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ABSTRACT

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Poor countries have low rates of wage employment and high rates of self-employment. This paper shows that they also have high rates of unemployment relative to wage employment, and that self-employment is particularly high where the unemployment-wage employment ratio is high. I interpret high unemployment-employment ratios as evidence of labor market frictions, and develop a simple heterogeneous-firm search and matching model with choice between job search and self-employment to analyze their effect. Quantitative analysis of the model, separately calibrated to eight countries, shows that variation in labor market frictions can explain almost the entire variation in not only unemployment, but also wage employment and self-employment across the calibration countries. The model generates joint variation in unemployment and self-employment accounting for at least a third of their relationship in the data. Labor market frictions reduce output not only by affecting employment, but also by pushing searchers into low-productivity own-account work.

JEL Classification: O40, L26, J64, J23

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

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1 Introduction

Labor markets in low income countries differ fundamentally from those in advanced economies. A central distinguishing feature consists in their very low levels of wage employment. In Addis Ababa, the capital of Ethiopia, for example, only about half of the labor force is in wage employment, and almost all wage employment in Ethiopia is in firms with fewer than 10 workers. Instead, there is a very large number of own account workers and self-employed. These two groups account for more than a quarter of the labor force in Addis Ababa.[1]

The employment structure in poor countries contrasts with that in rich countries, where most workers are employed in large firms. In the United States for example, own-account workers account for only about 5% of employment, and wage and salary workers account for about 85% of the labor force. About half of them work in firms with more than 500 employees (Hipple (2010), Census Business Dynamics Statistics).

These differences matter. Indeed, the creation of wage jobs has been identified as a key development challenge – it is the topic of the World Bank's 2013 World Development Report, and the employment rate is part of the United Nations Millennium Development Goals (World Bank 2012, United Nations 2010).[2] 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 barriers to job creation and firm growth, the implications of regulation for firm size, and the effect of technology on the relative returns of wage work and self-employment.[3] 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 type of argument implies a negative relationship between wage employment and self-employment across countries.

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 hard to find, they not only cause high unemployment relative to wage employ-

[1]Data from Gindling and Newhouse (2012), World Bank (2012), and author's calculations using the Ethiopian Urban Employment and Unemployment Survey. Most of this article focusses on data for urban areas. Patterns at the level of the entire country are even starker.

[2]These references stress that for the purposes of this question, one should conceive of wage employment broadly, including both formal and informal employment. This paper takes the same approach.

[3]See e.g. Hsieh and Klenow (2014), Buera, Kaboski and Shin (2015); Restuccia and Rogerson (2008), Guner, Ventura and Xu (2008), Albrecht, Navarro and Vroman (2009); Gollin (2007) and Poschke (2018).

ment (few searchers are successful), but also promote self-employment, as an alternative to unattractive job search. 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 difficulty of job search and self-employment across countries.

The first contribution of this paper is to investigate these relationships among measures of labor force status, and to provide evidence for the new channel that is proposed here. I do so using harmonized census data from more than 60 countries provided by IPUMS International (Minnesota Population Center 2017). This analysis reveals two relevant new facts. First, the ratio of unemployment to the sum of unemployment plus wage employment, $\tilde{u} \equiv u/(u+n)$, is much higher in poor countries.[4] On average, it decreases by two and a half percentage points every time income per capita doubles. As a result, it is almost 10 percentage points larger in the poorest countries compared to the richest ones. High $\tilde{u}$ suggests that job seekers are not very successful in poor countries, indicating strong labor market frictions.[5] Second, in urban areas, self-employment is particularly high in countries with high $\tilde{u}$, even after controlling for GDP per capita. The relationship is quantitatively strong: an increase in $\tilde{u}$ by one percentage point is associated with an increase in the self-employment rate by around 0.7 percentage points. This finding suggests higher self-employment entry in countries where job search is less attractive.

An accounting analysis of a simple flow model of the labor market, with fixed flow rates among the three states of wage-employment, self-employment and unemployment, illustrates that these patterns cannot be generated by cross-country differences in self-employment entry rates alone, but that differences in job finding rates are required. The key reason is that differences in self-employment entry rates cannot generate the correlation between self-employment and $\tilde{u}$ that is observed in the data. Low wage employment and high self-employment in poor countries must thus at least partly be due to labor market frictions. This also implies that labor market frictions may have implications for aggregate productivity and welfare beyond their direct and obvious effect on unemployment, given that small firms and own-account workers typically are less productive.

What is the quantitative importance of labor market frictions for differences in wage employment, self-employment, and productivity? Answering this question requires quantitative analysis of a theoretical model. However, the literature on job search has scarcely addressed

[4] This ratio is a monotonic transformation of the unemployment to wage employment ratio mentioned above. In a world without self-employment, it would be identical to the unemployment rate as usually measured, namely the ratio of unemployment to the labor force. In a world with self-employment, it provides a more focussed measure of labor market outcomes for those who actually search for jobs in wage employment.

[5] The ratio of unemployment to the labor force in contrast does not vary systematically with income per capita (in line with the findings of Caselli (2005) for a more limited set of countries).

self-employment (see e.g. the review by Rogerson and Shimer (2011)), while the literature linking the firm size distribution and aggregate productivity has almost exclusively analyzed the allocation of employment across employer firms, and largely ignored both unemployment and self-employment – despite their importance in poor economies. (The few exceptions are discussed below.) The second contribution of this paper consists in filling this gap. To do so, I develop a theoretical framework that allows linking wage employment, unemployment, self-employment, and productivity, and allows exploring their connections via counterfactual analysis.

My model builds on a version of the standard Diamond-Mortensen-Pissarides (DMP) search and matching model with firms that are heterogeneous in size and productivity, as in Elsby and Michaels (2013), augmented with a choice between job search on the one hand and entry into entrepreneurship on the other hand. The key assumption is that job search is subject to search and matching frictions, while entry into entrepreneurship is always possible at a cost.[6] Success, however, is uncertain, as an entrepreneur's productivity is only revealed after entry. This set of assumptions delivers a meaningful distinction between own-account workers and employers, and also allows addressing the determinants of the small size of firms in low income economies. The firm size distribution and the entry rate into entrepreneurship then are endogenous model outcomes. Finally, I also model casual jobs in a very simple way, to reflect their importance in poor countries.

I then calibrate the model using data on labor market states and flows and the firm size distribution for the urban areas of eight countries, ranging in income level from Ethiopia via Indonesia and Mexico all the way to some European economies and the United States. The use of information on labor market flows in poor countries is an important, novel feature of the analysis. Calibrating the model to various countries shows how it can accommodate very different labor market conditions. It also permits analyzing quantitatively which cross-country differences, out of a large set of potential candidates, are the determinants of the strongly dispersed wage employment, unemployment and entrepreneurship rates observed in the data.

This analysis points to variation in labor market frictions as the main determinant of cross-country differences not only in unemployment, but also in wage employment and self-employment. Differences in labor market frictions explain almost all the variation in unemployment, wage employment and self-employment across the eight calibration economies. The model also accounts for at least a third of the positive relationship between self-

[6]This also presupposes that job search and self-employment are mutually exclusive activities, i.e., only one can be pursued at a time. This assumption is in line with the empirical evidence that self-employment tends to be a full time, persistent activity. See below for details.

employment and the unemployment-employment ratio found in the data. In contrast to this, variation in parameters more directly related to self-employment, like entry costs or the relative productivity of own-account workers compared to employer firms, could in principle explain observed patterns in self-employment, but would generate counterfactual variation in unemployment. Size-dependent distortions do not account for much of the variation in labor force status either.

The quantitative analysis leads to two further interesting findings. First, it reveals that while labor market frictions always reduce wage employment, they do so via higher unemployment when firm entry costs are high, as in rich economies, but via higher self-employment when firm entry is cheap, as in poor economies. Second, labor market frictions also affect aggregate output. Part of this comes simply from their effect on unemployment. This effect is largest in developed economies. But another part, which is quantitatively very important in poor, low-entry cost economies, comes from the fact that strong labor market frictions induce individuals to take up low-productivity own-account work instead of searching for employment. Labor market frictions thus cause misallocation of labor.

To summarize, there is a strong relationship between self-employment and unemployment in cross-country data. There also is a clear theoretical link: potential job seekers or entrants compare the two options, so that their relative attractiveness affects the number of people engaging in each activity. My quantitative findings suggest that this channel is important, and that variation in labor market frictions can account for a large fraction of the univariate and joint variation in wage employment, self-employment and unemployment rates across countries observed in the data. Combined with the effect of labor market frictions on output, this calls for more attention to systematic variation in labor market frictions across countries as a determinant of cross-country differences in economic outcomes. Improving labor market functioning in low income economies can thus have multiple benefits: not only reduced unemployment, but also a lower incidence of low-profit own-account work.

My findings naturally lead to the question of the precise nature of frictions in urban labor markets of poor countries. Since the model used for the analysis was on purpose kept simple, this question goes beyond the scope of this paper, and should be the subject of future research. There is no shortage of competing candidate explanations. Are matches hard to form because information on vacancy and worker attributes is costly or difficult to convey, e.g. because of low levels of use of information technology, or low levels of skill certification? Is screening hard, with the consequence that matches are experience goods and lasting matches may take time to form?[7] Does something prevent workers from exercising

[7]See Jovanovic (1984) and Pries and Rogerson (2005) on matches as experience goods. This interpretation is also in line with the finding by Blattman and Dercon (2018) that manufacturing firms in Ethiopia do not

the optimal amount of search effort? Or do workers have unrealistic expectations, leading them to search in suboptimal market segments or to have high reservation wages? Some of the experimental work cited in the literature discussion on the next pages takes a first stab at these questions.

Related literature. While existing work on unemployment and job search in developed economies is abundant, there are only a few papers studying poorer economies.[8] Albrecht et al. (2009), Margolis, Navarro and Robalino (2012), Narita (forthcoming), Bradley (2016) and Galindo da Fonseca (2018) are most closely related to this paper, in that they also allow for self-employment.[9] Yet, their focus is not on labor market frictions and self-employment, but on the effect of taxes, unemployment insurance benefits, severance pay and entry costs on output and/or the size of the informal sector.

The present paper is also different in terms of methodology. First, none of the papers mentioned conducts a cross-country analysis. Second, the papers all assume that self-employment or entrepreneurship opportunities arrive at a fixed, exogenous rate. The exogenous arrival rate implies that the self-employment rate can respond to changes in the environment only via a selection effect. This limits variation in the self-employment rate, and limits the impact of occupational choice on aggregate outcomes, which I find to be large.

There also is a small set of papers studying how labor market aggregates vary with income per capita across countries. The seminal paper by Gollin (2007) showed that the self-employment rate declines with income per capita across countries, and analyzed the relationship in a frictionless span of control model building on Lucas (1978). More recently, Donovan, Lu and Schoellman (2017) document labor market flows for 13 countries with medium to high per capita incomes. Bick, Fuchs-Schündeln and Lagakos (2018) document how hours worked vary with income per capita within and across countries. Bridgman, Duernecker and Herrendorf (2018) study variation in time spent on household production

face a shortage of applicants to their vacancies, but experience high rates of quits and turnover.

[8]It is also true that little of the work on labor market search in developed countries considers self-employment. Two recent exceptions are Kredler, Millan and Visschers (2014) and Delacroix, Fonseca, Poschke and Ševčík (2016), who study the joint determination of unemployment and self-employment over the business cycle in the United States, Canada and Europe. To the best of my knowledge, this has been a dormant question since the earlier paper by Fonseca, Lopez-Garcia and Pissarides (2001), who focus on the effect of entry barriers in the OECD.

[9]Zenou (2008), Ulyssea (2010), Bosch and Esteban-Pretel (2012), and Meghir, Narita and Robin (2015) consider the related but different problem of firms' choice of formality versus informality in macroeconomic models of search and analyze how policies, in particular the enforcement of regulations, affect the share of formal jobs, unemployment and aggregate output. None of them allows for an occupational choice by workers or job seekers, ruling out the analysis of self-employment by construction. Rud and Trapeznikova (2016) do allow for self-employment, but do not model occupational choice. They assume that all workers who do not find a job in a constant-returns sector engage in self-employment.

with GDP per capita. Most closely related is the recent paper by Feng, Lagakos and Rauch (2018), who study patterns in the unemployment rate by income per capita, focussing on data covering the entire country, including rural areas. Their analysis emphasizes the role of structural change and differences in frictions across sectors, not countries.

Finally, there is an emerging literature studying search behavior, labor market frictions and self-employment in developing economies at the micro level, using surveys and experiments. Several papers in this literature find support for the existence of various types of labor market frictions in the specific settings they study. Both Franklin (2018) and Abebe, Caria, Fafchamps, Falco, Franklin and Quinn (2018) find that reducing search costs at the individual level improves job search outcomes in Addis Ababa. Bassi and Nansamba (2018) find that certifying worker skills affects labor market outcomes in urban areas of Uganda. Banerjee and Chiplunkar (2018) find that there is great scope for improving the process of matching graduates of an Indian vocational training institute to vacancies, even when it is already done by professionals. Blattman and Dercon (2018) show, again in Ethiopia, that unpleasant jobs are often taken temporarily, to cope with adverse shocks or finance search for better jobs or future self-employment, and that self-employment is considered desirable by many. Lagakos, Moll, Porzio, Qian and Schoellman's (2018) finding of flatter experience-wage profiles in poorer countries is also consistent with more severe search frictions in poorer countries. All this work is highly complementary to this paper, and gives indications of the precise nature of frictions in urban labor markets in some poor countries.

The paper is organized as follows. The next section documents the joint relationship of wage employment, self-employment, unemployment and GDP per capita across countries. Section 3 contains a simple accounting analysis that identifies potential drivers of the cross-country patterns. Section 4 presents the economic model. Quantitative results are shown in Sections 5 to 7. Section 5 describes the calibration of the model economy using data from eight countries. Section 6 identifies the main quantitative determinants of cross-country differences in wage employment, unemployment and self-employment, and Section 7 analyzes the effects of labor market frictions on unemployment, self-employment and productivity in more detail. Section 8 concludes. Appendices contain additional figures and tables, and additional details on theory and numerical methods.

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. I begin by describing data sources.

2.1 Data sources and measurement issues

My main source of data consists in the censuses available via the International Integrated Public Use Microdata Surveys (IPUMS International, Minnesota Population Center (2017)). IPUMS International provides access to micro data from almost 200 censuses collected in more than 60 economies since 1960. This data source has very broad coverage, both in terms of countries and in terms of individuals within each country. It is also very versatile, as it allows computing measures of wage employment, self-employment and unemployment not only for the aggregate economy, but also for subgroups (like urban residents, young workers, etc.) for many countries. For example, an urban wage employment and unemployment rate can be computed for 150 censuses from 58 countries, ranging in GDP per capita from very poor countries like Ethiopia, Mozambique and Uganda to rich economies like the United States. My main sample consists of urban residents of both sexes between the ages of 20 and 65.[10]

Income per capita throughout is in 2011 US dollars, converted at PPP, from the Penn World Tables 9 (Feenstra, Inklaar and Timmer 2015), computed using the variables rgpde and pop.

My definitions of the states of wage employment, self-employment and unemployment follow those in the UN System of National Accounts (United Nations 2008). Employees, or the wage-employed, receive remuneration for their labor. The self-employed include both employers and own-account workers. "An unemployed person is one who is not an employee or self-employed but available for work and actively seeking work." (ibid., p.408.)

In the IPUMS Census data, individuals can be classified into these three categories using the harmonized EMPSTAT and CLASSWK variables. EMPSTAT (employment status) classifies individuals as employed (including both wage and self-employed), unemployed, or inactive. Typically, those who worked at least one hour in the reference period, including

[10]While the bulk of the data was collected after 1980, there are 40 censuses collected between 1960 and 1980. The number of censuses per country ranges from one to nine, with a median of four. Censuses typically take place every ten years. Throughout, I limit the analysis to countries with a population of at least one million.

informal work or day labor, are considered employed. The union of the employed and the unemployed constitutes the labor force. CLASSWK (class of worker) categorizes the employed as either self-employed, wage or salary workers, unpaid workers, or other, according to their main job. For the self-employed, most censuses distinguish employers and own-account workers.

These classifications mirror the UN definitions. The only concern regarding comparability comes from the fact that the reference period for job search used to classify a respondent as unemployed varies across censuses, and occasionally is not specified. Therefore, I group the censuses into quality tiers, like Feng et al. (2018). The top tier contains censuses where the reference period for the employment status question is clearly specified as the past week. In the second tier, the reference period consists of the last four weeks. Censuses using any other reference period, or lacking a clear specification of one, make up the third tier. Robustness checks reported below show that, apart from somewhat smaller statistical significance due to lower sample size, results are generally similar when restricting the analysis to the top comparability tier.

Finally, countries differ strongly in their economic structure and, as is well known, the structural composition of the economy is strongly associated with development (see e.g. Herrendorf, Rogerson and Valentinyi 2014). Most importantly, in poor countries, many workers work in agriculture, often on the family farm. To minimize the effect of these differences, my main analysis uses data not for the entire country, but for urban areas, which are more similar across countries both in their economic structure and in the functioning of labor markets. The IPUMS data are key for being able to do this. I report results for the entire country when it is informative.[11]

For robustness, I also consult aggregate measures of unemployment and self-employment from the ILO. These are mostly computed from labor force surveys, and are typically annual. An important disadvantage of this source is that only country-level measures are available. Given the importance of agriculture in poor countries, these are less comparable across countries than the measures for urban areas computed using IPUMS data.

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 proportion of unemployed labor force

[11] Ideally, one might also want to account for sectors directly. However, apart from the conceptual difficulty of assigning job seekers to a particular sector, the number of censuses reporting the sector of (un)employment is also much more limited than that reporting urban versus rural status, at 88 compared to 150.

members (the unemployment rate), the difference between the black dot and the triangle shows the share of wage/salary workers, and the difference between the grey dot (at the top of the figure) and the black dot shows the fraction of the labor force that is self-employed. Finally, the difference between the grey dot and one gives the fraction of "other". Since this is negligible, I ignore this category in the following. I also exclude unpaid workers. In urban areas, they account for a very small share of the labor force even in the poorest countries.

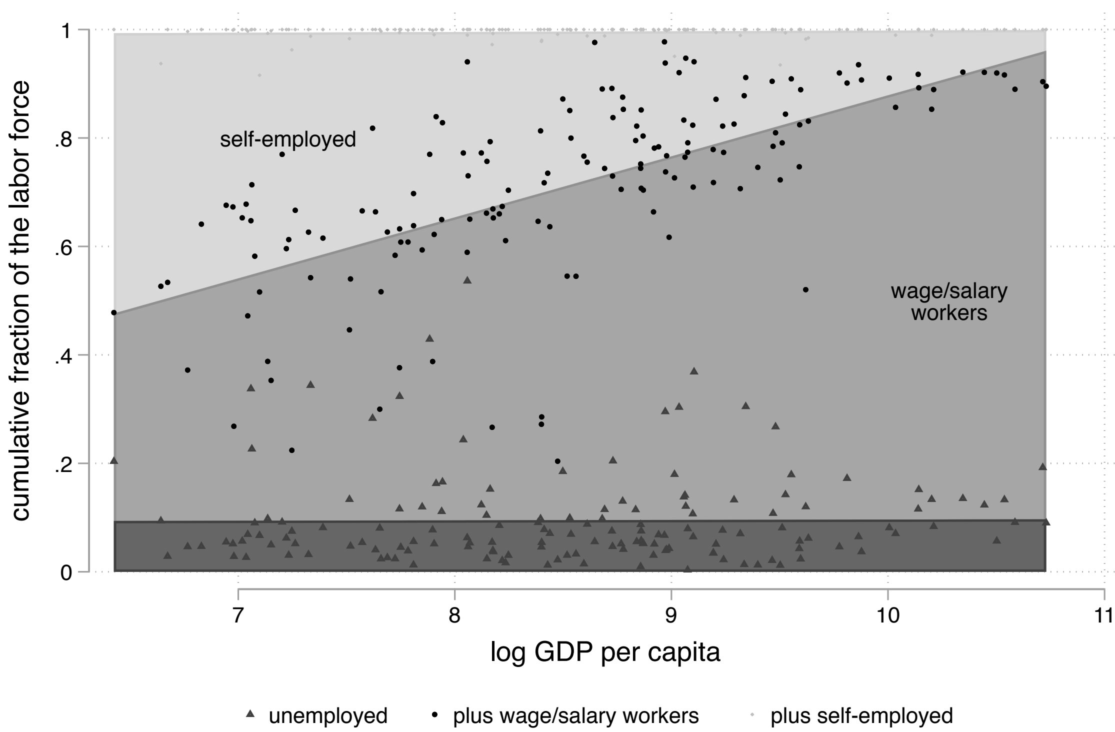


Figure 1: Composition of the labor force and development

Sources: GDP per capita: PWT 9.0. Employment status: IPUMS International. 150 censuses covering 58 countries over the years 1960 to 2011. Data for urban areas. Bottom area: unemployment rate.

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 makes the prevalence of different employment statuses across the country income distribution very clear.

It is immediate from the figure that wage employment is much less common in poor countries. Wage employment rates range from about 40% of the labor force 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, echoing the well-known finding of Gollin (2007). Self-employment rates range from almost 50% of the labor force in the poorest countries to about 10% in the richest ones. The unemployment rate, in contrast, does not vary systematically with development, although it is quite variable across countries.

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***	-0.132***	0.003	-0.035**
	(0.017)	(0.017)	(0.009)	(0.014)
R^2	0.543	0.507	0.002	0.099
observations	150	150	165	150
countries	58	58	65	58
Entire country:				
log GDP per capita	0.183***	-0.187***	0.012*	-0.033***
	(0.014)	(0.016)	(0.007)	(0.011)
R^2	0.718	0.670	0.041	0.121
observations	214	214	235	214
countries	68	68	77	68

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1. Results for a regression using pooled data are similar and are shown in Table A.1.

Regression results underlying the lines in Figure 1 are reported in Table 1. They are similar no matter whether the regression is run on country averages (as in the table), or whether censuses are pooled (as in the figure and in Table A.1 in the Appendix). The unemployment rate does not vary systematically with log income per capita, whereas the wage employment rate and the self-employment rate vary symmetrically: the self-employment rate declines by 0.13 percentage points for each 1% increase in income per capita, and the wage employment rate increases by roughly the same amount. This translates into a decline in the self-employment rate, and an equivalent increase in the wage employment rate, by 9 percentage points every time income per capita doubles. The lower panel of the table shows that regression results for the entire country are similar, with even larger coefficients in absolute terms. Figure A.1 shows results for the entire country graphically. 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: The relationship between entrepreneurship rates and income per capita

dependent variable:	fraction own-account workers, urban	fraction employers, urban	fraction own-account workers, entire country	fraction employers, entire country
log GDP per capita	-0.143***	0.012***	-0.190***	0.010***
	(0.020)	(0.003)	(0.019)	(0.002)
R^2	0.512	0.236	0.629	0.273
observations	140	140	189	189
countries	53	53	63	63

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1. Results for a regression using pooled data are similar (not reported).

Table 2 shows that the pattern in self-employment is driven by own-account workers. The fraction of employers actually is higher in richer economies. These two results hold both for urban areas and overall. Since on average, employers account for only 18% of the self-employed, and account for less than half almost everywhere, it is clear that the overall pattern for the self-employed is driven by own-account workers.

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. (Let u denotes the unemployment rate, n the employment rate, and e the self-employment rate, as fractions of the labor force.) Yet, 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 unemployment as a fraction of the labor force is not higher in poor countries despite low levels of wage employment consists in their high rates of self-employment.

In fact, there is a mechanical negative relationship between the self-employment rate and the unemployment rate: higher self-employment must reduce the unemployment rate, unless it arises from a one for one reduction in wage employment. These considerations imply that in a setting with significant self-employment, the unemployment rate, computed as a fraction of the labor force, captures the prevalence of unemployment, but does not accurately reflect the incidence of failed job search, i.e. how many people are searching for a job as an employee, but failing to find one.

An alternative measure of unemployment is the "UN ratio" $\tilde{u} \equiv u/(u + n)$. This is of course identical to the unemployment rate in a model without self-employment. Unlike u, this measures does capture the incidence of failed search, no matter how important self-employment is. It also has the advantage that it is not mechanically related to the self-employment rate. (Obviously, it is not a good measure of the prevalence of unemployment for the labor force as a whole.)[12]

Since the *UN* ratio differs from the unemployment rate only in its denominator, it has a similar order of magnitude. While the unemployment rate has a median of 7% (10th percentile: 2%, 90th percentile: 19%) in the IPUMS data, the *UN* ratio has a median of 11% (10th percentile: 4%, 90th percentile: 33%).

Given how few employees there are in poor countries, 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. They show that the *UN* ratio declines by 2.5 percentage points as country income per capita doubles.

Table 3 in the main text as well as Table A.4 and Figure A.2 in the Appendix show that this finding is robust to several potential concerns. First, the pattern is not due to differences in demographics, since it holds within age group, both in urban areas and at the level of the entire country. Second, the relationship between the non-participation rate and GDP per capita is very similar to that between the *UN* ratio and GDP per capita. The same is true for the fraction of the population that is not working (inactive plus unemployed). This implies that even if there may be some misclassification between unemployment and non-participation, the negative relationship between the *UN* ratio and GDP per capita appears very robust.[13] Finally, the relationships between the unemployment rate, the *UN* ratio, and log GDP per capita are similar when a narrow measure of the unemployment rate is used. All of this holds both for the entire country and for urban areas only. Table A.3 in the Appendix shows that the relationships between the self-employment rate, the unemployment rate and GDP per capita are also similar in ILO data.

Finally, note that at the level of the entire country, the unemployment rate u increases

[12] The unemployment to wage employment rate u/n would have similar properties, and using it leads to similar results. I prefer to use the *UN* ratio throughout because its order of magnitude is closer to the familiar unemployment rate, making it easier to interpret.

[13] The relationship established here differs from that in Bick et al. (2018), who find higher employment to population rates (including self-employment) in poorer countries. The difference is not driven by data quality or sample period: even when only using tier 1 data and limiting the sample to the year 2000 and later, I still find significantly lower participation in urban areas of poor countries. Instead, the difference appears to be driven by sample composition. Notably, Bick et al.'s (2018) sample does not include several poor countries with low participation rates from the IPUMS data. This is because these countries lack comparable hours data, which are the focus of the analysis in that paper.

Table 3: Unemployment and development, subsamples

dependent variable:	unemployment rate age 20-29	unemployment rate age 30-60	unemployment rate age 61-65	*UN* ratio age 20-29	*UN* ratio age 30-60	*UN* ratio age 61-65
Urban areas:						
log GDP per capita	0.004	0.006	0.009	-0.052***	-0.022*	-0.034**
	(0.013)	(0.008)	(0.008)	(0.018)	(0.013)	(0.014)
R^2	0.001	0.008	0.023	0.123	0.053	0.095
observations	165	165	159	150	150	145
countries	65	65	62	58	58	56
Entire country:						
log GDP per capita	0.018*	0.011**	0.013**	-0.046***	-0.023**	-0.036***
	(0.010)	(0.005)	(0.005)	(0.015)	(0.010)	(0.012)
R^2	0.044	0.051	0.081	0.127	0.078	0.123
observations	235	235	226	214	214	208
countries	77	77	75	68	68	68

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1.

in GDP per capita (Table 1), at a rate close to that found by Feng et al. (2018) using similar data. However, my preferred measure, the *UN* ratio, decreases in income per capita at a similar rate in both urban areas and the entire country.

To summarize, there are large differences in the distribution of employment status across countries at different points of the global income distribution. Comparing countries, doubling income per capita goes along with an increase in the fraction of the labor force engaged as wage and salary workers by 9 percentage points, a corresponding decrease in the fraction engaged in self-employment, and a decline in the *UN* ratio of 2.5 percentage points.

These patterns imply that the apparent constancy of the unemployment rate with development is misleading: among those who are not self-employed, the share of unemployed people is much higher in poorer countries. This suggests that the functioning of labor markets differs systematically with development: while the fraction of the labor force searching for a job does not vary systematically with income per capita, the fraction that actually ends up with a job is much lower in poorer countries, as captured by the higher *UN* rate.

This failure to transform job seekers into employees suggests either very limited hiring by firms, difficulties in matching, very quick destruction of jobs, or any combination of these. All of these imply that job search is less attractive in poorer countries, either because it is less likely to be successful, or because jobs, once found, do not last long. This should 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. This argument suggests that there should be an independent connection between the *UN* ratio, as a measure of the (un)attractiveness of search, and self-employment. I now turn to examining this relationship.

2.3 Self-employment and unemployment

Figure 2 shows the bivariate relationship between the self-employment rate and the *UN* ratio, again using IPUMS census data. It is clear that there is a positive relationship between the two variables, both in urban areas (left panel) and in countries as a whole (right panel). The figures show this relationship up to the 90th percentile of the *UN* ratio. (For urban data, the relationship flattens above this level of the *UN* ratio due to the influence of a few censuses; see Figure A.3 in the Appendix.) The relationship is both economically and statistically significant, with a regression coefficient of 0.79 for both samples, implying an almost one-to-one relationship between the self-employment rate and the *UN* ratio.

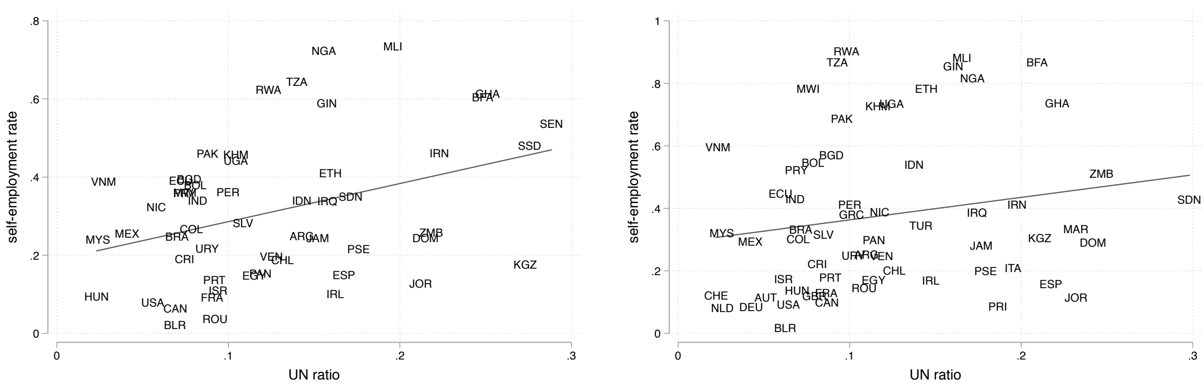


Figure 2: The self-employment rate versus the *UN* ratio $u/(u+n)$, urban (left) and overall (right)

Notes: The solid line shows the fit from an OLS regression. Graphs and regressions exclude observations of *UN* ratio above the 90th percentile of the variable (0.31). Full range shown in Figure A.3 in the Appendix. The regression coefficients are 0.97 (standard error 0.35) for urban areas and 0.72 (standard error 0.49) for the entire country.

Table 4 shows that this relationship is robust to also controlling for log GDP per capita.

The table reports results for urban areas, again for a sample truncated at the 90th percentile of the *UN* ratio, in line with the findings in Figure A.3. This table shows that the coefficient on the *UN* ratio is positive, and economically and statistically significant. It is clear that the relationship is driven by own-account workers. These results imply that an increase in the *UN* ratio by one percentage point, at a constant level of GDP per capita, is associated with an increase in the self-employment rate by 0.7 percentage points, due to an increase in the fraction of own-account workers by 0.8 percentage points. Results also indicate that self-employment is lower in richer countries, with a coefficient that is similar to that of the bivariate relationship between the self-employment rate and income per capita. Results for a pooled regression are similar (see Table A.5 in the Appendix). When using only data for countries in the top data comparability tier, the point estimate in the first column is essentially identical, only the standard error a bit larger, as the sample is a third smaller (see Table A.6).

Results are different when using data for the entire country. Here, the inclusion of GDP per capita in the regression leads to an insignificant coefficient on the *UN* ratio (see Table A.7 in the Appendix, and also Table A.8 using ILO data). This is not entirely surprising. When using data for the entire country, data for poor countries includes many respondents in rural areas, where small-scale agriculture is highly prevalent, and where there are few large employers, limiting opportunities for wage employment. As a result, it is plausible that in these areas, opportunities for wage employment will have hardly any effect on employment choices by individuals. To ensure comparability across countries, I will focus on the results for urban areas shown in Table 4.

Summarizing the analysis in this section, the comparison of urban labor markets of countries at different stages of development reveals three regularities: Labor markets in poor countries feature (1) systematically lower wage employment and higher self-employment rates, (2) higher rates of unemployment relative to wage employment (a higher *UN* ratio), and (3) self-employment is higher in countries with high unemployment relative to wage employment, even conditional on GDP per capita.

3 What drives differences in labor force status across countries? An accounting analysis

The previous section has documented very large differences in the composition of the labor force across countries. What can drive these differences? Before analyzing the data using

Table 4: The relationship between self-employment and the *UN* ratio, controlling for GDP per capita, urban areas

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
UN ratio	0.702**	0.802**	0.058
	(0.285)	(0.312)	(0.051)
log GDP per capita	-0.122***	-0.136***	0.012***
	(0.018)	(0.020)	(0.003)
R^2	0.556	0.575	0.229
observations	136	126	126
countries	54	48	48

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1. Results for a regression using pooled data are similar (Table A.5).

a full economic model with optimal choices between the different labor market states, I perform a simple accounting analysis. The objective of this is to give a first indication of the differences in labor market *flow* rates across countries that are consistent with the observed patterns in *stocks*. This is useful, because in a dynamic model, the individual choices modelled explicity in the next section map directly into flows, and therefore differences in flow rates can easily be linked to fundamentals that could be driving them.

So, consider a labor market where individuals can be in any of the following three states: unemployment (U), self-employment (SE), or wage employment (N). In this section, I do not differentiate between own-account workers and employers, and treat them all as self-employed. Every period, individuals can transition across employment states at rates summarized in the matrix shown in Table 5: The unemployed enter self-employment at a rate h or, conditional on not doing so, find a job with probability f, the employed lose their job with probability s, and the self-employed close their firm and transition into unemployment with probability λ. For tractability, the analysis in the main text abstracts from flows from N to SE. Appendix B shows that results are similar when this flow is permitted. I also set the flow from self-employed to wage employment to zero. (See the next section for a discussion.)

Table 5: Accounting analysis: flow rates across labor market states

from/to	U	N	SE
U	$(1-h)(1-f)$	$(1-h)f$	h
N	s	$1-s$	0
SE	λ	0	$1-\lambda$

The table shows per period flow rates from the states in rows to those in columns.

These flows imply the following steady state stocks for the three labor market states:

$$
\begin{aligned}
u &= \frac{s}{s+(1-h)f+hs/\lambda} \\
n &= \frac{(1-h)f}{s+(1-h)f+hs/\lambda} \\
e &= \frac{h}{\lambda}u = \frac{hs/\lambda}{s+(1-h)f+hs/\lambda} \\
\tilde{u} &\equiv \frac{u}{u+n} = \frac{s}{s+(1-h)f}
\end{aligned}
$$

where u (e) [n] denotes the unemployment (self-employment) [wage employment] rate. Clearly, each state increases in its own inflow rates, decreases in its own outflow rates, and of course there is the adding up constraint $1 = u + n + e$. The first equation looks very similar to the Beveridge curve well-known from the analysis of labor markets without self-employment. The presence of self-employment leads to an additional term in the denominator of the unemployment rate. The expression for the UN ratio, or $\tilde{u}$, comes close to the standard expression $u/(s + f)$. The only difference is the $(1 - h)$ term in the denominator, which captures that larger flows from unemployment to self-employment (higher h) imply smaller flows from unemployment to wage employment.

Clearly, cross-country differences in any of the flow rates can generate differences in labor market outcomes. For example, high unemployment could be due to a low job finding rate or a high separation rate (as usual). The unemployment rate also depends on h. Given very limited information about flow rates in the cross-country data, many combinations of flow rates could be consistent with observed stocks.

However, the previous section provided evidence not only of dispersion in stocks, but also showed a significant and sizeable positive relationship between the self-employment rate e and the UN ratio $\tilde{u}$. This piece of information is informative about the type of variation in flow rates required to match cross country data. In particular, I will show next that it implies that despite the strong dependence of both the self-employment rate and the unemployment rate on the entry rate into self-employment (h), variation in h alone does not generate a relationship between e and $\tilde{u}$ as observed in the data.

To see this, consider the derivates of $u, \tilde{u}$ and e with respect to h:

$$\frac{\partial e}{\partial h} = \frac{\lambda e^2}{h^2} \frac{s+f}{s} = \frac{u^2}{\lambda} \frac{s+f}{s} \tag{1}$$

$$\frac{\partial u}{\partial h} = -\frac{u^2}{s} \left(\frac{1}{\lambda} - \frac{f}{s} \right) \tag{2}$$

$$\frac{\partial \tilde{u}}{\partial h} = \tilde{u}^2 \frac{f}{s} = \frac{u^2}{(1-e)^2} \frac{f}{s} > 0 \tag{3}$$

Clearly, e and $\tilde{u}$ both increase in h. The unemployment rate decreases in h if individuals who enter self-employment stay out of unemployment longer than those who remain in unemployment and search for a job, i.e. if $1/\lambda > f/s$. This condition generally holds in country-level data, so I will assume that it is satisfied. The model equivalents of the coefficients of the regressions of e on u and $\tilde{u}$, respectively, are given by

$$\left. \frac{de}{du} \right|_{\text{vary only } h} = \frac{s+f}{\lambda f - s} < 0 \tag{4}$$

$$\left. \frac{de}{d\tilde{u}} \right|_{\text{vary only } h} = \frac{(1-e)^2}{\lambda} \frac{s+f}{f} > 0 \tag{5}$$

if only h varies across countries. The accounting framework thus predicts that if only h varies across countries, there should be a negative relationship of self-employment with the unemployment rate, and a positive relationship with the *UN* ratio.

What is the size of these model-implied relationships? Given that λ is generally close to 1% at a monthly frequency, so that λf is negligible compared to s, de/du is approximately $-(s+f)/s$. This is minus the inverse of the steady state unemployment rate in a model without self-employment, and therefore it is generally on the order of minus 5 to minus 30. This large number of course reflects that if only self-employment entry differs across countries, differences in the entry rate affect self-employment much more strongly and directly than unemployment, and therefore de/du is much larger than 1. This is even more pronounced for $de/d\tilde{u}$. Reflecting the fact that changes in h hardly affect the *UN* ratio, this is on the order of 40 to 300.

The equivalent of Figure 2 from this simple accounting model for the case where countries differ only in the self-employment entry rate h would thus feature a near-vertical line of best fit – implying essentially no relationship between the self-employment rate and the *UN* ratio. Clearly, this does not even come close to the empirical relationship between e and $\tilde{u}$, which is given by a regression coefficient of about 0.7 (Table 4). Hence, variation only in self-employment entry – due for example to differences in the cost of entry or the regulatory burden – cannot account for the cross-country data.

If only f varies across countries, the model equivalents of the coefficients of the regressions of e on u and $\tilde{u}$, respectively, are given by

$$\left.\frac{de}{du}\right|_{\text{vary only } f} = \frac{h}{\lambda} = \frac{e}{u} \tag{6}$$

$$\left.\frac{de}{d\tilde{u}}\right|_{\text{vary only } f} = (1-e)^2 \frac{de}{du} = (1-e)^2 \frac{h}{\lambda}. \tag{7}$$

In practice, these expressions have values around 1.5-2 and 1-1.5, respectively. As a result, variation only in f comes much closer to matching the empirical relationship between the self-employment rate and the UN ratio. However, it predicts a counterfactual strong positive relationship between the self-employment rate and the unemployment rate.

This analysis suggests that variation in both the self-employment entry rate and the job finding rate, probably with a larger share of the latter, is required to account for the joint variation of labor market states observed in the cross-country data.

This analysis assumed that flows across labor market states are exogenous and independent of each other. In the model presented in the next section, both the self-employment entry rate h and the job finding rate f will be endogenous objects, and functions of fundamentals, like the strength of labor market barriers or the ease of entry, which can in turn vary across countries. One can already anticipate their joint variation: Anything that makes self-employment entry easier will tend to raise h. If some of these new firms hire workers, f could in turn increase. As a result, if the most important variation across countries was in factors primarily driving self-employment entry, h and f should be positively correlated. This would exacerbate the problems with the model $de/d\tilde{u}$ illustrated above. In turn, anything that reduces the job finding rate f should raise the self-employment entry rate h, as some job seekers find it more attractive to start a firm rather than engage in now lengthier search for a job. As a result, if countries mostly vary in factors determining job finding rates, like labor market frictions, h and f should be negatively correlated. Such a situation would allow for values of de/du and $de/d\tilde{u}$ more in line with the values observed in the cross-country data.

A simple accounting analysis thus clearly shows that data patterns cannot be generated by cross-country differences only in self-employment entry. Differences in job finding rates are also required, and probably need to be large relative to differences in entry rates.[14] The theoretical and quantitative analysis in the following sections will pin this down more precisely.

4 A model of frictional labor markets with endogenous entry into self-employment and entrepreneurship

Having documented the relationship between wage employment, self-employment and unemployment, the second objective of this paper is to develop a simple benchmark model that can account for key features of labor markets not just in advanced economies, but for a broad cross section of countries. This section sets out such a model.

I base the model on a version of the Diamond-Mortensen-Pissarides (DMP) model of random search and matching in labor markets with firms that differ in size and productivity. Compared to a standard DMP model, I extend the model in three ways. First, the unemployed can choose whether to search for a job or enter entrepreneurship (occupational choice). Second, firms are heterogeneous in their productivity, so that some entrants become own-account workers, while others become employers. The latter in turn differ in the optimal size of their firms. Finally, the unemployed periodically engage in casual work to sustain their job search. As a result, the model generates an equilibrium partition of the population into the unemployed, employees, own-account workers, employers and causal workers, as well as a distribution of firm sizes.

These features constitute the minimum extension of the DMP model required to be able to reproduce the above-mentioned facts, and to study the effect of labor market frictions on wage employment, unemployment, self-employment, and firm sizes. Clearly, endogenizing the entrepreneurship rate requires giving model agents the ability to choose between entrepreneurship and employment or job search.[15] Allowing for firm heterogeneity allows capturing the difference between own-account workers and employer firms, and it also allows frictions to affect not only the quantity of entrepreneurs, but also their quality and size. It also enables the analysis to address the observed small size of firms in low income

[14]Differences in s only have exactly the same implications as differences in f only, and could therefore also be part of the mix. Differences in λ only, in contrast, would lead to variation in e but not $\tilde{u}$, and thus do not help account for data patterns.

[15]I also explored a version of the model where not only the unemployed can become self-employed, but where the employed can also leave their jobs to engage in entrepreneurship. (For this to occur in equilibrium, it has to be the case that entry is more favorable for them compared to the unemployed, for example because they are on average better entrepreneurs.) Quantitative results for that model are broadly similar, but it is computationally more cumbersome.

economies. Finally, casual jobs are introduced in a simple way because they are so common in poor economies. Their presence allows the unemployed to sustain job search for prolonged periods of time.

4.1 States, flows and the labor market

Time is discrete. The economy consists of a measure one of homogeneous individuals. They value the net present value of income, discounting future income using a discount rate r. In any period, individuals die with a fixed, exogenous probability ϕ, and a measure ϕ of newborn individuals enter unemployment. An individual can be in exactly one of four states: unemployment, employment, own-account work, or being an employer. Let their measures be u, n, e_s and e_f. A fraction of the unemployed engages in casual work in any period.

Flows. Any period, a number of endogenous and exogenous flows across the four states in the economy can occur. The exogenous flows occur with fixed, exogenous rates, and are as follows. Existing matches dissolve with a probability ξ. Own-account workers and employers need to close their business with probabilities λ_s and λ_f, respectively. All of these flows move the affected individuals into the unemployment pool. For firm closures, employees also lose their jobs and move to unemployment. To simplify notation, denote the total job separation rate for workers by $s \equiv 1 - (1-\phi)^2(1-\xi)(1-\lambda_f)$, and the exit rates for firms by $\tilde{\lambda}_s \equiv \lambda_s + (1-\lambda_s)\phi$ and $\tilde{\lambda}_f \equiv \lambda_f + (1-\lambda_f)\phi$, respectively. Separations can be caused by death of either the worker or the employer, by firm shutdown, or by an exogenous match separation.

Any period, a fraction δ of individuals in the unemployment pool need to engage in casual work. I model this state as a result of a shock instead of a choice to keep the model simple. Modeling it as a choice would require introducing saving, which would substantially complicate the model. While engaged in casual work, individuals cannot search for jobs. In the following period, they return to the unemployment pool and again face the probability δ of casual work. Given its exogenous nature, income from casual work does not affect equilibrium outcomes unless it is so high that individuals would voluntarily choose it over job search. Hence, to save on notation, I assume that both the unemployed and individuals in casual work enjoy an income flow of b.

In addition to these exogenous flows, there are two key endogenous flows. As usual in such models, the job finding rate for job seekers is an equilibrium object. In addition, the entry rate into entrepreneurship, h, is endogenous. Its determination is described below.

The labor market. Job seekers and vacancies posted by employer firms intending to hire meet in a standard labor market with matching frictions. Employers posting a vacancy incur a per period cost of k_v. I assume that the number of matches per period is given by a standard Cobb-Douglas matching function. Let the number of vacancies be v. The measure of job seekers is $\bar{u} = (1-\delta)(1-h)(1-\phi)u$. Defining labor market tightness as $\theta \equiv v/\bar{u}$, the probability that a vacancy is filled in any given period is $q(\theta) \equiv A\theta^{-\mu}$, and the probability that a job seeker finds a job is θq, where μ is the exponent on vacancies in the matching function. A parameterizes the efficiency of the matching process.[16]

The distribution of employment states. These flows generate a partition of individuals in the economy into the four states. I will focus on stationary equilibria of this economy. In a stationary equilibrium, the measure of agents in each state is constant. Each measure can be derived by equating flows into and out of a state. In this way, the equilibrium measures of own-account workers and employers can be obtained as

$$e_s = \frac{(1-\delta)h(1-\phi)p_s}{\tilde{\lambda}_s}u \tag{8}$$

and

$$e_f = \frac{(1-\delta)h(1-\phi)p_f}{\tilde{\lambda}_f}u, \tag{9}$$

where p_s and p_f denote the probability that an entrant chooses to become an own-account worker or an employer, respectively. These two endogenous objects are described below.

The unemployment rate in a stationary equilibrium is given by the *modified Beveridge curve* (MBC)

$$u = \frac{(1-e_f-e_s)s + e_f\tilde{\lambda}_f + e_s\tilde{\lambda}_s}{s + (1-\delta)(1-h)(1-\phi)\theta q + (1-\delta)(1-\phi)h(p_f+p_s)}. \tag{10}$$

For $\lambda_f = \lambda_s$, this simplifies to

$$u = \frac{s}{s + (1-\delta)(1-h)(1-\phi)\theta q + (1-\delta)h(1-\phi)(p_f+p_s)s/\tilde{\lambda}_f}. \tag{11}$$

[16] This process describes the creation of productive matches, which then survive until destroyed at a common match destruction rate s. As usual, the process does not describe in detail how these matches are formed. That is, it is not designed to capture the high rates of turnover that may occur in the first days of a match (as documented by Blattman and Dercon (2018) for some Ethiopian manufacturing firms), and it does not exclude that successful matches are discovered, at some cost, in a high-frequency process of selection.

This expression is analogous to the usual Beveridge curve, with two differences. First, unemployment outflows occur not only to employment (at a rate θq for searchers), but also to entrepreneurship. As a result, the job finding rate and the unemployment outflow rate are not identical in this economy. Second, employees and entrepreneurs have different flow rates into unemployment. This is captured in the different terms in the numerator of equation (10), and results in the final fraction in the denominator in equation (11). Intuitively, if the flow rate into unemployment is lower for entrepreneurs than for employees, then a larger entrepreneurship rate tends to reduce unemployment.

Finally, the measure of employees follows as

$$n = 1 - u - e_s - e_f. \tag{12}$$

Next, I describe the values and optimal behavior for firms, employees, and the unemployed.

4.2 Agents' problems, value functions, and occupational choice

Firms. All firms produce a homogeneous good that they sell in a perfectly competitive market. Firms differ in their productivity z. An entrepreneur learns about the current firm's productivity when starting the firm, and keeps that level of productivity as long as the firm is active. Given z, an entrepreneur can decide to hire employees, to become an own-account worker, or to exit to unemployment.

Employer firms produce with the production function $y = zn^{\gamma}, \gamma \in (0, 1)$, where y denotes the firm's output, and n denotes its employment. The parameter γ captures the degree of decreasing returns to scale in production. In this setting, optimal firm employment is an endogenous, determinate object that depends on the expected wage, labor market tightness, and on a firm's productivity. The model can thus generate employers of different sizes, which coexist with own-account workers.

Own-account workers produce with the production function $y = \zeta z$. ζ is a parameter governing relative productivity of own-account workers. It could be either smaller than one, as the self-employed have to spend some time managing their business and therefore produce less than a single employee without management duties, or larger than one, as own-account workers are not subject to the same incentive and contracting problems employers face. In addition, they may *de jure* or *de facto* be treated differently in terms of regulations and taxes. A typical presumption is that own-account workers are much less subject to regulatory oversight and taxation (see e.g. Albrecht et al. 2009).

At optimal size $n(z)$, the values of own-account work and being an employer are given by

$$F_s(z) = \zeta z + \frac{(1-\phi)(1-\lambda_s)}{1+r} F_s(z) + \frac{(1-\phi)\lambda_s}{1+r} U \tag{13}$$

$$F_f(z) = zn(z)^\gamma - wn(z) - \frac{k_v}{q}\hat{\xi} n(z) + \frac{(1-\phi)(1-\lambda_f)}{1+r} F_f(z) + \frac{(1-\phi)\lambda_f}{1+r} U \tag{14}$$

respectively. They consist in flow profits plus the expected, discounted continuation value. For own-account workers, flow profits are simply equal to output. For employers, they equal output minus the wage bill, minus the cost of rehiring workers who depart, either due to match destruction or due to death. These departures occur at a rate $\hat{\xi} \equiv \xi + (1-\xi)\phi$.

Firm entry and type decision. The unemployed can decide to start a firm instead of searching for a job. Doing so involves first paying an entry cost k_f. They then draw their productivity z from a known distribution $G(z)$.[17] Based on the realization of z, they decide whether to hire workers and become an employer, whether to continue as own-account workers, or whether to return to unemployment.

The optimal choice is characterized by two thresholds, z_s and z_f. (See Figure 3.) It is clear that the value of unemployment, U, is independent of z. It is also clear from equation (13) that the value of own-account work increases linearly in productivity z. Finally, given optimal employment choices discussed below, the net value of operating an employer firm at optimal employment, net of the cost $n(z)k_v/q$ of reaching that level, is increasing and convex in z.[18] As a result, continuation values as a function of z are as depicted in Figure 3. Entrants with productivity above z_f become employers. Those with productivity below z_s exit, and those with z between z_s and z_f become own-account workers. (This structure is analogous to that in Gollin (2007).) Given a productivity distribution $G(z)$ for new entrants, this implies that new entrants exit with probability $G(z_s)$, and become employers with probability $p_f \equiv 1 - G(z_f)$. With the remaining probability p_s, they become own-account workers. The definition of p implies that the productivity distribution of employers is

$$\tilde{g}(z) = \frac{g(z)}{1 - G(z_f)}, \quad z \geq z_f, \tag{15}$$

[17] The assumption of uncertainty about post-entry productivity is in line with the literature on firm dynamics, and is motivated by the large rates of turnover of young firms.

[18] Convexity reflects the ability of employers to leverage their own productivity z by hiring workers accordingly. Given constant firm-level productivity and constant, linear hiring costs due to labor market frictions, it is optimal for firms to move to optimal employment directly upon entry.

where g is the *pdf* associated to G. There are no employers with $z < z_f$.

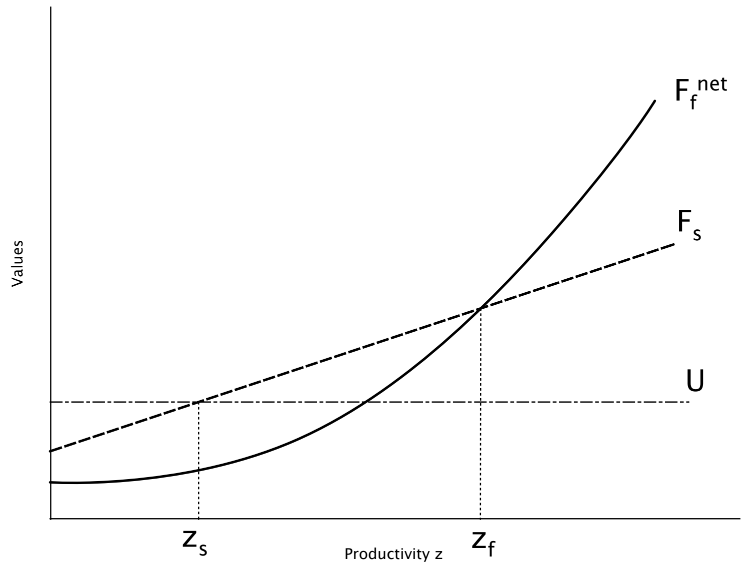


Figure 3: The values of unemployment (U), self-employment (F_s), and the value of being an employer net of hiring costs at entry ($F_f^{\text{net}}(z) = F_f(z) - n(z)k_v/q$), with associated productivity cutoffs

Combining these possibilities, the value of entry is given by

$$Q = \frac{1-\phi}{1+r}\left[-k_f + \int \max\left(F_f(z) - \frac{k_v}{q(\theta)}n(z), \; F_s(z), \; U\right) \mathrm{d}G(z)\right] \tag{16}$$

I now turn to workers and the unemployed.

Workers. Employed workers receive a wage w per period. They lose their job with the combined separation probability s, and keep it otherwise. Wage determination is discussed below. Since wages are common across jobs in this economy, workers have no incentive to leave a job voluntarily. As a result, the value of employment is given by

$$W = w + \frac{1-s}{1+r}W + \frac{s-\phi}{1+r}U. \tag{17}$$

The unemployed, and occupational choice. Recall that a fraction δ of the unemployed needs to engage in casual work in any period. The remainder can choose between job search and entrepreneurial entry. Job search yields a per period flow value of b, and results in success with probability θq. As a result, the values of search, S, and that of casual employment, $\underline{U}$, are given by

$$S = b + \frac{1-\phi}{1+r}\left[\theta q W + (1-\theta q) U\right] \tag{18}$$

$$\underline{U} = b + \frac{1-\phi}{1+r} U. \tag{19}$$

With occupational choice, the value of unemployment is given by

$$U = \delta \underline{U} + (1-\delta)\max\left\{S, Q\right\}. \tag{20}$$

With probability δ, the unemployed need to engage in casual work and cannot search. With the complementary probability, they can either search, or choose to start a firm. Since workers are ex ante identical, it is clear that in an equilibrium with entry it must be true that $S = Q$. If this holds, an endogenous fraction h of the unemployed start a firm. In the following, I focus on such an equilibrium.[19]

Who can search? A key model assumption is that self-employment and job search constitute distinct activities between which individuals need to choose, i.e., they cannot engage in both at the same time. Of course, the assumption that individuals can engage in only one activity at a time is typical for models of occupational choice. It is relaxed in models with on the job search, but even those typically assume that search on the job is less effective than full-time search. This appears to be particularly true for job search in poor countries. In Addis Ababa, for example, job search requires time consuming travel to peruse job ads at centralized job boards, and to drop off CVs in person at companies (Franklin 2014). The cost of job search is substantial in terms of both time and money (Abebe, Caria and Ortiz-Ospina 2017).

Abebe et al. (2018) show that even over longer time spans, it is rare for the unemployed to engage in self-employment. In fact, the unemployed report working only an average 1.3 hours per week in the Ethiopian Urban Employment and Unemployment Survey for 2012. The self-employed in contrast report working an average of 50 hours per week, similar to employees. Self-employment also is highly persistent – substantially more persistent than wage employment – and the self-employed are less likely to transition to wage employment than to unemployment (Bigsten, Mengistae and Shimeles 2007). Self-employment thus truly appears to be a distinct activity from job search, in line with my analysis.

[19] In principle, an equilibrium with only own-account work may also arise. This could be the case if the relative productivity of own-account workers is very high. I abstract from this equilibrium for lack of empirical relevance for urban labor markets.

A possible reason for this is that self-employment typically requires some amount of capital, and therefore is not practical as a temporary activity intended to financially sustain job search. It is more common to see occasional casual employment, often day labor, used to finance job search (Abebe et al. 2017). This does not require the worker to have capital.

4.3 Wage determination and vacancy posting

Upon matching, a firm and a worker bargain over the wage. Like Cahuc, Marque and Wasmer (2008) and Elsby and Michaels (2013), I assume that workers and firms split the surplus from a match, with workers receiving a fixed share proportional to their bargaining weight η.[20] Wages are bargained upon hiring, and remain constant thereafter. Then it can be shown (see Appendix C.2 for a detailed derivation) that

$$w = \frac{r+\phi}{1+r}U + \frac{\eta}{1-\eta}\left[1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right] \cdot \frac{k_v}{q\left(\theta\right)}. \tag{21}$$

Three remarks are in order. First, the wage curve given by equation (21) is analogous to the wage curve in a standard DMP model, with the exception of the constants. In particular, wages increase in labor market tightness θ, reflecting the fact that match surplus is larger when the expected hiring cost k_v/q is larger. Second, self-employment opportunities enter bargaining workers' outside option U, and can affect wages in this way. Finally, although firms vary in productivity, all matches are paid the same wage. This is because upon hiring, any worker is marginal, and the relevant surplus to consider in bargaining is that of a marginal job. When firms are at their optimal employment, more productive firms have more employees, and the marginal surplus is equalized across firms. As a consequence, wages are also equalized across firms of heterogeneous productivity.

A firm's optimal employment is given by

$$n\left(z\right) = \left(z\gamma\right)^{\frac{1}{1-\gamma}}\left\{\left(\eta(\gamma-1)+1\right)\left[\left(1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \hat{\xi}\right)\frac{k_v}{q} + w\right]\right\}^{\frac{-1}{1-\gamma}}. \tag{22}$$

Optimal firm size increases in productivity, and decreases in the cost of employing a worker, which comprises both the wage and the expected cost of replacing departing workers.

Continuing employer firms face departures of workers at a rate of $\hat{\xi}$ per period, and thus need to post $\hat{\xi}n(z)/q$ vacancies per period to replace them. New entrants find it optimal to hire $n(z)$ workers all at once, and therefore post $n(z)/q$ vacancies. From equation (9), new

[20] See Stole and Zwiebel (1996) and Bruegemann, Gautier and Menzio (forthcoming) for the game-theoretic foundations of this assumption.

entrants account for a fraction $\tilde{\lambda}_f$ of employers. As a result, total vacancies in the economy are given by

$$v = \frac{\tilde{\lambda}_f + (1-\tilde{\lambda}_f)\hat{\xi}}{q} e_f \int n(z)\tilde{g}(z)\mathrm{d}z. \tag{23}$$

4.4 Equilibrium

A stationary equilibrium consists in values $W, U, S, \underline{U}, F_f(z), F_s(z), Q$, a distribution described by u, n, e_s, e_f and $\tilde{g}(z)$, probabilities h, p_f and p_s, a function $n(z)$, and numbers v, θ, w such that

1. values $W, U, S, \underline{U}, F_f(z), F_s(z), Q$ are given by equations (13) to (14) and (16) to (20),
2. households are indifferent between occupational choices: $Q = S$,
3. wages fulfill equation (21),
4. the equilibrium distributions are generated by household choices and are stationary, according to equations (8) to (12) and (15),
5. firms post vacancies optimally (equations (22) and (23)), and
6. labor market tightness $\theta = v/[(1-\delta)(1-h)(1-\phi)u]$ is generated by unemployment in- and outflows and by firms' vacancy posting decisions.

The key equilibrium objects are θ, w, and h. The values W, U, S, $\underline{U}$, F_s, F_f and Q depend only on w and θ. Hence, the same holds for the thresholds z_s and z_f and for the probabilities p_s and p_f. Tightness and the wage also determine each firm's optimal employment $n(z)$ and the productivity distribution of employers, and hence also the average size of employer firms. The entry rate h then has to take a value such that the number of employers e_f generates a consistent value of tightness, combining equations (9), (11) and (23).

Figure 4 depicts the key equilibrium relationships, and how they determine the equilibrium values of θ, w and h. The top panel plots the wage curve and the occupational choice (OC) condition in θ, w-space. The wage curve, given by equation (21), is familiar from the standard DMP model. It shows that workers can bargain higher wages when the labor market is tighter. The OC curve depicts the combinations of θ and w at which the equilibrium condition $Q = S$ holds. Since the value of search S increases in both θ and w, while the value of firm entry declines in both θ and w, it is clear that this locus is negatively

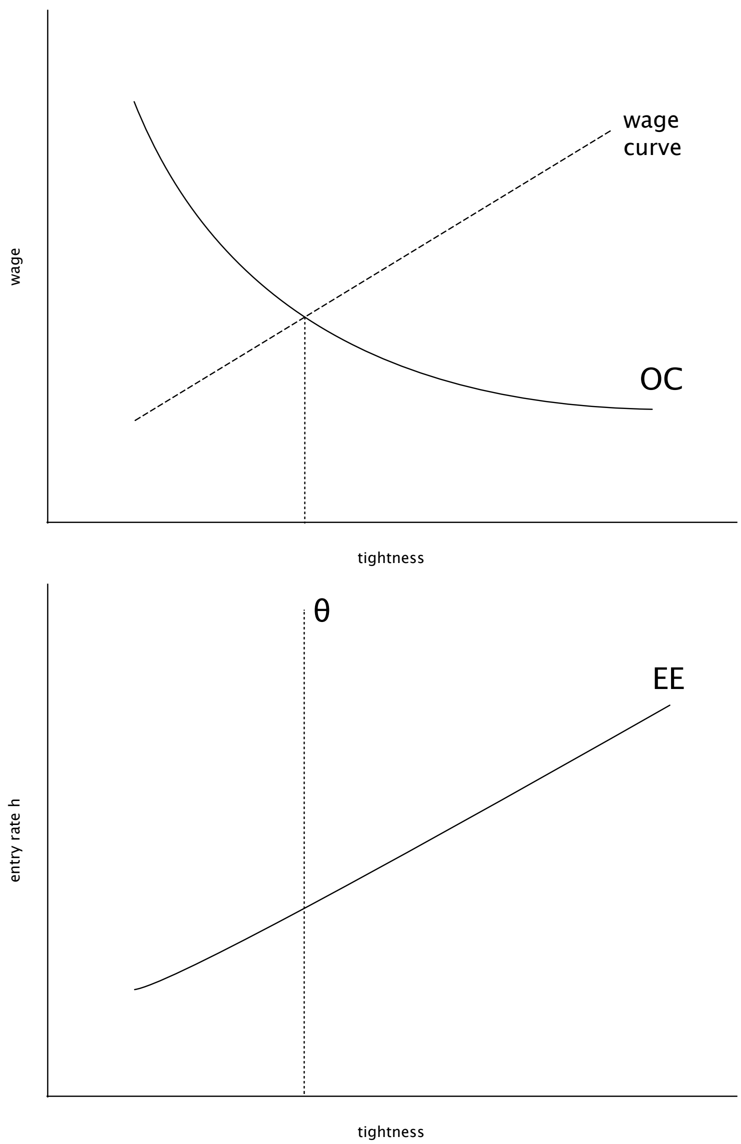


Figure 4: A sketch of equilibrium determination

sloped. Neither the wage curve nor the OC condition depends on h. As a result, these two conditions on their own determine equilibrium θ and w.

The third key condition, the entrepreneurial entry (EE) condition, then determines the equilibrium entry rate h. Tightness and the wage pin down average firm size and vacancies per firm. However, the aggregate number of vacancies given in equation (23) and thus market tightness depend on the entry rate, which enters equation (23) via equations (9) and (11) (determining u). It is a consistency condition, showing the value of h required to generate equilibrium tightness. Intuitively, for a given wage, higher θ implies more costly hiring and thus smaller firms. Then many firms, and thus a high entry rate h, are needed to actually generate a high θ. This is depicted in the upward-sloping EE curve in the lower panel of Figure 4. Given θ from the upper panel, equilibrium h can be read off the EE curve in the lower panel.

Given the evidence shown in Section 2, the comparative statics I focus on are those with respect to the cost of posting vacancies. Lower vacancy posting costs raise the value of entry relative to that of unemployment, shifting OC up. They also reduce rents from matches, implying that the wage curve tilts down. As a result, tightness clearly increases, while the change in the wage is ambiguous. It can be shown that optimal firm size increases, shifting the EE curve down. Since equilibrium θ increases, the overall change in h is ambiguous.

The changes in equilibrium variables also affect entrants' continuation decisions, and the composition of the population of firms. Lower vacancy posting costs raise the value of being an employer, and higher tightness raises the value of unemployment. The value of being an own-account workers, in contrast, is only affected via the value U. As a result, the threshold z_f shifts down and z_s shifts up, implying an increase in the probability p_f that an entrant becomes an employer. The probability of becoming an own-account worker decreases.

It is clear that higher tightness, by increasing job finding, tends to reduce unemployment. At the same time, a decline in self-employment entry and an increase in the number of job seekers mitigates the decline in unemployment. In quantitative simulations, it is generally the case that the first effect dominates, and unemployment declines, and that self-employment also declines. To quantify all effects, I next turn to an empirically guided examination of the quantitative properties of the model.

5 Calibration

In the remaining sections of the paper, I analyze the quantitative properties of the model, and assess its ability to account for the joint cross-country variation in wage employment, unemployment and self-employment. To do so, I calibrate the model separately for eight economies at very different levels of development and with very different levels of wage employment, unemployment and self-employment, ranging from Ethiopia to the United States. I then analyze which model parameters are central in driving observed variation in these labor market outcomes. This analysis suggests that differences in labor market frictions are key. To obtain a more nuanced understanding of their role and functioning, I then explore the effect of varying labor market frictions in a variety of settings.

Can the model account for the strong variation in unemployment and self-employment across countries shown in Section 2? To verify this, I calibrate the model for eight economies at very different stages of economic development: Ethiopia, Indonesia, Mexico, Italy, France, Germany, Canada, and the US (in increasing order of GDP per capita). The choice of countries is driven by data availability. These countries essentially span the entire spectrum of country GDP per capita, with a ratio of US GDP per capita to that for Ethiopia of about 60 in 2010, for example. Rates of self-employment and unemployment also differ widely across these economies: self-employment ranges from around 9% in Germany to almost 50% in Indonesia, and the unemployment rate ranges from about 4% in Mexico to over 20% in Ethiopia. Fitting the model to this broad range of settings is a challenge, but also an opportunity: it reveal which parameters are key in driving the observed large differences in wage employment, unemployment and self-employment.

Calibrating the model requires using statistics on the structure of employment, on some flows between different labor force statuses, and on the firm size distribution. The choice of statistics and of calibration countries is limited by data availability. As discussed below, the nine key target moments required for the calibration are the unemployment outflow rate, the unemployment rate, the self-employment rate and fraction of own-account workers, the fraction of casual workers, the firm exit rate, the share of employment in firms with at least 10 employees, the labor income share, and the ratio of income in unemployment to the wage. While the wage employment rate is not targeted directly, it is implied by targeting the unemployment and self-employment rates. The statistics that define the set of calibration countries – because their availability is most limited – are the unemployment outflow rate, information on *urban* (as opposed to country-wide) unemployment, self-employment, and own-account work, employment concentration, and the firm exit rate.[21]

Next, I describe sources for the calibration targets. To begin, there is no "easy" source giving unemployment outflow rates for a broad range of countries. For the US, I take the

[21]For some of the developed economies, only country-level statistics are available. Since urbanization rates in these countries are very high, this is less of a concern. It is however key to use information on urban areas for the poor countries.

postwar average US unemployment outflow rate from Shimer (2012). I take information on the unemployment outflow rate for Ethiopia from the 2015 Urban Employment and Unemployment Surveys (UEUS) conducted by the Ethiopian Central Statistical Agency. Data processing is described in Appendix D. For the remaining countries, I compute the unemployment outflow rate using ILO data on unemployment by duration and the method of Elsby, Hobijn and Şahin (2013).[22] Urban self-employment, own-account work, and unemployment rates are from IPUMS Censuses, using the lastest available census for each country. For Ethiopia, they are taken from the UEUS. For the US, they are computed using information from Hipple (2010). Information on the concentration of employment is from Poschke (2018) for most countries, from Berry, Rodriguez and Sandee (2002) for Indonesia, and from Bartelsman, Haltiwanger and Scarpetta (2004) for Mexico. For the US, it is computed by combining data from Hipple (2010) with information from the Statistics of US Businesses (SUSB) published by the US Census Bureau. Finally, the firm exit rate is from Bartelsman et al. (2004) for most countries, and from Bigsten et al. (2007) for Ethiopia (see also below). For Indonesia, I assume it to be identical to that for Mexico. Finally, I set the rate of casual employment by job seekers to zero for European countries, Canada, and the US, take it from the UEUS for Ethiopia, and from IPUMS Censuses for Indonesia and Mexico. I set targets for the labor income share and for b/w to common values of 0.67 and 0.4, respectively. The former is in line with levels of the labor income share documented by Gollin (2002) for a very broad range of countries. The latter essentially reflects lack of information.[23] Direct information on job destruction rates or the length of employment relationships would help, but is not available for such a broad set of countries. The eight countries included in the calibration are the ones for which all these target moments are available.

As usual in such models, some parameters need to be calibrated outside the model. The model time period is set to one month. I set the interest rate such that the annual interest rate is 4%. I set the retirement probability ϕ such that the expected duration of working life is 40 years. I set μ, the exponent on unemployment in the matching function, to 0.5,

[22] I compute the steady state unemployment exit hazard using information on the unemployment rate and the fraction of spells of less than six months for the maximum available years for each country. (Depending on country, this spans 2003 to 2013 up to 2015 or 2016.) Unlike the US Bureau of Labor Statistics or the OECD, the ILO unfortunately does not report unemployment by duration for shorter durations, like one month. Yet, for the OECD member countries in the sample, my measures are generally very close to those computed by Elsby et al. (2013) using durations up to one month, which is to be expected if there is no or only weak duration dependence. For the US, where evidence for duration dependence is strong, there is a larger discrepancy, and I use the figure from Shimer (2012).

[23] It appears that for assessing the importance of labor market frictions, assuming common b/w is conservative. The most plausible alternative is that b/w is lower in poor countries, since they do not provide unemployment insurance benefits. In this case, even larger labor market frictions, either in the form of higher k_v or higher job destruction ξ, would be required to match their unemployment rates.

and γ, the exponent on labor in the production function, to 0.85 (Atkeson and Kehoe 2005). Finally, I impose that the exogenous firm exit rates λ_f and λ_s are equal within each country.

Next, I normalize two parameters. These are the average productivity draw of an entrant and the productivity of the matching function, A. First, with homothetic preferences, the overall level of productivity in the model is not identified. I thus normalize the mean productivity draw of entrants to one. The levels of the other parameters that are in the same units, namely the standard deviation of $G(z)$, the flow value of unemployment b, and the cost levels k_f and k_v, then are to be interpreted relative to this mean productivity. Second, as is typical in search and matching models, the matching function productivity and the vacancy posting cost k_v cannot be identified separately without direct information either on the cost of hiring, or on tightness or the number of vacancies. Such information is only available for a few, rich countries. I therefore normalize A to one. This implies that differences in k_v discussed below combine the effect of differences in the vacancy posting cost and differences in the productivity of the matching function. That is, a calibrated high level of k_v could either reflect a truly high cost of posting vacancies, low efficiency of matching, or a combination of the two. Hence, the exercises analyzing the effect of varying k_v conducted in the following sections should be interpreted as varying frictions in labor markets overall, not necessarily k_v specifically.

The remaining parameters are calibrated internally to match a set of nine targets. Heuristically, one can think of a mapping of targets to parameters as follows.[24] First, the key parameters controlling flows between unemployment and employment are the per period cost of posting a vacancy k_v, and the match destruction rate ξ. Given a productivity level of the matching function, the vacancy posting cost is key for employers' hiring efforts, and thus for the unemployment outflow rate of the unemployed. Hence, I use the unemployment outflow rate as a target for k_v. This outflow rate ranges from 4.5% in Ethiopia to almost 45% in the US. Given the unemployment outflow rate and moments on entrepreneurship, the level of the unemployment rate identifies the job destruction rate ξ.

A second set of moments relates to self-employment and entrepreneurship. Here, I set the parameters k_f, ζ, λ_f and σ_z to match the self-employment rate, the fraction of own-account workers, the firm exit rate, and the share of employment in large firms. Clearly, higher fixed entry costs k_f discourage entrepreneurship, and thus affect the overall level of entrepreneurship (own-account workers plus employers). The parameter ζ controls the relative productivity of own-account workers. Higher ζ thus leads to a higher level of own-

[24] Of course, it is actually the case that targets have to be matched jointly by setting all parameters, and cannot be matched individually one by one. Nevertheless, each parameter clearly affects some targets more strongly than others.

account work given an overall level of entrepreneurship. The fraction of employers is around 4-5% of employment in almost all countries, and is slightly lower in poorer countries.[25] Own-account workers account for the remainder of the self-employed. Their fraction of employment ranges from 4% in Germany to over 30% in Indonesia, in line with the broad variation in self-employment rates. The mapping between the exogenous firm exit rate in the model, λ_f, and the data exit rate is immediate. Exit rates from Bartelsman et al. (2004) range from 5% per year in Germany to 14% in Mexico. Finally, since most firms in the model are (very) small, a higher dispersion of the productivity draws of entrants, generated by higher σ_z, generates more employment in large firms. The share of employment in firms with at least 10 employees lies between 80 and 90% in rich countries. Employment is less concentrated in the poorer countries.[26]

Three further moments are closely related. Conditional on the unemployment rate, the rate of casual employment in an economy identifies δ. The labor income share is informative about workers' bargaining power η. To pin down the flow value of unemployment, b, I set b/w to 0.4 in all economies (see the discussion above).

As a benchmark for the analysis below, I also calibrate the model to an average economy, described by average values of all target moments. For the few statistics that are not consistently available for all countries, like the share of employment in firms with at least 10 employees, I take the average using actual data where available, and model-predicted data from the country calibration for those countries where data availability forced us to use a slightly different, related moment in the country calibration.

To save space, I do not report all calibration results and parameters in the main text – see Table A.10 for these. Here, I discuss the calibration for the most extreme case, Ethiopia, in some detail, and then compare it to the calibrations for the other extreme, the US, and for the average economy.

Table 6 shows the model fit for Ethiopia. It is overall very close. The table also shows model predictions for some non-targeted moments. For the ones shown in Table 6, no direct data counterparts are available, but their orders of magnitude are still instructive. First, the entrepreneurial entry rate from unemployment is 1.4% per month, whereas the job finding rate for searchers is 6%. This implies that about one fifth of the outflows from unemployment

[25] I take this target from IPUMS Census data. For Ethiopia, there is a large discrepancy between the Census figure and that from the UEUS, which contains more detailed information on firm employment, so I target the average of the two values.

[26] For Mexico and Indonesia, I have information on the share of employment in firms with at least 20 employees. (76% and 33%, respectively, from Bartelsman et al. (2004) and Berry et al. (2002).) For Ethiopia, I target the share of employer firms with less than 10 persons engaged, which is 87% in UEUS data.

Table 6: Calibration: model and data moments (Ethiopia)

	model	data
Targeted moments:		
Unemployment outflow rate	0.044	0.045
Unemployment rate	0.237	0.237
Casual employment	0.245	0.236
Fraction own-account workers	0.288	0.29
Fraction employers	0.05	0.048
4-year entrepreneurship persistence	0.582	0.538
Share firms with $n \leq 10$	0.871	0.874
Labor income share	0.67	0.67
b/w	0.4	0.4
Not targeted:		
Wage employment	0.505	0.504
UN ratio	0.320	0.308
Entry rate h	0.0138	
Job finding rate	0.063	
Total job separation rate	0.046	
Annual firm exit rate	0.142	
Mean firm employment	2.2	
Mean employment (employers)	7.3	
Share of employment in firms with $n > 10$	0.089	
Mean SE income/w	1.1	
Mean employer income/w	5.1	
Business income/Y	0.656	
Own-account income/Y	0.250	

are due to entry into self-employment. (Note that for Ethiopia, the overall unemployment outflow rate is below the job finding rate since unemployed workers engaging in casual work cannot search.) The mean size of employer firms is 7, in line with UEUS data and much below mean firm sizes in rich economies. Due to the high self-employment rate, the fraction of business income (income of own-account workers plus employer profits) in aggregate output is 65%, and that of own-account workers is 25%.

Table 7 compares model predictions for flows across the states of entrepreneurship, employment and unemployment to data for the period from 2000 to 2004. The data matrix is adapted from Bigsten et al. (2007); see Appendix D for details. Unfortunately, no more recent flow matrix is available. In addition, the available data combine own-account workers

Table 7: Four-year transition matrix between the states of entrepreneurship, employment and unemployment (Ethiopia). Data values in parentheses.

	e'	n'	u'
e	0.582	0.114	0.208
	(0.538)	(0.107)	(0.221)
n	0.101	0.387	0.417
	(0.065)	(0.597)	(0.219)
u	0.152	0.343	0.410
	(0.068)	(0.261)	(0.528)

Source: Bigsten et al. (2007). Remaining probability is retirement/transition out of the labor force.

and employers in one group. Only the top left element of the matrix, showing persistence in entrepreneurship, is targeted in the calibration. In spite of this, model and data transitions overall have similar orders of magnitude. In particular the transitions out of entrepreneurship to both unemployment and employment are replicated very closely by the model, despite the fact that the latter can only occur indirectly in the model (via unemployment). In contrast, the model overstates entry rates into entrepreneurship, from both employment and unemployment, overstates employment to unemployment transitions, and understates unemployment persistence. This is due to the fact that the transition matrix is for the years 2000 to 2004, a period when the Ethiopian economy was significantly poorer. More specifically, it reflects the fact that the ergodic distribution over entrepreneurship, employment and unemployment implied by the data transition matrix is $[0.13, 0.55, 0.32]$, i.e. it implies much less entrepreneurship and higher unemployment than what is observed in more recent data. As a result, it is necessarily the case that when the model is calibrated to match recently observed entrepreneurship and unemployment rates (which are higher and lower, respectively), it will generate more entrepreneurship entry, larger unemployment outflows, and a lower persistence of unemployment than found in the data a decade earlier.

Table 8 shows the parameters generated by the calibration exercise. This reveals why the unemployment rate is so high in Ethiopia: the combination of a job finding rate that is low by global standards (6%, close to continental European levels) with a job destruction rate that is high by global standards (3.2%) results in a high level of unemployment.[27]

Overall, the model clearly replicates key features of the Ethiopian economy: high rates of unemployment, self-employment and casual work, and a preponderance of small or tiny firms. Table 9 compares calibration results for Ethiopia to those for the US and for the

[27]Recall that on top of this match destruction rate, separations can occur due to firm closures and to retirement of entrepreneurs or workers.

Table 8: Calibration: parameter values (Ethiopia)

externally calibrated:		
r	discount rate (annualized)	0.04
ϕ	retirement probability (annualized)	1/40
μ	matching function	0.50
γ	decreasing returns to scale	0.85
internally calibrated:		
k_f	entry cost	13.54
k_v	vacancy posting cost	69
η	worker bargaining power	0.432
b	utility flow of unemployment	0.188
λ_f, λ_s	firm exit rates (annualized)	0.12
ξ	separation rate	0.032
σ_z	productivity distribution	0.0224
ζ	relative own-account productivity	0.519
δ	casual job probability	0.440

average economy. Target moments are not shown, since they are almost identical to model moments. (See Table A.9 for details.) This table shows how the model is able to replicate the vastly different structures of the three calibrated economies. It also supports the arguments about how model moments identify parameters made above.

The table shows a subset of five parameters, to stress five salient differences across the calibrations. First, vacancy posting costs relative to productivity are very high in Ethiopia, and very low in the US. This is the first key reason for the high unemployment rate in Ethiopia. Second, the job destruction rate is high in Ethiopia relative to the US. This is the second key reason for the high unemployment rate in Ethiopia. Third, the entry cost is low in Ethiopia, and high in the US. On the face of it, this is the key reason for the high self-employment rate in Ethiopia. (Results below will show that labor market frictions, parameterized by k_v, also play a large role.) Fourth, the relative productivity of own-account workers, ζ, is low in Ethiopia. This indicates that the fraction of own-account workers in Ethiopia is high not because this state is very attractive here compared to other countries, but despite its low attractiveness. Finally, the dispersion of productivity in Ethiopia is tiny relative to the other countries. This is what is required to generate a small share of employment in large firms.

It should be noted here that the presence of size-dependent distortions (SDDs) – i.e., a burden of taxes, regulation, or other costs or frictions that increases in firm size – could generate a similar outcome as a low level of σ_z. This is clear if one models SDDs as productivity-specific taxes on firm revenue.[28] A popular specification assumes that firm revenue is taxed at a rate τ such that $1-\tau(z) = (z/\bar{z})^{-\nu}, \nu \geq 0$. (See e.g. Buera and Fattal-Jaef (2016).) The parameter ν controls the "progressivity" of SDDs, and the constant $\bar{z}$, together with ν, the average level. With this tax function, an employer's optimal labor demand is proportional to $z^{\frac{1-\nu}{1-\gamma}}$. From this, it is clear that the allocative consequences of a reduction in the standard deviation of $\log z$ can be replicated exactly by an increase in ν.

As a consequence, ν and σ_z cannot be identified separately in the calibration. Therefore, all country calibrations assume that there are no SDDs, and let σ_z be country-specific. An alternative approach would be to assume that σ_z is common, and that SDDs are country-specific. What both approaches have in common is that they can only identify variation in one of the two dimensions, productivity variation or SDDs, and not both at the same time. For reference, a calibration with σ_z of 0.2 and ν of 0.3 fits Ethiopia similarly well as the calibration shown in Table 6 and Table 8.

Table 9: Comparing calibrations – highlights

country:	Ethiopia	USA	average
Model moments:			
Unemployment outflow rate	0.044	0.453	0.180
Unemployment rate	0.237	0.051	0.106
Self-employment rate	0.348	0.098	0.193
Fraction own-account workers	0.288	0.050	0.149
Fraction employers	0.05	0.048	0.044
Share of employment in firms with $n > 10$	0.089	0.848	0.740
Parameter values:			
Vacancy posting cost k_v	69	12	45.4
Firm entry cost k_f	13.54	56	7.5
Job destruction rate ξ	0.032	0.0136	0.0143
Productivity dispersion σ_z	0.0224	0.164	0.32
Relative own-account productivity ζ	0.519	0.657	0.605

The top panel shows model moments for three calibrations: the ones targeting Ethiopia and the US, respectively, and that targeting average values of data moments. The model moments shown here are generally close to the targeted data moments. (See Table A.9 for details.)

[28]The modeling device of size- or productivity-specific taxes can capture both factors like a higher burden of taxes and regulation for larger firms (an interpretation taken by e.g. Guner et al. (2008)) or internal frictions that affect larger firms more strongly and limit their expansion, like frictions in delegation (see e.g. Akcigit, Alp and Peters (2017) and Grobovšek (2017)). Financial frictions also constrain more productive firms more, at least for a given amount of assets (see e.g. Cagetti and De Nardi (2006) and Buera (2009)).

How does the model stack up compared to dimensions of the data that were not directly targeted in the calibration? This comparison can be made for the total job separation rate, which can be compared to separation rates computed from ILO data or those reported in Elsby et al. (2013). The latter source allows comparing unemployment inflow rates for the five countries in the set of calibration countries that are OECD members. The correlation between model-implied separation rates and empirical ones is above 0.9. Some differences arise due to differences between the sample period for the data used by Elsby et al. (2013) and that used for the calibration targets here.

The fact that the model can be calibrated to a set of very different countries shows its versatility. In the following sections, I use it to analyze quantitatively the determinants of cross-country differences in labor market outcomes.

6 Which factors drive cross-country differences in wage employment, unemployment and self-employment?

It is clear from the figures shown in Section 2 that wage employment, self-employment and unemployment rates vary strongly across countries. Which factors account for this variation? To answer this question, I conduct two decomposition exercises. Both exercises use joint variation across model outcomes in reaction to parameter changes to assess the relative importance of different parameters. The first exercise evaluates, for each parameter, how the fit of the calibration targets changes when the parameter is chosen to match country-specific wage employment rates. The second exercise takes the opposite perspective: it evaluates which parameter, or combination of few parameters, is most important for matching the entire set of country-specific calibration targets when starting from a common benchmark.

In both cases, the starting point is the average country calibration. By construction, this does not provide a good match for statistics of individual countries, but it provides a common benchmark. For the first exercise, I then find, for each country and separately for each internally calibrated parameter, the value of the parameter that lets the model match the country's wage employment rate from the data, while keeping all the remaining parameters as in the calibration for the average target. This parameter change may improve or worsen the fit of the model in other dimensions. I therefore evaluate how the calibration loss function changes as each parameter is used, in turn, to match each country's wage employment rate. This exercise thus gives a first indication as to which parameters might plausibly account for variation in wage employment rates, without counterfactual implications in other dimensions.

Results from this exercise are reported in Table 10. The first column shows the improvement in the fit of the model as each parameter is allowed to be country-specific, to best match the country's wage employment rate. The measure of improvement shown in the table is computed as one minus the ratio of the sum of the calibration loss statistic across countries when the parameter is country specific to the sum when all parameters are common. This measure is one for a perfect fit to the calibration targets in all countries, between zero and one for an improvement relative to the fit of the model when the parameters from the average country calibration are used, and negative if fitting wage employment rates worsens the fit in other dimensions. Subsequent columns show the improvement in the model's explanatory power in terms of individual variables of interest. These statistics are computed as one minus the ratio of the sum of squared deviations between model and data values with one country-specific parameter to the sum of squared deviations with only common parameters.

The first column shows that while for some parameters, fitting a country's wage employment share improves other dimensions of the calibration, the calibration fit may worsen in other cases. In fact, it only improves when the vacancy posting cost k_v or the match destruction rate ξ are used to match the wage employment rate. When k_v is set to match each country's wage employment rate, the model fit noticeably improves, with a decline in the sum of calibration loss statistics across the eight countries of 22%.

The last three columns show how the model fit for key dimensions of interest changes. This shows that why fitting wage employment rates using k_v improves the model fit: apart from the perfect fit to each country's wage employment rate (which is not a calibration target), it leads to a closer fit of the unemployment outflow rate, the unemployment rate, and the self-employment rate. (More detail on this is provided in the next Section.)

It is generally the case that matching each country's wage employment rate also results in a closer match to the self-employment rates. The same cannot be said for the unemployment rate. For example, matching each country's wage employment rate by changing the entry cost k_f is feasible. However, doing so requires very high entry costs in countries with high wage employment. These high entry costs depress self-employment and promote wage employment – but at the cost of also reducing the number of employers, and thus raising unemployment. Hence the worse fit of the unemployment rate for this scenario. Matching wage employment rates with country-specific k_v instead requires reducing k_v to achieve high wage employment. This also results in lower self-employment and a lower UN ratio, in line with the data.

In a second approach to gauging the relative importance of the different model parameters, I assess their relevance for the overall model fit in the calibration. To measure this, I again start from the average country calibration, and then recalibrate the model for each

Table 10: Improvement in explanatory power of the model when only one parameter is country-specific – set to match each country's wage employment rate

	Improvement in fit of			
	all calibration targets	unemployment outflow rate	unemployment rate	self-employment rate
Country-specific parameter:				
k_f	-0.259	-0.109	-0.413	0.663
k_v	0.224	0.162	0.230	0.903
η	-0.525	-0.400	-0.870	0.312
b	-2.173	-0.288	-0.826	0.837
λ_F	-0.135	0.053	0.179	0.234
ξ	0.113	0.024	0.345	0.686
σ_z	-0.117	0.115	-0.059	0.590

Notes: The first column reports the reduction in the sum of the calibration loss statistic for all eight countries when one parameter is chosen to match each country's rate of wage employment, relative to the sum of loss statistics when the parameters for the calibration for the average target are used in all countries. The subsequent columns report the reduction in the sum of squared deviations between model predictions and data values for the indicated statistics.

country, keeping all parameters as in the calibration for the average target, except for one or a combination of few parameters. That is, I separately find which values of k_f, k_v, etc., give the model the best fit to the country-specific calibration targets for Ethiopia, the US, etc., when all remaining parameters are as in the "average" calibration. I then compute the share of variation in outcomes of interest in the data that the model can explain in these different scenarios. The question is: how much of the variation can be explained by optimally varying just a single parameter, or a small set of parameters?

Results for this exercise are shown in Table 11. The first column shows the improvement in the fit of the model when one, two, or three parameters are country-specific, computed as in Table 10. By construction, letting all internally calibrated parameters adjust would allow the model to fit all countries perfectly, implying an improvement measure of one. The remaining columns show the improvement in the model's explanatory power in terms of individual variables of interest, also computed as in Table 10.

It is very clear from these results that for the overall fit of the model, variation in k_v is key. Letting k_v adjust to allow the model to fit the calibration targets for each country as closely as possible results in a reduction of the calibration loss function by almost half compared to the case with common parameters (drawn from the average target calibration). Additionally allowing for the job destruction rate ξ to be country-specific results in a reduction in the loss by half again. Variation in only these two parameters can thus account for almost three quarters of the variation in calibration targets in the data. Finally, also allowing the utility flow in unemployment parameter b to be country-specific reduces the loss by more than half again, bringing it to one tenth of its value with common parameters.

In terms of individual outcome variables, the combination of k_v and ξ is also very powerful. Together, they explain almost the entire variation in the unemployment outflow rate, and a third of the variation in the UN ratio. They also explain 80% of the variation in the self-employment rate. Further allowing b to be country-specific allows the model to explain 90% or more of the variation in both the unemployment-related variables and in self-employment.

For some individual outcome variables, other parameters have more explanatory power. For example, allowing for only country-specific ζ explains more than 90% of the variation in the self-employment rate.[29] However, this scenario worsens the model's fit in terms of the unemployment rate compared to the situation with common parameters for all countries. The reason is that while high ζ implies high self-employment, it also reduces unemployment, generating a correlation between self-employment and unemployment that runs counter to the data. The same occurs for country-specific entry costs k_f.

To a lesser extent, the same is true for productivity dispersion σ_z. Country-specific dispersion achieves an improvement in the calibration targets jointly of not much more than 1/8. It does lead to a much improved match of wage employment rates to the data. This is because a reduction in dispersion (to take an example), because of selection, implies smaller employer firms and thus reduces wage employment. However, the counterpart to this is a strong increase in self-employment, with the implication that the unemployment rate hardly changes, and UN rates change little. This finding is important since, as mentioned above, changes in σ_z are isomorphic to changes in size-dependent distortions, parameterized in a popular way. SDDs thus do not appear to be a primary driver of variation in labor force status across the calibration countries.

Overall, these results suggest that cross-country variation in parameters encapsulating labor market frictions is key for understanding variation in labor market outcomes across countries. This is the case not only for the unemployment outflow rate (which is directly affected by the vacancy posting cost k_v) and the unemployment rate and the UN ratio (which are directly affected by k_v and by the job destruction rate ξ), but also for the self-employment rate.

[29] This exercise is similar to the one in Feng et al. (2018), who analyze the effect of an increase in productivity in a "modern" sector of employer firms relative to that in a "traditional" sector of own-account workers.

Table 11: Improvement in explanatory power of the model when only a subset of parameters is country-specific – set to improve each country's calibration

	Improvement in fit of					
	all calibration targets	wage employment rate	unemployment outflow rate	unemployment rate	UN ratio	self-employment rate
One country-specific parameter:						
k_f	0.173	0.687	0.099	-0.075	0.143	0.701
k_v	0.438	0.418	0.715	0.306	0.370	0.105
η	0.118	-0.142	0.209	0.213	0.117	-0.141
b	0.124	0.034	0.167	0.003	-0.013	0.224
λ_f	0.065	0.426	0.001	0.100	0.202	0.315
ξ	0.190	0.879	0.021	0.284	0.413	0.883
σ_z	0.159	0.730	0.079	0.019	0.204	0.591
ζ	0.138	0.623	-0.017	-0.113	0.003	0.915
Two country-specific parameters:						
k_v, ξ	0.708	0.748	0.939	0.191	0.336	0.808
Three country-specific parameters:						
k_v, b, ξ	0.915	0.787	0.987	0.984	0.988	0.890

Notes: The first column reports the reduction in the sum of the calibration loss statistic for all eight countries when one, two or three parameters are chosen to minimize each country's loss function, relative to the sum of loss statistics when the parameters for the calibration for the average target are used in all countries. The subsequent columns report the reduction in the sum of squared deviations between model predictions and data values for the indicated statistics. These numbers are akin to the R^2 of the model for these outcome variables.

Before turning to a more detailed analysis of the effect of labor market frictions in the model, I investigate whether, beyond the dispersion in unemployment and self-employment rates in the data, they can also account for the relationship between the UN ratio and self-employment shown in Section 2.

Figure 5 depicts the relationship between self-employment and the UN ratio in model and data. It shows model results for two cases: one ("2 specific parameters") where k_v and ξ are country-specific and chosen to best fit each country's set of calibration targets, and one ("3 specific parameters") where in addition, b is also country-specific. It shows the data as small dots, data for the eight countries used in the calibration as triangles, and model outcomes for three (two) country-specific parameters as black squares (grey diamonds). (The fit of the country calibrations and the model explanatory power for each individual variable separately thus is given in the two bottom rows in Table 11.) The solid and dashed lines in each figure show best fits of a linear regression of the variable on the vertical axis on that on the horizontal axis. The regression coefficients underlying these lines are 0.881 for the case with 2 specific parameters, and 0.374 with 3 specific parameters.

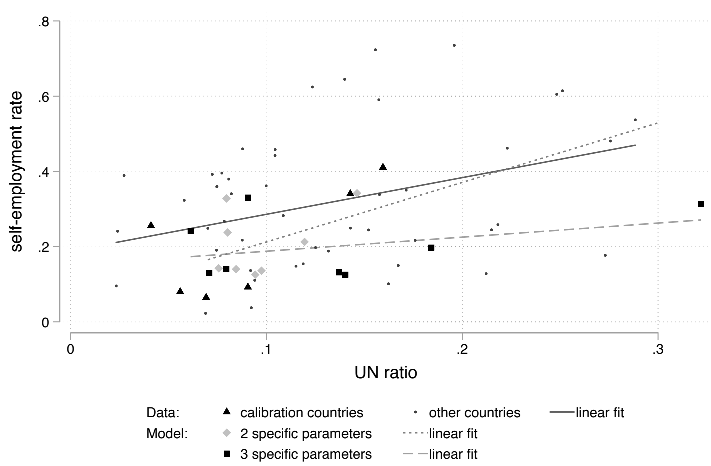


Figure 5: Self-employment and the UN ratio: data and model outcomes

Notes: Points labelled "model" show model outcomes with parameters from the calibration for the average economy, except for k_v and ξ, which are country-specific (series labelled "2 specific parameters"). In the series labelled "3 specific parameters", the parameters b is also country-specific. Regression coefficients: 0.881 with 2 specific parameters, 0.374 with 3 specific parameters.

It is immediately clear from the lines of best fit that the model outcomes are qualitatively in line with the data. Quantitatively, the model captures at least one third of the strength of the relationship between the self-employment rate and the UN ratio in the data.

With variation in variables capturing labor market frictions only, the model thus does an excellent job in reproducing not only each country's levels of wage employment, self-employment and the *UN* ratio individually – implying variation in the wage employment and self-employment rates across countries of more than 20 percentage points –, but also the bivariate relationship of self-employment and the *UN* ratio. This suggests that variation in labor market frictions across countries is not only a driver of differences in unemployment, but also in other labor market outcomes, in particular self-employment and wage employment.

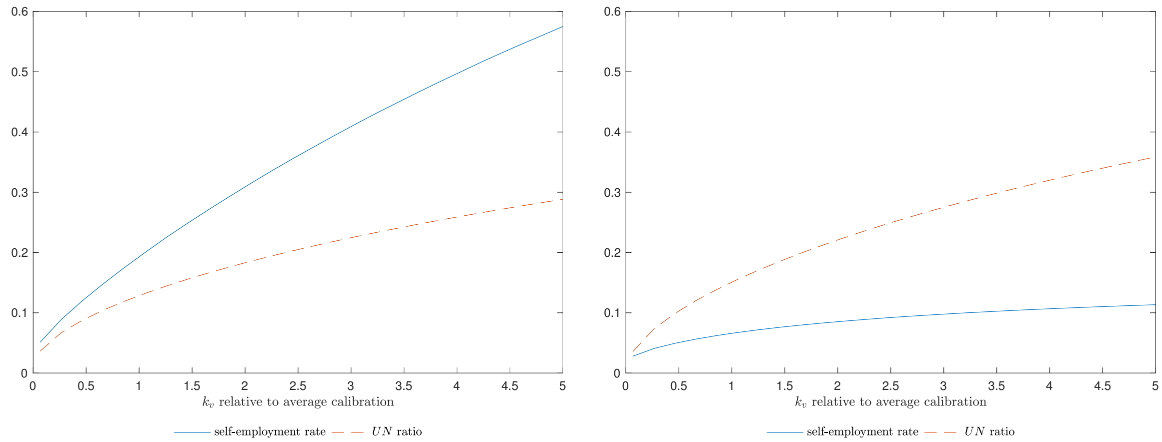
7 Labor market frictions, employment status, and productivity

Having shown the importance of labor market frictions in accounting for cross-country differences in labor market outcomes, I illustrate their effects in more detail in this section. I focus on the effects of hiring costs k_v, since they are the individual parameter with the greatest explanatory power. How do labor market frictions affect occupational choices and aggregate outcomes?

Lower hiring costs make running a business more profitable, and thus attractive. (OC shifts up in the top panel of Figure 4.) Lower costs of creating a match also reduce match surplus, shifting the wage curve down. The net effect is higher tightness, and an ambiguous change in the wage.

Figure 6 shows the effect of changes in k_v on the self-employment rate and the *UN* ratio. It is clear from Figure 6a that lower k_v not only leads to a lower *UN* ratio – this is as expected in a standard DMP model – but, by making job search more attractive, also reduces the self-employment rate. The second effect is sizeable: at the average country calibration, the self-employment rate declines more than the unemployment rate for a given change in k_v. For example, reducing k_v by half from its value in the calibration for the average country results in a reduction in the *UN* ratio by 3.8 and the self-employment rate by 6.8 percentage points.

Which margin reacts more strongly depends on parameters, in particular the cost of establishing new firms, as is clear from comparing the two panels of Figure 6. This shows that a reduction in k_v attracts fewer people from self-employment into job search when entry is costly (k_f is high), as in the right panel. For example, for a country as in the average calibration but with the (high) level of the entry cost of the US, the self-employment rate only falls by 1.5 percentage points as k_v is reduced by half. This pattern holds not only when starting from the average country calibration (shown here), but also when starting in



(a) Low k_f (from average country calibration) (b) High k_f (from US calibration)

Figure 6: The effect of vacancy posting costs k_v on labor market outcomes for different levels of the entry cost k_f (benchmark: average country)

Notes: All parameters except k_v and k_f as in the calibration to the average target (see Tables 9 and A.10 for parameter values). k_f as in the calibration for average targets in the left panel, and as in the calibration for the US in the right panel.

the calibration for the US (see Figure A.4).

Table 12 gives more detailed information on how these changes come about, for several different calibrations. Lower vacancy posting costs induce employer firms to post more vacancies, driving up labor market tightness. As in a standard DMP model, this results in higher job finding and unemployment outflow rates, higher wages, and a lower UN ratio.

Self-employment choices also change. First of all, despite the reactions of wage and tightness, lower k_v still implies a lower user cost of labor for employer firms, so that average firm size grows. This also prompts a larger fraction of entrants to become employers (except in the US calibration). As a consequence, the new equilibrium features slightly more, larger employer firms, and significantly fewer own-account workers. The fraction of own-account workers declines partly because more entrants decide to become employers, but even more because the outside option of search becomes more valuable – so much so that the lowest level of productivity at which own-account work is optimal, z_s, increases by 8% in the calibration to the average target.

The reduction in vacancy posting costs leads to an increase in aggregate output. This effect is shown in Table 13. To understand its sources, I show the effect of lower k_v on output for four different model calibrations, as in the previous table. Aggregate output gains range from 1.4 to almost 9 percent. Changes in output can stem from the increase in employment,

Table 12: The effect of labor market frictions

change in	calibration to average economy	average economy, high k_f	Ethiopia	US
tightness θ (%)	129.1	140.4	173.8	126.0
UN ratio (% pts)	-3.8	-4.8	-7.1	-1.8
u (% pts)	-2.6	-4.4	-1.0	-1.6
u outflow rate (% pts)	8.2	8.0	1.8	21.3
job finding rate θq (% pts)	9.7	8.1	4.1	21.6
fraction employees (% pts)	8.4	5.5	19.1	2.4
entrepreneurship (% pts)	-6.8	-1.5	-23.0	-1.0
own-account (% pts)	-7.0	-1.5	-25.3	-0.9
employers (% pts)	0.2	0.0	2.3	-0.1
mean firm n (%)	54.4	29.8	217.2	11.0
incomes:				
w (%)	5.6	6.3	3.1	6.4
SE/w (%)	-1.2	-2.0	-4.8	-4.7
employer/w (%)	-13.2	-13.9	-6.3	-13.8

Notes: The table shows the reaction of the model economy to a reduction in vacancy posting costs by half. Parameters for the respective benchmarks are given in Tables 9 and A.10. In the second column, k_f takes on the value from the calibration for the US, as also seen in Figure 6b.

changes in wages and profits due to lower k_v, and the changes in firm size and occupational choice induced by lower k_v. The relative importance of these channels is illustrated by the decomposition of output gains in the bottom rows of the table. This shows two main results. First, output gains are entirely due to changes in the amount and composition of employment, and not due to output gains within groups, which are close to zero throughout. The reason for this is that while lower hiring costs lead to higher wages, they also entice new, lower-productivity employers to enter, implying that average firm output does not rise. Second, both lower unemployment and changes in self-employment propensities and composition drive overall output gains. Their relative importance differs across economies.

The four calibrations for which output effects are shown in Table 13 differ mainly in their levels of k_v and k_f. The output changes and their sources reflect these differences. In economies with high entry costs, essentially the entire output gains come from lower unemployment. This is natural, given the small changes in self-employment in these economies, shown in Table 12. But in economies with low entry costs and high self-employment, changes

Table 13: The output effect of lower labor market frictions

% change in	calibration to average economy	average economy, high k_f	Ethiopia	US
output:				
aggregate output	4.0	5.2	8.8	1.4
aggregate output net of k_v	7.7	10.0	3.9	6.1
aggregate output net of k_v and k_f	10.6	10.8	16.7	7.0
output of employer firms/employee	-1.5	-0.5	-3.8	-0.7
counterfactual output:				
group sizes as in benchmark	0.0	0.1	-0.9	0.0
only u changes	2.9	5.1	2.6	1.7
only self-employment rates change	1.2	0.0	6.5	-0.4
all group sizes change (average group output as in benchmark)	4.1	5.1	9.2	1.3

Notes: The table shows the reaction of a set of model economies to a reduction in vacancy posting costs by half. Parameters for the respective benchmarks are given in Tables 9 and A.10. In the second column, k_f takes on the value from the calibration for the US, as also seen in Figure 6b. The last four rows of the table show counterfactual results. In these rows, "group" refers to the three groups of employees, own-account workers and employers. In the first of the four rows, counterfactual aggregate output is computed using group sizes from the benchmark, but average group output from the low-k_v economy (including spending on hiring). In the remaining rows, average output for each group is taken from the benchmark. In the second of the four rows, relative group sizes are as in the benchmark, but the unemployment rate is taken from the low-k_v economy. In the next row, the unemployment rate is taken from the benchmark, but relative group sizes (fractions of own-account workers and employers among those in work) from the low-k_v economy. In the final row, all group sizes are taken from the low-k_v economy.

in the self-employment rate can account for 30% (average economy) up to 70% (Ethiopia) of overall output gains. This is due to the large reduction in the rate of own-account work in response to lower k_v in these economies, combined with their relatively high output of employees relative to the self-employed.

While data limitation prevent a full analysis of the explanatory power of differences in labor market frictions in terms of cross-country output differences, these results suggest that differences in frictions have a sizable effect. As shown, reducing k_v in the model economy for Ethiopia by half results in an output increase by almost 9%. Such an increase in output would reduce the ratio of US to Ethiopian GDP per capita by 8%.

To summarize, the model not only predicts a strong effect of labor market frictions on unemployment and self-employment, but also a strong effect on output. A substantial part of that comes from the effect of labor market frictions on occupational choices. This effects is particularly large in economies with strong labor market frictions and low entry costs.

8 Conclusion

The distribution of employment states varies strongly with income per capita. Labor markets in poor countries are characterized not only by lower levels of wage employment and higher levels of self-employment, but also by more unemployment relative to wage employment (a high *UN* ratio), indicating difficulty of job search. In addition, the self-employment rate is particularly high where the *UN* ratio is high. A search and matching model with occupational choice is flexible enough to be able to reproduce these patterns and match labor market outcomes in a very diverse set of countries.

A quantitative analysis of the model points to variation in labor market frictions as the dominant driver of differences in unemployment and self-employment across countries. This is true both for the univariate and joint distribution of unemployment and self-employment. This analysis points to high hiring costs or low matching efficiency and a high job destruction rate as the root causes of not only high *UN* ratios, but also low wage employment and high self-employment in poor countries. The analysis also shows that reduced labor market frictions would not only imply more wage employment and less self-employment in poor economies, but also substantial output gains. These stem from reduced unemployment, but also from a more efficient allocation of resources, with fewer own-account workers and more wage employees, employed in relatively more productive firms. Evidently, changes in occupational choice are central for these results.

The theoretical analysis in this paper was guided by the objective to stay as close as possible to a standard DMP model, and to add only the minimum extensions required to capture key features of the economic environment under study. The quantitative performance of the model shows that these simple extensions already go very far. Nevertheless, identifying more precisely what kind of labor market frictions are so large in poor countries would clearly be valuable. Doing so would require using richer data and a richer model. In return, it would allow analyzing more specific policies than the present, fairly abstract setting. Two particular directions for further work come to mind.

First, part of the reason unemployment is so high relative to employment in a country like Ethiopia is that the job destruction rate is high, while the job finding rate is low. It is not clear why the destruction rate is so high, in particular given the high cost of creating productive matches. One possibility is that match quality is very uncertain and screening hard, leading both to a high destruction rate and a high cost of creating a lasting match. This appears to be consistent with the evidence documented by Blattman and Dercon (2018) for Ethiopia. Further analysis for more different settings could prove valuable.

Second, there is a variety of experimental work that has identified the presence of labor market frictions in specific settings. Extensions of the theory that allow relating it directly to this line of work also appear promising.

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Appendix

A Additional Tables and Figures

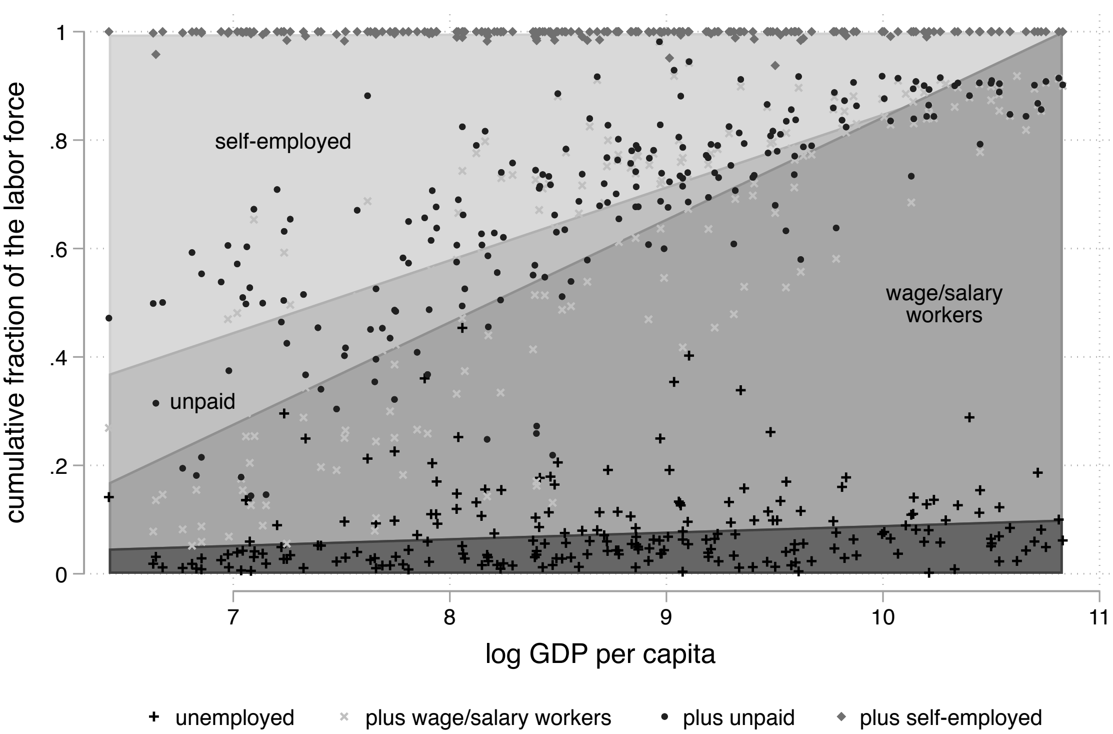


Figure A.1: Composition of the labor force and development, national, incl. unpaid workers

Sources: See Figure 1.

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

dependent variable:	self-employment rate	rate of wage employment	unemployment rate	*UN* ratio
Urban areas:				
log GDP per capita	-0.111***	0.112***	0.006	-0.022*
	(0.011)	(0.013)	(0.008)	(0.012)
R^2	0.433	0.422	0.005	0.037
observations	150	150	165	150
Entire country:				
log GDP per capita	-0.174***	0.168***	0.012**	-0.025**
	(0.012)	(0.012)	(0.005)	(0.010)
R^2	0.664	0.676	0.035	0.062
observations	214	214	235	214

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1.

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

dependent variable:	self-employment rate	rate of wage employment	unemployment rate	*UN* ratio
Urban areas:				
log GDP per capita	-0.145***	0.148***	0.002	-0.030**
	(0.023)	(0.023)	(0.008)	(0.013)
R^2	0.509	0.507	0.002	0.116
observations	93	93	101	93
countries	41	41	45	41
Entire country:				
log GDP per capita	-0.202***	0.189***	0.017***	-0.018
	(0.021)	(0.020)	(0.006)	(0.011)
R^2	0.656	0.639	0.135	0.054
observations	124	124	134	124
countries	50	50	55	50

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1.

Table A.3: 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	-0.109***	-0.114***	0.001	0.014***	-0.023***
	(0.008)	(0.008)	(0.003)	(0.004)	(0.009)
R^2	0.641	0.663	0.000	0.138	0.127
observations	1241	1334	1255	598	548
countries	106	107	107	71	54
earliest sample year	1976	1960	1976	1960	1992
latest sample year	2014	2014	2014	2014	2014

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data from the International Labour Organization (ILOSTAT).

Table A.4: Unemployment and development, participation rate and alternative measure of unemployment

dependent variable:	non-participation rate	fraction not working	narrow unemployment rate	*UN* ratio using narrow u rate
Urban areas:				
log GDP per capita	-0.028**	-0.027**	-0.008	-0.044***
	(0.012)	(0.013)	(0.011)	(0.014)
R^2	0.091	0.075	0.009	0.149
observations	150	150	150	150
countries	58	58	58	58
Entire country:				
log GDP per capita	-0.033***	-0.027**	0.002	-0.043***
	(0.011)	(0.012)	(0.009)	(0.011)
R^2	0.120	0.070	0.001	0.180
observations	214	214	214	214
countries	68	68	68	68

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). (Results for a pooled regression are similar.) Constant not reported. Standard errors in parentheses. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1.

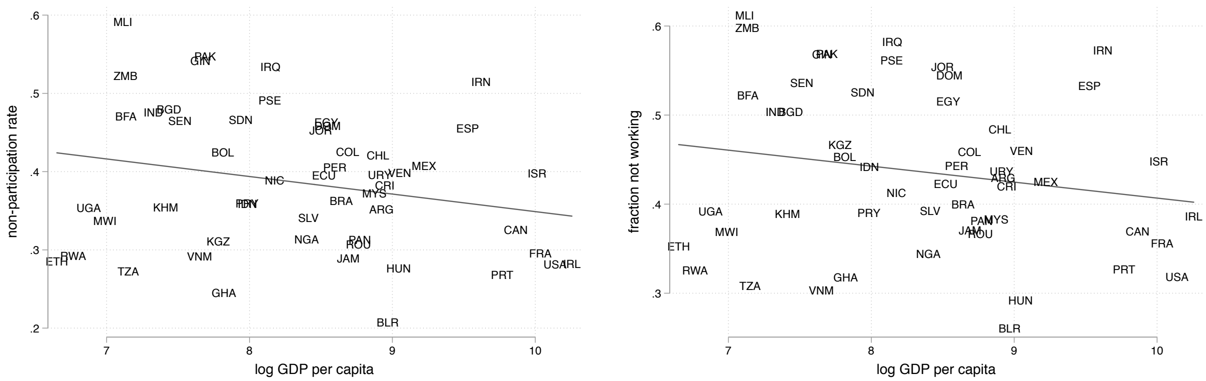


Figure A.2: Non-participation rate and fraction of the population not working versus log GDP per capita

Notes: Data for urban areas. For each country, the time average is shown. Regression outputs underlying the lines of best fit reported in Table A.4.

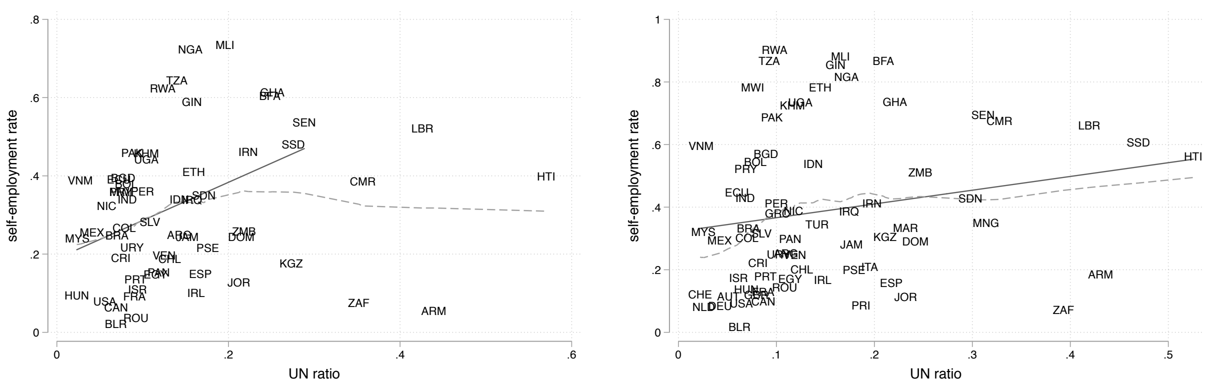


Figure A.3: The self-employment rate versus the UN ratio $u/(u+n)$, urban (left) and overall (right), full range of the UN ratio

Notes: Dashed line: linear regression. Dotted line: Fit from locally weighted regressions (`lowess` command in Stata).

Table A.5: The relationship between self-employment and the *UN* ratio, controlling for GDP per capita, urban areas, pooled regressions

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
UN ratio	0.542**	0.550**	0.026
	(0.222)	(0.217)	(0.033)
log GDP per capita	-0.112***	-0.125***	0.008***
	(0.010)	(0.011)	(0.003)
R^2	0.499	0.521	0.121
observations	136	126	126

Notes: The table shows regression coefficients from regressions of the dependent variable on the *UN* ratio and log GDP per capita, using pooled data. Constant not reported. Robust standard errors clustered at the country level in parentheses. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. 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	0.692**	0.594*	0.066
	(0.315)	(0.343)	(0.062)
log GDP per capita	-0.132***	-0.149***	0.012**
	(0.023)	(0.028)	(0.005)
R^2	0.562	0.513	0.146
observations	90	83	83
countries	41	37	37

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. 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

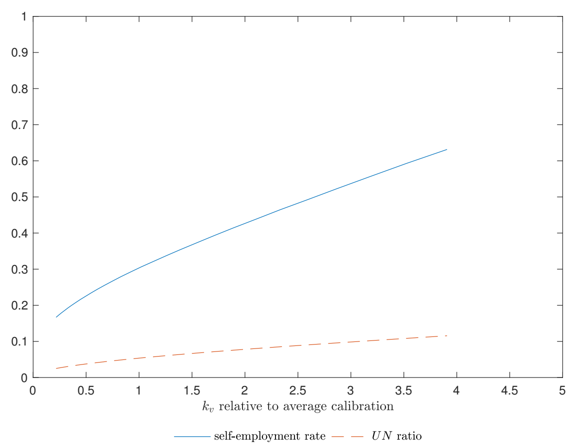
dependent variable:	self-employment rate	fraction own-account workers	fraction employers
Between regression:			
UN ratio	-0.067	-0.170	0.033
	(0.269)	(0.314)	(0.037)
log GDP per capita	-0.195***	-0.198***	0.010***
	(0.017)	(0.020)	(0.002)
R^2	0.684	0.633	0.242
observations	197	172	172
countries	64	59	59
Pooled regression:			
UN ratio	0.130	0.118	-0.006
	(0.193)	(0.208)	(0.026)
log GDP per capita	-0.175***	-0.191***	0.011***
	(0.013)	(0.015)	(0.002)
R^2	0.676	0.649	0.215
observations	197	172	172

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Data sources as in Figure 1.

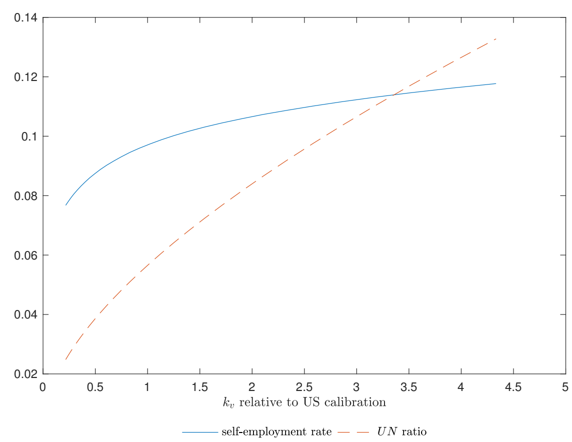
Table A.8: The relationship between self-employment and the UN ratio, controlling for GDP per capita, entire country (ILO data)

dependent variable:	self-employment rate	fraction own-account workers	fraction employers
UN ratio	-0.194	-0.373	0.179**
	(0.350)	(0.318)	(0.075)
log GDP per capita	-0.098***	-0.102***	0.005
	(0.018)	(0.017)	(0.004)
R^2	0.534	0.591	0.169
observations	254	254	254
countries	31	31	31

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. * (**) [***] indicates $p < 0.1$ (< 0.05) [< 0.01]. Results are virtually identical when years before 1995 are included.



(a) Low k_f



(b) High k_f

Figure A.4: The effect of vacancy posting costs k_v on labor market outcomes for different levels of the entry cost k_f (benchmark: US)

Notes: All parameters except k_v and k_f as in the calibration to the US (see Tables 9 and A.10 for parameter values). k_f as in the calibration for Ethiopia in the left panel, and as in the calibration for the US in the right panel. Note different scales of the vertical axes.

Table A.9: Calibration: model and data moments (8 countries and average, data values in parentheses)

country:	avg	USA	CAN	DEU	FRA	ITA	MEX	IDN	ETH
Targeted moments:									
Unemployment	0.180	0.440	0.256	0.062	0.086	0.062	0.398	0.091	0.044
outflow rate	(0.180)	(0.440)	(0.257)	(0.062)	(0.086)	(0.062)	(0.397)	(0.091)	(0.045)
Unemployment	0.106	0.051	0.069	0.107	0.130	0.152	0.042	0.058	0.237
rate	(0.106)	(0.051)	(0.069)	(0.107)	(0.129)	(0.152)	(0.042)	(0.058)	(0.237)
Casual	0.000	0.000	0.000	0.000	0.000	0.000	0.056	0.114	0.245
employment	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.056)	(0.114)	(0.240)
Fraction own-	0.149	0.049	0.069	0.046	0.040	0.157	0.221	0.311	0.288
account workers	(0.149)	(0.048)	(0.069)	(0.053)	(0.040)	(0.157)	(0.221)	(0.312)	(0.290)
Fraction	0.044	0.048	0.047	0.053	0.039	0.054	0.032	0.033	0.050
employers	(0.044)	(0.049)	(0.047)	(0.046)	(0.039)	(0.054)	(0.032)	(0.033)	(0.050)
Firm exit	0.109	0.110	0.105	0.060	0.090	0.085	0.140	0.140	0.142
rate (annual)	(0.109)	(0.110)	(0.105)	(0.060)	(0.090)	(0.085)	(0.140)	(0.140)	(0.142)
Firm size	0.740	0.846	0.876	0.830	0.923	0.816	0.755	0.316	0.871
target (see note)	(0.715)	(0.847)	(0.877)	(0.830)	(0.923)	(0.816)	(0.755)	(0.332)	(0.874)
Labor	0.670	0.670	0.670	0.670	0.670	0.670	0.673	0.670	0.671
income share	(0.67)	(0.67)	(0.67)	(0.67)	(0.67)	(0.67)	(0.67)	(0.67)	(0.67)
b/w	0.400	0.400	0.399	0.400	0.400	0.398	0.399	0.400	0.401
	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
Not targeted:									
UN ratio	0.128	0.057	0.077	0.117	0.139	0.185	0.055	0.086	0.320
	(0.129)	(0.056)	(0.077)	(0.117)	(0.139)	(0.185)	(0.055)	(0.086)	(0.320)
Entry rate h	0.077	0.018	0.014	0.005	0.004	0.009	0.072	0.439	0.014
Separation rate	0.026	0.025	0.020	0.007	0.013	0.012	0.052	0.027	0.046
Mean firm employment	5.175	10.298	8.617	10.091	12.627	4.730	3.731	2.577	2.235
Mean income relative to w for									
own-acct wkrs	1.03	1.16	1.36	1.04	1.22	1.29	3.37	1.04	1.10
employers	9.05	6.25	9.24	8.37	11.62	7.17	10.80	8.77	5.07
Business inc./Y	0.41	0.25	0.37	0.35	0.35	0.43	0.63	0.55	0.66

Notes: Countries are Ethiopia (ETH), United States (USA), Canada (CAN), Germany (DEU), France (FRA), Italy (ITA), Mexico (MEX), Indonesia (IDN). "avg" stands for the calibration targeting average values of data moments. Targeted model moments are in square brackets. The firm size target varies by country depending on data availability: For ETH, it is the share of firms with less than 10 employees; for MEX and IDN, it is the share of employment in firms with at least 20 employees; and for the remaining countries, it is the share of employment in firms with at least 10 employees.

Table A.10: Calibration: parameter values (8 countries and average)

country:		avg	ETH	USA	CAN	DEU	FRA	ITA	MEX	IDN
externally calibrated:										
r	discount rate (annualized)					common: 0.04				
ϕ	retirement probability (annualized)					common: 1/40				
μ	matching function					common: 0.5				
γ	decreasing returns to scale					common: 0.85				
internally calibrated:										
k_f	entry cost	26.2	13.54	61	55.5	36	56.3	36	73.5	44
k_v	vacancy posting cost	30.1	69	10.4	24.1	285	106	144	12	66.7
η	worker bargaining power	0.225	0.432	0.12	0.158	0.19	0.239	0.295	0.207	0.364
b	utility flow of unemployment	0.235	0.188	0.196	0.205	0.26	0.198	0.208	0.177	0.204
λ_f, λ_s	firm exit rates (annualized)	0.0874	0.120	0.077	0.087	0.026	0.093	0.057	0.118	0.118
ξ	job destruction rate	0.018	0.03185	0.0194	0.0105	0.0001	0.00164	0.0066	0.012	0.014
σ_z	productivity dispersion	0.2	0.0224	0.162	0.18	0.27	0.155	0.11	0.022	0.1
ζ	relative self-employment productivity	0.6845	0.5191	0.661	0.72	0.535	0.743	0.704	1.55	1.078
δ	casual job probability	0	0.44	0	0	0	0	0	0.537	0.4

Notes: Countries are Ethiopia (ETH), United States (USA), Canada (CAN), Germany (DEU), France (FRA), Italy (ITA), Mexico (MEX), Indonesia (IDN). "avg" stands for the calibration targeting average values of data moments. The firm exit rate reported in this table differs from that reported in Table A.9 since the latter also includes exits due to the owner's retirement.

B Details on the accounting model

B.1 Self-employment entry from unemployment only

The flows among the three states u, n and e are given in Table 5. They result in the steady state stocks for u, n and e given in (1). Comparative statics of these stocks with respect to the flow rates are:

$$
\begin{aligned}
\frac{\partial u}{\partial h} &= -\frac{u^2}{s}\left(\frac{s}{\lambda} - f\right) < 0 \quad \text{if } s/f > \lambda \\
\frac{\partial u}{\partial f} &= -u^2\frac{1-h}{s} < 0 \\
\frac{\partial u}{\partial s} &= u^2\frac{(1-h)f}{s^2} \\
\frac{\partial u}{\partial \lambda} &= u^2\frac{h}{\lambda^2} \\
\frac{\partial e}{\partial h} &= \frac{\lambda e^2}{h^2}\frac{s+f}{s} = \frac{u^2}{\lambda}\frac{s+f}{s} \\
\frac{\partial e}{\partial f} &= -\lambda e^2\frac{(1-h)}{hs} = -u^2\frac{h}{s\lambda}(1-h) \\
\frac{\partial e}{\partial s} &= \frac{1-h}{h}\frac{\lambda f e^2}{s^2} = u^2(1-h)\frac{h}{\lambda}\frac{f}{s^2} \\
\frac{\partial e}{\partial \lambda} &= -e^2\frac{s+(1-h)f}{hs} = -u^2\frac{h}{\lambda^2}\frac{s+(1-h)f}{s} \\
\frac{\partial \tilde{u}}{\partial h} &= \tilde{u}^2\frac{f}{s} = \frac{u^2}{(1-e)^2}\frac{f}{s} \\
\frac{\partial \tilde{u}}{\partial f} &= -\tilde{u}^2\frac{1-h}{s} = -\frac{u^2}{(1-e)^2}\frac{1-h}{s} \\
\frac{\partial \tilde{u}}{\partial s} &= \tilde{u}^2\frac{(1-h)f}{s^2} \\
\frac{\partial \tilde{u}}{\partial \lambda} &= 0.
\end{aligned}
$$

A key observation is that in the data, e and $\tilde{u}$ are positively correlated. This could be generated by variation in h, f or s, with

$$\left.\frac{de}{d\tilde{u}}\right|_{\text{vary only } h} = \frac{(1-e)^2}{\lambda}\frac{s+f}{f}$$
$$\left.\frac{de}{d\tilde{u}}\right|_{\text{vary only } f} = (1-e)^2\frac{h}{\lambda}$$
$$\left.\frac{de}{d\tilde{u}}\right|_{\text{vary only } s} = (1-e)^2\frac{h}{\lambda}.$$

As discussed in the main text, the first of these expressions takes on very large values in practice, whereas the other two have plausible values in the range from 1 to 1.5.

Variation in h, f or s also implies

$$\left.\frac{de}{du}\right|_{\text{vary only } h} = \frac{s+f}{\lambda f - s}$$
$$\left.\frac{de}{du}\right|_{\text{vary only } f} = \frac{h}{\lambda}$$
$$\left.\frac{de}{du}\right|_{\text{vary only } s} = \frac{h}{\lambda}.$$

As discussed in the main text, the first of these expressions takes on values around minus 7-20 in practice, whereas the other two have plausible values in the range from 1.5 to 2.

B.2 Self-employment entry from both employment and unemployment

Now consider the case where the employed also enter self-employment, at a per period rate of $\hat{g} \equiv gh$. This implies that the stocks are

$$u = \frac{\lambda(gh+s)}{(1-h)f(gh+\lambda)+gh(h+\lambda)+s(h+\lambda)}$$
$$e = \frac{(1-h)fgh+h(gh+s)}{(1-h)f(gh+\lambda)+gh(h+\lambda)+s(h+\lambda)}$$
$$n = \frac{(1-h)f\lambda}{(1-h)f(gh+\lambda)+gh(h+\lambda)+s(h+\lambda)}$$
$$\tilde{u} \equiv \frac{u}{u+n} = \frac{gh+s}{(1-h)f+gh+s}.$$

(gh now is an employment outflow and shows up accordingly.)

Here, the derivatives look more complicated, but one can show that comparative statics imply

$$
\begin{array}{cccc}
 & \dfrac{\partial e}{\partial h} > 0 & sign\left(\dfrac{\partial e}{\partial f}\right) = sign(g-h) & \dfrac{\partial e}{\partial s} > 0 & \dfrac{\partial e}{\partial \lambda} < 0 \\
sign\left(\dfrac{\partial u}{\partial h}\right) = sign(\lambda - s/f) & & \dfrac{\partial u}{\partial f} < 0 & \dfrac{\partial u}{\partial s} > 0 & \dfrac{\partial u}{\partial \lambda} > 0 \\
 & \dfrac{\partial \tilde{u}}{\partial h} > 0 & \dfrac{\partial \tilde{u}}{\partial f} < 0 & \dfrac{\partial \tilde{u}}{\partial s} > 0 & \dfrac{\partial \tilde{u}}{\partial \lambda} = 0.
\end{array}
$$

C Proofs and derivations

C.1 Summary of model timing

The following summarizes the timing of events within a period in this economy.

1. If individuals chose to enter, they pay the entry cost k_f and their productivity $z \sim f(z)$ is realized.
2. Depending on z, entrants decide whether
   (a) to keep the business and post vacancies to reach the optimal employment level,
   (b) to be self-employed, or
   (c) to exit and go to the unemployment pool.
3. Shocks $(\phi,\ \lambda_f,\ \lambda_s,\ \xi,\ \delta,\ \theta \cdot q(\theta))$ are realized.
4. Value functions are measured and occupational choices take place.
5. Production takes place and payoffs $(w,\ b)$ are realized.

C.2 Detailed Derivation of Wage

As stated in the main part of the paper, workers and firms split the surplus according to workers' bargaining weight η. The total surplus is the sum of workers' and firms' surplus, explicit expressions of which are given below.

Worker's Surplus The value of employment is given by

$$W = w + \frac{1-s}{1+r}W + \frac{s-\phi}{1+r}U$$

Rewrite this to obtain $W-U$:

$$W-U \quad = \quad \frac{1+r}{r+s}w-\frac{r+\phi}{r+s}U$$

Firm's Surplus From equation (14),

$$F_f(n,z)=\frac{1+r}{(1+r)-(1-\phi)(1-\lambda_f)}\left(zn(z)^\gamma-n(z)w-\frac{k_v}{q(\theta)}n(z)(\xi+(1-\xi)\phi)\right) \qquad (24)$$
$$+\frac{(1-\phi)\lambda_f}{(1+r)-(1-\phi)(1-\lambda_f)}U.$$

Then the marginal value of hiring an additional worker the firm has just met, and keeping that worker until either the firm shuts down or some type of separation occurs, is given by

$$c_0\left(y'\left(n\right)-w-n\cdot w'\left(n\right)\right),$$

where c_0 is derived as follows. From the firm's sequence problem, the marginal value of an additional worker is

$$\sum_{j=0}^{\infty}\left(\frac{\left(1-\phi\right)\left(1-\lambda_f\right)}{1+r}\right)^j\left[\left(1-\phi\right)\left(1-\xi\right)\right]^j\left(y'\left(n\right)-w-n\cdot w'\left(n\right)\right)$$

Let

$$c_0\equiv\sum_{j=0}^{\infty}\left(\frac{\left(1-\phi\right)^2\left(1-\lambda_f\right)\left(1-\xi\right)}{1+r}\right)^j=\frac{1+r}{\left(1+r\right)-\left(1-\phi\right)^2\left(1-\lambda_f\right)\left(1-\xi\right)}=\frac{1+r}{r+s},$$

where $s\equiv 1-(1-\phi)^2(1-\lambda_f)(1-\xi)$.

Nash Bargaining The bargaining rule implies that the wage solves

$$\left(1-\eta\right)\left(W-U\right)=\eta c_0\cdot\left(y'\left(n\right)-w-n\cdot w'\left(n\right)\right)$$

Using the expressions above, solving this for w yields the differential equation

$$w=(1-\eta)\frac{r+\phi}{1+r}U+\eta\left(y'\left(n\right)-n\cdot w'\left(n\right)\right). \qquad (25)$$

At a firm's optimal employment, the solution to this equation (details below) is

$$w = \frac{r+\phi}{1+r}U + \frac{\eta}{1-\eta}\left[1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi\right] \cdot \frac{k_v}{q(\theta)}. \tag{26}$$

For this wage, a firm's optimal employment policy is

$$n(z) = (z\gamma)^{\frac{1}{1-\gamma}} \left\{(\eta(\gamma-1)+1)\left[\left(1 - \frac{(1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi\right)\frac{k_v}{q} + w\right]\right\}^{\frac{-1}{1-\gamma}}. \tag{27}$$

Solution of the differential equation for w. Without the constant, the equation is

$$w'(n) + \frac{w}{\eta n} - \frac{y'(n)}{n} = 0. \tag{28}$$

The solution of the homogeneous equation

$$w'(n) + \frac{w}{\eta n} = 0$$

then is

$$w(n) = Cn^{-1/\eta}. \tag{29}$$

C is a function of integration that can be a function of n. So take the derivative of equation (29) with respect to n:

$$\frac{\partial w}{\partial n} = C'(n)\, n^{-1/\eta} - \frac{C}{\eta} n^{-1/\eta - 1}$$

Substituting this into (28) yields

$$C'(n) = y'(n)\, n^{1/\eta - 1}$$

Integrating this gives $C(n)$ as

$$C(n) = \int_0^n y'(z)\, z^{1/\eta-1} dz + D$$

so the wage w is

$$w(n) = n^{-1/\eta} \int_0^n y'(z)\, z^{1/\eta-1} dz + Dn^{-1/\eta}$$

The constant D can be dealt with assuming that the wage bill goes to zero as employment goes to zeros. This implies $D = 0$. The solution to equation (25) then is

$$w\left(n\right) = n^{-1/\eta} \int_0^n y'\left(z\right) z^{1/\eta - 1} dz + (1-\eta) \frac{r+\phi}{1+r} U$$

Integrating yields

$$w\left(n\right) = (1-\eta) \frac{r+\phi}{1+r} U + \frac{y'(n)}{\gamma - 1 + 1/\eta}. \tag{30}$$

The division in the last term here comes from the overhiring effect.

To obtain the wage at the firm's optimal constant level of employment (replacing any workers who leave), use the labor demand condition. To obtain this, equate the marginal value of having an additional employee for the firm's entire life, from (24), to the expected hiring cost. This results in

$$y'\left(n\right) = w + n \cdot w'\left(n\right) + \frac{k_v}{q} \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi \right].$$

To simplify, take the derivative of (30) with respect to n, multiply by n, and replace the $n \cdot w'\left(n\right)$ term in the labor demand condition. This yields

$$y'\left(n\right) = w + \frac{z\gamma\left(\gamma-1\right) n^{\gamma-1}}{\gamma - 1 + 1/\eta} + \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi \right] \frac{k_v}{q}$$

or

$$y'(n) = [\eta(\gamma-1)+1] \left\{ w + \left[\frac{1 + r - (1-\phi)(1-\lambda_f)}{1+r} + \xi + (1-\xi)\phi \right] \frac{k_v}{q} \right\}.$$

Solve this for n to obtain the labor demand condition in (27). Substituting this expression into (30) yields the wage at the optimal employment level given in equation (26).

D Data

In this section, I lay out how I compute durations and the distribution of employment status from IPUMS, UEUS and LFS data, and from Bigsten et al. (2007). I also thank the statistical offices that provided the data underlying IPUMS.

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.

D.2 UEUS and LFS data for Ethiopia

I use the Urban Employment and Unemployment Surveys (UEUS) for 2012 and 2015, and the 2013 Labor Force Survey (LFS). Throughout, I use only data for Addis Ababa (ID101=14), and use weights (WGT_LB).

For the calibration, I use the distribution of employment status from the UEUS for 2012 (variable U311). I define the following groups: unemployed (23%), public sector worker (including government, government development organizations; 16%), private sector worker (14%), own-account worker (13%), employer (7%), domestic employee (8%), casual or temporary worker (13%), other (coops, unpaid family workers, "other", apprentices; 5%). I then ignore public sector employees and unpaid family workers (1.9% of employment). To further map the groups into model categories, I treat the sum of private sector workers, other, and half of casual or temporary worker as employees, and treat the other half of casual and temporary workers plus domestic workers as casual workers. This leaves us with 42% of private sector employees, 24% of casual workers, 24% of own-account workers, and 9% of employers. The implied unemployment rate is 24%.

In the UEUS for 2012 only, the self-employed provide a measure of "persons participating in the activities of their enterprise." To distinguish own-account workers and employers, I use this measure, not the reported own-account worker versus employer status.

To compute the unemployment outflow rate, I use the employment duration variable, U410. I drop observations with durations over 90 months. The data exhibit severe bunching, first at 0 and 6 months and then at each full year. I smooth this by assuming that a fraction of individuals reports a duration that is rounded downward to the closest year (or 6 months for durations between 6 and 11 months), with a propensity to round that can vary by year of duration. These assumptions generate a duration distribution similar to that in the data, for a common fixed (implied) unemployment outflow rate of 4.5%.

D.3 Employment status transitions

Table 7 shows a transition matrix over employment states for model and data. The data matrix is from Bigsten et al. (2007, Table 3, years 2000-2004). Their matrix contains seven employment states: self-employed, government worker, public enterprise worker, formal private sector worker, other private sector worker, unemployment, and out of the labor force. In line with the model, I ignore the second, third, and last groups. Since the model has no formal/informal distinction, I combine groups 4 and 5. I treat group 1 as applying to the union of own-account workers and employers.

D.4 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)