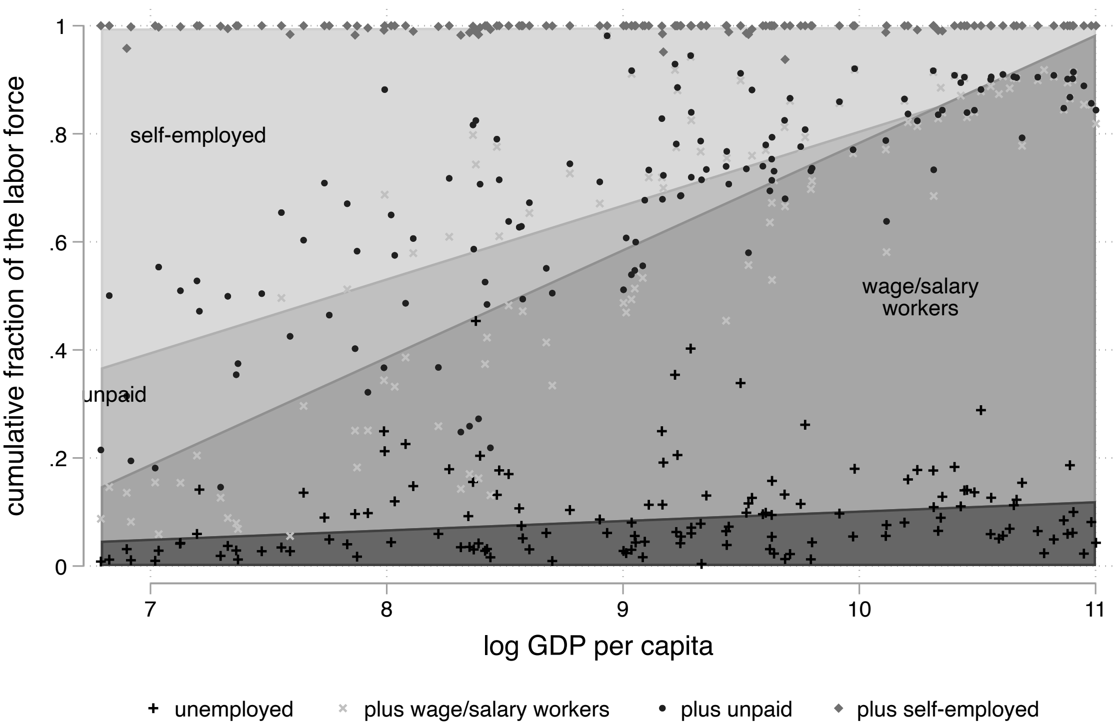
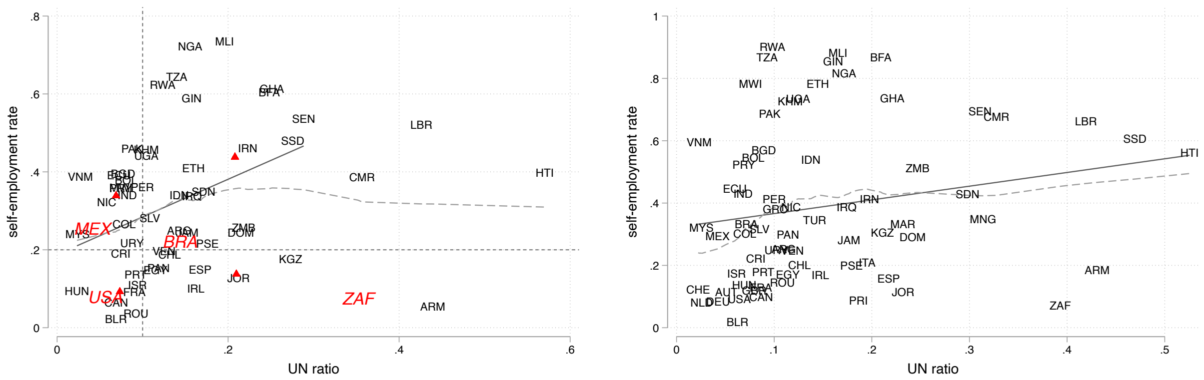


Figure A.1: Composition of the labor force and development, national, incl. unpaid workers

Sources: See Figure 1.

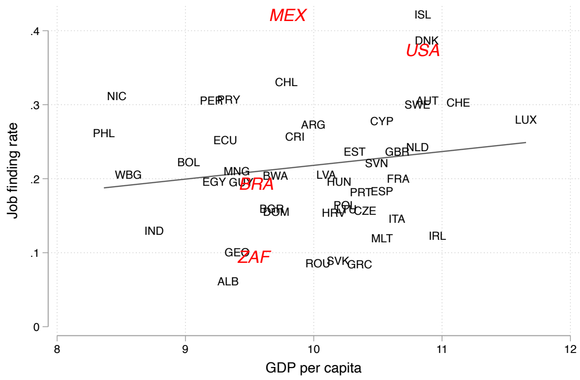


(a) Urban residents, full range of the *UN* ratio

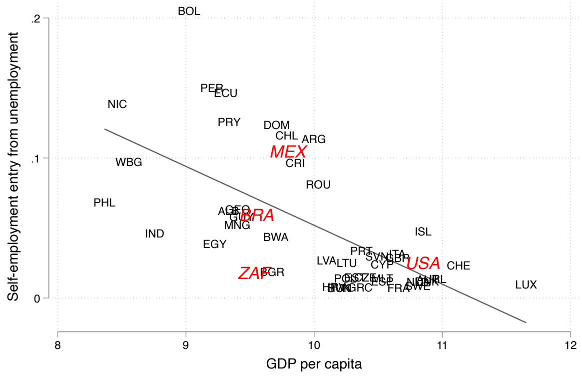
(b) Entire country

Figure A.2: The self-employment rate versus the *UN* ratio $u/(u+n)$

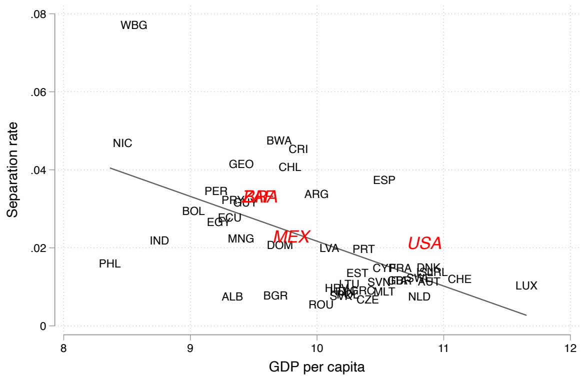
Notes: Solid line: linear regression. Regression coefficients: Left: 1.31, SE 0.38. Right: 0.472, SE 0.25. Dashed line: Fit from locally weighted regressions (`lowess` command in Stata). Red triangles in the left graph indicate mean *UN* ratio and mean self-employment rate in each quadrant. Focus countries highlighted.



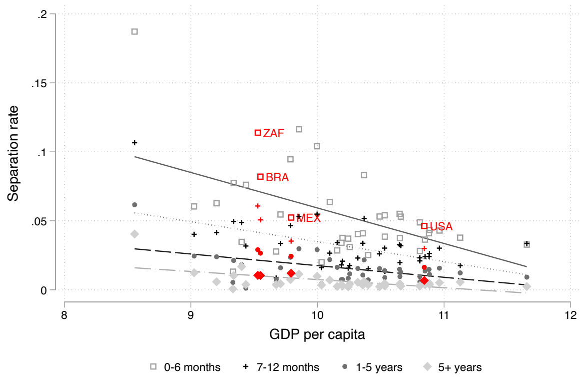
(a) Job finding rate (UW)



(b) Self-employment entry rate out of u (UB)



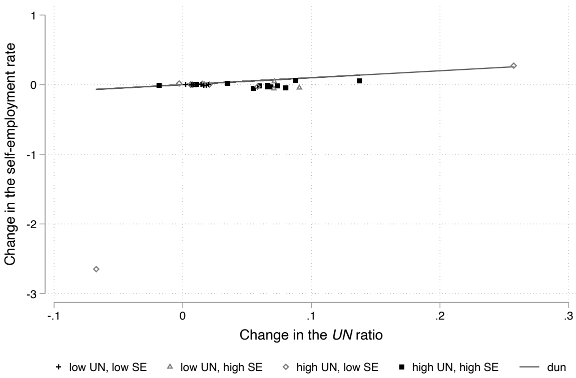
(c) Job separation rate to unemployment (WU)



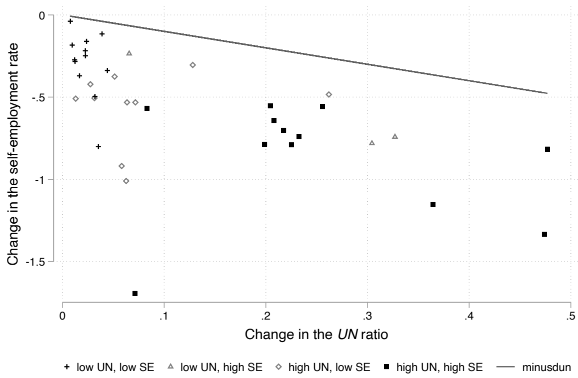
(d) Job separations (WU) by job tenure

Figure A.3: Labor market flows across countries

Notes: Source: Donovan et al. (2023). Focus countries highlighted in red.



(a) An increase in the rate of screening p_0



(b) An increase in fixed costs $\bar{k}_f$

Figure A.4: The effect of changing additional labor market frictions and entry costs on the *UN* ratio and on self-employment across countries.
Notes: Each panel shows the effect of changing a parameter by one tenth of its standard deviation across the 37 countries on the *UN* ratio and the self-employment rate, in percentage points, and a 45 degree line. Regression coefficients for a median regression of the change in self-employment on the change in the *UN* ratio (regression line not shown in the figure) are 0.07 (0.12) and -1.71 (0.37) respectively. OLS regression coefficients are similar, but the regressions are noisier.

Table A.1: Composition of the labor force and development, pooled regressions

dependent variable:	rate of wage employment	self-employment rate	unemployment rate	*UN* ratio
Urban areas:				
log GDP per capita	0.124***	-0.125***	0.011	-0.023**
	(0.015)	(0.015)	(0.007)	(0.011)
R^2	0.499	0.480	0.017	0.045
observations	100	100	111	100
Entire country:				
log GDP per capita	0.170***	-0.180***	0.017***	-0.025***
	(0.012)	(0.013)	(0.005)	(0.009)
R^2	0.726	0.696	0.070	0.064
observations	137	137	151	137

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita, pooling all observations. Constant not reported. Robust standard errors, clustered by country, in parentheses. Data sources as in Figure 1.

Table A.2: Composition of the labor force and development, data from top comparability tier

dependent variable:	rate of wage employment	self-employment rate	unemployment rate	*UN* ratio
Urban areas:				
log GDP per capita	0.152***	-0.142***	-0.002	-0.046**
	(0.026)	(0.026)	(0.010)	(0.018)
R^2	0.525	0.490	0.001	0.178
observations	58	58	64	58
countries	33	33	36	33
Entire country:				
log GDP per capita	0.182***	-0.196***	0.019**	-0.024*
	(0.020)	(0.021)	(0.007)	(0.014)
R^2	0.673	0.691	0.139	0.066
observations	77	77	83	77
countries	42	42	45	42

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita, using time averages of country data (between regression). Constant not reported. Data sources as in Figure 1.

Table A.3: Unemployment and development, subsamples

dependent	unemployment rate			*UN* ratio		
variable:	age 20-29	age 30-60	age 61-65	age 20-29	age 30-60	age 61-65
Urban areas:						
log GDP per capita	0.008	0.009	0.012	-0.054**	-0.018	-0.028*
	(0.014)	(0.009)	(0.008)	(0.021)	(0.014)	(0.016)
R^2	0.005	0.019	0.039	0.113	0.031	0.057
observations	110	110	105	99	99	95
countries	58	58	56	52	52	51
Entire country:						
log GDP per capita	0.023**	0.014**	0.016***	-0.049***	-0.022*	-0.029**
	(0.010)	(0.005)	(0.005)	(0.016)	(0.011)	(0.013)
R^2	0.069	0.087	0.117	0.125	0.057	0.074
observations	150	150	144	136	136	132
countries	73	73	69	66	66	64

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita, using time averages of country data (between regression). Constant not reported. Standard errors in parentheses. Data sources as in Figure 1.

Table A.4: Composition of the labor force and development, ILO data

dependent variable:	self-employment rate	fraction own-account workers	fraction employers	unemployment rate	*UN* ratio
log GDP per capita	-0.120***	-0.126***	0.005**	0.016***	-0.024***
	(0.008)	(0.008)	(0.002)	(0.004)	(0.008)
R^2	0.666	0.691	0.047	0.153	0.124
observations	1221	1289	1247	707	651
countries	106	108	107	77	59

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita, using time averages of country data (between regression). Constant not reported.
Data from the International Labour Organization (ILOSTAT).

Table A.5: The relationship between self-employment, income per capita, and the *UN* ratio, pooled data

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
Self-employment and income per capita:			
log GDP per capita	-0.125***	-0.139***	0.010***
	(0.015)	(0.016)	(0.003)
R^2			
observations	100	94	94
countries	53	49	49
Self-employment and the UN ratio:			
UN ratio	0.885**	0.923***	0.018
	(0.332)	(0.342)	(0.045)
R^2			
observations	89	83	83
countries	48	43	43
Self-employment and the UN ratio, controlling for GDP per capita:			
UN ratio	0.508**	0.509**	0.048
	(0.227)	(0.223)	(0.046)
log GDP per capita	-0.122***	-0.136***	0.010***
	(0.014)	(0.015)	(0.003)
R^2			
observations	89	83	83
countries	48	43	43

Notes: The table shows regression coefficients from regressions of the dependent variable on log GDP per capita and/or the *UN* ratio, using pooled data. Constant not reported. Robust standard errors clustered at the country level in parentheses. Data sources as in Figure 1.

Table A.6: The relationship between self-employment and the *UN* ratio, controlling for GDP per capita, urban areas, data from top comparability tier only

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
UN ratio	0.745*	0.530	0.137*
	(0.395)	(0.430)	(0.073)
log GDP per capita	-0.118***	-0.142***	0.017***
	(0.029)	(0.033)	(0.006)
R^2	0.540	0.539	0.259
observations	56	53	53
countries	32	30	30

Notes: The table shows regression coefficients from regressions of the dependent variable on the *UN* ratio and log GDP per capita, using time averages of data (between regression). Constant not reported. Standard errors in parentheses. Data sources as in Figure 1.

Table A.7: The relationship between self-employment and the *UN* ratio, controlling for GDP per capita, entire country

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
Between regression:			
UN ratio	-0.061	-0.143	0.059
	(0.257)	(0.302)	(0.041)
log GDP per capita	-0.189***	-0.197***	0.013***
	(0.016)	(0.019)	(0.003)
R^2	0.725	0.685	0.332
observations	125	107	107
countries	61	55	55
Pooled regression:			
UN ratio	-0.088	-0.057	0.032
	(0.212)	(0.236)	(0.034)
log GDP per capita	-0.181***	-0.193***	0.013***
	(0.014)	(0.017)	(0.002)
R^2	0.711	0.684	0.296
observations	125	107	107
countries			

Notes: The table shows regression coefficients from regressions of the dependent variable on the *UN* ratio and log GDP per capita, using time averages of data (between regression). Constant not reported. Standard errors in parentheses. Data sources as in Figure 1.

Table A.8: The relationship between self-employment and the *UN* ratio, controlling for GDP per capita, entire country (ILO data)

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
UN ratio	-0.200	-0.359	0.159**
	(0.335)	(0.301)	(0.075)
log GDP per capita	-0.104***	-0.109***	0.005
	(0.019)	(0.017)	(0.004)
R^2	0.538	0.601	0.138
observations	259	259	259
countries	32	32	32

Notes: The table shows regression coefficients from regressions of the dependent variable on the *UN* ratio and log GDP per capita, using ILO data for 1995 to 2007. The regressions use time averages of data (between regression). Constant not reported. Standard errors in parentheses. Results are virtually identical when years before 1995 are included.

Table A.9: Labor market stocks and flows, focus countries

	USA			**South Africa**		
Transition matrix from \to						
	u	n	e	u	n	e
u	77.3	21.3	1.4	95.0	4.2	0.8
n	0.95	98.7	0.36	1.2	98.4	0.4
e	0.65	3.5	95.9	1.5	2.2	96.3
Stocks	6.4	85.1	8.6	25.0	64.6	10.4
UN ratio	6.9			27.9		
	Mexico			**Brazil**		
Transition matrix from \to						
	u	n	e	u	n	e
u	63.7	29.4	6.8	87.2	9.8	3.0
n	1.25	95.9	2.82	1.3	97.5	1.2
e	0.72	7.8	91.5	1.3	3.9	94.8
Stocks	4.2	68.9	27.0	12.3	65.8	21.9
UN ratio	5.7			15.8		

Notes: Source: Stocks and flows: DLS. Monthly transition rates implied by the quarterly rates reported by DLS. All transition probabilities and shares are in percent. Flows and stocks for all individual countries are shown in Figures A.2a and A.3 in the Appendix.

Table A.10: Calibration results: country-specific parameters

country	k_v	λ (%)	p_0 (%)	p_1 (%)	$\bar{k}_f$	z_m	δ (%)	χ (%)
ALB	133.9	0.10	64.8	6.1	641	0.677	0.19	0.57
ARG	5.6	0.45	47.8	14.1	49.6	0.688	2.09	1.68
AUT	7.8	0.27	56.2	11.0	2759.8	0.740	0.20	0.10
BGR	23.8	0.24	88.5	24.0	1503.6	0.605	0.11	0.09
BOL	3.4	0.70	65.9	10.3	28.6	0.703	1.26	4.17
BRA	15.4	0.54	50.0	11.4	168.1	0.655	1.29	1.18
CHE	6.0	0.35	80.6	16.4	1049.7	0.690	0.33	0.12
CHL	5.4	0.53	24.3	16.1	50.9	0.665	1.78	2.08
CRI	7.9	0.67	31.3	17.6	72.9	0.699	1.85	1.22
CYP	13.1	0.32	51.1	12.7	1756.7	0.770	0.34	0.06
CZE	30.7	0.21	83.5	10.6	5359.7	0.777	0.10	0.04
DNK	3.7	0.31	67.2	11.5	1114.6	0.534	0.35	0.30
DOM	22.9	0.35	40.7	11.2	164.6	0.730	0.57	0.81
EST	11.1	0.31	75.8	12.1	2135.5	0.741	0.40	0.13
FRA	31.2	0.26	20.3	12.0	9485.5	0.839	0.21	0.04
GBR	10.9	0.30	72.7	13.4	868.7	0.695	0.35	0.19
GRC	210.0	0.24	22.7	5.5	16317.6	0.795	0.08	0.03
HRV	74.6	0.15	0.0	3.6	4850.4	0.642	0.08	0.05
HUN	24.1	0.22	63.6	12.3	5991.8	0.666	0.07	0.04
IRL	50.8	0.34	56.0	8.4	5020.5	0.838	0.30	0.04
ITA	19.6	0.22	60.4	11.1	782.3	0.739	0.35	0.27
LTU	28.8	0.27	79.3	12.0	1886.0	0.768	0.36	0.12
LVA	14.5	0.40	68.9	17.9	1129.9	0.735	0.41	0.13
MEX	1.6	0.58	73.3	10.0	70.9	0.578	0.72	2.82
MNG	26.1	0.85	0.0	2.3	283.4	0.649	0.69	0.74
NLD	9.5	0.22	59.2	6.9	2480.1	0.676	0.11	0.08
PER	4.4	0.41	34.0	10.2	49.8	0.748	1.60	2.54
POL	25.9	0.18	68.3	16.3	2855.2	0.671	0.08	0.07
PRT	25.0	0.28	45.1	10.8	378.3	0.614	0.71	0.50
PRY	5.6	0.59	44.1	11.1	67.6	0.705	1.48	2.00
ROU	76.7	0.19	79.0	5.1	395.0	0.623	0.20	0.25
SVK	95.4	0.23	79.1	12.9	12345.4	0.750	0.08	0.03
SVN	11.8	0.11	71.9	13.4	552.9	0.534	0.26	0.57
SWE	11.2	0.25	46.6	15.3	3917.6	0.684	0.15	0.09
USA	3.9	0.49	54.7	10.5	411.9	0.642	0.65	0.36
WBG	13.6	1.82	30.6	15.8	91.7	0.744	3.23	1.81
ZAF	73.1	0.60	35.8	14.4	849.1	0.669	1.46	0.80

Table A.11: Relative deviations of model flows from data when some parameters are common across countries

	Median relative deviation of					
common	Job finding	SE entry	Separation rate	Separation rate by tenure:		
parameter	rate $P(UN)$	rate $P(UE)$	$P(NU)$	0-6 months	7-12 months	60+ months
k_v	0.35	0.05	0.50	0.09	0.15	1.00
λ	0.00	0.00	0.22	0.00	0.00	0.37
p_0	0.05	0.01	0.19	0.04	0.20	0.26
$\bar{k}_f$	0.00	0.77	0.25	0.00	0.03	0.08

Notes: The table shows the median (across countries) relative deviation of model from data moments when an individual parameter is set to the cross-country median in all countries, and the other parameters are re-calibrated to minimize the sum of squared deviations of model from data moments in each country. Median parameter values are shown in Table 4.

Table A.12: The effect of frictions on unemployment and self-employment, by quadrant

Quadrant	Effect on ...						
	u		UN ratio		self-employment rate		output
	(pp)	(ela.)	(pp)	(ela.)	(pp)	(ela.)	(%)
				Higher λ:			
high UN, high SE	0.15	0.37	0.24	0.44	0.26	0.17	-0.16
high UN, low SE	0.25	0.77	0.31	0.83	0.27	0.38	-0.28
low UN, high SE	0.07	0.41	0.12	0.46	0.21	0.13	-0.07
low UN, low SE	0.12	0.80	0.15	0.82	0.13	0.18	-0.13
Total	0.16	0.62	0.22	0.67	0.22	0.23	-0.17
				Higher k_v:			
high UN, high SE	0.23	0.30	0.42	0.40	0.79	0.26	-0.38
high UN, low SE	0.27	0.42	0.34	0.47	0.41	0.30	-0.37
low UN, high SE	0.08	0.23	0.18	0.34	0.75	0.22	-0.21
low UN, low SE	0.14	0.46	0.16	0.48	0.24	0.17	-0.17
Total	0.20	0.38	0.30	0.44	0.51	0.24	-0.29
				Higher $\bar{k}_f$:			
high UN, high SE	0.26	0.24	0.25	0.17	-0.86	-0.18	-0.46
high UN, low SE	0.11	0.10	0.08	0.06	-0.56	-0.26	-0.24
low UN, high SE	0.18	0.32	0.23	0.26	-0.59	-0.11	-0.29
low UN, low SE	0.03	0.06	0.02	0.04	-0.29	-0.13	-0.10
Total	0.14	0.15	0.13	0.11	-0.57	-0.18	-0.27

Notes: The table shows the mean effect in each quadrant of countries of raising k_v, λ or $\bar{k}_f$ by 0.1 log standard deviations.

Table A.13: The effect of frictions on selection, output and wages, lower value of ε

$\varepsilon = 0.5$						
Change	Effect on ...					
	u		UN ratio		self-employment rate	
	(pp)	(ela.)	(pp)	(ela.)	(pp)	(ela.)
λ	0.16	0.61	0.22	0.67	0.23	0.24
k_v	0.18	0.35	0.28	0.42	0.57	0.27
p_0	0.03	0.33	0.04	0.30	-0.08	-0.25
$\bar{k}_f$	0.26	0.29	0.24	0.20	-1.08	-0.34
Change	Effect on ... (in %)					
	mean y	mean w	mean z	output	output (constant u, e)	
λ	-0.04	-0.1	-0.11	-0.17	-0.05	
k_v	-0.11	-0.33	-0.44	-0.26	-0.19	
p_0	-0.09	-0.03	0.21	-0.09	-0.03	
$\bar{k}_f$	-0.01	-0.01	0	-0.51	-0.01	

Notes: The table shows the mean effect across the 37 countries of raising k_v, λ or $\bar{k}_f$ by 0.1 standard deviations, or reducing p_0 by the same amount. The top panel shows changes in outcomes in percentage points and as elasticities. The bottom panel shows percent changes. Recall that in the benchmark, ε is 1.

Appendix B. Additional model equations

The value of an unscreened match to a firm:

$$J^u(y) = y - w^u(y) + \beta(1-\chi^u(y))\{p_1\pi[(1-\lambda)J^s(y) + \lambda E(\max(J^s(y'),0))] \\ + (1-p_1)[(1-\lambda)J^u(y) + \lambda E(\max(J^u(y'),0))]\}. \tag{B.1}$$

Inserting the wage, this becomes

$$J^u(y) = \{(1-\eta)[y-(1-\beta)U + \beta\chi^u(y)k_f] + \beta(1-\lambda)(1-\chi^u(y))p_1\pi J^s(y) \\ + \beta\lambda(1-\chi^u(y))\left[p_1\pi G(R^s)E(J^s(y')|y'>R^s) + (1-p_1)G(R^u)E(J^u(y')|y'>R^u)\right]\} \\ /(1-\beta(1-\lambda)(1-\chi^u(y))(1-p_1))$$

The reservation productivity of an unscreened match is

$$R^u = (1-\beta)U - \beta\chi k_f - \frac{\beta(1-\lambda)(1-\chi)}{1-\eta}p_1\pi J^s(y) \\ - \frac{\beta\lambda(1-\chi)}{1-\eta}\left[p_1\pi G(R^s)E(J^s(y')|y'>R^s) + (1-p_1)G(R^u)E(J^u(y')|y'>R^u)\right] \tag{B.2}$$

Appendix C. Equilibrium computation and calibration

Appendix C.1. Algorithm for solving for the model equilibrium

1. Guess k_f.
2. Solve the system of equations (2), (JD) and (B.2) to obtain U, R^s and R^u.
3. Compute $w(y)$, $W^i(y)$ and $J^i(y)$. Compute $J^i(y_0)$.
4. Compute θ using equation (JC).
5. Compute $F(z)$.
6. Compute Q using equation (11).
7. If $k_f = Q - U$, it is the equilibrium value. Otherwise, adjust the guess in Step 1.
8. Use k_f to compute e_{in}. Compute y^i_Q and z^i_W.
9. Iterate on equation (1) to obtain u, n^s, n^u and e.

Appendix C.2. Algorithm for model calibration

The following steps constitute the algorithm for jointly solving the model and calibrating the eight country-specific parameters to match flows across labor market states and the hazard of flows from wage employment to unemployment.

1. **Obtain** δ: Set $\delta = P(BU)$.

2. Guess values for χ and z_m.

3. Guess values of k_f and $\bar{z}$.

4. The definition of the self-employment entry rate, $P(UB) = h^e G(\bar{z})$, implies $h^e = P(UB)/G(\bar{z})$.

5. Guess R^s.

6. **Obtain** λ: $P(WU)$ at long tenures equals $\lambda G(R^s)$. So R^s and $P(WU)$ imply λ.

7. By equations (JD) and (11) λ and R^s imply U and, with k_f, Q. Equation (B.2) then gives R^u.

8. **Obtain** p_0, p_1: λ, R^s and R^u imply the separation rates for screened and unscreened matches. Using these, simulate the job tenure distribution to find the values of p_0 and p_1 that match the exit hazards for 0 to 6 and 7 to 12 months.

9. The definition of the job finding rate, $P(UW) = (1 - h^e)\theta q(1 - p_0 + p_0\pi)$, then determines the equilibrium value of θq and thus θ.

10. λ and p_1 imply $W^{i'}(y)$ and $J^{i'}(y)$. Then k_f implies the thresholds y_Q^s and y_Q^u below which wage workers accept self-employment opportunities. This, combined with R^s and R^u, implies the value of successful new matches to workers and firms, $W^i(y_0)$ and $J^i(y_0)$.

11. Using equation (**??**), compute the value of search S. If $S = U$, the guess of R^s in Step 5 is confirmed. Otherwise, return to Step 5 and adjust the guess.

12. **Obtain** k_v: From the free entry condition (JC), the expected value of a new match, $(1 - p_0)J^u(y_0) + p_0\pi J^s(y_0)$, implies the vacancy posting cost.

13. Using equation (10), compute the value of self-employment $F(z)$ (which depends on the value of jobs because of the arrival of job opportunities). Compute self-employment reservation output $\bar{z}$ for entrants from unemployment ($\bar{z} \equiv z$ s.t. $F(z) = U$), the expected value of self-employment entry, $Q = E(\max(F, U))$, and the implied marginal willingness to pay for self-employment entry, $k_f = Q - U$. If $\bar{z}$ and k_f equal the guesses in Step 3, they are confirmed. Otherwise, return to Step 3 and adjust the guesses.

14. **Obtain** $\bar{k}_f$: It follows from the assumption that $k_f = \bar{k}_f h^{e\varepsilon}$.

15. Using $F(z)$ and $W^i(y)$, compute z^i_W, the self-employment output level below which the self-employed accept a job of type i. ζ, θ, p_0 and $z^i_W(z)$ imply $P_{BW^i}(z)$, which in turn implies the self-employment productivity distribution, $e(z)$. Integrate over $P_{BW^i}(z)e(z)$ to compute model aggregate $P(BW^i)$. Model $P(BW) = P(BW^u) + P(BW^s)$.

16. Guess model $P(W^iB)$. (This is not equal to χ because only workers with $y < y^i_Q$ accept self-employment opportunities, and because not all self-employment entrants succeed.) This is the final unknown element of the flow matrix across labor market states. Compute the state distribution. Using this and the flow matrix, compute the mass of matches with productivity y_0, and the density with lower productivity. Using these and y^i_Q, compute implied $P(W^iB)$. If this does not equal the guess of $P(W^iB)$, update the guess and repeat.

17. **Obtain** χ and z_m: Compare model $P(BW)$ and $P(WB)$ to the data. If they do not equal data values, update the guesses of χ and z_m in Step 2.

Appendix D. Data

In this section, I lay out how I compute the distribution of employment status from IPUMS data, and flows from Donovan et al. (2023). I also thank the statistical offices that provided the data underlying IPUMS.

Appendix D.1. IPUMS data

IPUMS International data (see Minnesota Population Center, 2017) is available at `https://international.ipums.org`. I use the variables EMPSTAT (employment status), CLASSWK (class of worker), URBAN (urban-rural status) and AGE, and use the provided weights.

The variable EMPSTAT (employment status) takes the values 0 (not in universe), 1 (employed), 2 (unemployed), 3 (inactive), 9 (unknown/missing). More detailed 3-digit codes are also provided. The proportion missing is generally small. I code the value 3 as out of the labor force, and 1 and 2 as indicated. The labor force is the union of 1 and 2. My measure of unemployment includes those who are unemployed because no work was available (code 230) and the inactive unemployed (240). (These categories are specified separately only for some countries.) For the narrow measure of unemployment used in some tables, I exclude these two groups, where possible.

The variable CLASSWK (class of worker) is available for the employed. It takes the values 0 (not in universe), 1 (self-employed), 2 (wage/salary worker), 3 (unpaid worker), 4 (other), 9 (unknown/missing). More detailed 3-digit codes are also provided. I use them to distinguish own-account workers (120) and employers (110). Again, the proportion missing is small. I drop unpaid workers and "other".

The main analysis uses categories of CLASSWK and EMPSTAT as proportions of the labor force.

Appendix D.2. Donovan et al. (2023) data

Donovan et al. (2023) have graciously made the data they gathered and harmonized available on the website `https://www.lfsdata.com/home`. I thank the authors for making the data available.

This paper uses the data on aggregate flows. In addition, the authors have provided data on exit hazards from wage employment specifically to unemployment.

Appendix D.3. Country codes and acknowledgements

I thank the statistical offices that provided the data underlying IPUMS:

National Institute of Statistics and Censuses, Argentina (ARG)

National Statistical Service, Armenia (ARM)

National Bureau of Statistics, Austria (AUT)

Bureau of Statistics, Bangladesh (BGD)

Ministry of Statistics and Analysis, Belarus (BLR)

National Institute of Statistics, Bolivia (BOL)

Institute of Geography and Statistics, Brazil (BRA)

National Institute of Statistics and Demography, Burkina Faso (BFA)

National Institute of Statistics, Cambodia (KHM)

Central Bureau of Census and Population Studies, Cameroon (CMR)

Statistics Canada, Canada (CAN)

National Institute of Statistics, Chile (CHL)

National Administrative Department of Statistics, Colombia (COL)

National Institute of Statistics and Censuses, Costa Rica (CRI)

National Statistics Office, Dominican Republic (DOM)

National Institute of Statistics and Censuses, Ecuador (ECU)

Central Agency for Public Mobilization and Statistics, Egypt (EGY)

Central Statistical Agency, Ethiopia (ETH)

National Institute of Statistics and Economic Studies, France (FRA)

Federal Statistical Office, Germany (DEU)

Ghana Statistical Services, Ghana (GHA)

National Statistical Office, Greece (GRC)

National Statistics Directorate, Guinea (GIN)

Institute of Statistics and Informatics, Haiti (HTI)

Central Statistical Office, Hungary (HUN)

Ministry of Statistics and Programme Implementation, India (IND)

Statistics Indonesia, Indonesia (IDN)

Statistical Center of Iran, Iran (IRN)

Central Statistical Office, Iraq (IRQ)

Central Statistics Office, Ireland (IRL)

Central Bureau of Statistics, Israel (ISR)

National Institute of Statistics, Italy (ITA)

Department of Statistics, Jordan (JOR)

National Statistical Committee, Kyrgyz Republic (KGZ)

National Statistical Office, Malawi (MWI)

Department of Statistics, Malaysia (MYS)

National Directorate of Statistics and Informatics, Mali (MLI)

National Institute of Statistics, Geography, and Informatics, Mexico (MEX)

High Commission of Planning, Morocco (MAR)

Statistics Netherlands, Netherlands (NLD)

National Institute of Statistics and Censuses, Nicaragua (NIC)

National Bureau of Statistics, Nigeria (NGA)

Statistics Division, Pakistan (PAK)

Census and Statistics Directorate, Panama (PAN)

General Directorate of Statistics, Surveys, and Censuses, Paraguay (PRY)

National Institute of Statistics and Informatics, Peru (PER)

National Institute of Statistics, Portugal (PRT)

National Institute of Statistics, Romania (ROU)

National Institute of Statistics, Rwanda (RWA)

National Agency of Statistics and Demography, Senegal (SEN)

Statistical Office, Slovenia (SLV)

Statistics South Africa, South Africa (ZAF)

National Institute of Statistics, Spain (ESP)

Central Bureau of Statistics, Sudan (SDN)

Federal Statistical Office, Switzerland (CHE)

National Bureau of Statistics, Tanzania (TZA)

Turkish Statistical Institute, Turkey (TUR)

Bureau of Statistics, Uganda (UGA)

Office of National Statistics, United Kingdom (GBR)

Bureau of the Census, United States (USA)

National Institute of Statistics, Uruguay (URY)

National Institute of Statistics, Venezuela (VEN)

General Statistics Office, Vietnam (VNM)

Central Statistical Office, Zambia (ZMB)