Unemployment and Development

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Abstract

This paper draws on household survey data from countries of all income levels to measure how average unemployment rates vary with income per capita. We document that unemployment is increasing with GDP per capita. This fact is accounted for almost entirely by low-educated workers, whose unemployment rates are strongly increasing in GDP per capita, rather than by high-educated workers, whose unemployment rates are not correlated with income. We interpret these facts in a model with frictional labor markets, a traditional self-employment sector and skill-biased productivity differences across countries. A calibrated version of the model explains around two-thirds of the cross-country patterns we document. We conclude that unemployment is largely a consequence of development rather than a source of low income per capita levels.

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1 Introduction

No single measure of labor-market performance receives more attention in advanced economies than the unemployment rate. It is well known, for example, that average unemployment rates are higher in Western Europe than in the United States and Japan (see, e.g., Blanchard and Summers, 1986; Ljungqvist and Sargent, 2008; Nickell, Nunziata, and Ochel, 2004). Unemployment has been found to have a robust negative association with life satisfaction across advanced economies (Frey and Stutzer, 2002) and a positive association with property crime in the United States (Raphael and Winter-Ebmer, 2001).

Much less is known about unemployment outside the world's most advanced economies, and existing studies make contradictory claims about how average unemployment rates vary with income per capita across the full world income distribution. For example, Caselli (2005) finds, using data from the International Labor Organization (ILO), that unemployment rates do not systematically vary with GDP per capita. Poschke (2018) uses micro labor force surveys to reach a similar conclusion about urban unemployment rates. Banerjee, Basu, and Keller (2016) draw on more recent data from the World Bank and conclude that unemployment rates are higher on average in lower income countries.

More generally, there is little agreement on how unemployment *per se* is distinct from low-skilled self-employment in the developing world, which is the dominant form of economic activity in the world's poorest countries (e.g. Gollin, 2008; Schoar, 2010). Some observers think of low-skilled self-employment and unemployment as synonymous, capturing the economic situation of many of the countless individuals who eke out marginal livings without working for wages. In this view, measured unemployment rates and subsistence self-employment rates have little distinction, rendering comparisons of average unemployment rates across advanced and developing countries largely uninformative (World Bank, 2012).

In this paper we draw on new evidence and theory to better understand how unemployment rates vary across the world income distribution, and why. We pay particular attention to the question of whether unemployment is distinct from low-skilled self-employment in the developing world, and whether empirical comparisons of unemployment rates by the level of development contain informative economic patterns. To do so, we build a new database of national unemployment rates covering countries of all income levels, drawing on evidence from 199 household surveys from 84 countries spanning 1960 to 2015. The database covers numerous rich countries and around two dozen nations from the bottom quartile of the world income distribution. Since measures of employment and job search vary across surveys, we divide the data into several tiers based on scope for international comparability. We then construct unemployment rates at the aggregate level and for several broad demographic groups, and compare how they vary with average income.

We find, perhaps surprisingly, that unemployment rates are *increasing* in GDP per capita. This finding is present for men and for women, for all broad age groups, within urban and rural areas, and across all comparability tiers of our data. For prime-aged adults, a regression of the country average unemployment rate on log GDP per capita yields a statistically significant positive coefficient of 1.8 percent. In addition, we document that unemployment patterns across countries differ markedly by education level. Among high-educated workers (secondary school or more), unemployment rates *do not* vary systemically with GDP per capita. Among low-educated workers, in contrast, unemployment rates are substantially higher in rich countries. Regressing the country average high-educated unemployment on log GDP per capita yields an insignificant slope coefficient of 0.5 percent, whereas the slope coefficient for the low-educated is a significant 3.2 percent.

Taken together, these patterns highlight how unemployment is empirically distinct from low-skilled self-employment. Our data imply, in particular, that in rich countries low-educated workers are more likely than high-educated workers to be unemployed, whereas in poor countries the opposite is true. This empirical regularity suggests that searching for wage jobs, and the resulting unemployment, is linked tightly to education in poorer countries, but not in richer countries. Moreover, working hours of the low-skilled self-employed are almost as high as those of wage employees in both poor and rich countries (Bick, Fuchs-Schuendeln, Lagakos, and Tsujiyama, 2020). None of these patterns is consistent with the view that unskilled self-employment and unemployment are synonymous, capturing the same economic fundamentals.

To interpret these patterns, we build a simple two-sector model with frictional labor markets, based on Diamond (1982) and Mortensen and Pissarides (1994), and heterogeneous workers that sort by ability as in Roy (1951). In the modern sector, labor markets are governed by search frictions, and worker productivity is determined by a worker's ability level. In the traditional sector, workers are self-employed and do not need to search for jobs; however, productivity is independent of ability. Countries differ exogenously in their ratios of modern- to traditional-sector productivity. This assumption builds on the mounting evidence that cross-country productivity differences are skill-biased, as opposed to skill neutral (see, e.g., Caselli and Coleman, 2006; Hjort and Poulsen, 2019; Jerzmanowski and Tamura, 2019; Malmberg, 2016).

The main predictions of our simple model are qualitatively consistent with the facts we document. First, as modern-sector productivity increases, the aggregate unemployment rate increases. This occurs because as the modern sector expands, a greater fraction of workers now search for jobs in frictional labor markets rather than working in self-employment. Moreover, the job-finding rate falls in equilibrium, since average ability is lower in the modern sector. Second, as modern-sector productivity increases, unemployment rates rise faster for less able than for more able workers, since a greater share of less able workers are drawn into job search. This prediction is consistent with the rising ratio of unemployment for low- to high-educated workers with GDP per capita that we document.

To assess the model's quantitative predictions, we calibrate the distributions of ability for high-educated and low-educated workers using moments of the U.S. wage distribution, and parameterize other aspects of the model to match key moments of the U.S. labor market—in particular the average unemployment rate and the ratio of the unemployment rate for low- to high-educated workers. Our main quantitative experiment lowers productivity in the modern relative to the traditional sector and the fraction of high-educated workers from the U.S. levels, and then computes how the model's predictions for unemployment – in the aggregate and by education level – vary with GDP per capita.

The calibrated model predicts that unemployment rates are increasing in GDP per capita, as in the data, though the model underpredicts the magnitude of the relationship. Compared to the observed 1.8 percentage-point increase in unemployment for an increase in one log point of GDP per capita, the model predicts an increase of 1.2 percent. For unemployment by education, the model correctly predicts that the ratio of low- to high-educated unemployment is increasing in GDP per capita. Yet it again somewhat underpredicts the magnitude of the relationship, with a semi-elasticity of 0.47 in the data compared to 0.38 in the model. Our mechanism therefore explains around two thirds of the relationship between aggregate unemployment and average income, and somewhat more of the relation between the unemployment ratio and average income.

As an alternative and complementary theory, we incorporate the less generous unemployment benefits of poor countries relative to richer countries. In the model, lower unemployment benefits in poorer countries discourage search, thus lowering unemployment rates in equilibrium. We find that adding this alternative mechanism increases the explanatory power of our quantitative model from 65 percent to 72 percent of the slope of the aggregate unemployment rate in GDP per capita. On the other hand, it offers little additional explanatory power for the relation between the ratio of low- to high-educated unemployment and income. We conclude that unemployment is largely a consequence of the development process, which itself is driven by skill-biased technological progress, rather than a cause of the low average income levels in poor countries.

We close the paper by presenting historical data on unemployment from the United States and four other advanced countries for which long time series on unemployment are available: Australia, France, Germany and the United Kingdom. We ask whether unemployment rates are higher now than they were before World War I, which is the earliest period for which unemployment data are available, to our knowledge. We find that for all countries, average unemployment rates are indeed higher now than they were before World War I, and for four of the five countries, the difference is statistically significant. Using the U.S. data, which we have at a more disaggregated level, we ask in addition whether unemployment is particularly higher now for the less-educated. We find that average unemployment has indeed risen faster for the less-educated than for the more-educated, at least since 1940. In 1940, the less-educated were about 1.5 times as likely to be unemployed as the more-educated. Today, the ratio is close to 2.5. Historical unemployment data are therefore broadly consistent with our conclusion that unemployment is a consequence of development.

Related Literature. Our work is most related to the literature that tries to document and understand cross-country patterns of labor market outcomes. Older studies did not have sufficient data points to draw firm conclusions about cross-country patterns but tended to find relatively low unemployment rates in poor countries, as in our study (e.g., Fields, 1980, 2004; Squire, 1981; Turnham, 1993). More recently, Poschke (2018) draws on surveys from 68 countries to study the relationship between self-employment and the ratio of unemployment to wage employment. He excludes unpaid family workers and focuses only on urban data, which makes his findings not directly comparable to ours. In complementary work to ours, Donovan, Lu, and Schoellman (2020) use surveys from 42 countries to document high-frequency labor market patterns in the urban areas of middle and high income countries. Our paper covers more low income countries, whereas their study brings in repeated observations from the same individuals. Bick, Fuchs-Schuendeln, and Lagakos (2018) document how patterns of average hours worked vary across countries, but they do not touch on unemployment either empirically or theoretically.

Our paper is closely related to the growing literature on structural change, though our two sectors do not fit neatly into the standard agriculture-manufacturing-services division (used by e.g. Duarte and Restuccia, 2010; Herrendorf, Rogerson, and Valentinyi, 2014; Mestieri, Comin, and Lashkari, 2018). In our modern and traditional sectors, we emphasize skilled wage employment versus unskilled self-employment, similar to the split between high-educated services and low-educated services taken by Buera and Kaboski (2012) and Buera, Kaboski, and Rogerson (2015). Our paper also builds on the literature on home production in macroeconomics and its role in development (e.g. Gollin, Parente, and Rogerson, 2004; Parente, Rogerson, and Wright, 2000). The transition from home to market production with development is a key theme in the model of Ngai and Pissarides (2008), for example, as in our paper. Empirically, Bridgman, Duernecker, and Herrendorf (2018) show that the share of household production in total hours decreases with GDP per capita. None of these studies focuses on the link between unemployment and development, however.

Our paper also builds on the old literature on two-sector models in development, that beginning with Todaro (1969) and Harris and Todaro (1970) showed the potential for unemployment to increase with development in the presence of labor market frictions. This literature did not capture the increase with development of unemployment of less relative to more educated workers, and did not clearly distinguish low-skilled urban self-employment from unemployment, seeing both as a consequence of rural-urban migration. The rural-urban divide plays no role in our theory; we find similar unemployment patterns in both rural and urban areas and, hence, abstract from them. Finally, negative selection into our traditional sector is quite related to the negative selection into the "informal sector" as characterized by Rauch (1991), La Porta and Shleifer (2008, 2014) and others.

2 Data

We begin by describing our data, starting from the household surveys we draw on to measure unemployment in the aggregate and by demographic group across our set of countries.

2.1 Data Sources

Our data come from household surveys or censuses that are nationally representative. Many, but not all, are available from the International Integrated Public Use Microdata Surveys (IPUMS) (Minnesota Population Center, 2017) or the World Bank's Living Standards Measurement Surveys (LSMS). Tables A.1, A.2 and A.3 in the Appendix list the full set of surveys employed, plus their sources. The key benefit of nationally representative surveys, as opposed to (say) administrative records on unemployment, is that they cover all individuals, including the self-employed. In total, our analysis includes 199 country-year surveys, covering 84 countries, and spanning 1960 to 2015. Most of our data come from the 1990s and 2000s.

To measure GDP per capita, we divide output-side real GDP at chained PPPs (in 2011 US$) by population, both taken from the Penn World Tables 9.0. Unlike in previous studies, our data have a high representation of the world's poorest countries, with 23 countries from the bottom quartile of the world income distribution, and 27 from the second quartile.

In our main analysis, we restrict attention to prime-aged adults (aged 25-54) of both sexes. We also report our results for males and females separately, for broader age groups, and for urban and rural regions. Throughout, we exclude those with missing values of key variables and those living in group quarters. We use sample weights whenever they are available.

2.2 Unemployment Definition and Data Tiers

We define an unemployed person as one who (1) is not employed, and (2) has searched recently for a job. We define employment following the U.N. System of National Accounts as "all persons, both employees and self-employed persons, engaged in some productive activity that falls within the production boundary of the SNA" (United Nations, 2008). Thus, we count those working in self-employment as employed. We define the unemployment rate as the ratio of unemployed workers to employed plus unemployed workers.[1]

The key measurement challenge we face is that not all surveys allow us to define unemployment in exactly the same way. To ensure that our cross-country comparisons are as informative as possible, we divide the surveys into tiers, based on their international comparability. Tier 1 has the highest scope for comparability, followed by Tier 2 and then Tier 3. We describe these further below.

In Tier 1 and Tier 2 countries, employment specifically covers all economic activities that produce output counted in the National Income and Product Accounts (NIPA). In other words, employment specifically comprises wage employment, self-employment or work at a family business or farm, whether or not the output is sold or consumed directly.[2] With regard to recent job search, Tier 1 includes surveys in which workers who searched did so either in the last week or the last four weeks. Tier 2 includes surveys in which workers are searching "currently" (without specifying a time frame) or in some time period other than the last week or last four weeks, such as the last two months.

In Tier 3 countries, the employment question has lower scope for comparability. It may, for example, consider those working for their own consumption or those not working for a monetary wage as non-employed. It may include a minimum number of hours worked, or cover only a specific period of time, such as the last seven days. Appendix Table A.3 lists the way in which each country in Tier 3 has a non-standard employment question. In terms of job search, Tier 3 countries cover any time frame.

All in all, our dataset consists of 131 Tier 1 surveys, 37 Tier 2 surveys and 31 Tier 3 surveys. In our empirical findings below, we begin with data from all tiers, which maximizes the number of observations available. We then restrict attention to Tier 1 first, followed by Tiers 1 and 2, to explore how our results change when we take into consideration a smaller but more comparable set of countries.

[1] The BLS *Handbook of Methods* defines an unemployed individual as one who (1) is not employed, (2) has searched recently for a job, and (3) is "available to work" (U.S. Bureau of Labor Statistics, 2016). However, only 49 of our 199 country-year surveys asked whether the interviewee is "available for work" in some way.

[2] See e.g. Gollin, Lagakos, and Waugh (2014) for a more detailed treatment of which outputs are covered in the NIPA. Not counted is work on home-produced services such as cooking, cleaning or care of one's own children. Studies of time use, such as Aguiar and Hurst (2007), Ramey and Francis (2009) and Bick, Fuchs-Schuendeln, and Lagakos (2018), treat these categories as "home production" rather than as work.

2.3 Comparison to ILO and World Bank Data

Two readily downloadable sources of data on unemployment rates at the country level are the "ILO modeled estimates" from the International Labor Office (ILO), and the World Bank's World Development Indicators (WDI). The WDI data are derived directly from the ILO data, but the WDI include data for more countries. Many of the ILO modeled estimates are, by definition, modeled or imputed rather than computed directly from an underlying survey. By the ILO's own admission, the modeled estimates are fraught with serious non-comparabilities. For example, some estimates cover only metropolitan areas, while others use non-standard employment definitions that exclude self-employed workers or first-time job seekers.

Acknowledging the lack of international comparability in its full database, the ILO also publishes "ILO-comparable" unemployment rates from 30 countries, which are always based on a household labor force survey (Lepper, 2004). Unfortunately, the ILO-comparable unemployment rates have very limited coverage of the bottom half of the world income distribution, covering just one such country. Therefore, the ILO-comparable unemployment dataset is ill-suited to answer the question of how average unemployment rates vary between poor and rich countries. In addition, it does not provide disaggregated unemployment rates, such as by education level, which we show are crucial to understanding the aggregate patterns.

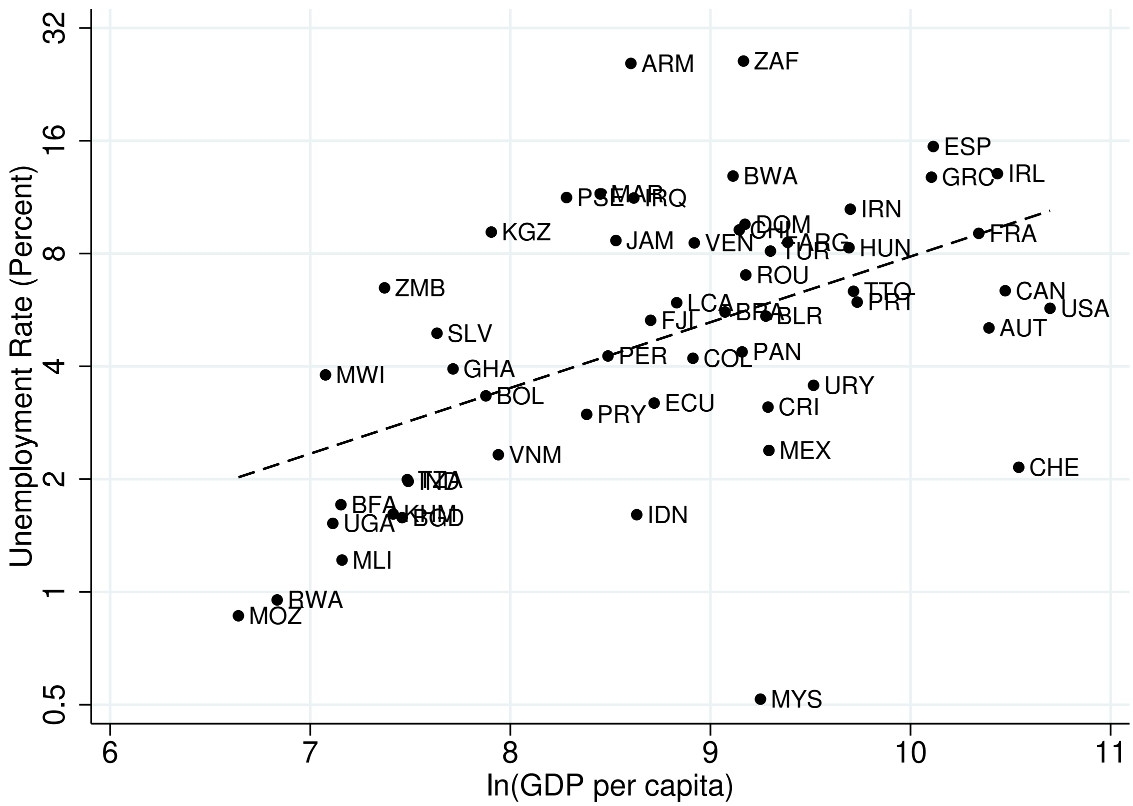
If one nonetheless uses ILO data to estimate how average unemployment rates vary with income per capita, one will find a statistically insignificant or negative relationship. Using the ILO modeled unemployment estimates for 2014, the most recent year for which GDP per capita is available from the Penn World Tables 9.0, a regression of the unemployment rate on log GDP per capita using the ILO sample yields a slope coefficient of 0.07 with a p-value of 0.89, and using the WDI sample yields a slope coefficient of 0.5 with a p-value of 0.11. This lack of correlation between unemployment and income is comparable to what Caselli (2005) found. With the much smaller ILO comparable database, available from 1994 to 2003, a regression of the country-average unemployment rate over the period on the log of the country-average GDP per capita yields a slope coefficient of -3.44 with a p-value of 0.01. Thus, as we will show below, any of the readily available unemployment databases paints a misleading picture of how unemployment rates vary with income level.

3 Empirical Findings

In this section, we report how average unemployment rates vary with GDP per capita. We first compare aggregate unemployment rates, and then look beneath the surface at unemployment by sex, by age group and by rural-urban status. We also provide evidence that the patterns of employment rates and unemployment rates do not imply each other. Lastly, we examine the working hours of low-skilled self-employed workers in poor and rich countries.

3.1 Aggregate Unemployment Rate

Figure 1: Unemployment Rates by GDP per capita



Note: This figure plots the average unemployment rate for prime-aged adults in each country with at least two observations across all years of data from all tiers.

Figure 1 plots the country average unemployment rate for prime-aged adults (on a log base 2 scale) against log GDP per capita. The figure includes countries from all three tiers with at least two years of data. The dotted black line – the linear regression line – shows a substantial positive slope. The slope coefficient for a regression of the unemployment rate in natural units on log GDP per capita is 1.8 and is statistically significant at the one-percent level. Taking simple averages by country income quartile, the bottom (poorest) quartile has an average unemployment rate of 2.5 percent. By contrast, the top (richest) quartile has an average unemployment rate of 8.7 percent.

Besides the positive slope, Figure 1 highlights the large variation in average unemployment rates within each income group. To what extent does this variation simply reflect measurement error? To what extent does the correlation of unemployment rates and GDP per capita survive once we restrict attention to more comparable data?

To help answer these questions, we report the slope coefficient of average unemployment on log GDP per capita using various alternative cuts of the data. The first data column of Table 1 reports these slopes. When considering all 199 country-year surveys separately, the slope is 1.2, compared to 1.8 for country averages shown in Figure 1. When using only Tier 1 surveys, the slope coefficient becomes 1.4, and with Tier 1 and 2 surveys, the slope becomes 1.3. All four slopes are statistically significant at the one percent level. We conclude that the pattern of increasing unemployment is not an artifact of our choice of countries in the main analysis.

3.2 Unemployment Rate by Education Level

In this subsection, we report our findings by education level, which are helpful in accounting for the aggregate patterns we document above. Later we present results by other demographic groups. We define two education groups, which can be measured consistently across nearly all of our countries. The *low education* group are those that did not finish secondary school. This could mean no school, some or all of primary school completed, some secondary education, or some other specialty education that lasts less than 12 years. The *high education* group are those that completed secondary school or more. This could mean exactly secondary school, some college or university completed, or an advanced degree.

Table 1: Slope Coefficients of Unemployment Rate on GDP per capita

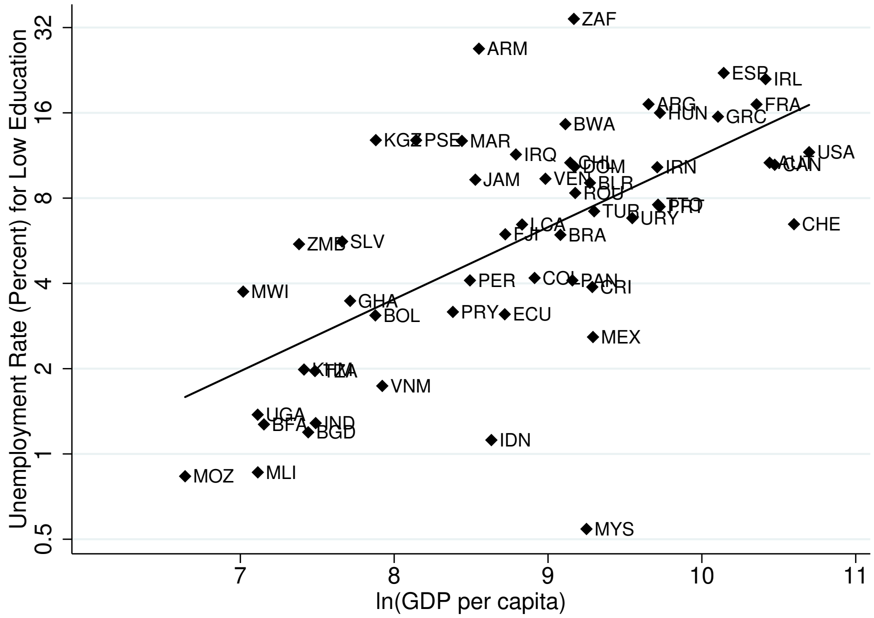
	All Workers	N	Low Education	High Education	Ratio
All surveys	1.2***	199	3.0***	-.2	.51***
	(.3)		(.4)	(.3)	(.03)
Country average	1.8***	55	3.4***	.6	.48***
	(.5)		(.6)	(.4)	(.05)
Only Tier 1 surveys	1.4***	131	3.1***	.4	.46***
	(.3)		(.4)	(.3)	(.03)
Only Tier1 + 2 surveys	1.3***	168	3.1***	.01	.50***
	(.3)		(.4)	(.3)	(.03)

Note: The table reports the slope coefficient from a regression of the prime-age unemployment rate on log GDP per capita and a constant. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. The first row includes all surveys in our data. The second row includes one observation per country, taking the average unemployment rate for those with at least two observations across all years from all tiers. The third row includes only Tier 1 surveys. The fourth row includes only Tier 1 and Tier 2 surveys. Surveys with missing education level data are dropped in the last three columns.

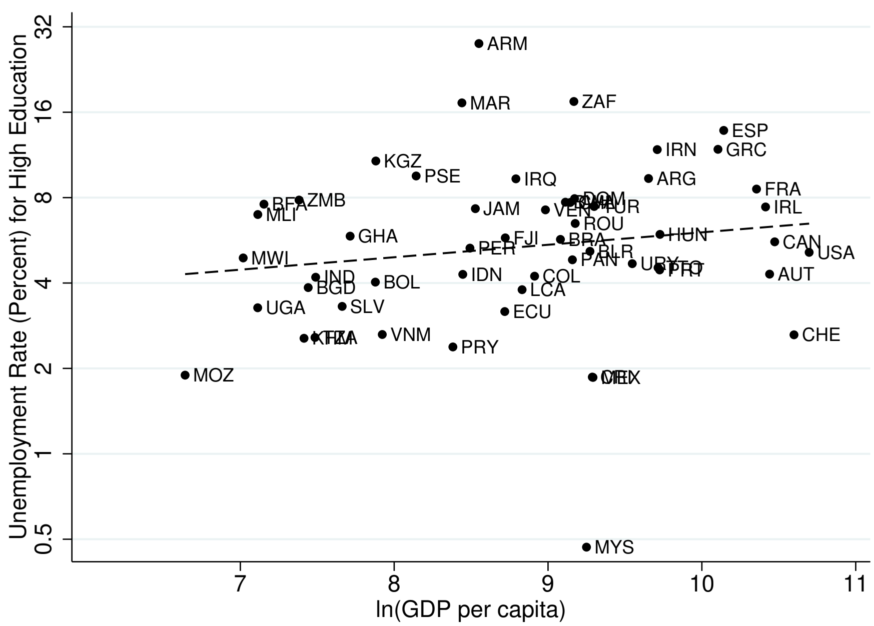
Figure 2 plots the unemployment rates for prime-aged adults by education group. As before, we plot the unemployment rates in log base 2 and GDP per capita in natural logs. As one

Figure 2: Unemployment Rates by GDP per capita and Education

(a) Low-Education Group



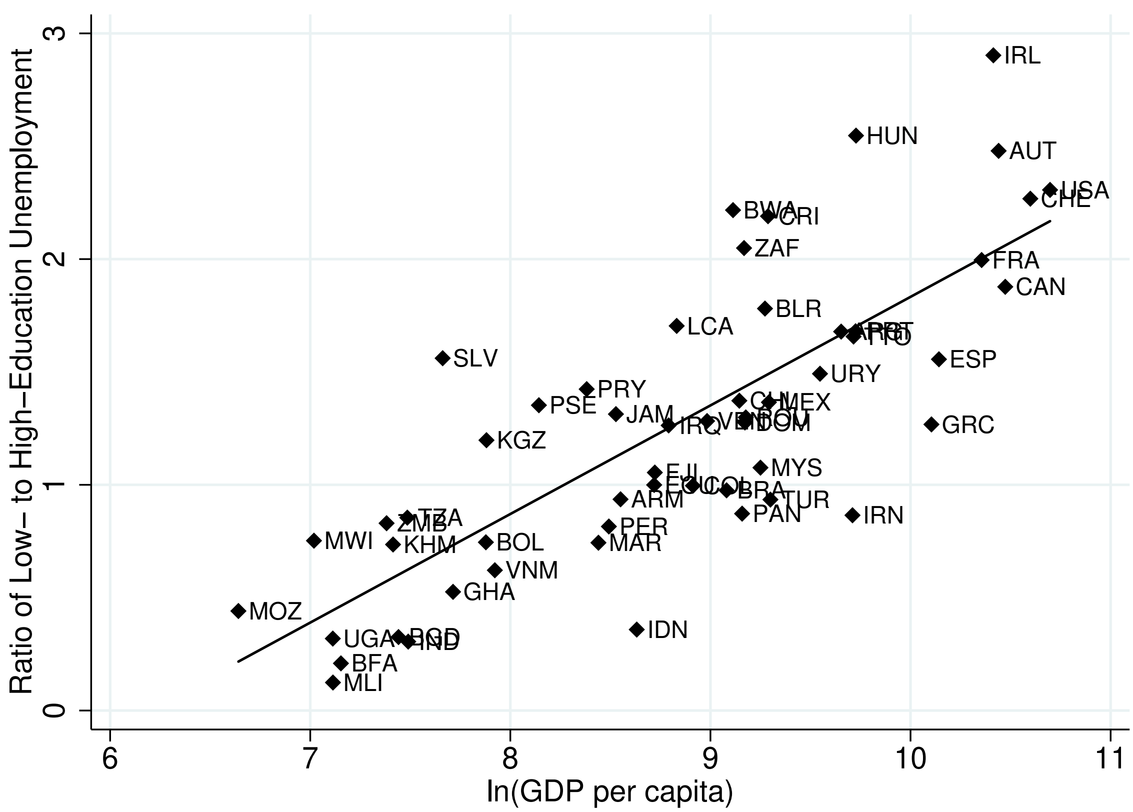
(b) High-Education Group



Note: This figure plots the average unemployment rate for prime-aged adults by education level in each country with at least two observations across all years of data from all tiers. Low education means less than secondary school completed; high-education means secondary school completed or more.

can see, the patterns differ sharply by group. For the low-educated group, unemployment is strongly increasing in GDP per capita. For the high-educated group, unemployment rates are roughly constant across income levels. Again, there is quite a lot of variation in unemployment rates for each income level, though somewhat less than for the aggregate unemployment rates. Taking simple averages by income quartile, for the low-educated workers in the bottom quartile, the average unemployment rate is 2.7 percent. This rises to 8.1 percent in the second quartile, 9.5 in the third and 14.3 in the richest quartile. For the high-educated, the average unemployment rate is not monotonically increasing in income per capita. It rises from 4.9 percent in the bottom quartile to 7.7 in the second, and then falls to 6.2 and 7.3 in the third and fourth quartiles.

Figure 3: Ratio of Unemployment Rates for Low- to High-Educated



Note: This figure plots the average unemployment ratio of low-educated workers over high-educated workers for prime-aged adults in each country with at least two observations across all years of data from all tiers.

The third and fourth data columns of Table 1 report the regression coefficients for the low-educated and the high-educated separately. For the low-educated, the coefficient is 3.0 across all surveys, and statistically significant at the one-percent level. When restricted to country averages (i.e., the average across all surveys available for each country), we get a significant slope of 3.4. Across our Tier 1 surveys only, the slope is 3.1, and when including both Tier 1 and Tier 2 surveys, the slope is also 3.1, with statistical significance at the one-percent level in both cases. For the high-educated, in contrast, the slope is statistically insignificantly different from zero in all cases. Across all surveys, the slope coefficient is -0.2 with a standard error of 0.3. The estimated slopes are statistically insignificant for country averages, for Tier 1 and for both Tiers 1 and 2, as well.

Figure 3 plots the ratio of unemployment for the low-educated to that for the high-educated group. As the figure shows, this ratio is strongly increasing in GDP per capita. It is also less variable across countries within each broad income level than in Figure 1, for example. Virtually all of the poorest countries have ratios less than one, meaning that the low-educated workers are *less* likely to be unemployed than the high-educated. All of the richest countries have a ratio above one, meaning that the less-educated are more likely than the high-educated to be unemployed. For the poorest quartile of the world income distribution, the average ratio is 0.52. It rises to 1.1 in the second quartile, 1.5 in the third and 2.1 in the richest quartile. Table 1 reports that a regression of this ratio on log GDP per capita yields an estimated slope coefficient that is quite close to 0.5 across all surveys, with little variation by data comparability tier.

3.3 Robustness of Unemployment-to-GDP per capita Patterns

In this section, we report how unemployment patterns vary by sex, age, and within rural and urban areas. Table 2 presents the slope coefficients from a regression of unemployment rates on log GDP per capita for various disaggregated categories of individuals. We do this separately for the low-education and high-education groups, first over all of our surveys (left panel), and then using only country averages over all available years (right panel).

The first row of Table 2 reports the slope for prime-aged males only. Across all surveys and country averages, low-educated prime-aged males have a statistically significant positive slope with GDP per capita, whereas high-educated ones have an insignificant slope. This pattern is replicated and even stronger in the full sample of households (second row), which includes household members aged 16 to 24, those above age 55, and both sexes. The patterns hold separately for males of all ages (third row) as well, whereas for females (fourth row), there is even a significant negative trend with GDP per capita among the high-educated. We conclude that our patterns hold for both sexes.

When looking by age group, the low-educated always have a significant and positive relationship with GDP per capita, with the strongest relationship for those aged 16 to 24. The high-educated have no trend or a weak upward trend in general. Looking separately by urban and rural individuals we see the same patterns: strong positive increases in low-educated un-

Table 2: Robustness of Slope Coefficients of Unemployment Rate on log GDP per capita

	All Surveys			All Country Averages		
	Low Edu.	High Edu.	N	Low Edu.	High Edu.	N
Prime males	2.5*** (.4)	-.2 (.3)	195	3.0*** (.5)	.4 (.3)	54
Full sample	3.4*** (.4)	-.4 (.4)	197	3.6*** (.6)	.6 (.6)	54
Males	3.0*** (.4)	-.4 (.3)	197	3.2*** (.6)	.4 (.5)	54
Females	3.9*** (.4)	-.8* (.4)	197	4.1*** (.8)	.5 (.7)	54
Age 16-24	6.4*** (.7)	-1.1 (.7)	196	6.5*** (1.2)	.4 (1.3)	54
Age 25-54	3.0*** (.4)	-.2 (.3)	195	3.4*** (.6)	.6 (.4)	54
Age 55+	2.1*** (.3)	.5* (.2)	185	2.5*** (.5)	.7* (.4)	51
Rural	2.9*** (.5)	.03 (.6)	113	3.4*** (1.0)	1.7* (1.0)	30
Urban	2.7*** (.8)	-.9 (.6)	113	3.5*** (1.2)	.6 (.8)	30

Note: The table reports the slope coefficients from regressions of the unemployment rate on log GDP per capita and a constant. Observations include aggregate unemployment rates across all Tier 1, 2, and 3 surveys. Country averages are restricted to countries with at least two years' observations. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.

employment with GDP per capita and no trend or weak positive slopes for the high-educated. Thus, our findings are present in both rural and urban areas.

3.4 Employment, Unemployment, and Not in the Labor Force

Other data sets show that average *employment* rates are lower in rich countries than in poor countries, at least for males (see e.g. Bick, Fuchs-Schuendeln, and Lagakos, 2018). Does this imply that unemployment rates are higher in rich countries? Basic accounting identities show that the answer is no. Those not employed can be either unemployed or not in the labor force. The lower employment rates of rich countries could in principle correspond to lower labor force participation rates, or higher unemployment rates, or both. In practice, we show that the relationship between employment rates, unemployment rates, the percent not in the labor force (NLF), and income per capita varies considerably by gender and education, and cannot be inferred directly from evidence on employment rates alone.

Table 3: Employment, Unemployment and Not in the Labor Force

		Low Education			High Education		
		Q1	Q4	Difference	Q1	Q4	Difference
Male	Employed	86.5	72.8	-13.7***	82.7	86.3	3.6*
	Unemployed	2.0	11.2	9.2***	3.9	6.1	2.3**
	Not in labor force	11.5	16.0	4.5	13.4	7.6	-5.8**
Female	Employed	59.3	46.0	-13.4*	62.7	69.7	6.9
	Unemployed	1.2	9.1	7.9***	3.8	6.7	2.9*
	Not in labor force	39.5	44.9	5.4	33.5	23.7	-9.8

Note: This table reports the means of country averages for countries with at least two observations of unemployment across all three tiers of our data. The rows present means for the poorest quartile of these countries, for the richest quartile, and the difference between the poor and rich means, plus the results of a permutation test of the differences in means. All figures are in percent.

Table 3 reports the average percent of prime aged adults – by sex and education level – that are employed, unemployed, and not in the labor force, for countries in the bottom (Q1) and top income (Q4) quartiles. For low-educated males, employment rates are substantially lower in the richest quartile than in the poorest. This reflects a substantially higher percent of low-educated males not in the labor force in the richest quartile, as well as their higher unemployment rates in the richest quartile. A similar pattern also holds for women, though with lower employment levels in both quartiles.

Among high-educated males, employment rates are modestly higher in the richest quartile than in the poorest quartile (though the difference is statistically insignificant). Yet the percent of high-educated males that are unemployed is also modestly higher in the richest quartile. The reason that both are higher in the richest quartile is that, as Table 3 shows, the percent not in the labor force is substantially *lower* for high-educated males in the richest quartile. A similar pattern again holds for females, though with larger increases in employment rates and labor force participation rates than for the males. In sum, although cross-country differences in unemployment rates reflect cross-country differences in employment rates for the low-educated, the same is not true for the high-educated. We conclude that one cannot in general infer cross-country unemployment patterns by looking solely at data on employment rates, which reflect a margin of labor force participation as well.

3.5 Unemployment, Self-Employment and Home Production

As highlighted in our Introduction, one concern about comparing unemployment rates across countries is that low-skilled self-employment gets confounded with unemployment in developing countries. A central part of this concern is the possibility that both categories of individual work very few hours in practice, or none at all, making them difficult to distinguish empirically. In fact, cross-country evidence on hours worked shows that those in low-skilled self employment work similar hours to those in wage employment. The study by Bick, Fuchs-Schuendeln, Lagakos, and Tsujiyama (2020) measures average hours worked for adults in the "traditional sectors" of 48 countries of all income levels, defined (as in the current study) as own-account workers (self-employed without employees) in low-skill occupations and unpaid family workers.[3] They find that traditional sector workers average 37 hours of work per week, which is nearly as high as the 41 hours on average worked by the rest of the workforce.

A related comparability concern is that the unemployed in poor countries spend substantially different amounts of time on home production work than the unemployed in rich countries, where home production is defined as hours spent cooking, cleaning, caring for children or shopping. This concern would also make cross-country comparisons of unemployment rates substantially harder to interpret. Though there are only a few internationally comparable time use surveys available, these surveys do not point to important differences in home production hours by the unemployed across countries. Appendix Table D1 reports data on home production hours by unemployed individuals from the American Time Use Survey and Multinational Time Use Survey for countries in the top and bottom quartiles of the world income distribution. Home production hours by the unemployed average 19.7 hours per week in the bottom quartile, and 20.2 in the top quartile.

4 A Model of Unemployment and Development

We now present a model to interpret the facts about average unemployment rate across countries and by education group that we document above. Since the main focus of the paper is on unemployment rates, we abstract from the decision of whether to join the labor force. Because our empirical patterns are present for both sexes, all age groups and within both rural and urban areas, we abstract from demographics and regional considerations. In order to match the large decrease in the traditional sector that coincides with development, we allow for two sectors in our model. We relegate all derivations and proofs to Appendix B.

[3] Low-skilled occupations are defined as shop and market sales, agricultural and fishery workers, crafts and related trade workers, plant and machine operators and assemblers, and "elementary occupations." As shown in Figure 5 below, the labor force share of the traditional sector is strongly decreasing in GDP per capita, ranging from more than 80 percent in poor countries to less than two percent in the richest countries.

4.1 Environment

We model steady-state unemployment. To capture the impact of development on unemployment, we show how steady-state unemployment rates vary with exogenous changes in productivity. We also allow countries to differ in the proportions of their labor forces that have high versus low education. Otherwise we assume that all parameters in our model are the same across countries.

In our model economy there is a unit measure of risk-neutral, infinitely-lived workers. Countries differ exogenously in the fraction λ of their workers that are in the low-education group. The remaining $1-\lambda$ are in the high-education group. Each worker is endowed with efficiency units drawn from a fixed distribution $G_i(x)$ on $[\underline{x}, \bar{x}]$, $i = h, l$, where h denotes high-educated workers and l denotes low-educated workers. We assume that $G_i(x)$ is differentiable and let $g_i(x) \equiv G_i'(x)$ be its probability density function. We also assume that the distribution of ability for the high-education group first-order stochastically dominates the distribution of ability for the low-education group: $G_h(x) < G_l(x)$ for all $x \in (\underline{x}, \bar{x})$.

Workers can choose to work in one of two sectors: a modern sector, in which firms hire workers subject to matching friction and production displays constant returns to ability, and a traditional sector, in which workers are self-employed without returns to ability. The technologies in the modern and traditional sectors, respectively, are given by:

$$Y_M = A_M X_M, \qquad \text{and} \tag{1}$$

$$Y_T = A_T N_T, \tag{2}$$

where Y_M, A_M, and X_M are output, productivity, and the total number of efficiency units in the modern sector, and Y_T, A_T, and N_T are output, productivity, and the number of workers in the traditional sector.

In the modern sector there are two types of risk-neutral, infinitely-lived firms, with a continuum of each type. One type matches only with high-educated workers and the other type matches only with low-educated workers. Each firm of either type can employ one worker. We assume employers can observe workers' education credentials ex ante and divide the modern sector labor market into two search markets, one for each education level. We treat the outputs of modern-sector firms that search in the high-education and low-education labor markets as perfect substitutes, and add them to obtain Y_M.

There is a well-known tendency for the relative price of non-traded services, in which the traditional sector is intensive, to rise with GDP per capita. With this in mind, we specify that traditional- and modern-sector outputs are imperfect substitutes in a constant-elasticity-of-substitution (CES) aggregate production function:

$$Y = \left[\gamma Y_T^{\sigma} + (1-\gamma) Y_M^{\sigma}\right]^{\frac{1}{\sigma}}, \tag{3}$$

where $\frac{1}{1-\sigma}$ is the elasticity of substitution between the outputs of the traditional and modern sectors. Denote the price of traditional-sector output relative to modern-sector output by P_T. In a competitive market, the ratio of prices equals the ratio of marginal productivities:

$$P_T = \frac{\partial Y/\partial Y_T}{\partial Y/\partial Y_M} = \frac{\gamma}{1-\gamma}\left(\frac{Y_M}{Y_T}\right)^{1-\sigma}. \tag{4}$$

Technological change that is skill-biased across countries is a core assumption of our model. We assume an elasticity of technological change in the traditional sector with respect to technological change in the modern sector that is less than one:

$$\ln(A_T) = \psi_0 + \psi_1 \ln(A_M), \tag{5}$$

where $\psi_1 < 1$. In our quantitative exercise in Subsection 5.2 below we target the elasticity of the relative price of traditional goods with respect to GDP per capita to calibrate ψ_1. Differences in GDP per capita are driven by exogenous differences in A_M. The smaller is ψ_1 the faster A_M/A_T increases with A_M, leading to a faster increase in Y_M/Y_T and hence a faster increase in P_T.

Steady State. In the steady state, workers sort as in Roy (1951) and do not switch sectors over time. Denote by x_i^*, $i = h, l$, the efficiency units of the marginal high- or low-educated worker who is indifferent between self-employment and entering the modern sector as unemployed. We will show below that the value of being unemployed is increasing in x; hence, in steady state, workers with $x < x_i^*$ prefer self-employment in the traditional sector, and workers with $x \geq x_i^*$ prefer to enter the modern sector as unemployed.

Modern Sector. In order to hire a worker, a firm must post a vacancy at flow cost $A_M c$. The idea is that since hiring skilled labor requires skilled labor, the cost of posting vacancies should scale up with the productivity of skilled labor (and hence their wages). Let the flow of matches be given by the constant returns to scale function

$$m(u_i, v_i) = \eta u_i^{\alpha} v_i^{1-\alpha}, \tag{6}$$

where u_i is the endogenous measure of unemployed high- or low-educated workers and v_i is the endogenous measure of vacancies in the labor market for high- or low-educated workers. Define $\theta_i \equiv \frac{v_i}{u_i}$ as "market tightness" for high- or low-educated workers. The job-finding rate is then $f(u_i, v_i) \equiv \frac{m(u_i,v_i)}{u_i} = \eta\theta_i^{1-\alpha}$, and the vacancy hiring rate is $q(u_i, v_i) \equiv \frac{m(u_i,v_i)}{v_i} = \eta\theta_i^{-\alpha}$.

We assume that workers and firms separate at an exogenous rate s_i for $i \in \{h, l\}$. We assume that $s_h \leq s_l$, which is consistent with the evidence on labor separations (discussed below). This is the only parameter we allow to differ across the two labor markets.

We let the unemployment flow payoff equal $A_M b(A_M)x$, and assume $0 \leq b(A_M) < 1$. We show in Appendix B that wages are proportional to x in equilibrium, so that for any given A_M our unemployment flow payoff is proportional to wages. One rationale for this choice is that unemployment benefits are typically indexed to wages. A second rationale is that job finding rates are approximately constant across skill groups, which is consistent with a model where unemployment benefits scale with the expected wage (Hall and Mueller, 2018; Mincer, 1991; Mueller, 2017). In the special case where $b(A_M) = b$, a constant, unemployment benefits increase exactly in proportion to modern-sector productivity. However, our specification allows for a more general, nonlinear relationship between unemployment benefits and A_M. For example, for very poor countries with very low A_M we can have $b(A_M) = 0$, and we can allow $b'(A_M) > 0$ so that unemployment benefits increase faster than linearly with A_M.

Denoting by δ the rate of time discount for all agents, the values of unemployment and employment for an individual with efficiency units x are given, respectively, by

$$U_i(x) = A_M b(A_M)x + \delta\big[f_i E_i(x) + (1 - f_i)U_i(x)\big], i = h, l \tag{7}$$

$$E_i(x) = w_i(x) + \delta\big[s_i U_i(x) + (1 - s_i)E_i(x)\big], i = h, l \tag{8}$$

where $w_i(x)$ is the endogenous flow wage. Since firms will be matched only with agents in the modern sector, who have efficiency units $x \geq x_i^*$, we can specify the value of a job to a firm if matched with a worker with efficiency units x and the value of maintaining a vacancy as:

$$J_i(x) = A_M x - w_i(x) + \delta\big[s_i V_i + (1 - s_i)J_i(x)\big], i = h, l \tag{9}$$

$$V_i = -A_M c + \delta\big[q_i \mathbb{E}\big(J_i|x > x_i^*\big) + (1 - q_i)V_i\big], i = h, l \tag{10}$$

where $\mathbb{E}\big(J_i|x > x_i^*\big) = \frac{\int_{x_i^*}^{\bar{x}} J_i(x)g_i(x)dx}{1-G_i(x_i^*)}$ is the expected value to the firm of a job match conditional on the workers having entered the modern sector.

Because of the free-entry condition for firms, we have $V_i = 0$. Let $S_i(x) \equiv E_i(x) - U_i(x) + J_i(x)$, $i = h, l$, denote the total surplus of a match, and $\beta \in (0, 1)$ be the Nash bargaining power of the worker. The firm then receives $(1 - \beta)S_i(x)$ when a vacancy is filled. Combining this division of the surplus with equations (7) to (10) allows us to solve for $U_i(x)$ and $w_i(x)$ with the former given by:

$$U_i(x) = \frac{1}{1-\delta}\Big(A_M b(A_M)x + \delta\eta\theta_i^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x\big(1 - b(A_M)\big)(1-\beta)}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i}\Big). \tag{11}$$

Equation (11) shows that $U_i(x)$ is increasing, as we asserted previously. The steady state in the modern sector is characterized by the following relationship between θ_i and x_i^*:

$$c = \frac{(1-\beta)\delta\eta\theta_i^{-\alpha}}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i}\big(1 - b(A_M)\big)\mathbb{E}_i(x|x > x_i^*), \tag{12}$$

where $\mathbb{E}_i(x|x > x_i^*)$ is computed using $g_i(x)$.

Indifference Conditions. The value of staying in the traditional sector is $\frac{P_T A_T}{1-\delta}$, since any traditional worker produces output with value $P_T A_T$ in every period. The high- or low-educated worker with efficiency units x_i^* is indifferent between staying in the traditional sector and entering the modern sector as unemployed when:

$$\frac{P_T A_T}{1-\delta} = U(x_i^*) = \frac{1}{1-\delta}\left(A_M b(A_M) x_i^* + \delta\eta\theta_i^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x_i^*\big(1-b(A_M)\big)(1-\beta)}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i}\right). \tag{13}$$

Unemployment Rates. Denote by L_{Mi} the measure of high- or low-educated labor that participates in the modern sector, where $L_{Mh} = (1-\lambda)\big(1-G_h(x_h^*)\big)$ and $L_{Ml} = \lambda\big(1-G_l(x_l^*)\big)$. In the steady state, the flow into unemployment equals the flow out of unemployment: $s_i(L_{Mi} - u_i) = f_i u_i$. Solving for u_i, dividing by the respective labor forces $1-\lambda$ and λ, and recalling that $f_i = \eta\theta_i^{1-\alpha}$ yields the unemployment rates for high- and low-educated workers:

$$\tilde{u}_i = \frac{s_i\big(1 - G_i(x_i^*)\big)}{s_i + \eta\theta_i^{1-\alpha}}, i = h, l. \tag{14}$$

Each unemployment rate depends on the separation rate, s_i, the (endogenous) market tightness, θ_i, and the (endogenous) cutoff x_i^* for working in the modern sector. Note that the greater is the share of workers in the modern sector, $1-G(x_i^*)$, the higher is the unemployment rate, all else equal. Similarly, the lower is market tightness, all else equal, the higher is the unemployment rate. The aggregate unemployment rate then equals the unemployment rates for high- and low-educated workers weighted by their labor force shares:

$$u = (1-\lambda)\tilde{u}_h + \lambda\tilde{u}_l. \tag{15}$$

4.2 Model Predictions

We consider two mechanisms by which development can affect unemployment in our model: skill-biased technological progress and changes in unemployment benefit rates. It is useful to first illustrate how, absent either mechanism, the model predicts that unemployment is unchanged across different levels of development. Specifically, shutting down the skill-biased nature of technological progress means setting $\psi_1 = 1$, so that A_M/A_T is constant by equation

(5), and keeping a constant degree of unemployment benefits means setting $b(A_M) = b$, a constant. With these restrictions, the claim is that increases in A_M leave $\tilde{u}_i$ unchanged, and u unchanged for a given λ.

To see this, provisionally assume that the x_i^* cutoffs are unchanged when A_M increases. It follows from equation (12) that the θ_i are unchanged, and then from equation (14) that the $\tilde{u}_i$ are unchanged, and further from equation (15) that $\tilde{u}$ is unchanged for given λ. It is then straightforward to show that Y_M/Y_T is unchanged and therefore P_T is unchanged by equation (4). Finally, inspection of equation (13) shows that with A_M/A_T, $b(A_M)$, P_T, and θ_i all unchanged, x_i^* must also be unchanged, confirming our provisional assumption.

Skill-Biased Technological Progress and Aggregate Unemployment. With skill-biased technological progress, the model allows for an increasing unemployment rate with development. Skill-biased technological progress implies $\psi_1 < 1$ so that modern-sector productivity, A_M, increases faster than the traditional-sector productivity, A_T. As a result, the relative price P_T increases. This increase will be less, the greater is the ability to substitute away from traditional-sector output to modern-sector output in response to the increase in P_T. For a sufficiently high elasticity of substitution, then, the marginal value products of high- and low-educated labor in the modern sector rise relative to their marginal value product in the traditional sector. Both high- and low-educated workers shift out of the traditional sector into the modern sector, meaning that x_h^* and x_l^* both fall.

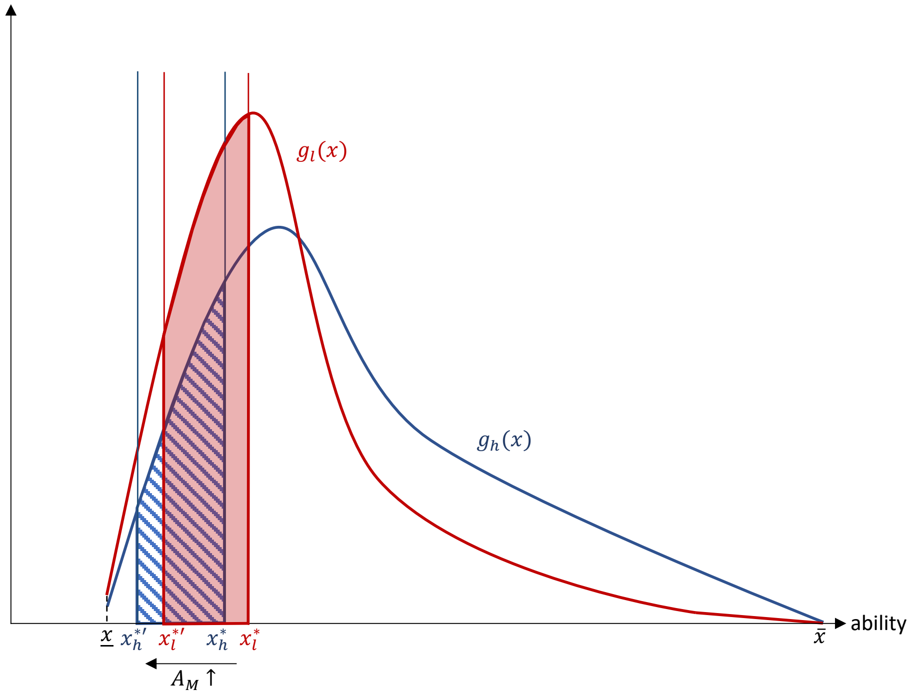
This leads to an increase in the unemployment rates for both high- and low-educated workers for two reasons. First, because modern-sector jobs involve regular separations, a larger modern sector means larger steady-state unemployment, all else equal. Second, because the workers drawn into the modern sector are of lower ability than existing modern-sector workers, the expected value of a match to a firm falls. For the free-entry condition to hold, the job filling rate for a vacancy must rise. This means fewer vacancies per unemployed person, i.e., a smaller θ_i. Inspection of equation (14) shows that a lower x_i^* and a smaller θ_i imply a higher $\tilde{u}_i$.[4]

Note that the aggregate unemployment rate u does not necessarily increase with A_M, despite increases in both $\tilde{u}_h$ and $\tilde{u}_l$. The aggregate unemployment rate is a weighted average of the unemployment rates of high- and low-educated workers, with weights $1 - \lambda$ and λ. In the data, as modern-sector productivity and thus GDP per capita increases, the share of low-educated workers λ tends to decrease. If the low-educated unemployment rate is greater than the high-educated unemployment rate, it is possible for the aggregate unemployment rate predicted by equation (15) to decrease with A_M and GDP per capita.

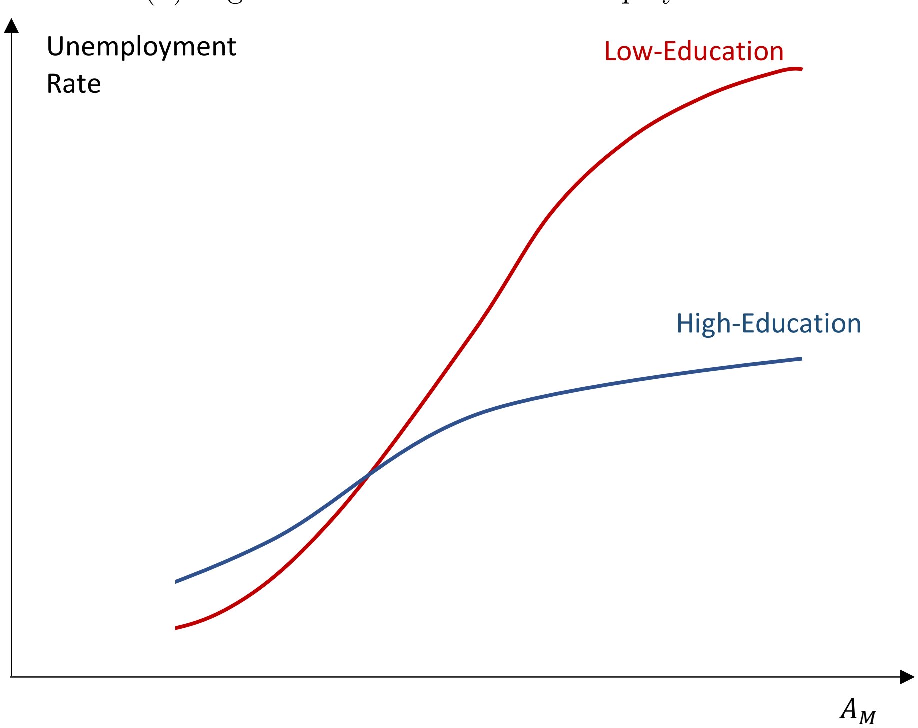
[4]Feng, Lagakos, and Rauch (2018) prove, for the special case $b(A_M) = b$, that a decrease in x_i^* in response to an increase in A_M causes an increase in $\tilde{u}_i$. Since, as noted below, an increase in b also increases $\tilde{u}_i$, this result is reinforced if $b'(A_M) > 0$.

Figure 4: Comparative Statics when A_M Increases

(a) Cutoff values on the ability distributions



(b) High- and Low-educated Unemployment



Skill-Biased Technological Progress and Unemployment by Skill Level. Our model with skill-biased productivity growth also allows for a faster increase in the unemployment rate of the low-educated, as in the data. The reason is that as A_M increases, participation in the modern sector of low-educated workers increases proportionately faster than participation of high-educated workers. In turn, this occurs because participation of low-educated workers in the modern sector is much less than participation of high-educated workers at low levels of modern-sector productivity, but both participation rates approach 100 percent as A_M increases. This is illustrated in Panel (a) of Figure 4, in which the share of low- (high-) educated agents working in the modern sector is the area under $g_l(x)$ ($g_h(x)$) to the right of x_l^* (x_h^*). The taller (shorter) shaded area is the increase in the share of low- (high-) educated agents in the modern sector for greater A_M. Panel (b) of Figure 4 shows the model predictions of high- and low-educated unemployment as A_M increases.[5]

As is clear from Panel (a) of Figure 4, if modern sector productivity was so low that nearly all agents choose the traditional sector regardless of education level, then the ratio of low- to high-educated unemployment would actually decrease as A_M increases. Thus our model makes the prediction in panel (b) of Figure 4 because, even in the poorest countries, modern sector productivity is sufficiently high that most high-educated agents choose the modern over the traditional sector. In the Appendix Figure D1, we present the model predictions of high- and low-educated unemployment starting from A_M such that nearly all agents choose the traditional sector. Which case is prevalent in reality is a quantitative question, addressed below, and not pre-determined in the model by assumption.

Modern-sector participation in our model is less for low- than for high-educated workers for two reasons. First, by assumption the distribution of ability for low-educated workers is first-order stochastically dominated by the distribution of ability for high-educated workers, making the modern sector less attractive relative to the traditional sector for low-educated workers. Second, $G_l(x) > G_h(x)$ generates a smaller expected value of a job match for employers of low- than high-educated workers. Moreover, as noted in Subsection 5.1 below, data indicate a greater separation rate for low- than high-educated workers, further reducing the expected value of a job match for their employers. As proven in the working-paper version of our study (Feng et al. 2018, Appendix B.5), $G_l(x) > G_h(x)$ and $s_l \geq s_h$ imply $x_l^* > x_h^*$. The combination of $G_l(x) > G_h(x)$ and $x_l^* > x_h^*$ in turn implies $G_l(x_l^*) > G_h(x_h^*)$, a greater share of low- than high-educated workers in the traditional sector.

Rising Unemployment Benefits with Development. Our model predicts that greater unemployment benefits raise steady-state unemployment levels, which is standard in this class of models. It follows that if $b'(A_M) > 0$, unemployment benefits are an additional

[5] The figure is drawn to reflect a lower separation rate for high-educated workers, which we find when calibrating our model to U.S. data in the next section.

mechanism leading to higher unemployment as A_M and thus GDP per capita increases. We should note that in our model a higher b increases unemployment not only by reducing market tightness θ_i, the standard mechanism, but also by increasing participation in the modern sector (reducing x_i^*).

In Appendix Section C, we extend the model to allow worker churn between the traditional and modern sectors at a given level of modern sector productivity. This change does not affect the qualitative responses of unemployment to increases in modern sector productivity or unemployment benefits.

5 Quantitative Analysis

We have laid out a model of unemployment and development that has the potential to match the cross-country patterns that we document above. Whether this model is actually consistent with the data is a quantitative question. In this section we calibrate the model to match features of the U.S. labor market and the cross-country differences in traditional-sector shares of employment and relative prices, which help govern the extent of skill-biased technical progress. Then we assess the model's predictions on unemployment in the aggregate and by education level over the full range of the world income distribution, focusing on the relative importance of skill-biased technological change and rising unemployment benefits with development.

5.1 Parameterizing the Model

We begin by directly setting some parameter values following the literature. We set the quarterly discount factor to $\delta = 0.99$, consistent with an annual interest rate of around four percent. We set the worker's bargaining weight to $\beta = 0.7$ and the elasticity parameter of the matching function to $\alpha = 0.7$, which are the values used in Fujita and Ramey (2012) and are in line with the standard parameter choices used in macro search models. We set the quarterly separation rate for the high-educated workers to $s_h = 0.045$, which is the value estimated in Wolcott (2018). We set the unemployment benefits replacement rate to be 45 percent in all countries, to first focus on the model's predictions with skill-biased technological progress but not varying unemployment benefits. Our model's replacement rate is in line with the 40 percent used by Shimer (2005), the 42 percent in Braxton, Herkenhoff, and Phillips (2018), and the 50 to 60 percent range in Krueger and Mueller (2010). We also use log normal distributions for the workers' ability and normalize the mean of the ability for low-educated workers to be one.

We calibrate the remaining ten parameters to jointly match ten moments in the data. These

Table 4: Calibrated Parameters

Parameter	Value
Panel A: Pre-Assigned Parameters	
δ - Discount factor (quarterly)	0.99
β - Workers' bargaining power	0.7
α - Matching parameter	0.7
s_h - Separation rate (quarterly) for high-educated workers	0.045
b - Unemployment benefits	0.45
A_T^{US} - U.S. traditional-sector productivity	1
m_l - Mean of ability for low-educated workers	1
Panel B: Calibrated Parameters	
m_h - Mean of ability for high-educated workers	1.66
v_l - Variance of ability for low-educated workers	0.45
v_h - Variance of ability for high-educated workers	1.15
c - Vacancy cost	0.15
η - Matching efficiency	0.85
γ - Traditional-sector share in aggregate production function	0.01
s_l - Separation rate (quarterly) for low-educated workers	0.112
$max(A_M)$ - Modern-sector productivity for the richest country	0.04
$\frac{1}{1-\sigma}$ - Elasticity of substitution	3.5
ψ_1 - Elasticity of traditional-sector w.r.t. modern-sector productivity	0.19

Note: The table reports the values and interpretations of the parameters of the quantitative model under the benchmark calibration.

parameters are: (i) the mean of the ability distribution for the high-educated workers, m_h; (ii) and (iii): the variances of the ability distributions for the low- and high-educated workers, v_l and v_h; (iv) the vacancy cost c as a share of modern-sector productivity for a worker with one unit of ability; (v) the efficiency term, η, of the matching function; (vi) the traditional-sector share in the aggregate production function, γ; (vii) the quarterly separation rate for low-educated workers, s_l; (viii) the maximum value of A_M, which corresponds to the U.S. level;[6]; (ix) the elasticity of substitution between traditional and modern goods $\frac{1}{1-\sigma}$; and, finally, (x) the elasticity of traditional-sector productivity with respect to modern-sector productivity, ψ_1.

The ten moments are: (i) the ratio of average modern-sector wages for the high- over low-educated that we calculated using the 2000 Census 5 percent sample (1.60); (ii) and (iii) the variances of log wages for the high- and low-educated (0.34 and 0.28), using the same 2000

[6]Note that although the absolute value of A_M is smaller than A_T, the modern sector is more productive than the traditional sector in value terms. The traditional and modern sectors produce different goods, and the relative price of the traditional good, P_T, is around 0.01 in the United States in our calibrated model.

census; (iv) the vacancy cost of 17 percent of average output in the modern sector as used in Fujita and Ramey (2012); (v) the average U.S. unemployment rate of 5.71 percent in the United States among the 18 samples in our data from 1960 to 2014; (vi) the U.S. expenditure share in the traditional sector, which we conjecture to be smaller than two percent; (vii) the ratio of unemployment for the the low-educated to high-educated (2.31); (viii) an average employment share of two percent in the traditional sector (as we explain below); (ix) the slope of aggregate traditional sector employment share on log GDP per capita; and (x) the slope of log relative price of traditional sector output on log GDP per capita (as we specify later).[7]

Table 4 reports the value of each parameter used in the calibration. Our calibrated quarterly separation rate for the low-educated is 0.112, similar to the direct estimate of 0.06 - 0.12 during 1980 to 2010 computed by Wolcott (2018) for low-educated workers. Our estimate is also broadly consistent with the separation rate in low-skilled services in the United States. For example, according to the 2017 Job Openings and Labor Turnover Survey, the monthly separation rate in wholesale and retail trade, transportation and utilities is around 3.5 percent. This corresponds to a quarterly separation rate of around 10 percent. The parameter ψ_1 is calibrated to be 0.19, with the intercept ψ_0 in the equation $\ln(A_T) = \psi_0 + \psi_1 \ln(A_M)$ determined implicitly by our normalization of A_T to be one in the United States.

We report each moment and its model counterpart in Table 5. Overall, the model matches the desired moments quite well. Although all of the ten moments reported above jointly discipline all the parameters, it is useful to provide some intuition about which moments are most informative about each parameter. In particular, the mean of the ability distribution for high-educated workers, m_h, largely governs the ratio of average wage of the high- to low-educated workers. The variances of the two ability distributions govern the variances of log wages for the low- and high-educated workers. The model vacancy cost and model unemployment benefit are most informative about the relative size of vacancy cost and unemployment benefits to the average output per worker in the modern sector. The matching efficiency parameter η mostly informs the average unemployment rate, and the sector share parameter in the aggregate production function mostly informs the expenditure share of traditional-sector output. The quarterly separation rate for low-educated workers is most informative about the unemployment ratio of low- to high-educated workers. The maximum

[7] Recall that we define the traditional sector as low-skilled own-account self-employed workers or unpaid family workers. Unfortunately, the U.S. data after 1960 distinguish only between incorporated and unincorporated businesses among the self-employed, rather than between own-account workers and employers as in the countries in Figures 5 and Figure D3. Considering that the Canada samples have an average of 2.8 percent prime-aged employment in the traditional sector, which is defined consistently with the other countries, we conjecture that the United States has a smaller share of two percent. As with our benchmark unemployment measures, all traditional sector employment shares reported in this section are calculated for prime-aged workers.

Table 5: Moments Targeted in the Model vs Data

Moment	Target	Model
Ratio of average wage for the high- to low-educated	1.60	1.61
High-edu ln(wage) variance	0.34	0.33
Low-edu ln(wage) variance	0.28	0.28
U.S. vacancy cost as % of average output in modern sector	17	16.9
U.S. unemployment rate	5.71	5.70
U.S. % expenditure share of traditional sector	<2.0	0.62
U.S. ratio of unemployment rates u_l/u_h	2.31	2.33
U.S. traditional sector employment share	2	1.76
Slope of traditional sector employment share on log GDP per capita	-19.9	-20.0
Slope of log relative price on log GDP per capita	0.6	0.6

Note: The table reports the moments targeted in the benchmark calibration of the quantitative model and the model's predictions for each moment.

A_M value governs the traditional sector employment share in the richest country (the United States). Finally, the remaining two parameters are the elasticity of substitution between traditional and modern goods ($\frac{1}{1-\sigma}$) and the elasticity of the traditional sector productivity with respect to modern sector productivity (ψ_1). These two elasticities jointly determine the slope of traditional sector share and the slope of relative price on log GDP per capita.

Mechanically, we begin with values for σ and ψ_1 and then calibrate the model to match the eight moments from the United States. We then solve the model for poorer countries by lowering A_M and λ, the fraction of workers that are low-educated. We discipline λ directly using data on the fraction of workers with less than high school education across our set of countries (see Appendix Figure D2). After solving each economy, we use the equilibrium prices P_T and sectoral outputs from each economy to compute the chained-type weighted indexes used by NIPA and the Bureau of Economic Analysis. We then scale all output values such that the richest economy matches the U.S. GDP per capita of exp(10.7) or $44,355. We iterate on σ and ψ_1 until we match the traditional-sector employment and relative price slopes.

Regarding the relative price P_T, we draw on disaggregated data on average national prices for specific products from the 2011 International Comparison Program (ICP). The ICP data are the best available data on the prices of identical (or nearly identical) goods and services around the world, and are available for almost every country in the world. How do we define traditional goods in these data? Consistent with our definition of the traditional sector, we pick goods or services that have low skill content and are likely to be provided by

Table 6: Slope of Log Relative Prices on log(GDP) in Data

Women's shoe repair	.39*** (.002)	Men's basic haircut	.61*** (.001)
Men's shoe repair	.53*** (.004)	Ladies haircut - curlers	.63*** (.002)
Shoeshine	.56*** (.002)	Manicure	.44*** (.003)
Local taxi ride	.42*** (.006)	Ladies haircut - long hair	.68*** (.002)

Note: Data come from the unpublished ICP 2011 disaggregated price data for the Global Core list of goods and services. See Appendix Table D2 for the exact definition of each good and service. The table reports the slope coefficient from a regression of the log of the item price relative to the investment goods price on log GDP per capita and a constant. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.

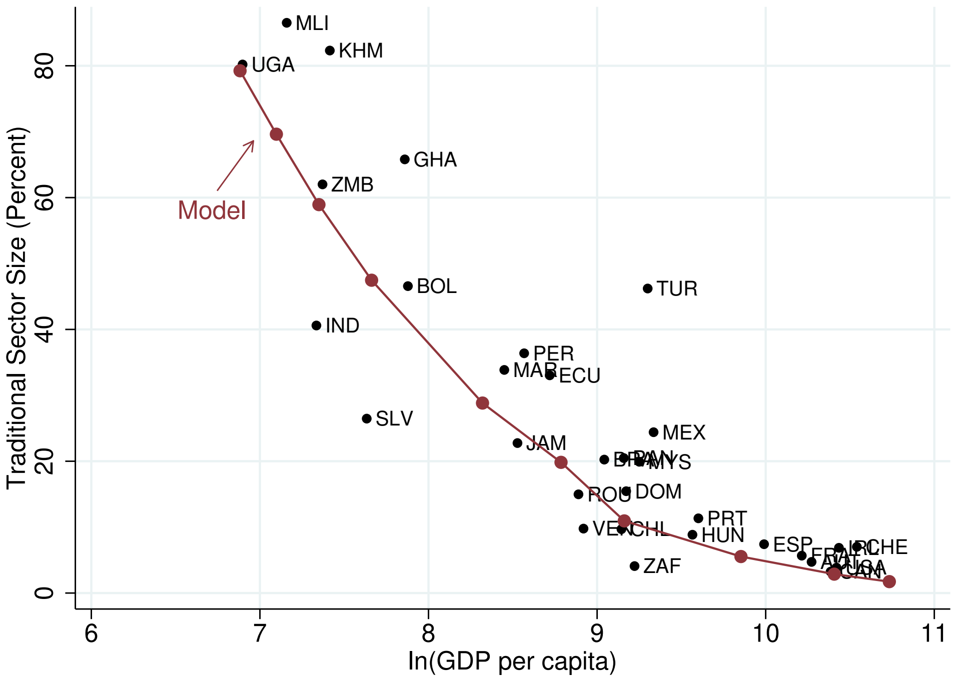
self-employed workers. We identified eight specific services that plausibly meet these criteria: (i) a shoe repair for women's street shoes; (ii) a shoe repair for men's classic shoes; (iii) a shoeshine; (iv) a 7 km taxi ride from the town center; (v) a men's basic haircut; (vi) a ladies haircut with curlers; (vii) a manicure; (viii) a ladies haircut, long hair. Appendix Table D2 provides the exact definitions of these eight traditional sector services. Since investment goods largely fit our definition of modern output, we take the aggregate price level of investment from the Penn World Table as a proxy for our modern sector price. For each traditional-sector service, we then compute the relative price of the service compared to investment goods in each country.

Table 6 reports the slope coefficient from a regression of the log of the item relative price on log GDP per capita and a constant. As shown in the table, the elasticity of the relative price ranges between 0.39 to 0.68. We target the median of these relative price elasticities, which is around 0.6.

5.2 Quantitative Predictions

Figure 5 plots the traditional sector size in the model and data. As GDP per capita decreases from the U.S. level, our model matches (by construction) the increase in the traditional sector's share of employment from two percent to around 80 percent. Our model also predicts the convex relationship between traditional sector share and GDP per capita, which is not targeted. This occurs partly because in richer economies almost all high-educated workers in the model are in the modern sector, so when those workers start to switch to the traditional sector, its size increases faster. To emphasize the mechanisms further, Appendix Figure D3 plots the traditional sector shares by education level. Crucially, the model predicts much

Figure 5: Traditional-Sector Share in Model and Data



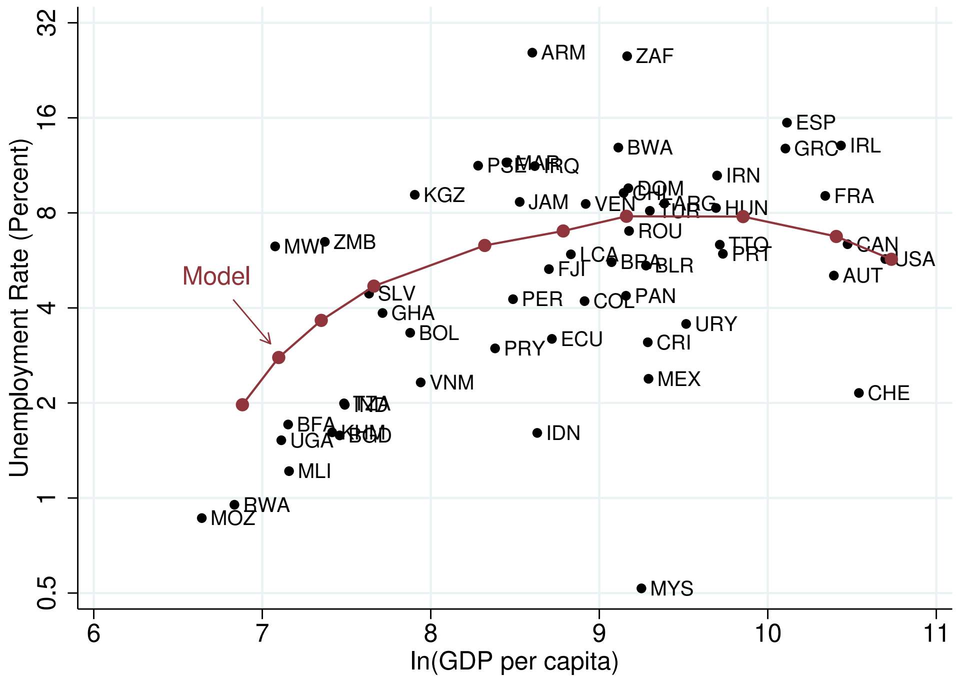
Note: This figure plots the size of the traditional sector against log GDP per capita in the data and model. Each dot represents the average in a country with at least two observations across all years of data, and the solid line is the prediction of the quantitative model.

higher shares of traditional sector employment for the low-educated than for the high-educated in poor countries, as in the data. This differential rate of exodus from the traditional sector as A_M rises is key to our theory.

Figure 6 plots the aggregate unemployment level in the model and data. As GDP per capita increases, our model predicts that the unemployment rate will increase from about 2 percent to the calibrated value of 5.7 percent. This is similar to the magnitudes in the data, though the model slightly under-predicts the steepness of the relationship. Further, consistent with the data, our model predicts a sharper increase when GDP per capita is lower. This is a result of the faster decrease in the traditional-sector share when GDP per capita is lower. For the richest countries, the model predicts that aggregate unemployment decreases because decreased weight on low-educated unemployment dominates any increases in unemployment within education group.

Figure 7 plots the ratio of unemployment for the low-educated to the high-educated in the model and data. The model is calibrated to obtain the correct ratio for the United States. For lower levels of GDP per capita, the model predicts a decline in this ratio, as in the data. Again, the model underpredicts the steepness of this relationship. The model predicts this

Figure 6: Unemployment Rates in the Model and Data



Note: This figure plots the aggregate unemployment rate against log GDP per capita. Each dot represents one country in our database as in Figure 1, and the solid line is the prediction of the quantitative model.

ratio to be just below one for the poorest countries, whereas in the data, the ratio is closer to 0.5.

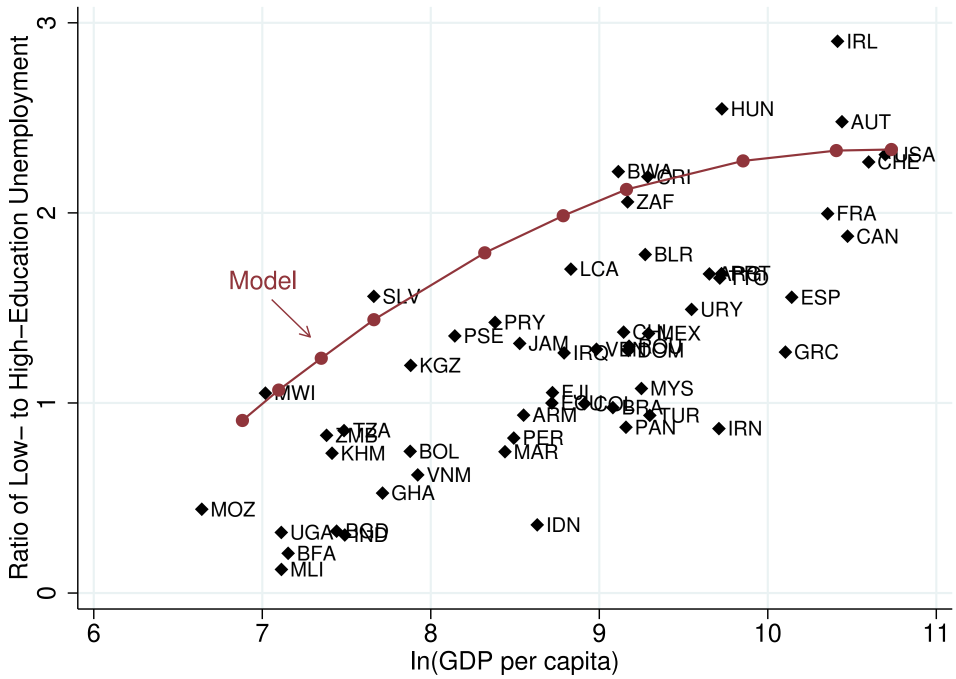
Table 7: Slope Coefficients in Data and Quantitative Model

	Data	Model
Traditional-sector share for low educated	-21.0	-19.3
Traditional-sector share for high educated	-5.1	-10.5
Aggregate unemployment rate	1.8	1.2
Unemployment rate for low-educated	3.4	2.4
Unemployment rate for high-educated	.58	.60
Ratio of unemployment rates $\frac{u_l}{u_h}$	.47	.38

Note: The table reports estimated slope coefficients from regressions of the statistics in each row on log GDP per capita. The first data column reports the slopes from our cross-country database, and the second data column reports the slopes from the quantitative model.

Table 7 reports the slope coefficients from regressions of the unemployment rate and other key variables for prime age workers on log GDP per capita and a constant, in our model and in the data. For the aggregate unemployment rate, the model yields a semi-elasticity of 1.2

Figure 7: Unemployment Ratio in the Model and Data



Note: This figure plots the ratio of unemployment for the low-educated to unemployment for the high-educated. Each dot represents one country in our database as in as in Figure 3, and the solid line is the prediction of the quantitative model.

compared to 1.8 in the data. Thus, the model accounts for around two thirds (1.2/1.8) of the empirical relationship between unemployment and log GDP per capita. Unemployment rates for the low-educated have a semi-elasticity of 2.4 in the model, compared to 3.4 in the data. The high-educated semi-elasticities match at 0.6, both in the data and in the model. The semi-elasticity for the ratio of low- to high-educated unemployment rates is 0.5 in the data and 0.4 in the model.

In our benchmark model, the unemployment benefits replacement rate b is set to 0.45 in all economies. But in reality, the benefits replacement rate is higher in richer countries. To study the quantitative impact of varying b values, we now calibrate the model by increasing b linearly across the ten model points from 0 in the poorest country to 45 percent in the United States.

Table 8 reports the slope coefficients from regressions of the unemployment rate and unemployment ratio on log GDP per capita and a constant, in our benchmark model and in the model with varying b values. The model with varying b values predicts an aggregate unemployment rate elasticity of 1.27, compared to 1.15 in the benchmark model. This accounts for 72 percent of the empirical relationship in the data, which is 7 percentage points

Table 8: Slope Coefficients in Benchmark and in Model with Varying Unemployment Benefits

	Data	Benchmark	Explained	Varying b	Explained
Unemployment	1.76	1.15	65%	1.27	72%
u_L/u_H	0.47	0.38	81%	0.39	83%

Note: This table reports the slope coefficients from regressions of the unemployment rate and unemployment ratio on log GDP per capita and a constant. The first data column reports the values from our cross-country database. The second and third data columns report the values from the benchmark model and the percent of the data explained. The fourth and fifth columns report the values from the alternative model, with varying unemployment benefits b, and the percent explained by that model.

higher than in our benchmark model. For the unemployment ratio, the model with varying b values has an elasticity of 0.39, very similar to 0.38 in the benchmark model.

5.3 Sensitivity Analysis

In this section, we explore the sensitivity of our model's predictions to the value for the elasticity of substitution. Our elasticity of substitution relates to some extent to the elasticity of substitution between home and market goods that is emphasized by the large literature studying home production in the macroeconomy (e.g. Baxter and Jermann, 1999; Ngai and Pissarides, 2008; Rogerson, 2008). Aruoba, Davis, and Wright (2016) choose a value around 2 based on previous estimates in this literature.

Though our model's elasticity is related to this, it is not exactly comparable, and one may imagine that there are greater substitution possibilities between modern and traditional goods than between home and market production, since modern and traditional goods are both purchased in the market. For example, one type of substitution between the modern and traditional sectors may be getting older shoes shined and repaired (from a self-employed shoe repairer) rather than purchasing newer shoes (from a modern shoe factory). Another example is buying produce from an informal road-side vendor versus buying produce at a modern supermarket. It is therefore worth looking at alternative evidence on substitution between different categories of purchased goods and services. In a widely cited study, Broda and Weinstein (2006) estimate elasticities of substitution across a diverse set of goods varieties, finding median estimates of around 2.2 to 3.7 across goods categories.

Ex-post, our calibrated benchmark value of 3.5 is in the middle of their estimates, but since there is not a more precise value suggested by the literature we explore a lower value of 3 and a higher value of 4. We compute the model's predictions while keeping all the other parameter values as in the benchmark.

We present the results in Table 9. Each row reports the slope coefficient from a regression of

Table 9: Sensitivity Analysis of Model Elasticity of Substitution

		Model Elasticity $\frac{1}{1-\sigma}$		
Slope Coefficients	Data	Lower	Benchmark	Higher
Aggregate traditional sector share	-19.9	-15.7	-20.0	-23.3
Traditional-sector share for low educated	-21.0	-15.0	-19.3	-22.5
Traditional-sector share for high educated	-5.1	-6.7	-10.5	-13.8
Aggregate unemployment rate	1.8	.77	1.2	1.4
Unemployment rate for low-educated	3.4	1.9	2.4	2.7
Unemployment rate for high-educated	.58	.43	.60	.75
Ratio of unemployment rates $\frac{u_l}{u_h}$	.47	.29	.38	.43
Relative price P_T	.60	.65	.63	.61

Note: This table reports the slope coefficients from regressions of the statistics in each row on log GDP per capita and a constant. The second column (Data) reports the slopes from our cross-country database, the third column (Lower) is for an elasticity of substitution between modern and traditional output of 3, the fourth column (Benchmark) is the benchmark model with an elasticity of 3.5, and the fifth column (Higher) is for an elasticity of 4.

the variable on log GDP per capita. The second column is the data slope coefficients, and the third to fifth are the slope coefficients in the model with the lower, benchmark, and higher values of the substitution elasticities. For the lower value of 3, the model underpredicts the slope of the traditional sector shares on log GDP per capita. As a result, the aggregate unemployment rate varies less with GDP per capita (0.8 versus 1.2 in the benchmark model), as do unemployment rates for low-educated workers (1.9 versus 2.4 in the benchmark) and high-educated workers (0.4 versus 0.6 in the benchmark). The ratio of low-to-high unemployment rates also varies less with GDP per capita than in the benchmark (0.29 versus 0.38). The relative price varies slightly more than in the benchmark (0.65 versus 0.63).

For the higher value of 4, the model over-predicts the slope of the traditional sector share on log GDP per capita. The unemployment rate varies more with GDP per capita than in the benchmark, both in the aggregate and by education level. The unemployment ratio has a slope of 0.43 compared to 0.38 in the benchmark, and is closer to the slope of 0.47 in the data. The relative price has a slightly smaller slope of 0.61 compared to 0.63 in the benchmark.

The intuition for these results is as follows. The change in the level of unemployment is driven by the exodus from the traditional sector, which, in turn, is driven by the increase in the ratio of marginal value products of labor: $\frac{A_M}{P_T A_T}$. The smaller is the elasticity of substitution, the less this ratio changes because the rise in P_T offsets the rise in A_M as we move from the poorest to the richest country. In the benchmark model, the slope of this ratio on log GDP per capita is 0.69, only 0.60 when the elasticity is 3, and 0.77 when the elasticity is 4. That is why the model predicts so much more change in unemployment when the elasticity is 4 than when it is 3.

Alternatively, for different elasticities of substitution 3 and 4, we can re-calibrate ψ_1 to match the slope of the aggregate traditional sector share on log GDP per capita. Appendix Table D3 reports the model predictions. Across all values of elasticities of substitution, our model stably accounts for more than 60 percent of the slopes of unemployment rates, and around 80 percent of the slope of the unemployment ratio.

We conclude that the model is sensitive to values of the elasticity of substitution between modern- and traditional-sector output if we do not target the slope of the traditional sector share. Yet for all three of the values chosen, the model accounts for a significant part of the slope of the relationship between unemployment and GDP per capita.

6 Historical Evidence

In this section, we report historical evidence from countries that have high income per capita today to explore how their average unemployment rates have evolved over the long run with income levels. We first look at aggregate unemployment rates from Australia, France, Germany, the United Kingdom and the United States in the period before World War I compared to the most recent evidence. We then look at more disaggregate evidence from the United States.

6.1 Historical Unemployment Rates

The earliest evidence on unemployment that we can find comes from the late 19th century or early 20th century. For simplicity, we consider two periods: an early period containing all data pre-World War I, and a recent period comprised of the most recently available data covering the same number of years. There are five countries for which we found aggregate unemployment data for at least ten years before WWI started in 1914: Australia, France, Germany, the United Kingdom and the United States. The recent period is then defined as 2004 - 2016 for Australia, 1998 - 2016 for France, 1990 - 2016 for Germany, 1984 - 2016 for the UK, and 1972 - 2016 for the U.S. The recent aggregate unemployment rate data are compiled from the World Bank, the U.K. office for National Statistics, and the U.S. BLS.

Table 10 reports the average unemployment rates in the early and recent periods for these five countries, the difference between the recent and early periods, and a permutation test of the difference between the recent and early periods. The recent unemployment rate is larger than the early period for all five countries. Among them, Australia's unemployment rate is very similar in the two periods, and the difference is statistically insignificant. For the

Table 10: Historical Unemployment Rates

Country	Early Period (source)	Unemployment Early	Unemployment Recent	Difference (p-value)
Australia	1901 - 1913 (Mitchell 1992)	5.17	5.26	0.09 (.48)
France	1895 - 1913 (Mitchell 1992)	7.35	8.91	1.55*** (.00)
Germany	1887 - 1913 (Mitchell 1992)	2.37	7.55	5.18*** (.00)
United Kingdom	1881 - 1913 (UK Central Statistical Office)	4.71	7.29	2.57*** (.00)
United States	1869 - 1913 (Vernon 1994, Mitchell 1992)	5.11	6.38	1.27*** (.00)

Note: The table reports the average unemployment rates in the early and recent periods, and the results of a one-sided permutation test of whether the recent period has a larger unemployment rate. The early period is defined as the years before WWI; and the recent period is defined as a corresponding year to 2016 such that we have the same number of years for the two periods for each country; see the text for exact dates.

remaining four, average unemployment is economically and statistically significantly higher in the recent period. France's unemployment is the highest overall in both periods, and rises from 7.4 to 8.9 percent. Germany's unemployment rises from 2.4 to 7.6 percent. The United Kingdom rises from 4.7 to 7.3 percent, and the United States rises from 5.1 to 6.4 percent. All of these countries had very large increases in GDP per capita over this period. We conclude that the historical evidence is consistent with our cross sectional finding that the aggregate unemployment rate increases when GDP per capita increases.

6.2 Disaggregated U.S. Time Series Evidence

We now turn to evidence from U.S. time series micro data. These data allow us to go beneath the aggregate unemployment rates and to study what happens to unemployment and traditional sector employment by education group. The data allow us to test our theory's prediction that unemployment rates rose, particularly for the low-educated.

To do so, we draw on the U.S. census every decade from 1910 to 2010 from IPUMS International (Minnesota Population Center, 2017). To maintain consistency across years, we restrict attention to workers aged 16 and over in all states except Alaska and Hawaii. The first row of Table 11 reports the slope coefficients from regressions of the unemployment rates on log GDP per capita and a constant. As the table shows, unemployment rates rose with log GDP per capita on average, particularly for the less-educated. The estimated slope of the ratio of low-educated unemployment to high-educated unemployment is 0.7 using these data,

Table 11: Slope Coefficients for U.S. Time Series

	All Workers	Worker Education Group Low	High	Ratio
Unemployment rate	3.3** (1.6)	10.6*** (2.3)	3.8** (1.6)	.7** (.3)
Traditional sector share	-2.6** (1.0)	-1.6 (1.3)	-.4 (.7)	

Note: The table reports the slope coefficients from regressions of unemployment rates and the traditional sector share on log GDP per capita and a constant. Observations include the U.S. data across all census years from 1910 to 2010. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.

compared with 0.5 in the cross-country data. We conclude that disaggregated unemployment rates from historical U.S. data are largely consistent with our theory and our cross-country evidence.

Our theory also predicts that the size of the traditional sector has fallen over time in the United States. To test this prediction, we use the census data from 1960 to 2010 to measure the size of the traditional sector according to our proxy of self-employed workers in low-skilled occupations. The second row of Table 11 reports the slope coefficient from a regression of the traditional sector share on log GDP per capita and a constant. As the theory predicts, the traditional-sector share decreases significantly with log GDP per capita, mostly driven by the decrease for the low-education group. We conclude that our theory performs adequately here as well.

7 Conclusions

This paper draws on household survey evidence from around the world to document that unemployment rates are higher, on average, in rich countries than in poor countries. The pattern is particularly pronounced for the less-educated, whose unemployment rates are strongly increasing in GDP per capita, whereas unemployment for the more-educated is roughly constant on average across countries. Our findings imply that the low-educated are more likely to be unemployed than the high-educated in rich countries, whereas the opposite is true in poor countries.

To interpret these facts, we build and calibrate a simple two-sector model that combines labor search, as in Diamond (1982) and Mortensen and Pissarides (1994), with a traditional self-employment sector, as in Parente, Rogerson, and Wright (2000). The proximate cause of development in the model is skill-biased technological progress, as emphasized by a growing literature in macroeconomics following Caselli and Coleman (2006). In spite of its simplicity, the model explains the bulk of the relationship between unemployment and development when parameterized to match plausible differences in the extent of cross-country differences in productivity by skill level. It also does well in matching the faster increase in unemployment for the low-skilled relative to the high-skilled, as in the data. The model's success in matching the data is only modestly higher when parameterized further to include higher unemployment benefits in richer countries. We conclude that as long as development is itself the result of skill-biased productivity growth, then unemployment is largely a consequence of the development process, as progressively less skilled individuals move from self-employment into wage work. Of course, the model does not explain the entire relationship between average unemployment and income per capita, and what accounts for the remaining differences are left for future research.

References

Aguiar, M., and E. Hurst (2007): "Measuring Trends in Leisure: The Allocation of Time Over Five Decades," *Quarterly Journal of Economics*, 122(3), 969–1006.

Aruoba, S. B., M. A. Davis, and R. Wright (2016): "Homework in Monetary Economics: Inflation, Home Production, and the Production of Homes," *Review of Economic Dynamics*, 21, 105–124.

Banerjee, A., P. Basu, and E. Keller (2016): "Cross-Country Disparities in Skill Premium and Skill Acquisition," Unpublished Working Paper, Durham University.

Baxter, M., and U. J. Jermann (1999): "Household Production and the Excess Sensitivity of Consumption to Current Income," *American Economic Review*, 84(4), 902–920.

Bick, A., N. Fuchs-Schuendeln, and D. Lagakos (2018): "How Do Hours Worked Vary with Income? Cross-Country Evidence and Implications," *American Economic Review*, 108(1), 170–99.

Bick, A., N. Fuchs-Schuendeln, D. Lagakos, and H. Tsujiyama (2020): "Why are Average Hours Worked Lower in Richer Countries?," Unpublished Working Paper, University of California San Diego.

Blanchard, O. J., and L. H. Summers (1986): "Hysteresis and the European Unemployment Problem," *NBER Macroeconomics Annual*, 1.

Braxton, J. C., K. Herkenhoff, and G. Phillips (2018): "Can the Unemployed Borrow? Implications for Public Insurance," Unpublished Manuscript, University of Minnesota.

Bridgman, B., G. Duernecker, and B. Herrendorf (2018): "Structural Transformation, Marketization, and Household Production around the World," *Journal of Development Economics*, 133, 102–126.

Broda, C., and D. E. Weinstein (2006): "Globalization and the Gains from Variety," *Quarterly Journal of Economics*, 121(2), 541–585.

Buera, F. J., and J. P. Kaboski (2012): "The Rise of the Service Economy," *American Economic Review*, 102, 2450–69.

Buera, F. J., J. P. Kaboski, and R. Rogerson (2015): "Skill-Biased Structural Change," NBER Working Paper No. 21165.

Caselli, F. (2005): "Accounting for Cross-Country Income Differences," in *Handbook of Economic Growth*, ed. by P. Aghion, and S. N. Durlauf.

Caselli, F., and W. Coleman (2006): "The World Technology Frontier," *American Economic Review*, 96(3), 499–522.

Chodorow-Reich, G., and L. Karabarbounis (2016): "The Cyclicality of the Opportunity Cost of Employment," *Journal of Political Economy*, 124(6), 1563–1618.

Diamond, P. A. (1982): "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, 90(8), 881–894.

Donovan, K., J. Lu, and T. Schoellman (2020): "Labor Market Flows and Development," Unpublished Manuscript, University of Notre Dame.

Duarte, M., and D. Restuccia (2010): "The Role of the Structural Transformation in Aggregate Productivity," *Quarterly Journal of Economics*, 125(1), 129–173.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015): "The Next Generation of the Penn World Table," *American Economic Review*, 105(10), 3150–3182.

Fields, G. S. (1980): "Education and Income Distribution in Developing Countries: A Review of the Literature," World Bank Staff Working Paper No. 402 (pp. 231 - 315).

——— (2004): "A Guide to Multi-sector Labor Market Models," Unpublished Working Paper, Cornell University.

Frey, B. S., and A. Stutzer (2002): "What Can Economists Learn from Happiness Research?," *Journal of Economic Literature*, 40(2), 402–435.

Fujita, S., and G. Ramey (2012): "Exogenous Versus Endogenous Separation," *American Economic Journal: Macroeconomics*, 4(4), 68–93.

Gollin, D. (2008): "Nobody's Business But My Own: Self-Employment and Small Enterprise in Economic Development," *Journal of Monetary Economics*, 55(2), 219–233.

Gollin, D., D. Lagakos, and M. E. Waugh (2014): "The Agricultural Productivity Gap," *Quarterly Journal of Economics*, 129(2), 939–993.

Gollin, D., S. L. Parente, and R. Rogerson (2004): "Farm Work, Home Work and International Productivity Differences," *Review of Economic Dynamics*, 7, 827–850.

Hall, R. E., and A. I. Mueller (2018): "Wage Dispersion and Search Behavior: The Importance of Non-Wage Job Values," *Journal of Political Economy*, 126(4), 1594–1637.

Harris, J. R., and M. P. Todaro (1970): "Migration, Unemployment and Development: A Two-Sector Analysis," *American Economic Review*, 60(1), 126–142.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2014): "Growth and Structural Transformation," in *Handbook of Economic Growth*, ed. by P. Aghion, and S. N. Durlauf, vol. 2, chap. 6, pp. 855–941. Elsevier.

Hjort, J., and J. Poulsen (2019): "The Arrival of Fast Internet and Employment in Africa," *American Economic Review*, 109(3), 1032–79.

Jerzmanowski, M., and R. Tamura (2019): "Directed Technological Change & Cross Country Income Differences: A Quantitative Analysis," *Journal of Development Economics*, 141.

Krueger, A. B., and A. Mueller (2010): "Job Search and Unemployment Insurance: New Evidence from Time Use Data," *Journal of Public Economics*, 94(3), 298 – 307.

La Porta, R., and A. Shleifer (2008): "The Unofficial Economy and Economic Development," *Brookings Papers on Economic Activity*, 2, 275–363.

——— (2014): "Informality and Development," *Journal of Economic Perspectives*, 28(3), 109–26.

Lepper, F. (2004): "Comparable Annual Employment and Unemployment Estimates," Discussion paper, Department of Statistics, International Labour Office, Geneva.

Ljungqvist, L., and T. J. Sargent (2008): "Two Questions about European Unemployment," *Econometrica*, 76(1), 1–29.

Malmberg, H. (2016): "Human Capital and Development Accounting Revisted," Unpublished Working Paper, IIES Stockholm.

Mestieri, M., D. Comin, and D. Lashkari (2018): "Structural Change with Long-run Income and Price Effects," Unpublished Working Paper, Northwestern University.

Mincer, J. (1991): "Education and Unemployment," NBER Working Paper No. 3838.

Minnesota Population Center (2017): "Integrated Public Use Microdata Series, International: Version 6.5 [dataset]," Minneapolis: University of Minnesota, http://doi.org/10.18128/D020.V6.5.

Mortensen, D., and C. Pissarides (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61, 397–415.

Mueller, A. I. (2017): "Separations, Sorting, and Cyclical Unemployment," *American Economic Review*, 107(7), 2081–2107.

Ngai, R. L., and C. A. Pissarides (2008): "Trends in Hours and Economic Growth," *Review of Economic Dynamics*, 11(2), 239–56.

Nickell, S., L. Nunziata, and W. Ochel (2004): "Unemployment in the OECD Since the 1960s. What Do We Know?," *Economic Journal*, 115(500), 1–27.

Parente, S. L., R. Rogerson, and R. Wright (2000): "Homework in Development Economics: Household Production and the Wealth of Nations," *Journal of Political Economy*, 108(4), 680–687.

Poschke, M. (2018): "Wage Employment, Unemployment and Self-Employment Across Countries," Unpublished Manuscript, McGill University.

Ramey, V. A., and N. Francis (2009): "A Century of Work and Leisure," *American Economic Journal: Macroeconomics*, 1(2), 189–224.

Raphael, S., and R. Winter-Ebmer (2001): "Identifying the Effect of Unemployment on Crime," *Journal of Law and Economics*, 44(1), 259–283.

Rauch, J. E. (1991): "Modelling the Informal Sector Informally," *Journal of Development Economics*, 35(1), 33–47.

Rogerson, R. (2008): "Structural Transformation and the Deterioration of European Labor Market Outcomes," *Journal of Political Economy*, 116(2), 235–259.

Roy, A. (1951): "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 3, 135–46.

Schoar, A. (2010): "The Divide between Subsistence and Transformational Entrepreneurship," in *Innovation Policy and the Economy*, ed. by J. Lerner, and S. Stern, chap. 3, pp. 57–81. University of Chicago Press.

Shimer, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95(1).

Squire, L. (1981): *Employment Policy in Developing Countries: A Survey of Issues and Evidence*. New York: Published for the World Bank by Oxford University Press.

Todaro, M. P. (1969): "A model of labor migration and urban unemployment in less developed countries," *The American economic review*, 59(1), 138–148.

Turnham, D. (1993): *Employment and Development: A New Review of Evidence*. Paris, OECD.

United Nations (2008): "System of National Accounts, 2008," https://unstats.un.org/unsd/sna1993/WC-SNAvolume2.pdf.

U.S. Bureau of Labor Statistics (2016): *Handbook of Methods*. U.S. Government Printing Office, Washington, D.C.

Wolcott, E. (2018): "Employment Inequality: Why Do the Low-Skilled Work Less Now?," Unpublished Working Paper, Middlebury College.

World Bank (2012): *World Development Report 2013: Jobs*. The World Bank, Washington, D.C.

Online Appendices

A Data Appendix

Among the 199 surveys listed below, there are 11 from earlier than 1990, 59 from the 1990s, 88 from the 2000s, and 41 from 2010 and later. Among the 84 countries, there are 55 for which we have at least two surveys.

Table A.1: **Tier 1, Most Comparable Surveys**

Tier 1a: Searched for work last week

Country	Year	Source
Azerbaijan	1995	Survey of Living Conditions
Bangladesh	2000, 2005, 2010	Household Income-Expenditure Survey (HIES)
Bolivia	1992, 2001	IPUMS-I
Botswana	2001, 2011	IPUMS-I
Brazil	2010	IPUMS-I
Burkina Faso	2014	LSMS
Burkina Faso	2006	IPUMS-I
Canada	2011	IPUMS-I
Chile	1992, 2002	IPUMS-I
Colombia	1993, 2005	IPUMS-I
Costa Rica	2000, 2011	IPUMS-I
Cuba	2002	IPUMS-I
Dominican	2002	IPUMS-I
Ecuador	1990, 2001, 2010	IPUMS-I
El Salvador	1992, 2007	IPUMS-I
Fiji	2007	IPUMS-I
Ghana	1984, 2000	IPUMS-I
Ghana	1998	Living Standards Survey
Ghana	2010	IPUMS-I
Greece	2001, 2011	IPUMS-I
Hungary	2011	IPUMS-I
India	1983, 1987, 1993, 1999, 2004	IPUMS-I
Indonesia	1990, 1995, 2010	IPUMS-I
Indonesia	2014	Indonesia Family Life Survey
Jamaica	1991, 2001	IPUMS-I
Kenya	2009	IPUMS-I

Malawi	2008	IPUMS-I
Malaysia	1991, 2000	IPUMS-I
Mexico	1990, 1995, 2000, 2010, 2015	IPUMS-I
Mongolia	2000	IPUMS-I
Mozambique	1997, 2007	IPUMS-I
Nigeria	2010	IPUMS-I
Pakistan	1973	IPUMS-I
Panama	1990, 2000, 2010	IPUMS-I
Paraguay	1992	IPUMS-I
Peru	2007	IPUMS-I
Peru	1994	Living Standards Survey
Philippines	1990	IPUMS-I
Poland	2002	IPUMS-I
Portugal	1991, 2001	IPUMS-I
Romania	1992, 2002, 2011	IPUMS-I
Rwanda	2002	IPUMS-I
Saint Lucia	1980, 1991	IPUMS-I
South Africa	1993	Integrated Household Survey
South Sudan	2008	IPUMS-I
Spain	2011	IPUMS-I
Sudan	2008	IPUMS-I
Tajikistan	1999	LSMS
Tanzania	2002, 2012	IPUMS-I
Trinidad and Tobago	1970, 1980, 1990, 2000, 2011	IPUMS-I
Uganda	1991, 2002	IPUMS-I
Venezuela	2001	IPUMS-I
Zambia	1990, 2010	IPUMS-I

Tier 1b: Searched for work in the last 4 weeks

Argentina	1991	IPUMS-I
Armenia	2011	IPUMS-I
Belarus	2009	IPUMS-I
Bosnia and Herzegovina	2004	Living in Bosnia and Herzegovina Survey
Brazil	1997	Survey of Living Conditions
Brazil	2000	IPUMS-I
Bulgaria	2007	Multi-topic Household Survey
Canada	1991, 2001	IPUMS-I

Dominican Republic	2010	IPUMS-I
Iran	2011	IPUMS-I
Iraq	2012	Household Socio-economic Survey
Italy	2001	IPUMS-I
Jordan	2004	IPUMS-I
Malawi	2013	Integrated Household Panel Survey
Paraguay	2002	IPUMS-I
Serbia	2007	LSMS
South Africa	2007, 2001, 2011	IPUMS-I
Tanzania	2010	National Panel Survey
Uganda	2011	National Panel Survey
United States	1980, 1990, 2000	IPUMS
United States	2001-2014	American Community Survey (ACS)

Table A.2: **Tier 2, Comparable Search Questions, Less Comparable Duration Questions**

Country	Year	Source	Seeking window
Armenia	2001	IPUMS-I	Current
Bangladesh	1991, 2001	IPUMS-I	7 days main
Bangladesh	2011	IPUMS-I	Current status
Brazil	1980	IPUMS-I	Current
Burkina Faso	1996	IPUMS-I	At least three out of the last week
Cambodia	1998, 2008	IPUMS-I	6 month
Egypt	2006	IPUMS-I	current
France	2006, 2011	IPUMS-I	Current
Haiti	2003	IPUMS-I	Last month
Hungary	1990	IPUMS-I	Current
Iran	2006	IPUMS-I	Past 30 days
Iraq	1997	IPUMS-I	Current
Ireland	1991, 1996, 2002, 2006, 2011	IPUMS-I	Current
Kyrgyz Republic	1999, 2009	IPUMS-I	Current
Mali	1998, 2009	IPUMS-I	4 weeks
Morocco	1994, 2004	IPUMS-I	Current
Nicaragua	2005	IPUMS-I	2 weeks
Rwanda	1991	IPUMS-I	Most of the week
Senegal	2002	IPUMS-I	Continuously for at least 3 months
Sierra Leone	2004	IPUMS-I	4 weeks
South Africa	1996	IPUMS-I	Current
Switzerland	2000	IPUMS-I	Current
Turkey	1990	IPUMS-I	Current
Uruguay	2006, 2011	IPUMS-I	4 weeks
Venezuela	1990	IPUMS-I	Current
Zambia	2000	IPUMS-I	Primary activity 7 days

Table A.3: **Tier 3, Least Comparable Search or Activity Questions**

Country	Year	Source	Activity	Search
Argentina	2001, 2010	IPUMS-I	Exclude: for self-consumption	4 weeks
Austria	1991	IPUMS-I	A minimum average of 12 hours per week	Current
Austria	2001	IPUMS-I	7 days	Only previously employed
Austria	2011	IPUMS-I	No text	No text
Belarus	1999	IPUMS-I	Exclude: for self-consumption	Yes
Botswana	2011	IPUMS-I	4 Weeks	
Cameroon	2005	IPUMS-I	7 Days	Last 7 days for worked before; now for looking for the first job
China	1990	IPUMS-I	No text	No text
Ethiopia	2007	IPUMS-I	Standard	No text
Fiji	1996	IPUMS-I	Worked for money	Not comparable
France	1990, 1999	IPUMS-I	Current	Enrollment ANPE
Hungary	2001	IPUMS-I	Current	Unemployment benefit
India	2009	IPUMS-I	Standard	Only 12 months main activity available
Liberia	2008	IPUMS-I	12 Months	12 months
Netherlands	2001	IPUMS-I	No Text	Not comparable
Palestine	1997, 2007	IPUMS-I	7 Days	Included did not seek but want to work
Peru	1993	IPUMS-I	Not comparable	Not comparable
Portugal	1981	IPUMS-I	7 Days	Text not available
Portugal	2011	IPUMS-I	No text	No text
Slovenia	2002	IPUMS-I	Current	Registered as unemployed at the employment service of Slovenia

Spain	1991, 2001	IPUMS-I	7 Days	Unemployed, worked previously
Switzerland	1990	IPUMS-I	Principal occupation	Current
Turkey	2000	IPUMS-I	Earn cash or income in kind	Last week
Ukraine	2001	IPUMS-I	Status	Unemployment allowances, unemployed
United States	1960	IPUMS-I	Last week	Looking for work or laid off
Vietnam	2009, 1999	IPUMS-I	Earn income	4 weeks

B Model Derivations

In this appendix, we develop the expressions for $U_i(x)$ and $w_i(x)$, and show the intermediate steps to develop equation (12). We start by simplifying equations (7) - (10) to

$$(1-\delta)U_i(x) = A_M b(A_M)x + \delta\eta\theta_i^{1-\alpha}\big[E_i(x) - U_i(x)\big] \tag{B.1}$$

$$(1-\delta)E_i(x) = w_i(x) + \delta s_i\big[U_i(x) - E_i(x)\big] \tag{B.2}$$

$$J_i(x) = \frac{A_M x - w_i(x)}{1-\delta(1-s_i)} \tag{B.3}$$

$$\big(1 - G_i(x_i^*)\big)A_M c = \delta\eta\theta_i^{-\alpha}\int_{x_i^*}^{\bar{x}} J_i(x)g_i(x)dx. \tag{B.4}$$

The firm receives $(1-\beta)S_i(x) = (1-\beta)[E_i(x) - U_i(x) + J_i(x)] = J_i(x)$ when a vacancy is filled. Combining this division of surplus with equation (B.3) gives

$$E_i(x) - U_i(x) = \frac{\beta}{1-\beta}\frac{A_M x - w_i(x)}{1-\delta(1-s_i)}. \tag{B.5}$$

Substituting equation (B.5) into equation (B.1) yields

$$U_i(x) = \frac{1}{1-\delta}\Big(A_M b(A_M)x + \delta\eta\theta_i^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x - w_i(x)}{1-\delta(1-s_i)}\Big). \tag{B.6}$$

We can then solve for $w_i(x)$ by combining equations (B.6) and (B.5) with equation (B.2):

$$w_i(x) = \frac{A_M b(A_M)x}{1+k_i(\theta_i)} + \frac{k_i(\theta_i)}{1+k_i(\theta_i)}A_M x, \text{ where } k_i(\theta_i) = \frac{\beta(\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i)}{(1-\beta)(1-\delta+\delta s_i)}.$$

Substituting this solution into equations (B.3) and (B.6) gives us, respectively,

$$J_i(x) = \frac{A_M x\big(1 - b(A_M)\big)(1-\beta)}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i} \tag{B.7}$$

$$U_i(x) = \frac{1}{1-\delta}\Big(A_M b(A_M)x + \delta\eta\theta_i^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x\big(1-b(A_M)\big)(1-\beta)}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i}\Big). \tag{B.8}$$

Equation (B.8) appears as equation (11) in the text. Finally, substituting equation (B.7) into equation (B.4) and dividing both sides by $1 - G_i(x_i^*)$ yields equation (12) that determines θ_i for any given level of x_i^*:

$$c = \frac{(1-\beta)\delta\eta\theta_i^{-\alpha}}{\beta\delta\eta\theta_i^{1-\alpha} + 1 - \delta + \delta s_i}\big(1 - b(A_M)\big)\mathbb{E}(x|x > x_i^*).$$

C Model Extension with Worker Churn

For simplicity, our model has abstracted from any worker "churn" between the traditional and modern sectors. Donovan, Lu, and Schoellman (2020) assemble data on quarterly labor market transition rates for 42 countries, including transition rates out of self-employment. In their sample, the poorest countries by a wide margin are Nicaragua, Palestine, and the Philippines, for which the average share of low-skill occupations in self-employment in our data is 84 percent. Hence, the self-employment data for these three countries can approximately represent our traditional sector. For these countries, the average probability that a self-employed worker will be unemployed or a wage worker next quarter is 13 percent. This is not a trivial rate of transition to the modern sector, so we would like our model to be robust to incorporating such transitions.

Accordingly, we extend the model of Section 4 to allow worker movement between the traditional and modern sectors at a given level of modern sector productivity. Specifically, we introduce idiosyncratic shocks to worker productivity in the traditional sector. This volatility could be caused by weather or commodity price fluctuations, for example.

In the model of Section 4, workers below a cutoff ability level always remained in the traditional sector and workers above the cutoff always remained in the modern sector. In the stationary equilibrium of the modified model, there will still exist a cutoff ability level below which workers always remain in the traditional sector, and a cutoff above which workers will always remain in the modern sector. However, these cutoffs will no longer be equal. Instead, the cutoff above which workers always remain in the modern sector will be strictly greater than the cutoff below which workers always remain in the traditional sector, and workers with abilities between these cutoffs will move between the modern and traditional sectors in response to shocks to their traditional sector productivities. This change does not affect the qualitative responses of unemployment to increases in modern sector productivity or unemployment benefits.

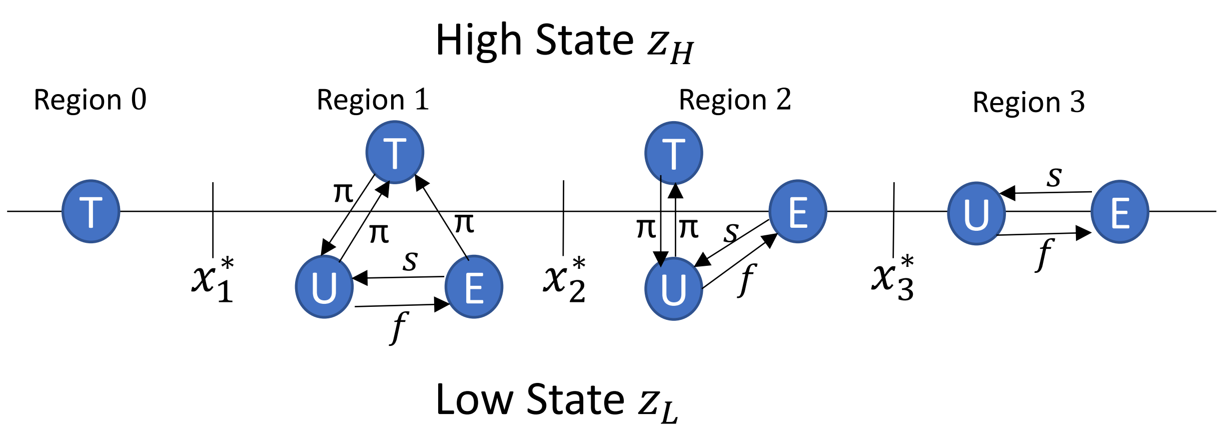
Environment and Stationary Equilibrium. For ease of exposition we develop the new features of our model for only one type of labor, rather than two types as in the model of Section 4. The extension to two types is mechanical. We therefore drop the subscripts $i = h, l$ wherever they occur, otherwise retaining the notation and equations from Section 4 except where specified.

We assume that the efficiency of any worker in the traditional sector fluctuates between a high state and a low state, taking the value $z_H > 1$ in the high state and $z_L < 1$ in the low state. The marginal product of any worker in the traditional sector therefore fluctuates between $A_T z_H$ and $A_T z_L$. Worker transition between the high and low states follows a Markov chain with transition matrix $\mathbf{\Pi} = \begin{pmatrix} 1-\pi & \pi \\ \pi & 1-\pi \end{pmatrix}$. It follows that in the stationary equilibrium the share of workers of any ability in each state equals 0.5.[8]

It is easily shown that, if z_L is close enough to 1, a worker with sufficiently low ability will prefer the traditional sector regardless of which state he is in. Similarly, it is easily shown that if z_H is close enough to 1, a worker with sufficiently high ability will prefer the modern sector regardless of which state he is in. Flows between the two sectors can therefore occur only for workers with abilities between these two cutoffs.

A worker with ability between the two cutoffs prefers to enter the modern sector as unemployed when his traditional sector productivity is low, but not when his traditional sector productivity is high. Now suppose such a worker has entered the modern sector, and transitions from the low to the high traditional productivity state. If he is unemployed at the time, he returns to the traditional sector. If he is employed, however, his decision will depend on how much he is earning, i.e., on his ability. Thus there is a third ability cutoff, above which a worker in the high state prefers the modern sector if he is employed but moves to the traditional sector if he is unemployed.

Figure 8: Equilibrium Labor Division across Traditional and Modern Sectors



Label the three ability cutoffs x_1^*, x_2^*, and x_3^*, where $x_1^* < x_2^* < x_3^*$. These three cutoffs divide labor market behavior into four ability regions as shown in Figure 8. Each blue circle represents a set of workers. Workers on the horizontal axis can be in the high or low state of traditional sector productivity, and workers above (below) the horizontal axis are in the high (low) state. Workers with abilities $x \in [\underline{x}, x_1^*)$ always stay in the traditional sector and workers with abilities $x \in [x_3^*, \bar{x}]$ always stay in the modern sector. Workers with abilities

[8] If we assume $0.5z_H + 0.5z_L = 1$, then in the stationary equilibrium traditional sector output produced by workers who always remain in the traditional sector is the same as what would be produced by these workers in the model of Section 4.

$x \in [x_1^*, x_2^*)$ prefer the traditional sector when their traditional sector productivity is high and the modern sector when their traditional sector productivity is low. Finally, workers with abilities $x \in [x_2^*, x_3^*)$ prefer the modern sector when their traditional sector productivity is low, and when their traditional sector productivity is high they prefer the traditional sector to modern sector unemployment but modern sector employment to the traditional sector.

The arrows in Figure 8 show the labor flows between employment and unemployment in the modern sector, the flows between the traditional sector and modern sector employment and unemployment, and the probabilities with which these flows occur. We can use these arrows to compute gross labor flows and unemployment rates in the stationary equilibrium of our modified model.

For workers with abilities between x_1^* and x_2^*, gross labor flows in any period equal $(0.5\pi + 0.5\pi)[G(x_2^*) - G(x_1^*)] = \pi[G(x_2^*) - G(x_1^*)]$, since half the workers are in each state, all workers in the high (low) state are in the traditional (modern) sector, and all workers in both sectors flow between sectors when they change states.

For workers between x_2^* and x_3^*, we must solve for the division of the labor force between the traditional sector, modern sector employment, and unemployment in order to compute the gross labor flows between the modern and traditional sectors and the unemployment rate. Note that only workers in the high state will be in the traditional sector, and only workers in the low state will be unemployed. In contrast, workers employed in the modern sector may be in either the high or low state. Using these facts, we show in Appendix Section C.1 that, for workers with abilities between x_2^* and x_3^*, gross labor flows in any period equal

$$2\pi \frac{s[0.5(f+s) + \pi(1-f-s)]}{(f+s)(\pi+s-2s\pi)+s\pi}[G(x_3^*) - G(x_2^*)],$$

where f denotes the job finding rate and s denotes the separation rate. The job finding rate f equals $\eta\theta^{1-\alpha}$, where θ is the market tightness that applies to all modern sector job-seekers and is determined in general equilibrium as in the model of Section 4.

Let u_1, u_2, and u_3 be the shares of unemployed workers with abilities within x_1^* and x_2^*, x_2^* and x_3^*, and above x_3^*, respectively. We derive in Appendix Section C.1 that the total unemployment rate u is given by:

$$\begin{aligned} u =& u_1\big(G(x_2^*) - G(x_1^*)\big) + u_2\big(G(x_3^*) - G(x_2^*)\big) + u_3\big(1 - G(x_3^*)\big) \\ =& \frac{0.5[\pi + s(1-\pi)]\big(G(x_2^*) - G(x_1^*)\big)}{\pi + (f+s)(1-\pi)} + \frac{s(\pi + 0.5s - s\pi)\big(G(x_3^*) - G(x_2^*)\big)}{(f+s)(\pi+s-2s\pi)+s\pi} + \frac{s\big(1-G(x_3^*)\big)}{f+s}. \end{aligned}$$

To solve the model with stochastic productivity, note that since we have three ability cutoffs, the indifference condition (13) in the model of Section 4 must be replaced by three indifference conditions. To express these we need some additional notation. We denote the value of traditional sector work by T, retaining E and U for the values of modern sector employment and unemployment, respectively. Letting $J = H, L$ denote the state of traditional sector productivity, and k denote region of Figure 8, we can more specifically denote the value functions for traditional sector work, modern sector employment, and unemployment respectively by $T_k(z_J; x), k = 0, 1, 2$; $E_k(z_J; x), k = 1, 2, 3$; and $U_k(z_J; x), k = 1, 2, 3$. The three indifference conditions can then be expressed as

$$
\begin{aligned}
T_0(z_L; x_1^*) &= U_1(z_L; x_1^*), \\
T_2(z_H; x_2^*) &= E_2(z_H; x_2^*), \\
T_2(z_H; x_3^*) &= U_3(z_H; x_3^*).
\end{aligned}
$$

At x_1^*, a worker in the low state is indifferent between traditional sector work and entering the modern sector as unemployed. (A worker in the high state with ability x_1^* strictly prefers traditional sector work.) At x_2^*, a worker in the high state is indifferent between modern sector employment and traditional sector work. Finally, at x_3^* a worker in the high state is indifferent between traditional sector work and entering the modern sector as unemployed.

In Appendix Section C.2, we also write out the value functions in these three indifference conditions, taking account of the potential labor flows and probabilities in the relevant regions of Figure 8. We then complete the characterization of the solution of the stationary equilibrium.

Under the same conditions as in the model of Section 4, skill-biased technological progress will increase the labor force share of the modern sector (reduce x_3^*) and decrease the labor force share of the traditional sector (reduce x_1^*). The impact on the share of the labor force that churns between the traditional and modern sectors is ambiguous: some workers who chose the traditional sector when their traditional sector productivity was low will now choose the modern sector and be subject to churning, but some workers who chose the traditional sector when their traditional sector productivity was high will now always choose the modern sector.

C.1 Stationary u_1, u_2, u_3 and Total Gross Labor Flows

For workers with abilities between x_1^* and x_2^*, denote by e_1 the share of them who are employed in the modern sector. To solve for the unemployment rate u_1 we use the fact that in the stationary equilibrium the inflow and outflow of employed workers are equal: $(1-\pi)fu_1 = (1-\pi)se_1 + \pi e_1$. Substituting for e_1 using the fact that $e_1 + u_1 = 0.5$ yields $u_1 = 0.5[\pi + s(1-\pi)]/[\pi + (f+s)(1-\pi)]$.

For workers between x_2^* and x_3^*, we have $e_H + t_2 = 0.5$ and $e_L + u_2 = 0.5$, where e_H, e_L, t_2, and u_2 respectively denote the shares of workers with abilities between x_2^* and x_3^* who are employed in the high state, employed in the low state, in the traditional sector, or unemployed. Within this region, labor flows out of the traditional sector then equal πt_2, and gross labor flows between the modern and traditional sectors equal $2\pi t_2$.

To solve for t_2 and u_2 we use the facts that in the stationary equilibrium, outflows from t_2, e_L, and e_H equal inflows into t_2, e_L, and e_H, respectively:

$$\begin{aligned}
\pi t_2 &= s(1-\pi)e_H + s\pi e_L + (1-f)\pi u_2, \\
e_H - (1-s)(1-\pi)e_H &= (1-s)\pi e_L + f\pi u_2, \\
e_L - (1-s)(1-\pi)e_L &= (1-s)\pi e_H + f(1-\pi)u_2.
\end{aligned}$$

These conditions automatically guarantee the condition that the inflows into and outflows from the unemployed are equal: $\pi t_2 + s(1-\pi)e_L + s\pi e_H = f u_2 + (1-f)\pi u_2$. Substituting for e_H and e_L yields two equations in the two unknowns t_2 and u_2:

$$\begin{cases} (f+s)u_2 + st_2 = s \\ (f+s-1)\pi u_2 + (\pi + s - \pi s)t_2 = 0.5s \end{cases} \Rightarrow \begin{cases} u_2 = \frac{s(\pi+0.5s-s\pi)}{(f+s)(\pi+s-2s\pi)+s\pi} \\ t_2 = \frac{s[0.5(f+s)+\pi(1-f-s)]}{(f+s)(\pi+s-2s\pi)+s\pi} \end{cases}$$

We can now compute total gross labor flows between the modern and traditional sectors for workers with ability between x_1^* and x_3^*:

$$\begin{aligned}
&\text{Total gross labor flows} \\
=&\pi[G(x_2^*) - G(x_1^*)] + 2\pi t_2[G(x_3^*) - G(x_2^*)]. \\
=&\pi[G(x_2^*) - G(x_1^*)] + 2\pi \frac{s[0.5(f+s)+\pi(1-f-s)]}{(f+s)(\pi+s-2s\pi)+s\pi}[G(x_3^*) - G(x_2^*)].
\end{aligned}$$

The labor market for workers with abilities above x_3^* is exactly like the modern sector in the model of Section 4, hence $u_3 = \frac{s}{f+s}$.

C.2 Value functions and solutions

The solution of the stationary equilibrium is characterized by four unknowns: $\{x_1^*, x_2^*, x_3^*, \theta\}$. Accordingly, we have four equations to solve the four unknowns, including the three indifference conditions $T_0(z_L; x_1^*) = U_1(z_L; x_1^*)$, $T_2(z_H; x_2^*) = E_2(z_H; x_2^*)$, and $T_2(z_H; x_3^*) = U_3(z_H; x_3^*)$, plus one free entry condition.

We now write out the value functions in these three indifference conditions, beginning with the two value functions that do not involve flows between the modern and traditional sectors,

$T_0(z_L;x)$ and $U_3(z_H;x)$. We have

$$T_0(z_L;x) = A_T z_L + \delta[(1-\pi)T_0(z_L;x) + \pi T_0(z_H;x)],$$
$$T_0(z_H;x) = A_T z_H + \delta[(1-\pi)T_0(z_H;x) + \pi T_0(z_L;x)].$$

Solve to obtain

$$T_0(z_L;x) \equiv T_0(z_L) = \frac{A_T z_L}{1-\delta} + \frac{\delta\pi A_T(z_H - z_L)}{(1-\delta)(1-\delta-2\delta\pi)}.$$

$U_3(z_H;x) \equiv U_3(x)$ is obtained through the same derivation that yields equation (11) in the text:

$$U_3(x) = \frac{1}{1-\delta}[A_M b(A_M)x + \delta f \frac{\beta}{1-\beta}\frac{A_M x(1-b(A_M))(1-\beta)}{\beta\delta f + 1 - \delta + \delta s}].$$

We solve for $U_1(z_L;x)$ using the following five equations:

$$U_1(z_L;x) = A_M bx + \delta[(1-\pi)fE_1(z_L;x) + (1-\pi)(1-f)U_1(z_L;x) + \pi T_1(z_H;x)],$$
$$E_1(z_L;x) = w_1(x) + \delta[(1-\pi)sU_1(z_L;x) + (1-\pi)(1-s)E_1(z_L;x) + \pi T_1(z_H;x)],$$
$$T_1(z_H;x) = A_T z_H + \delta[(1-\pi)T_1(z_H;x) + \pi U_1(z_L;x)],$$
$$J_1(z_L;x) = A_M x - w_1(z_L;x) + \delta(1-s)(1-\pi)J_1(z_L;x),$$
$$J_1(z_L;x) = (1-\beta)[E_1(z_L;x) - U_1(z_L;x) + J_1(z_L;x)],$$

where the last two equations use the free entry condition ($V = 0$) and Nash bargaining, respectively.

$E_2(z_H;x)$ and $T_2(z_H;x)$ must be solved simultaneously. We use the following eight equations:

$$E_2(z_H;x) = w_2(z_H;x) + \delta[(1-\pi)sT_2(z_H;x) + (1-\pi)(1-s)E_2(z_H;x) + \pi sU_2(z_L;x) + \pi(1-s)E_2(z_L;x)],$$
$$T_2(z_H;x) = A_T z_H + \delta[(1-\pi)T_2(z_H;x) + \pi U_2(z_L;x)],$$
$$E_2(z_L;x) = w_2(z_L;x) + \delta[(1-\pi)sU_2(z_L;x) + (1-\pi)(1-s)E_2(z_L;x) + \pi sT_2(z_H;x) + \pi(1-s)E_2(z_H;x)],$$
$$U_2(z_L;x) = A_M bx + \delta[(1-\pi)fE_2(z_L;x) + (1-\pi)(1-f)U_2(z_L;x) + \pi fE_2(z_H;x) + \pi(1-f)T_2(z_H;x)],$$
$$J_2(z_H;x) = A_M x - w_2(z_H;x) + \delta(1-s)[\pi J_2(z_L;x) + (1-\pi)J_2(z_H;x)],$$
$$J_2(z_L;x) = A_M x - w_2(z_L;x) + \delta(1-s)[\pi J_2(z_H;x) + (1-\pi)J_2(z_L;x)],$$
$$J_2(z_H;x) = (1-\beta)[E_2(z_H;x) - T_2(z_H;x) + J_2(z_H;x)],$$
$$J_2(z_L;x) = (1-\beta)[E_2(z_L;x) - U_2(z_L;x) + J_2(z_L;x)].$$

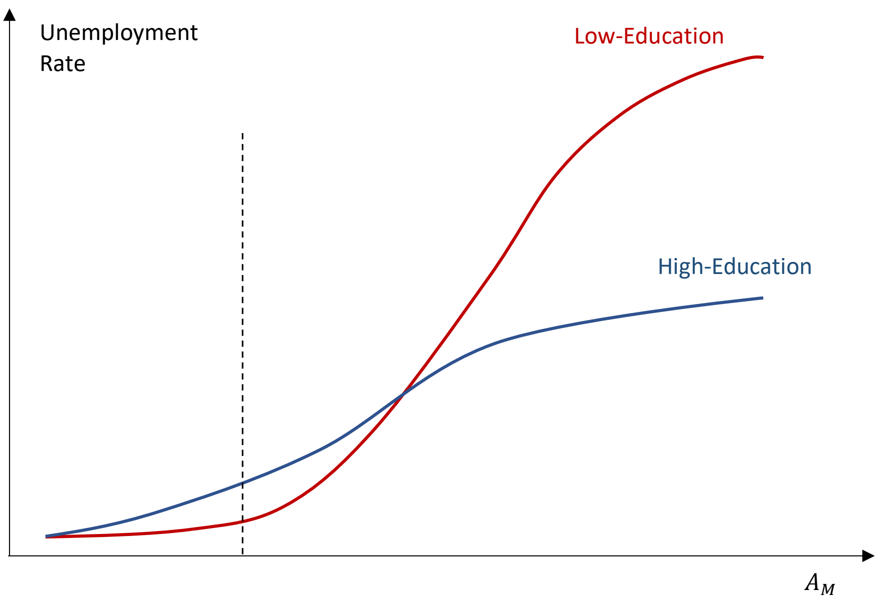
Finally, we complete the equations needed for the solution by expressing $\mathbb{E}\big(J(x|x \in \text{Modern})\big)$ in the simplified free entry condition $A_M c = \delta\eta\theta^{-\alpha}\mathbb{E}\big(J(x|x \in \text{Modern})\big)$:

$$\mathbb{E}\big(J(x|x \in \text{Modern})\big) = \frac{u_1(G(x_2^*)-G(x_1^*))\mathbb{E}J_1(z_L;x) + u_2(G(x_3^*)-G(x_2^*))\mathbb{E}J_2(z;x) + u_3(1-G(x_3^*))\mathbb{E}J_3(x)}{u_1(G(x_2^*) - G(x_1^*)) + u_2(G(x_3^*) - G(x_2^*)) + u_3(1 - G(x_3^*))},$$

where $\mathbb{E}J_1(z_L;x) = \frac{\int_{x_1^*}^{x_2^*} J_1(z_L;x)g(x)dx}{G(x_3^*)-G(x_2^*)}$, $\mathbb{E}J_2(z;x) = \frac{\int_{x_2^*}^{x_3^*} \left(\frac{e_L J_2(z_L;x)}{e_L+e_H} + \frac{e_H J_2(z_H;x)}{e_L+e_H}\right) g(x)dx}{G(x_3^*)-G(x_2^*)}$, and $\mathbb{E}J_3(x) = \frac{\int_{x_2^*}^{x_3^*} J_3(x)g(x)dx}{1-G(x_3^*)}$.

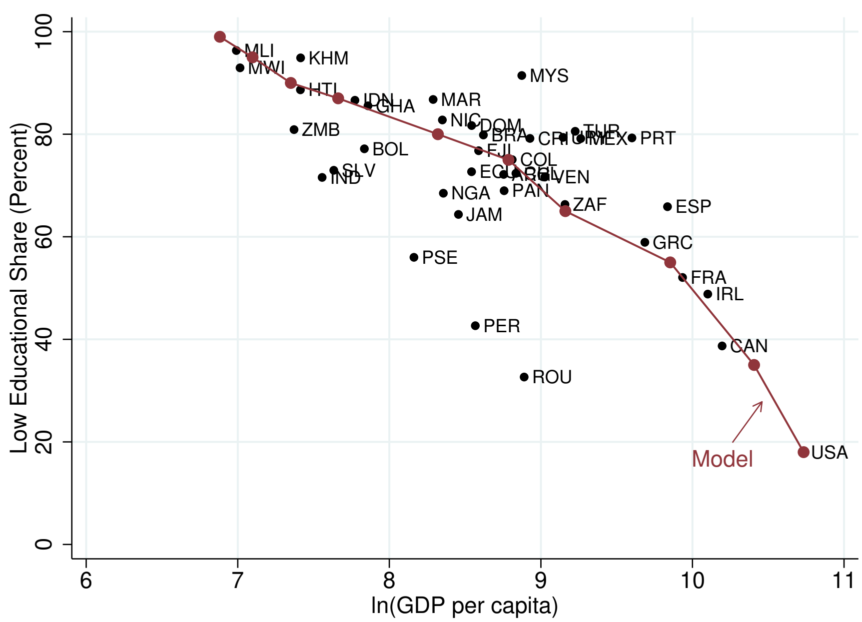
D Appendix Figures and Tables

Figure D1: High- and Low-educated Unemployment when A_M Increases



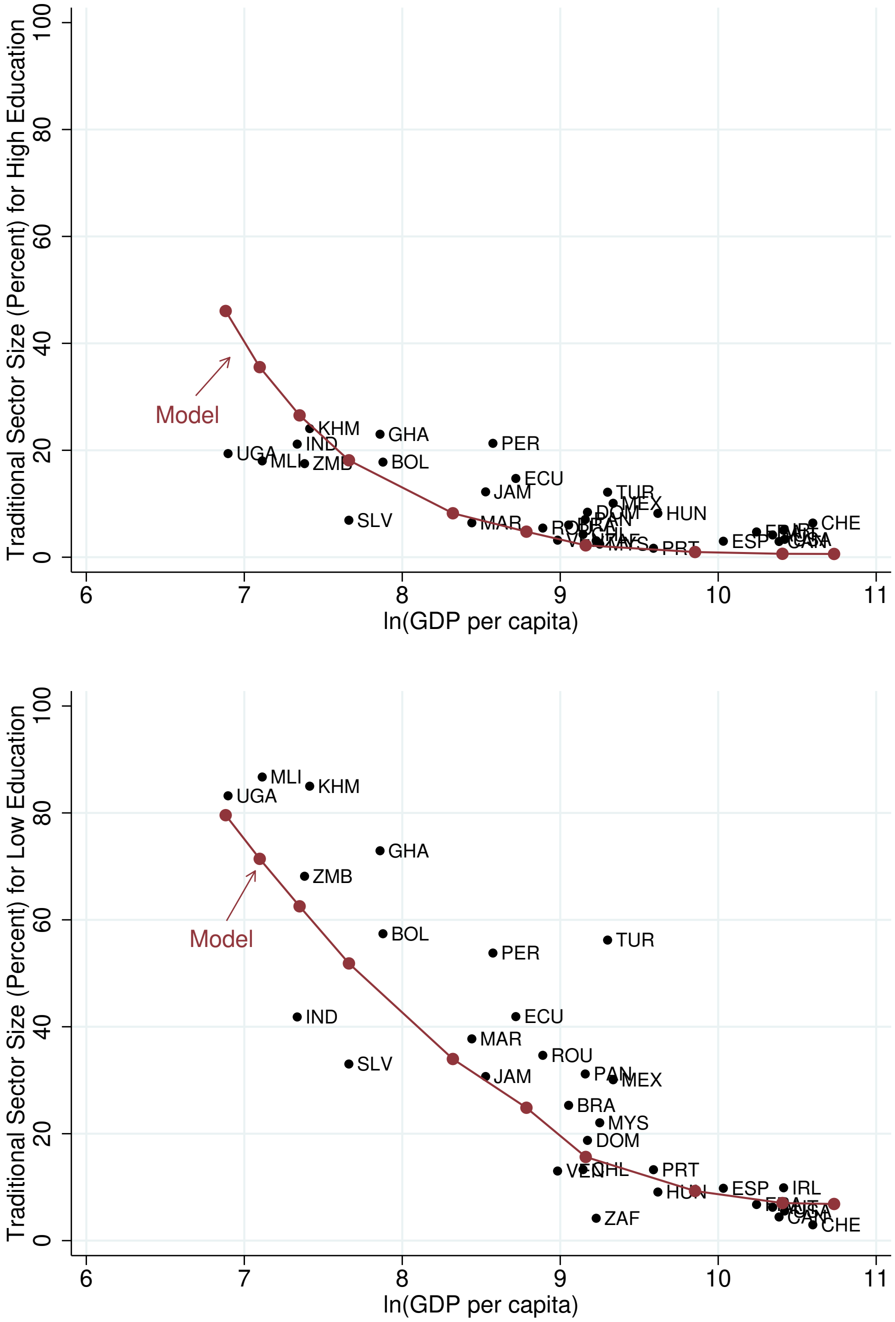
Note: This figure illustrates comparative statics of unemployment rates in A_M. The dashed line corresponds to the A_M at which Panel (b) of Figure 4 begins.

Figure D2: Low-Education Share, λ, in Model and Data



Note: This figure plots the values of λ used in the quantitative experiments of Section 5 (solid line), and the percent of the labor force that is low-educated in each of our countries (dots with identifiers). The data come from IPUMS. Low-educated individuals are defined to be those with less than a secondary school education.

Figure D3: Traditional-Sector Share by Education



Note: This figure plots the size of the traditional sector against log GDP per capita in the data and model. Each dot represents the average in a country with at least two observations across all years of data, and the solid line is the prediction of the quantitative model. The top panel is for high-educated workers, and the bottom is for low-educated workers.

Table D1: Home Production of the Unemployed

Income Quartile	Bottom	Top
Cooking	6.8 (3)	5.5 (5)
Cleaning	2.1 (1)	7.1 (5)
Childcare	5.6 (2)	4.1 (5)
Shopping	1.7 (1)	3.5 (5)
Collecting water and firewood	3.5 (3)	- (0)
Total Hours	19.7	20.2

Note: This table reports average weekly hours by the unemployed using data from the American Time Use Survey and Multinational Time Use Surveys. Average weekly hours for each activity are computed for the bottom and top quartile countries in which data have been collected. The number of countries is in parentheses. Observations in the bottom quartile include Ghana in 1998, Malawi in 2005, Uganda in 2005, and the top quartile Canada in 2005, France in 1998, Spain in 2002, the UK in 2014, the US in 2005.

Table D2: Definition of Traditional Sector Goods

Item	Details
Shoe Repair - Women Street Shoes	Replacement of 2 heels (glued and nailed); While-you-wait in shop service; Heel: Synthetic polyurethane, small heel.
Shoe Repair - Men Classic Shoes	Re-soling rubber soles (glued & nailed or stitched); Not "urgent" in shop service.
Shoeshine	Cleaning leather shoes with a brush and polishing; Manual work while keeping the shoes on; Exclude service in a shop.
Taxi	7 km in the town center on working days at 3 p.m.; Includes: Possible fixed starting fee + price per km; Excludes: Taxi called by telephone.
Men basic haircut	Scissor cut of short hair for male adults; Type of establishment: Common men's barber shop; No shampoo/washing nor styling/fixing products; Full price including tips if any.
Ladies haircut - curlers	Hair with curlers cut to medium (basic) for female adult; Shampoo/washing, blow drying, and styling/fixing products; Establishment: Common hairdresser (exclude hair stylist).
Manicure	Standard manicure on natural nails by nail technician; Establishment: Professional beautician; Full price including tips if any; Bath, filing, cuticles treatment, one-color varnishing.
Ladies haircut - long hair	Long hair cut to short for female adult; Shampoo/washing, blow drying, styling/fixing products; Establishment: Common hairdresser (exclude hair stylist).

Note: The table reports the definitions of each ICP traditional service used in Table 6, and described in Section 5.1. The services come from the unpublished ICP 2011 Global Core list of goods and services.

Table D3: Different Elasticity $\frac{1}{1-\sigma}$ but Matching Traditional Sector Slope

		Model Elasticity $\frac{1}{1-\sigma}$		
Slope Coefficients	Data	Lower	Benchmark	Higher
Aggregate traditional sector share	-19.9	-19.7	-20.0	-19.7
Traditional-sector share for low educated	-21	-19.0	-19.3	-19.0
Traditional-sector share for high educated	-5.1	-10.0	-10.5	-10.3
Aggregate unemployment rate	1.8	1.10	1.2	1.14
Unemployment rate for low-educated	3.4	2.4	2.4	2.3
Unemployment rate for high-educated	.58	.58	.60	.59
Ratio of unemployment rates $\frac{u_l}{u_h}$	.47	.37	.38	.37
Relative price P_T	.60	.78	.63	.52
Calibrated Elasticity of A_T to A_M, ψ_1		0.09	0.19	0.27

Note: This table reports the slope coefficients from regressions of the statistics in each row on log GDP per capita and a constant. The second column (Data) reports the slopes from our cross-country database, the third column (Lower) is for an elasticity of substitution between modern and traditional output of 3, the fourth column (Benchmark) is the benchmark model with an elasticity of 3.5, and the fifth column (Higher) is for an elasticity of 4.