Unemployment and Development

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Abstract

This paper draws on household survey data from countries of all income levels to measure how unemployment varies with income. We document that unemployment is increasing with GDP per capita. Furthermore, we show that 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. To interpret these facts, we build a model with workers of heterogeneous ability and two sectors: a traditional sector, in which self-employed workers produce output without reward for ability; and a modern sector, in which firms hire in frictional labor markets, and output increases with ability. Countries differ exogenously in the productivity level of the modern sector. The model predicts that as productivity rises, the traditional sector shrinks, as progressively less-able workers enter the modern sector, leading to a rise in overall unemployment and in the ratio of low-educated to high-educated unemployment rates. A calibrated version of the model accounts for some, but not all, of the cross-country patterns we document.

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1 Introduction

No single measure of labor-market performance receives more attention among academics and policy makers 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. But there is little systematic evidence about how unemployment rates vary across the entire world income distribution. Internationally comparable data from the poorest countries of the world are particularly lacking. This lack of data hampers research on the determinants of national average unemployment levels, and on the link between unemployment and development, to name two important topics.

This paper attempts to fill this gap by building a database of national unemployment rates covering countries of all income levels. To do so, we draw on evidence from 199 household surveys from 84 countries spanning 1960 to 2015. The database covers numerous rich countries and more than a 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 we 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. Our findings contrast with the (scarce) existing evidence in the literature, and in particular, the work of Caselli (2005), who finds in an earlier database that unemployment rates do not systematically vary with income per capita.

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. Our data imply that in rich countries, low-educated workers are more likely than high-educated workers to be unemployed. In poor countries, the opposite is true, and unemployment is concentrated among the high-educated.

To understand these facts, we build a two-sector model with frictional labor markets, based on the standard Mortensen and Pissarides (1994) framework, and heterogeneous workers that sort 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. Outputs of the modern and traditional sectors are gross substitutes, and firms operate competitively in the modern sector, with unrestricted entry. Countries differ exogenously in modern-sector productivity, with a single traditional-sector technology available to all countries. This assumption builds on the evidence in Caselli and Coleman (2006) and Malmberg (2016) showing that cross-country productivity differences are skill-biased, as opposed to the more common assumption of skill-neutral differences.[1]

Our model has several main theoretical predictions. First, in any economy, there is a unique cutoff in worker ability such that those below the cutoff work in the traditional sector, whereas those at or above the cutoff sort into the modern sector. Second, this cutoff is decreasing in the productivity of the modern sector. These two results hold since comparative advantage in the modern sector is increasing in both individual ability and modern-sector productivity. Third, the aggregate unemployment rate increases with modern-sector productivity, because workers are drawn out of the traditional sector into job search. Fourth, for any given ability level above the cutoff, the ratio of unemployment for workers lower than this ability level to those above it is increasing in productivity of the modern sector. Intuitively, this is because lower-ability workers are more likely than higher-ability workers to work in the traditional sector, where they are not searching. Hence, a greater share of them are drawn into job search when modern-sector productivity increases.

To assess the model's quantitative predictions, we calibrate a two-group extension of the model, in which each worker is either low-educated or high-educated, and the distribution of ability for the high-educated group stochastically dominates the low-educated distribution. We then draw on our micro data to compute the fraction of workers that have high or low education in each country. We calibrate the distribution of ability by type using the distribution of wages by education group in the United States, where the vast majority of labor force participants work for wages. We parameterize other aspects of the model according to the search literature and to match key moments of the U.S. labor market—in particular separation rates for low- and high-educated workers, and the U.S. average unemployment rate. We also allow productivity in the traditional sector to vary across countries, but by less than productivity in the modern sector.

Our main quantitative experiment is to lower productivity in the modern and traditional sectors, and then to compute how the model's predictions for unemployment – in the aggregate

[1] Micro evidence also points to skill-biased productivity growth in the developing world. In particular, Hjort and Poulsen (2018) show that the arrival of high-speed internet access in Africa raised employment almost entirely by increasing high-skilled jobs.

and by education level –vary with GDP per capita. We discipline the cross-country values of modern-sector productivity to match GDP per capita levels across the world income distribution, and we discipline traditional-sector productivity to match the relative prices of traditional goods. To compute the shares of employment in the traditional and modern sectors, we proxy the traditional sector in the data by the set of workers who are self-employed, with no employees other than other family members, and who work in occupations such as "day laborer" and "subsistence agriculture," which best correspond to our model's assumption that ability plays no role in traditional-sector production. Not surprisingly, we find that this share is strongly decreasing in GDP per capita, ranging from around three quarters of the workforce in the poorest countries to less than three percent in the richest countries. Note that this decrease in the traditional sector after excluding agriculture is also large, ranging from around fifty percent of the workforce to less than two percent.

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 0.8 percent. For unemployment by education, the model correctly predicts that the ratio of low- to high-educated unemployment is increasing in GDP per capita, with a ratio near one for the poorest countries. Yet it again underpredicts the magnitude of the relationship. We conclude that our mechanism explains some, but not all, of the relation between unemployment and average income. Though not targeted directly, the model's predicted employment share in the traditional sector by GDP per capita corresponds closely with the data.

We conclude by presenting historical data on unemployment from the United States and four other advanced countries: 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 at the one-percent level. Using the U.S. data, which we have at a more disaggregated level, we ask whether, in addition, 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. We conclude that historical unemployment data are broadly consistent with our cross-country findings.

Related Literature. Most of the literature on average unemployment differences across countries has focused on explaining Europe vs the U.S. (see, e.g., Blanchard and Summers, 1986; Ljungqvist and Sargent, 2008; Nickell, Nunziata, and Ochel, 2004). To our knowledge, no previous paper has used household survey data to measure how unemployment rates vary across countries of all income levels. Perhaps closest on this front is the handbook chapter by Caselli (2005), which compares unemployment rates in 1996 from the World Bank for countries covering a broad range of income levels (though none from the bottom quartile of the world income distribution). These data show no correlation between income per capita and average unemployment. A similar issue arises when comparing our study to Banerjee, Basu, and Keller (2016, p. 32), who find using World Bank statistics for 33 countries (none from the bottom third of the world income distribution) that unemployment rates for the high-educated are strongly decreasing in GDP per capita and unemployment rates for the low-educated are not related to GDP per capita. We conjecture that the discrepancies between our findings and those of Caselli and Banerjee, Basu, and Keller arise from the lower degree of international comparability in the World Bank data, and their smaller sets of countries.

Our paper is one of several recent studies that draw on detailed micro evidence to document new patterns in labor market indicators across countries. Bick, Fuchs-Schuendeln, and Lagakos (2018) use household surveys from 80 countries to measure average hours worked across countries by income level, documenting that hours worked are higher on average in poorer countries. Bridgman, Duernecker, and Herrendorf (2017) draw on household surveys from 43 countries to show that the share of household production in total hours decreases with GDP per capita. Note that neither of these studies on hours implies our findings for unemployment, since unemployment rates reflect additional information about individual job search and exclude information on hours of work.

In terms of the theory, our model is related to the frictional Roy model introduced by Moscarini (2001), as well as to several recent papers focusing on the sorting of heterogeneous workers in search and matching models, such as Lise and Postel-Vinay (2016) and Lindenlaub (2016). These papers are concerned with business cycle applications, while ours focuses on cross-country steady states. By its emphasis on the traditional sector, our paper relates to the work in macroeconomics focusing on home production to explain cross-country outcomes. For example, Parente, Rogerson, and Wright (2000) show that policies that distort capital accumulation can lead to bigger output losses once a home production sector is introduced into a standard neoclassical growth model; and Gollin, Parente, and Rogerson (2004) argue that measured output differences across countries may be overstated due to missing home production. Relatedly, Ngai and Pissarides (2008) present a model that emphasizes the transition into market production that comes with economic growth. None of these papers focuses on unemployment, per se, or models with frictional labor markets, as we do.

Finally, our paper builds on the old literature on two-sector models in development, particularly Lewis (1954) and Harris and Todaro (1970). However, our model is focused on the determinants of actual measured unemployment (often called "open unemployment"), as opposed to "underemployment" or "disguised unemployment," which corresponds to some extent to our traditional sector. Negative selection in our traditional sector is also quite related to the negative selection into the "informal sector" as characterized by Rauch (1991) and La Porta and Shleifer (2008, 2014). Unlike Harris and Todaro (1970), the urban-rural divide plays no role in our theory; we find similar unemployment patterns in both rural and urban areas and, hence, abstract from them. Our paper is also broadly related to the literature focusing on the prevalence of subsistence self-employment in poor countries (e.g. Feng and Rickey, 2016; Gollin, 2008; Schoar, 2010).

The rest of this paper is structured as follows. Section 2 describes the data and defines the survey tiers based on comparability. Section 3 presents the main empirical findings for unemployment rates by GDP per capita, in the aggregate and by education level. Section 4 presents the model and its main theoretical predictions. Section 5 discusses the parameterization and quantitative analysis. Section 6 presents supporting evidence from historical data before WWI and the U.S. time series. Section 7 concludes.

2 Data

This section describes the household survey data that we use 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 covers 199 country-year surveys, covering 84 countries, and spanning 1960 to 2015. Most of our data come from the 1990s and 2000s.[2]

In our main analysis, we restrict attention to males and females aged 25-54. We also report

[2]There are 11 surveys from earlier than 1990, 59 surveys from the 1990s, 88 surveys from the 2000s and 41 surveys from 2010 and later. Among them, there are 55 countries for which we have at least two surveys.

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.

Our GDP and population data are taken from Penn World Table 9.0. We divide output-side real GDP at chained PPPs (in 2005 US$) by population to obtain GDP per capita.

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 the labor force as all employed plus unemployed persons. We count those working in self employment as employed, consistent with the employment definition of the U.S. Bureau of Labor Statistics (BLS) and, to our knowledge, all other national statistical agencies.[3]

We measure the unemployment rate as the percent of workers in the labor force that are unemployed.[4]

The key measurement challenge we face is that not all of our surveys are conducted in the same way, and, more specifically, 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 covers all economic activities that produce output counted in the National Income and Product Accounts (NIPA). This definition comprises wage employment, self-employment or work at a family business, and it covers both agricultural and non-agricultural work, whether or not the output is sold. See e.g. Gollin, Lagakos, and Waugh (2014) for a more detailed treatment of which outputs are covered in NIPA. Not counted is work on home-produced services such as cooking, cleaning or care of one's own children. Home-produced services are not counted in NIPA, and previous studies of time use, such as Aguiar and Hurst (2007b), Ramey and Francis (2009) and Bick, Fuchs-Schuendeln, and Lagakos (2018), treat these categories as "home production" rather than as work.

[3]According to the 2008 U.N. System of National Accounts (SNA) Handbook, "Employment is defined 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).

[4]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 (from 24 countries) asked whether the interviewee is "available for work" in some way.

In Tier 3 countries, the employment question has lower scope for comparability. It may 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 how each country in Tier 3 has a non-standard employment question.

With regard to recent job search, Tier 1 includes surveys in which workers who searched either in the last week (Tier 1a) or the last four weeks (Tier 1b), in addition to having a standard employment question. 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. Appendix Tables A.1 and A.2 list the countries that comprise Tiers 1 and 2. Tier 3 includes surveys that use any time frame for job search, but have non-standard employment questions. There are 129 surveys of Tier 1, 40 of Tier 2 and 30 of Tier 3.

In our benchmark empirical findings below, we focus on surveys 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.

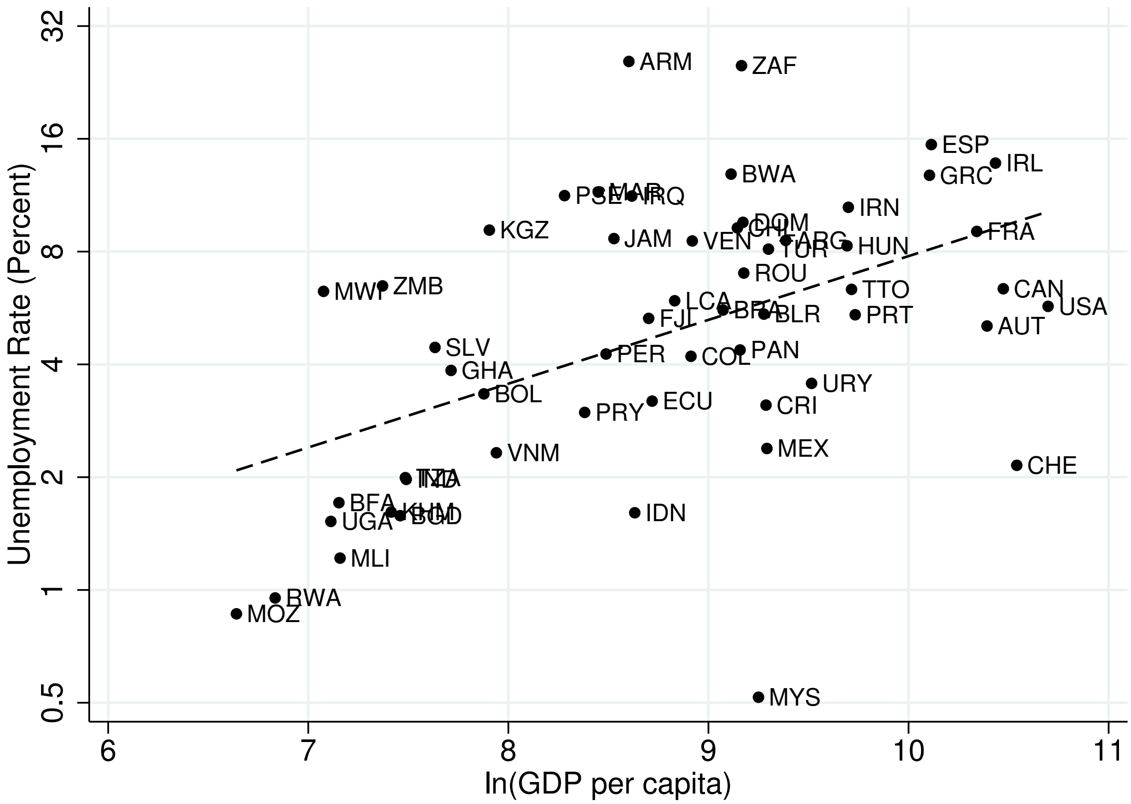
3 Empirical Findings

In this section, we report how unemployment varies with GDP per capita. We first compare aggregate unemployment rates, and then look beneath the surface at unemployment rates by sex, by age group and by rural-urban status.

3.1 Aggregate Unemployment Rate

Figure 1 plots the country average unemployment rate for prime-aged adults against log GDP per capita. The figure includes countries from all three tiers with at least two years of data. The vertical axis measures the base 2 log unemployment rate in order to compress the vertical dimension of the plot. 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. In the bottom quartile of the income distribution, average unemployment is 2.7 percent, whereas in the top quartile, it is 8.0 percent. Thus, average unemployment rates are increasing in GDP per capita.

Figure 1: Unemployment Rates by GDP per capita



Note: This figure plots the average unemployment rate for prime-aged adults across all years of data for each country with at least two years' observations, for Tiers 1, 2 and 3 of surveys. See the Data Appendix for more details.

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 falls somewhat to 1.1, and is again statistically significant at the one-percent level. When using only Tier 1 surveys, the slope coefficient becomes 1.4, and with Tier 1 and 2 surveys, the slope becomes 1.3. 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

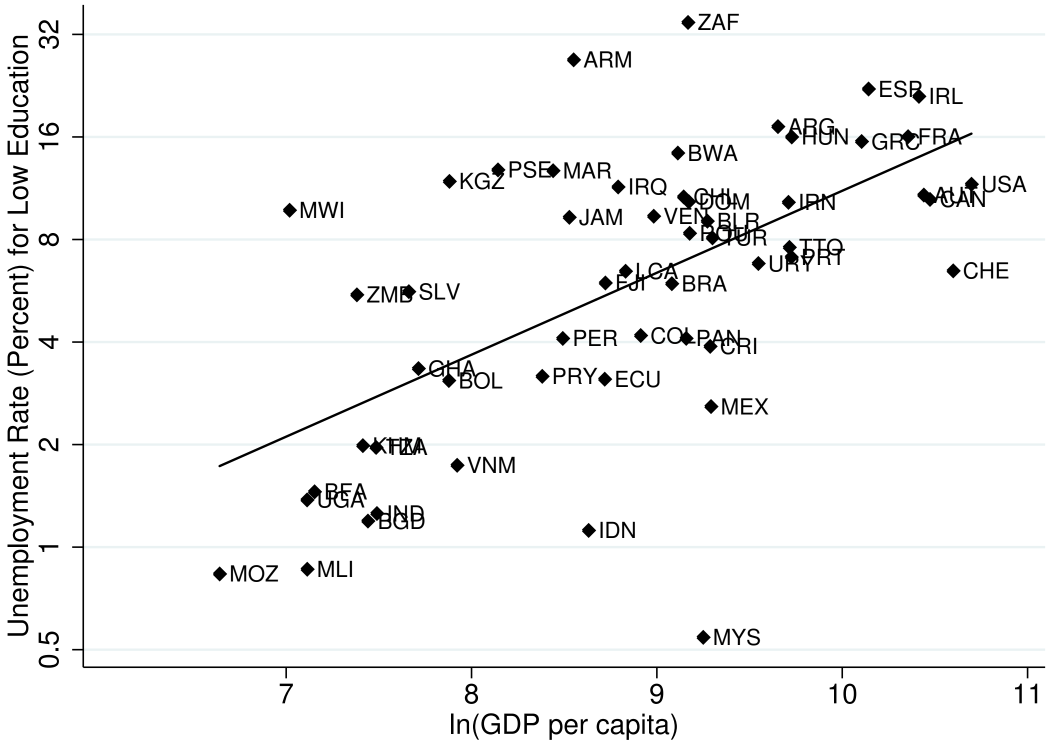
In this subsection, we report our findings by education level, which are quite helpful in accounting for the aggregate patterns we document above. Later we present results by other demographic groups.

We define two education groups, both for simplicity and because these two groups are sufficient for our purposes. We define the *low education* group to be workers whose highest education level is less than secondary school completed. 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. We define the *high education* group as those with at least secondary school completed. This could mean exactly secondary school, some college or university completed, or an advanced degree. Though our surveys are not standardized on educational attainment questions, there is a lot of comparability in practice, and it is unlikely that measurement error on this dimension is much of a limitation.

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 2.9 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 3.2. Across our Tier 1 surveys only, the slope is also 3.2, and when including both Tier 1 and Tier 2 surveys, the slope is 2.9, 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. All across surveys, the slope coefficient is -0.2 but with a standard error of 0.34. The estimated slopes are noisy and statistically insignificant for country averages, for Tier 1 and for both Tiers 1 and 2, as well.

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 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. Table 2 (third and fourth data columns) reports the average unemployment rates by income quartile, using country averages. For the poorest quartile of the world income distribution, the average unemployment rate is 2.9 percent for the less-educated. This rises to 8.2 percent in the second quartile, 9.4 in the third and 13.2 in the richest quartile. For the high-educated, the average unemployment rate is not monotonically increasing in income. It rises from 4.7 percent in the bottom quartile to 8.1 in the second, and then falls in the third and fourth quartiles. This is consistent with the relatively flat slope observed for the high-educated in

Figure 2: Unemployment Rates by GDP per capita, by Education Level



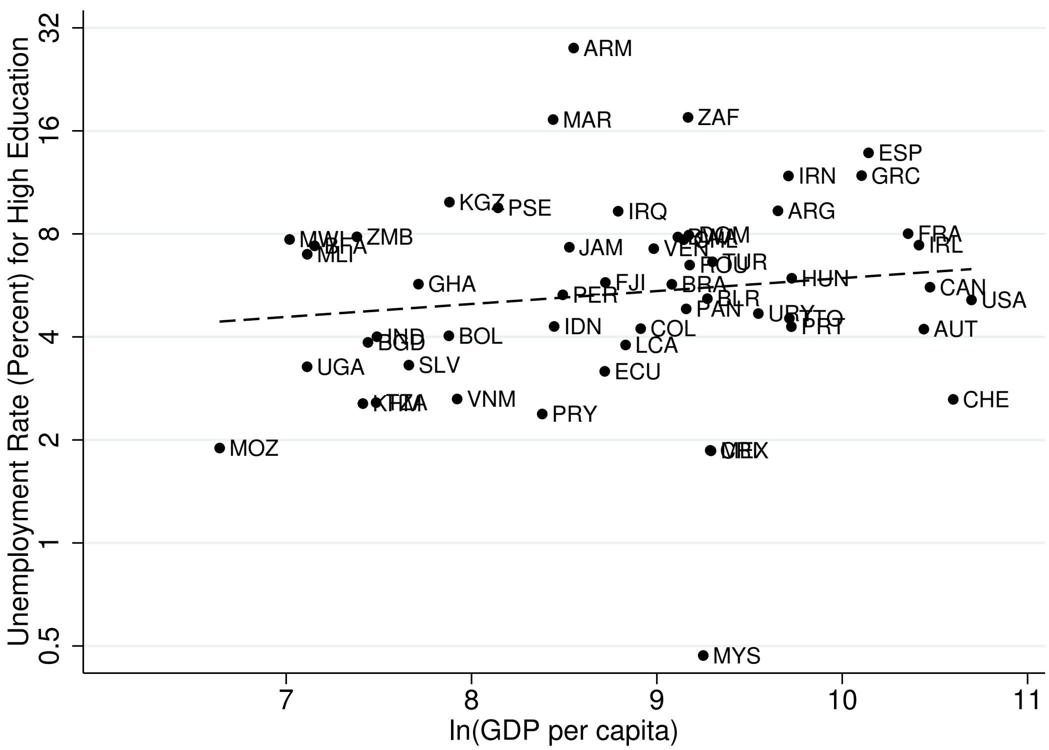


Table 1: Slope Coefficients from Regression of Unemployment Rate on log GDP per capita

	All Workers	N	Worker Education Group[a] Low	High	Ratio	N
All Surveys	1.1*** (.3)	199	2.9*** (.4)	-.2 (.3)	.5*** (.0)	195
Country Average	1.8*** (.5)	55	3.2*** (.6)	.5 (.4)	.5*** (.1)	54
Only Tier 1 Surveys	1.4*** (.3)	127	3.2*** (.4)	.4 (.3)	.5*** (.0)	127
Only Tier 1&2 Surveys	1.3*** (.3)	167	2.9*** (.4)	-.07 (.3)	.5*** (.0)	166

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: the average unemployment rate across all years for those with at least two years' observations. The third row includes only Tier 1 surveys. And the fourth row includes only Tier 1 and Tier 2 surveys. Surveys without education levels are dropped in the regressions by educational groups.

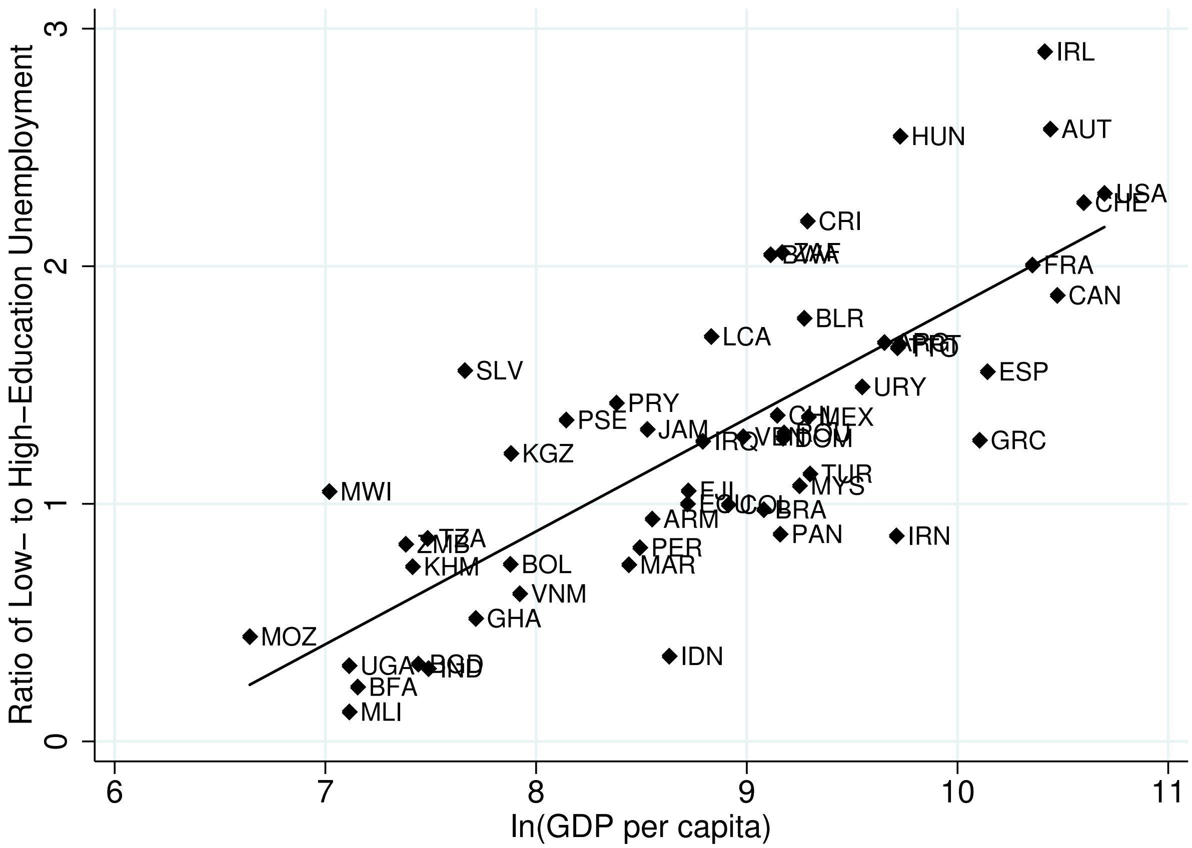
Figure 2.

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. Table 1 reports that a regression of this ratio on log GDP per capita yields a precisely estimated slope coefficient of 0.5 across all surveys, with little variation by data comparability tier.

3.3 Robustness

In this section, we explore whether our findings are present for different age groups, each gender alone, and in both rural and urban areas. Table 3 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

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



Note: This figure plots the average unemployment ratio of the low-educated workers over the high-educated workers for prime-aged adults across all years of data for each country with at least two years' observations, for Tiers 1, 2 and 3 of surveys. See the Data Appendix for more details.

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 3 reports the slope for prime-aged males only, excluding females due to potential concerns about labor force participation. Across all surveys and country averages, the low-educated have a statistically significant positive slope with GDP per capita, while the high-educated 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 25, those above age 55, and both sexes. The patterns hold separately for males only (third row), as well, while for females (fourth row), there is even a significant negative trend with GDP per capita among the high-educated. We conclude that our patterns are robust for both sexes.

When looking by age group, the low-educated always have a significant and positive rela-

Table 2: Unemployment Rates for Prime-Aged Adults by GDP per capita Quartile

			Worker Education Group			
	All Workers	N	Low Education	High Education	Ratio	N
Quartile 1	2.7	13	2.9	4.7	0.6	13
Quartile 2	7.6	14	8.2	8.1	1.1	14
Quartile 3	7.6	14	9.4	6.2	1.4	13
Quartile 4	8.0	13	13.2	7.3	1.9	13

Note: This table reports the average unemployment rate across all years available for each country, by quartile of the world income distribution.

tionship with GDP per capita, with the strongest relationship for those aged 16 to 24. The young high-educated have a significant negative slope with GDP, at least across all surveys; the prime-aged have an insignificant negative trend; and the old have a small but significant positive slope. Thus, our patterns are robust across age groups. Finally, we look separately at rural and urban individuals. For both groups, we see the same patterns: strong positive increases in low-educated unemployment with GDP per capita and insignificant slopes for the high-educated. Thus, our findings are present in both rural and urban areas.

Table 3: Robustness, Coefficients from 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***	-.3	195	2.9***	.4	54
	(.4)	(.3)		(.6)	(.3)	
Full Sample	3.3***	-.5	197	3.4***	.5	54
	(.4)	(.4)		(.7)	(.6)	
Males	2.9***	-.4	197	3.1***	.4	54
	(.4)	(.3)		(.6)	(.5)	
Females	3.8***	-.8*	197	3.9***	.3	54
	(.4)	(.5)		(.8)	(.8)	
Age 16-24	6.2***	-1.2	183	6.6***	.5	52
	(.7)	(.8)		(1.2)	(1.3)	
Age 25-54	2.9***	-.2	195	3.2***	.5	54
	(.4)	(.3)		(.6)	(.4)	
Age 55+	2.0***	.5*	173	2.4***	.8*	49
	(.4)	(.2)		(.6)	(.4)	
Rural	2.7***	-.02	107	3.4***	1.8*	29
	(.6)	(.7)		(1.0)	(1.0)	
Urban	2.5***	-.9	107	3.4***	.6	29
	(.9)	(.6)		(1.2)	(.8)	

Note: The table reports the slope coefficient from a regression 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.

4 Simple Model

4.1 Environment

We want our model to capture the transition from the traditional to the modern sector that occurs with development. With search frictions, this transition leads to increasing unemployment. The transition is especially strong for the low-educated, because they endogenously sort into the traditional sector at low levels of development. In our data, the traditional sector's employment share for prime-aged adults decreases by around 60 percentage points for the low-educated, but only by 15 percentage points for the high-educated, as we move from the poorest (Mali and Malawi) to the richest (Switzerland and Canada) countries.

Our model, therefore, has two sectors: a traditional sector in which workers are self-employed without returns to ability; and a modern sector in which firms hire workers subject to matching frictions, and production displays constant returns to ability.[5] We measure ability in efficiency units denoted by x. The technologies in the traditional and modern sectors, respectively, are given by:

$$Y_T = A_T N_T, \text{and} \tag{1}$$

$$Y_M = A_M X_M, \tag{2}$$

where Y_T, A_T and N_T are output, productivity and the number of workers in the traditional sector, and Y_M, A_M and X_M are output, productivity and the total number of efficiency units in the modern sector. Countries vary in their level of productivity A_M but not A_T, so technological change in our model is skill-biased.[6] Denote the price of traditional sector output relative to modern sector output by P_T . Here we assume the outputs of the modern and traditional sectors to be perfect substitutes for simplicity, so P_T is the unit price. We will relax this assumption in Section 5.

We now combine a Mortensen-Pissarides model of steady-state unemployment with a Roy model of selection into the modern versus the traditional sector. There is a unit measure of risk-neutral, infinitely-lived workers, each of whom is endowed with efficiency units drawn from a fixed distribution $G(x)$ on $[\underline{x}, \bar{x}]$. We assume that $G(x)$ is differentiable and let $g(x) \equiv G'(x)$ be its probability density function. There is also a continuum of risk-neutral, infinitely-lived firms, each of which can employ one worker. In this simple model, we assume undirected

[5] In Subsection 5.1 we will divide the modern sector into output from less- and more-educated workers, but the workings of the model are more easily understood if we begin with a unified modern sector. In addition, the modern sector is not equivalent to non-agriculture. For example, street vendors are non-agricultural producers but we would classify them into the traditional sector.

[6] In the quantitative version of our model below, we allow for countries to vary in A_T but less than in A_M.

search in the aggregate distribution of ability. In Section 5, relax these assumptions and allow for directed search in the group of less- or more-educated workers, and the two groups have different distributions of ability.

Steady State In the steady state, workers will not move between sectors in the absence of shocks. Denote by x^* the efficiency units of the marginal worker who is indifferent between self-employment and entering the modern sector unemployed. We will show below that the value of being unemployed is increasing in x; hence, in steady state, workers with $x < x^*$ prefer self-employment in the traditional sector, and workers with $x \geq x^*$ 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 $A_M c$.[7] Let the flow of matches be given by the constant returns to scale function

$$m(u, v) = \eta u^{\alpha} v^{1-\alpha}, \tag{3}$$

where u is the endogenous measure of unemployed workers and v is the endogenous measure of vacancies in the economy. Define $\theta \equiv \frac{v}{u}$ as "market tightness." The job-finding rate is then $f(u, v) \equiv \frac{m}{u} = \eta\theta^{1-\alpha}$, and the vacancy hiring rate is $q(u, v) \equiv \frac{m}{v} = \eta\theta^{-\alpha}$.

We assume that workers and firms separate at an exogenous rate s. Let $A_M bx$ denote the unemployment flow payoff,[8] where $0 < b < 1$. One rationale for this choice is that unemployment benefits are typically indexed to wages, which we will show scale with $A_M x$ in equilibrium. 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, Forthcoming; Mincer, 1991; Mueller, 2017). 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

$$U(x) = A_M bx + \delta\big[fE(x) + (1-f)U(x)\big] \tag{4}$$

$$E(x) = w(x) + \delta\big[sU(x) + (1-s)E(x)\big], \tag{5}$$

where $w(x)$ is the endogenous flow wage.

Because Firms will therefore be matched only with agents in the modern sector, who have efficiency units $x \geq x^*$. We can then specify the value of a job to a firm if matched with a

[7]We shall see later that, in equilibrium, wages scale with A_M. If the productivity of the vacancy posting process is not affected by A_M, the cost of posting a vacancy should also scale with A_M.

[8]Our results are qualitatively unchanged if we let $A_M b$ denote the unemployment flow payoff.

worker with efficiency units x and the value of maintaining a vacancy, respectively:

$$J(x) = A_M x - w(x) + \delta\big[sV + (1-s)J(x)\big] \tag{6}$$

$$V = -A_M c + \delta\big[q\mathbb{E}\big(J|x > x^*\big) + (1-q)V\big], \tag{7}$$

where $\mathbb{E}\big(J|x > x^*\big) = \frac{\int_{x^*}^{\bar{x}} J(x)g(x)dx}{1-G(x^*)}$ 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 $V = 0$. Let $S(x) \equiv E(x) - U(x) + J(x)$ denote the total surplus of a match, and $\beta \in (0, 1)$ be the Nash bargaining power of the worker. So the firm receives $(1-\beta)S(x)$ when a vacancy is filled. We can now solve the expressions for $U(x)$ and $w(x)$ in Appendix B.1. Equation (B.8) shows that $U(x)$ is increasing, as we asserted previously.

We also show in Appendix B.1 that steady state in the modern sector is characterized by the following relationship between θ and x^*:

$$c = \frac{(1-\beta)\delta\eta\theta^{-\alpha}}{\beta\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s}(1-b)\mathbb{E}(x|x > x^*). \tag{8}$$

Note that market tightness θ is unaffected by A_M for a given x^*. By equation (10) below, this implies that unemployment is unaffected by A_M for a given x^*. Thus, in the absence of a traditional sector, our model predicts that unemployment remains constant as per capita income increases. If b or c did not scale with A_M, θ would instead decrease with A_M for a given x^*, and in the absence of a traditional sector, our model would predict that unemployment decreases as per capita income increases.

Indifference Condition The value of staying in this sector is $\frac{A_T P_T}{1-\delta}$. The worker with efficiency units x^* is indifferent between staying in the traditional sector and entering the modern sector as unemployed:

$$\frac{A_T P_T}{1-\delta} = U(x^*) = \frac{1}{1-\delta}\left(A_M b x^* + \delta\eta\theta^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x^*(1-b)(1-\beta)}{\beta\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s}\right). \tag{9}$$

Unemployment Rate Let u_M denote the measure of the modern-sector unemployed and its steady-state value, we can write that the change in modern-sector unemployment $\dot{u}_M = (L_M - u_M)s - u_M f(\theta)$, where $f(\theta) = \eta\theta^{1-\alpha}$ is the steady state job finding rate and $L_M = 1 - G(x^*)$ is the labor that participates in the modern sector. We can then set $\dot{u}_M = 0$ to obtain the measure of steady-state modern sector unemployment $u_M = \frac{s\big(1-G(x^*)\big)}{s+\eta\theta^{1-\alpha}}$. Since the measure of workers is 1 and there is no unemployment in the traditional sector, the overall steady-state unemployment rate is the same as u_M:

$$u = \frac{s\big(1 - G(x^*)\big)}{s + \eta\theta^{1-\alpha}}. \tag{10}$$

4.2 Model Solution and Predictions

There are two endogenous variables in our model: market tightness θ and the cutoff ability level x^*. Proposition 1 summarizes the uniqueness of our model solution and the comparative statistics:

Proposition 1 *If an interior solution $x^* \in (\underline{x}, \bar{x})$ exists, the model solution (x^*, θ) is unique. And the cutoff ability x^* decreases as modern sector productivity A_M increases.*

Proof. See Appendix B.2. ■

Proposition 1 shows that an increase in modern sector productivity reduces x^*, drawing workers out of the traditional sector into the modern sector. This result has important implications on the unemployment rates. We demonstrate the two results below.

The first result is that aggregate unemployment increases with development. This occurs because development draws workers out of self-employment into search for wage employment. Because the workers drawn into search are less able, they reduce the expected value to the firm of a job match. Therefore market tightness decreases, i.e., the number of vacancies per unemployed worker declines.

Proposition 2 *The aggregate unemployment rate u increases as modern sector productivity A_M increases.*

Proof. See Appendix B.3. ■

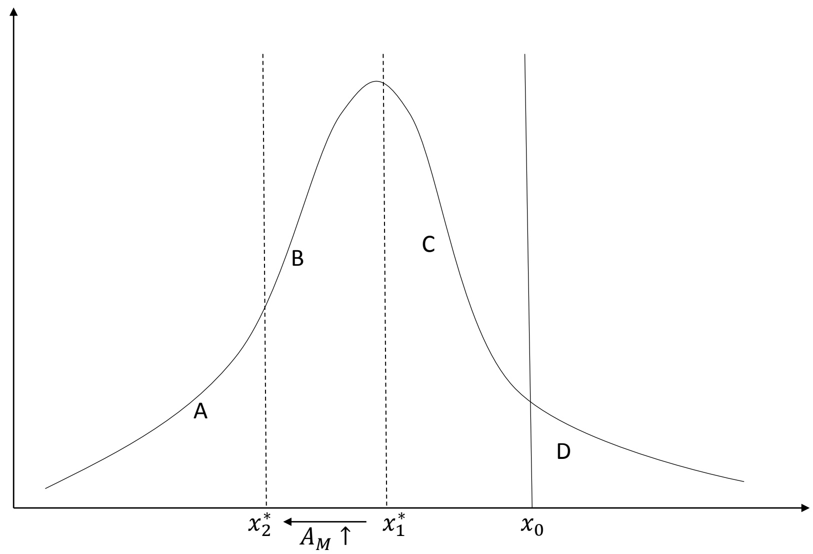
The second result is that unemployment of less able relative to more able workers increases with development. This occurs because less able workers are disproportionately drawn into job search. In this simple model, we think of the high-educated workers to be those have ability above a fixed value x_0. This value is set to be larger than the interior solution x^*.

Proposition 3 *The ratio of the unemployment rate for workers with ability lower than x_0 to that for workers with ability higher than x_0 increases as modern sector productivity A_M increases.*

Proof. The unemployment rate for workers with $x < x_0$ is a weighted average of $\frac{s}{s+\eta\theta^{1-\alpha}}$ for workers with $x^* < x < x_0$ and 0 for workers with $x < x^*$. Therefore

$$\mathbb{E}\big(u|x < x_0\big) = \frac{\frac{s}{s+\eta\theta^{1-\alpha}}\big(G(x_0) - G(x^*)\big) + 0G(x^*)}{G(x_0)} = \frac{\frac{s}{s+\eta\theta^{1-\alpha}}\big(G(x_0) - G(x^*)\big)}{G(x_0)}. \tag{11}$$

Figure 4: Comparative Statistics when A_M Increases



The ratio of this unemployment rate to the unemployment rate for workers with ability higher than x_0 is

$$\frac{\mathbb{E}\big(u|x < x_0\big)}{\mathbb{E}\big(u|x > x_0\big)} = \frac{\frac{s}{s+\eta\theta^{1-\alpha}}\big(G(x_0) - G(x^*)\big)}{G(x_0)} \Big/ \frac{s}{s+\eta\theta^{1-\alpha}} = 1 - \frac{G(x^*)}{G(x_0)}. \tag{12}$$

This ratio increases with A_M since x^* decreases with A_M, as proved in Proposition 1. ■

Figure 4 illustrates the comparative statistic results of Proposition 3. The area on the right-hand side of x^* represents the modern sector share and left-hand side the traditional sector. When the cutoff ability decreases from x_1^* to x_2^* as A_M increases, the modern sector share increases from area $C + D$ to $B + C + D$. The marginal workers in area B now enters the modern sector, increasing the unemployment rate of the low-educated workers relative to the high-educated. So the unemployment ratio increases with development.

5 Quantitative Analysis

In this section, we build a quantitative extension of the model and use it to assess the quantitative performance of the theory. To do so, we calibrate the model in quarterly measures to match features of the U.S. economy. We then lower A_M, use the data to discipline the changes in A_T, and compute the model's predictions over the full range of the world income distribution.

5.1 Quantitative Version of the Model

In the quantitative version of the model, we allow the outputs of the modern and traditional sectors to be imperfect substitutes. Let the aggregate production function take the constant-elasticity-of-substitution (CES) form:

$$Y = \left(\gamma Y_T^{\sigma} + (1-\gamma) Y_M^{\sigma}\right)^{\frac{1}{\sigma}},\ 0 < \sigma < 1, \tag{13}$$

where Y_T and Y_M are the aggregate outputs of the traditional and modern sectors, respectively, and the elasticity of substitution between them equals $\frac{1}{1-\sigma} > 1$. The importance of the assumption that the elasticity of substitution is greater than one will be made clear in the next subsection, and the assumption will be given empirical justification later. 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:

$$P_T = \frac{\partial Y / \partial Y_T}{\partial Y / \partial Y_M} = \frac{\gamma}{1-\gamma}\left(\frac{Y_M}{Y_T}\right)^{1-\sigma}. \tag{14}$$

Key predictions of our model concern traditional employment and unemployment by worker ability. Unfortunately, direct measures of ability across many countries are not available. Wage is a linear function of ability in our model, but we cannot observe wages for the self-employed in the traditional sector or the unemployed. Instead, for the purpose of quantifying our predictions regarding traditional self-employment and unemployment by ability, we use education as our proxy for ability. Specifically, we divide the labor force into two education groups: workers who did not finish high school and workers who have at least a high school diploma. These data are available for a relatively wide range of countries (in fact, for many more than for which we have wage data). We incorporate education into our model as a proxy for ability by assuming 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 $x \in (\underline{x}, \bar{x})$.[9] We assume employers can observe this education credential ex ante and divide the modern sector labor market into two search markets, one for each education level. Finally, we treat the outputs of modern-sector firms that search in the

[9]This condition is sufficient, but not necessary, for the results of this subsection. We verified that the distributions calibrated in the next subsection satisfy this condition.

high-education and low-education labor markets as perfect substitutes, and add them to obtain Y_M in equation (14).[10]

We also allow for the possibility that the separation rate for high-educated workers is less than for low-educated workers, though this is not necessary to obtain any of our qualitative results: $s_h \leq s_l$. All other parameters are assumed to be the same across the two labor markets.

We can now prove:

Lemma 1 *For any interior solution to the model with two labor markets, $x_h^* < x_l^*$.*

Proof. See Appendix B.4. ■

It follows from Lemma 1 and $G_h(x) < G_l(x)$ that the share of high-educated agents who are self-employed in the traditional sector is lower than the corresponding share of low-educated agents:

Proposition 4 *For any interior solution to the model with two labor markets, $G_h(x_h^*) < G_l(x_l^*)$.*

The equivalent comparative static results to Proposition 1 would be: increasing modern sector productivity A_M causes the shares of both high- and low-educated agents who are self-employed in the traditional sector fall (x_h^* and x_l^* both decrease). This result requires the endogenous relative price of traditional sector output P_T to increase but proportionately less than A_M. We will verify later this is true in the following sections.

The empirical application of an increasing unemployment rate in the simple model is less straightforward here. As A_M, and thus per capita GDP, increases, the high-educated relative to the low-educated labor force share tends to increase. If the high-educated unemployment rate is smaller than the low-educated unemployment rate, it is possible for the aggregate unemployment rate to decrease.

We cannot prove that the ratio of low-educated to high-educated unemployment rates must increase with A_M, which would be the equivalent of Proposition 3. However, we can establish a strong presumption that our calibrated model will display this property. The basis for Proposition 3 is that, as A_M increases, participation in the modern sector by workers with low ability increases relative to participation by workers with high ability. We can expect, similarly, that as A_M increases, participation in the modern sector of less-educated workers will increase proportionately faster than participation of more-educated workers. The reason is that less-educated workers' participation in the modern sector must be lower according to

[10] Equivalently, these outputs could be imperfect substitutes but traded internationally, so that their price relative to each other is fixed, and both prices vary together against the price of (non-traded) traditional sector output.

Proposition 4, but both participation rates must approach 100 percent as A_M increases. In our quantitative predictions in Subsection 5.3 below, participation of less-educated relative to more-educated workers in the modern sector does indeed increase as A_M, and thus per capita GDP, increases.

5.2 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 use the unemployment benefits replacement rate of 45 percent. This is in line with the 40 percent used by Shimer (2005) and the 50-60 percent in Krueger and Mueller (2010). We also normalize the mean of the ability for low-educated workers to be one.

We set the elasticity of substitution between traditional and modern goods to be 3 in our benchmark calibration, though we explore sensitivity to this parameter, as we describe below. Our elasticity of substitution relates to some extent to the elasticity of substitution between home and market goods that is the subject of the large literature emphasizing home production in the macroeconomy (see e.g. Benhabib, Rogerson, and Wright, 1991). Aruoba, Davis, and Wright (2016) choose a value of 1.8, and argue that this is close to the midpoint of the range suggested by previous estimates in this literature. For example, Rupert, Rogerson, and Wright (1995) use panel data from the PSID with evidence on time spent in home production and market work, and estimate an elasticity of substitution between 1.8 and 2.0. McGrattan, Rogerson, and Wright (1997) and Chang and Schorfheide (2003) use U.S. time series data and come up with estimates of 1.5 to 1.8 and 2.3 respectively. Aguiar and Hurst (2007a) draw on detailed household-level data on market goods consumption and time spent on home production, such as cleaning, cooking and home repair. They estimate an elasticity of substitution of 2.1 when considering all home production categories in their data.

Though our model's elasticity is related to these, 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 sector may be getting older shoes shined and repaired (from an own-account 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 a median estimate of around 2.2 to 3.7 across goods categories.[11] Our benchmark value of 3 is right in the middle of their estimates, though since there is not a more precise value suggested by the literature, we explore a lower value of 2.5, closer to the home-production literature, and a higher value of 3.5, close to the upper end of the values estimated by Broda and Weinstein (2006).

We calibrate the remaining eight parameters to jointly match eight moments in the data. These 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 the 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 the low-educated workers, s_l; and, finally, (viii): the maximum value of A_M, which corresponds to the U.S. level.

The eight moments are: (i) the ratio of the average modern-sector wages for the high- over low-educated that we calculated using the 2000 Census 5% 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 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); and (viii) an average employment share of two percent in the traditional sector (as we explain below).

We define the traditional sector as the intersection of own-account self-employed workers and occupations with low skill content – in particular, shop and market sales, skilled agricultural and fishery workers, crafts and related trades workers, plant and machine operators and assemblers, and elementary occupations. 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 6

[11] We are not aware of any estimates of substitution elasticities between goods with low and high levels of skill inputs. On the production side, the closest estimate would be for the substitution elasticity between high- and low-skilled labor in the aggregate production function; Autor (2002, pg. 11) argues that the "consensus across estimates for the U.S." is that this elasticity is approximately two.

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 - unemployed benefits	0.45
$\frac{1}{1-\sigma}$ - elasticity of substitution	3
$A_{T(US)}$ - US traditional-sector productivity	1
m_l - mean of ability distribution for low-educated workers	1
Panel B: Calibrated Parameters	
m_h - mean of ability distribution for high-educated workers	1.66
v_l - variance of ability distribution for low-educated workers	0.45
v_h - variance of ability distribution for high-educated workers	1.15
c - vacancy cost	0.15
η - matching efficiency	0.85
γ - 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

below. 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 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.

Table 5: Moments Targeted in the Model vs Data

Moment	**Target**	**Model**
Ratio of average wage for the high- vs low-educated	1.60	1.61
High-edu log(wage) variance	0.34	0.33
Low-edu log(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	5.69
U.S. % expenditure share of traditional sector	$<$2.0	0.67
U.S. ratio of unemployment rates u_l/u_h	2.31	2.32
U.S. traditional sector employment share	2	1.84

This corresponds to a quarterly separation rate of around 10 percent.[12]

We report each moment and its model counterpart in Table 5. Overall, the model matches the desired moments quite well. Although all of the eight parameters 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. Finally, the maximum A_M value governs the traditional sector size in the richest country (the United States).

Technological change that is skill-biased across countries is a core assumption of our model. The assumption that technological change in the traditional sector is zero, however, is an oversimplification. In our quantitative exercise we allow for an elasticity of technological

[12]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 price of traditional relative to modern output, P_T, is around 0.01 in the United States in our calibrated model.

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

Shoe Repair - Women's Street Shoes	.39*** (.002)	Men's basic haircut	.61*** (.001)
Shoe Repair - Men's Classic Shoes	.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 C1 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.

change in the traditional sector with respect to technological change in the modern sector that is less than one. We calibrate this elasticity by using the fact that greater increases in A_T will result in smaller increases in P_T as GDP per capita increases, all else equal. Specifically, we target the elasticity of the relative price of traditional goods with respect to GDP per capita.

We draw on disaggregated evidence 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 are have low skill content and are likely to be provided by 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 7km 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 C1 provides the exact definitions of these eight traditional sector services. Since investment goods largely fit our definition of a 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 0.60. In our calibration procedure, we assume that $\log(A_T) = \theta_0 + \theta_1 \log(A_M)$, where θ_1 is the parameter used to target the relative price elasticity. This yields $\theta_1 = 0.26$, with the intercept θ_0 determined implicitly by our normalization of A_T to be one in the United States.[13]

5.3 Quantitative Predictions

With the model calibrated to the U.S. data, we then lower A_M, A_T and the fraction of workers that are low-educated, which we denote by λ. We discipline λ directly using data on the fraction of workers with less than high school education across our set of countries.[14] After solving each economy, we use the equilibrium prices P_T from all economies to compute a single international price, the average of P_T weighted by traditional-sector output in each economy. We use this international price to compute the values of model outputs for all economies, including the U.S., and then scale all output values such that the richest economy matches the U.S. GDP per capita of exp(10.7) or \$44,355.

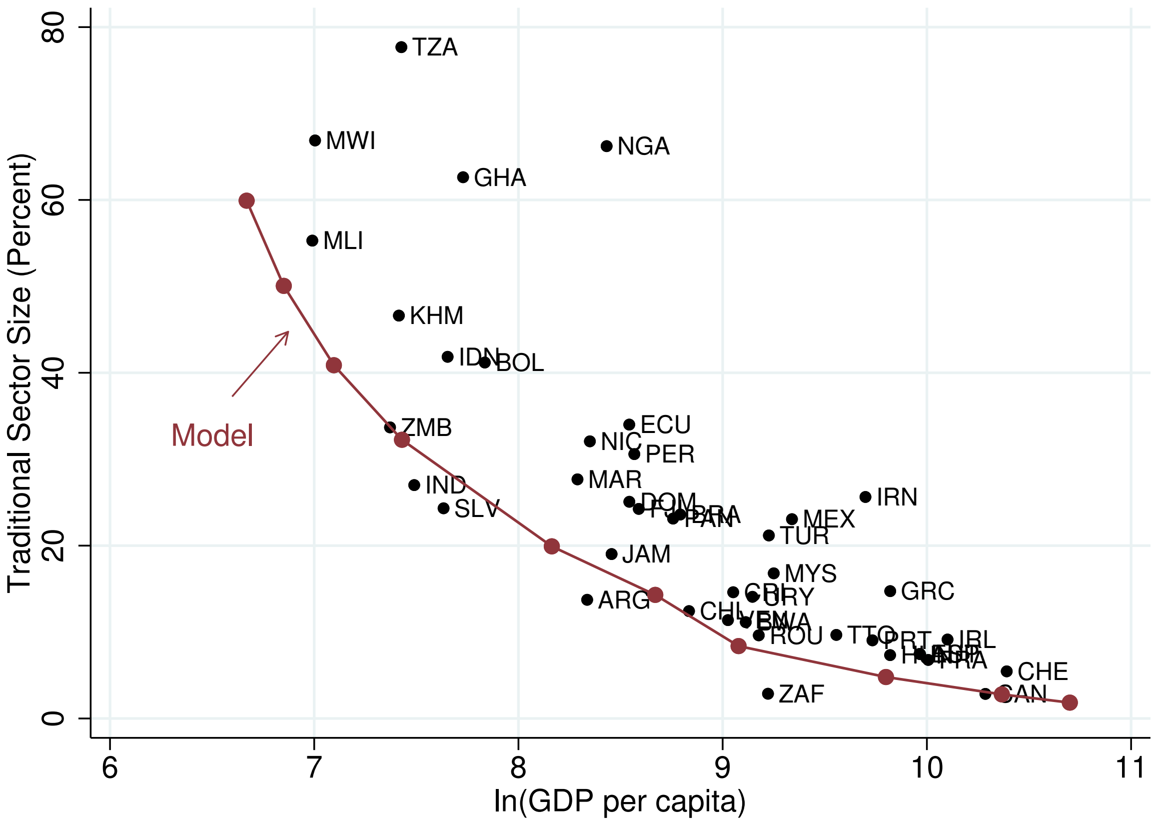
Figure 5 plots the traditional-sector size in the model and data. As GDP per capita decreases from the U.S. level, our model predicts an increase in the traditional-sector size from two percent to almost 60 percent. This is largely in line with our data. Furthermore, our model gets the curvature largely correct – in particular, the convex relationship between traditional-sector share and GDP per capita. 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 at a faster rate, its size increases faster.

To emphasize the mechanisms further, Figure 6 plots the traditional-sector shares by education level. As in the data, the model predicts decreasing relationships between the traditional sector shares and per capita GDP for both groups. Crucially, it predicts much higher shares of traditional sector employment for the low-educated in poor countries. As A_M rises, there are more low- than high-educated workers to sort out of the traditional sector, and as a result unemployment rises more for the low-educated (as in the data). This differential rate of exodus from the traditional sector as A_M rises is thus key to our theory, and Figure 6 shows that the magnitudes here are largely consistent with the data. Note that the aggregate traditional-sector share in Figure 5 is nearly the same as the low-educated traditional sector share in Figure 6, because the labor force in poor countries is dominated by low-educated

[13] Specifically, to match the elasticity of relative price to GDP per capita, we have to solve the full set of countries in the model with potential values of θ_1. In contrast, we only need to solve one country in the model to calibrate the eight U.S. moments.

[14] Appendix Figure C1 plots the low-education shares in our model and data.

Figure 5: Traditional-Sector Share in Model and Data



workers.

Figure 7 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 less than 4 percent to the calibrated value of 5.7 percent. This is similar to the magnitudes in the data, though the model somewhat 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.

Figure 8 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 the model underpredicts the steepness of this relationship. The model predicts that this ratio is just above one for the poorest countries, whereas in the data, the ratio is closer to 0.5.

Table 8 reports the slope coefficients from regressions of the unemployment rate and other

Figure 6: Traditional-Sector Share by Education

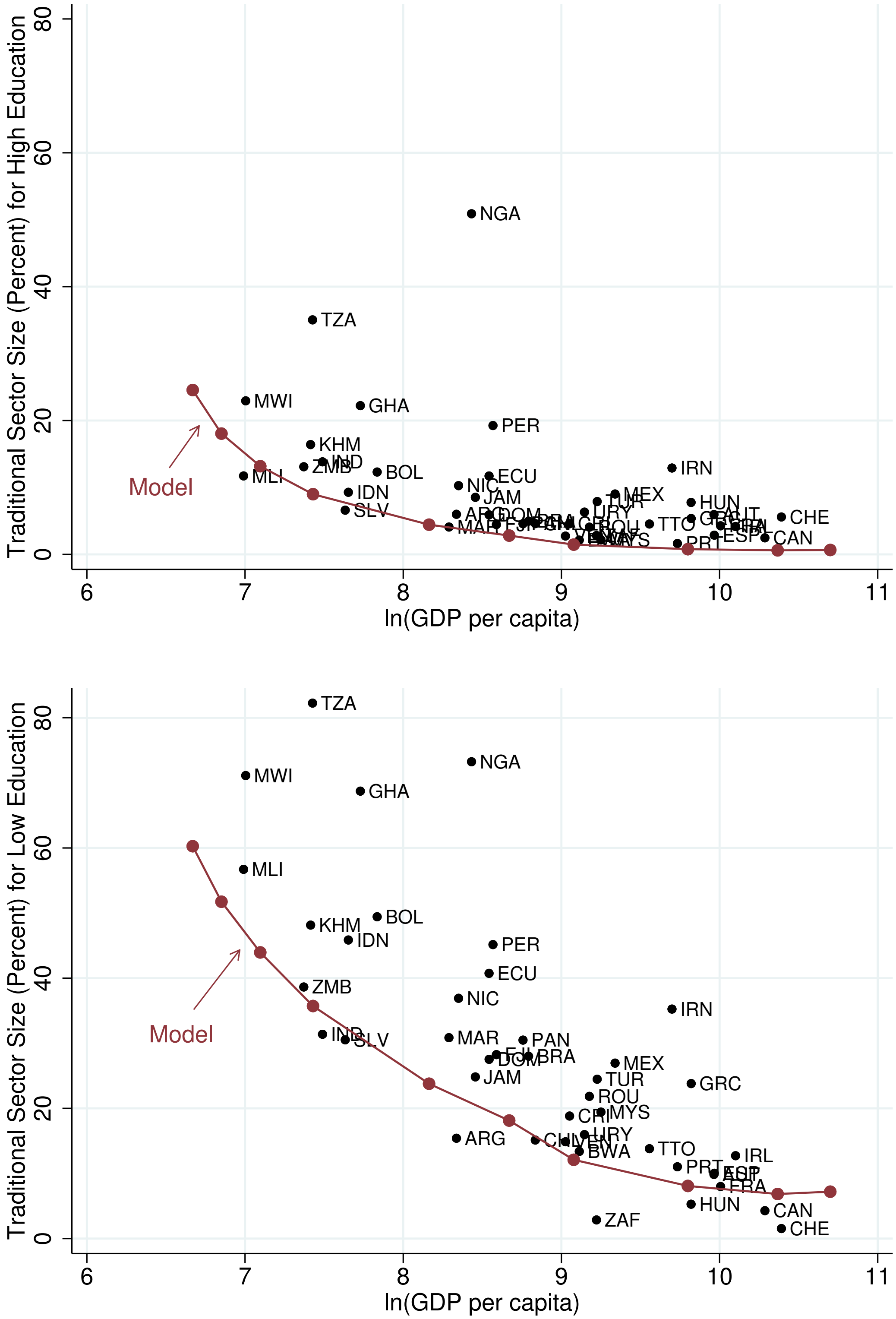


Figure 7: Unemployment Rates in the Model and Data

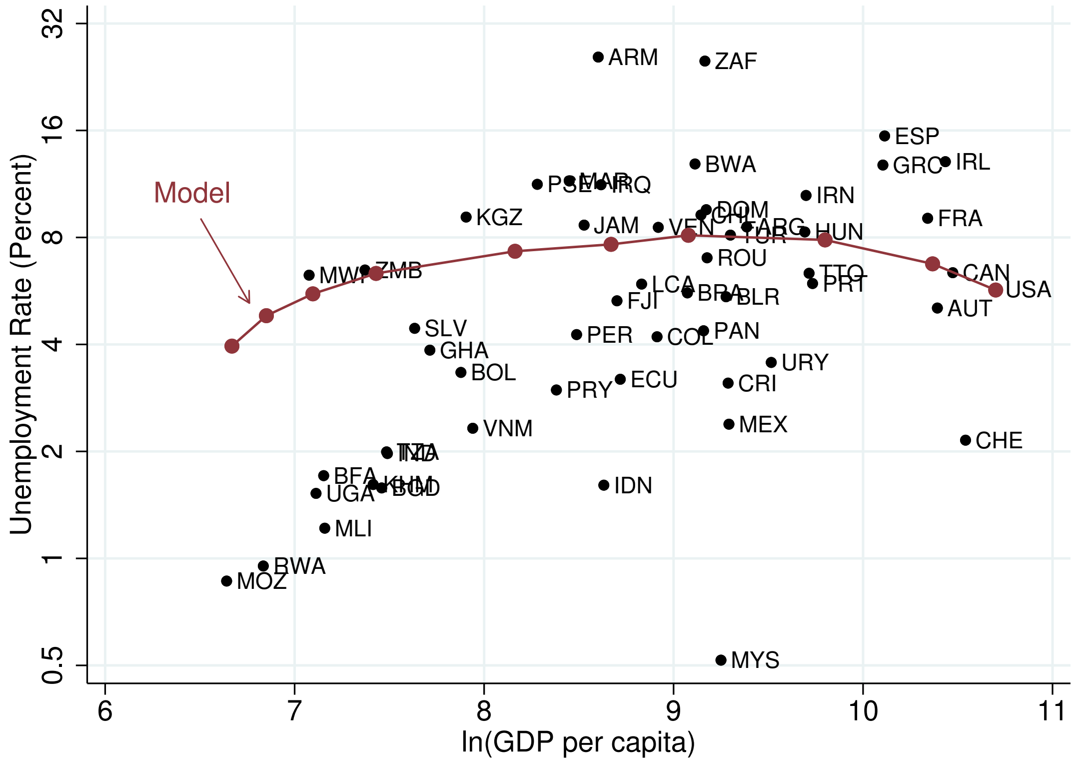
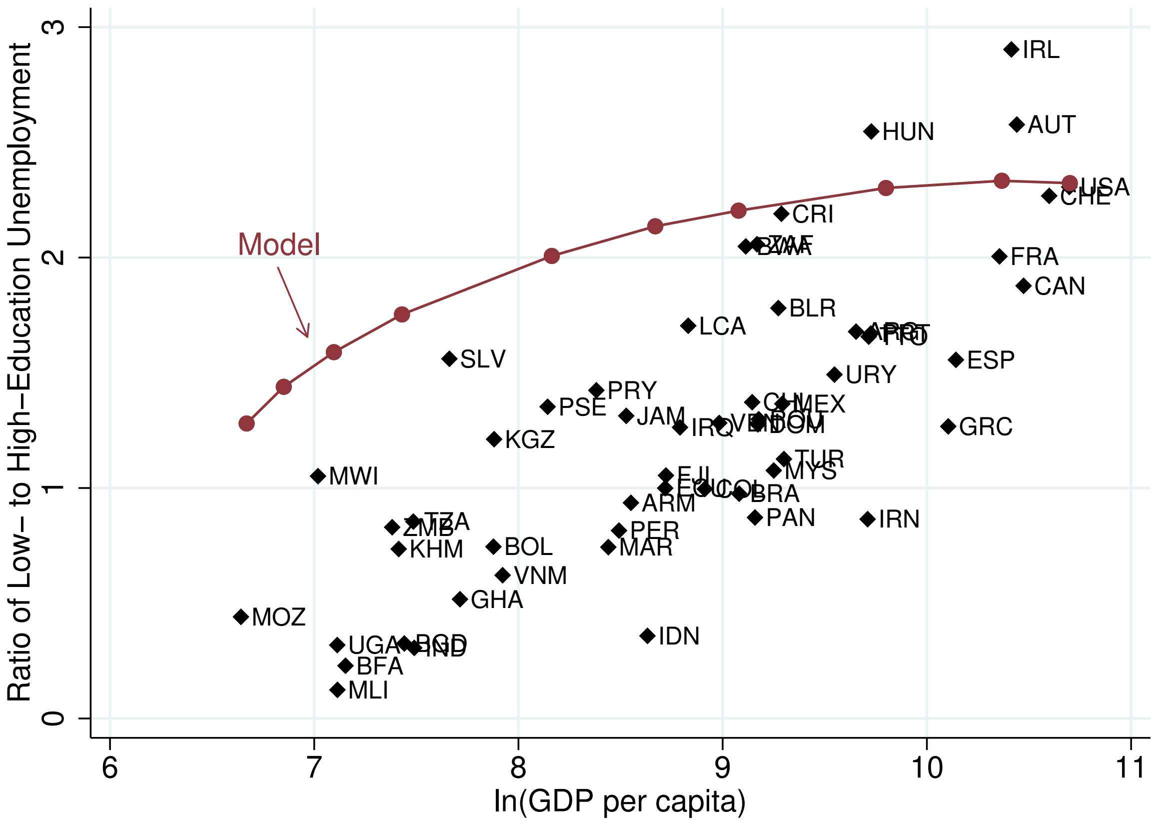


Table 7: Slope Coefficients in Data and Model

	Data	Model
Aggregate Traditional Sector Share	-15.9	-13.4
Traditional-Sector Share for Low Educated	-16.7	-12.7
Traditional-Sector Share for High Educated	-4.9	-5.0
Aggregate Unemployment Rate	1.8	0.5
Unemployment Rate for Low-Educated	3.2	1.7
Unemployment Rate for High-Educated	0.5	0.4
Ratio of Unemployment Rates u_l/u_h	0.5	0.3
Relative price P_T	0.6	0.6

key variables for the 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 0.7 compared to 1.8 in the data. Thus, the model accounts for around 30 percent (0.5/1.8) of the empirical relationship between unemployment and log GDP per capita. Unemployment

Figure 8: Unemployment Ratio in the Model and Data



rates for the low-educated have a semi-elasticity of 1.7 in the model, compared to 3.2 in the data. The high-educated semi-elasticities are fairly similar, at 0.4 in the model and 0.5 in the data. The ratio of low- to high-educated unemployment rates is 0.5 in the data and 0.3 in the model. Largely consistent with the above discussions, the model yields magnitudes similar to the data but underpredicts the empirical elasticities. Traditional-sector slopes are similar in the model and data, at -15.9 in the model and -13.4 in the data.

In our baseline 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. Furthermore, in the model, higher benefits in richer countries do help explain the aggregate unemployment patterns but are largely unrelated to the ratios. To study the quantitative role of varying b values, we now calibrate the model using increasing b values from 0 in the poorest country to 45% in the US.

Panel A of 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 baseline model and the model with varying b values. The model with varying b values predicts an aggregate

Table 8: Aggregate Unemployment Rate and Ratio in Model and Data

Panel A: Slope Coefficients

	Data	Baseline	Explained %	Varying b	Explained %
Aggregate Unemployment Rate	1.76	0.52	30	0.72	41
Ratio of Unemployment Rates u_l/u_h	0.47	0.25	53	0.26	55

Panel B: Top Quartile Minus Bottom Quartile

	Data	Baseline	Explained %	Varying b	Explained %
Aggregate Unemployment Rate	5.32	2.24	42	2.78	52
Ratio of Unemployment Rates u_l/u_h	1.28	0.66	51	0.69	54

unemployment rate elasticity of 0.72, compared to 0.52 in the baseline model. This accounts for 41 percent of the empirical relationship in data, which is 11 percentage points higher than our baseline model. For the unemployment ratio, the model with varying b values has an elasticity of 0.26, very similar to 0.25 in the baseline model. In addition, Panel B of Table 8 reports the difference of average unemployment rates and ratios for the top and bottom income countries, both in the data and in two versions of the model. The top quartile income countries in our sample has an average unemployment rate of 8.02 percent compared to the 2.70 for the bottom quartile countries. The difference is 5.32 percentage points. The model with varying b values can account for 52 percent of this unemployment rate difference, compared to 42 percent for the baseline model. For the unemployment ratio difference, the two versions of model have similar explanatory power, 51 percent for the baseline model and 54 percent for the model with increasing b values.

5.4 Sensitivity Analysis

As noted above, the literature provides us with a range of plausible elasticities of substitution rather than a single firm value. In this section, we explore the sensitivity of our model's predictions to the value for the elasticity of substitution. We compute the model's predictions in particular for elasticities 2.5 and 3.5 in addition to the benchmark value of 3.

We present the results in Table 9. Each row reports the slope coefficient from a regression of the variable in question on log GDP per capita. The first column is the data slope coefficients; the second is that of the benchmark model (reproduced from Table 7); and the third and fourth columns are slopes coefficients in the model with the lower and higher values of the substitution elasticities. For the lower value of 2.5, the model underpredicts the slope of the traditional sector shares in log GDP per capita. As such, the aggregate unemployment rate

Table 9: Sensitivity Analysis of Model Elasticity, $\frac{1}{1-\sigma}$

	Data	Benchmark	$\frac{1}{1-\sigma}=2.5$	$\frac{1}{1-\sigma}=3.5$
Aggregate Traditional Sector Share	-15.9	-13.4	-9.2	-17.1
Traditional-Sector Share for Low Educated	-16.7	-12.7	-8.4	-16.4
Traditional-Sector Share for High Educated	-4.9	-5.0	-2.6	-7.8
Aggregate Unemployment Rate	1.8	0.5	0.1	0.9
Unemployment Rate for Low-Educated	3.2	1.7	1.2	2.1
Unemployment Rate for High-Educated	0.5	0.4	0.2	0.5
Ratio of Unemployment Rates u_l/u_h	0.5	0.3	0.2	0.3
Relative price P_T	0.6	0.60	0.64	0.56

varies less with GDP per capita (0.1 versus 0.5 in the benchmark model), as do unemployment rates for low-educated (1.2 versus 1.7 in the benchmark) and high-educated (0.2 versus 0.4 in the benchmark). The ratio of low-to-high unemployment rates is also lower than in the benchmark (0.2 versus 0.3). The relative price varies more than in the benchmark (0.64 versus 0.60).

For the higher value of 3.5, the model over-predicts the slope of the traditional sector share in log GDP per capita. The unemployment rate varies substantially more with GDP per capita than in the benchmark, both in the aggregate and by education level. The unemployment ratio has a slope of 0.5 compared to 0.3 in the benchmark, and matching the 0.5 in the data.

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 undoes the rise in A_M as we move from the poorest to the richest country. In the benchmark setup, the slope of this ratio on log GDP per capita is 0.87 in the benchmark model, just 0.79 when the elasticity is 2.5, and 0.95 when the elasticity is 3.5. That is why the model predicts so much more change in unemployment when the elasticity is 3.5 than when it is 2.5.

We conclude that the model is sensitive to values of the elasticity of substitution between modern- and traditional-sector output. For our benchmark value of 3 the model explains the traditional-sector employment share across countries quite well, suggesting that this may be a sensible value ex-post. In all three of the values chosen, the model underpredicts 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 Rate

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 starts 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 rates data are combined from World Bank, the UK office for National Statistics, and the U.S. BLS.

Table 10 reports the average unemployment rates in the early and recent period for these five countries, the difference between the recent and early period, and a permutation test of the difference between the recent and early period. 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 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.

Table 10: Historical Unemployment Rates (permutation test)

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 period, and the results of a two-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 period in each country. Specifically, the recent period is 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.

6.2 U.S. Time Series Evidence

We now turn to evidence from the U.S. time series micro data. These data allow us to go beneath the aggregate unemployment rates and 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.[15]

To do so, we draw on the U.S. census every decade from 1910 to 1950 from IPUMS (Ruggles, Genadek, Goeken, Grover, and Sobek, 2017), and 1960 to 2010 from IPUMS International (Minnesota Population Center, 2017). To maximize the measurement consistency over time, we include only workers at least 16 years old in the households under 1970 definition. We also drop Alaska and Hawaii for all years because 1940-1950 samples do not include them, and they were not U.S. states before then. In addition, to get a flat sample in 1940 and 1950 1% census, we only select entire households with a value of "2" for the variable "SELFWTHH". Following Section 2, we use the variable "looked for work" to define unemployment of 1950 and years after 1980, but we have to directly use the reported "unemployed" status in the

[15]Strictly speaking, our theory applies to comparisons across steady states, so the predictions in this section are suggested by our theory rather than directly derived from it.

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 coefficient from a regression of the unemployment rate, and the traditional sector share on log GDP per capita and a constant. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.

years 1910, 1930, 1940, 1960, and 1970, where the "looked for work" variable is not available.

The first row of Table 11 reports the slope coefficient from a regression of the unemployment rate 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. Note that the slope for all workers is smaller than either education group in Table 11. This can be seen in Appendix Table C2, even though the aggregate unemployment rate is between the two unemployment rates by education group, the aggregate unemployment declines the smallest amount during this period. This happens because of the change in the composition of education group. In addition, the unemployment ratio of the low-education to the high-education group also increased significantly. In 1940, the less educated were around 1.4 times as likely to be unemployed. This ratio had risen to an average of 2.5 between 2000 to 2010. We conclude that the U.S. history is 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 employment of workers in low-skilled occupations. Unfortunately, the "own-account" status of US self-employment is not available, so we can not define traditional sector exactly as before: the intersection of own-account self-employed workers and occupations including service workers and shop and market salespeople, skilled agricultural and fishery workers, crafts and related trades workers, plant and machine operators and assemblers, and elementary occupations according to ISCO codes. In 1960, we have to use self-employment instead of "own-account" self-employment, and from 1970, we have to use "unincorporated" instead of "own-account" self-employment (and the same set of 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

We draw 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 explain these facts, we build a 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). In our model, countries differ exogenously in the productivity of the modern sector, in which worker productivity depends on ability, and workers offer their services in a labor market with search frictions. All countries have access to an identical traditional sector governed by self employment and production in which ability plays no role. As such, our model features skill-biased technology differences across countries, as emphasized by, for example, Caselli and Coleman (2006). Workers are heterogeneous and sort as in Roy (1951). As productivity of the modern sector rises, progressively more workers sort into the modern sector. Unemployment levels rise, and particularly so for the less able, as proxied by low education in our empirical findings. A quantitative analysis of the model shows that the model explains a reasonable fraction – perhaps 40 percent – of the cross-country facts that we document.

Our model suggests that at least some rise in unemployment is a natural consequence of the development process, as skilled workers search for jobs, rather than a sign of worsening economic opportunities as countries grow. At the same time, by making open unemployment more predictable, we take the first steps toward providing a benchmark against which policy makers can judge the efficiency of their modern-sector labor markets. Our research suggests that only unemployment greater than this benchmark should concern policy makers.

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Appendices

A Sample Tables by Tier

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	IPUMS-I
Fiji	2007	IPUMS-I
Ghana	1984, 2000	IPUMS-I
Ghana	1998	Living Standards Survey
Greece	1996, 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
Ireland	2011	IPUMS-I
Jamaica	1991, 2001	IPUMS-I
Kenya	2009	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
United States	1960	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
Brazil	2000	IPUMS-I
Canada	1991, 2001	IPUMS-I
Dominican Republic	2010	IPUMS-I
Italy	2001	IPUMS- I
Jordan	2004	IPUMS-I
Panama	2010	IPUMS-I
Paraguay	2002	IPUMS-I

South Africa	2007, 2011	IPUMS-I
United States	1970, 1980, 1990, 2000, 2005	IPUMS
United States	2001-2014	American Community Survey (ACS)
Bosnia and Herzegovina	2004	Living in Bosnia and Herzegovina Survey
Brazil	1997	Survey of Living Conditions
Bulgaria	2007	Multi-topic Household Survey
Iran	2011	IPUMS-I
Iraq	2012	Household Socio-economic Survey
Malawi	2013	Integrated Household Panel Survey
Serbia	2007	LSMS
Uganda	2011	National Panel Survey

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
El Salvador	2007	IPUMS-I	Current/ last week
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	IPUMS-I	Current
Kyrgyz Republic	1999, 2009	IPUMS-I	Current
Malawi	2008	IPUMS-I	Last year
Mali	1998, 2009	IPUMS-I	4 weeks
Morocco	1994, 2004	IPUMS-I	Current
Nicaragua	2005	IPUMS-I	2 weeks
Portugal	2011	IPUMS-I	Current
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, 2000	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
France	1990, 1999	IPUMS-I	Current	Enrollment ANPE
Fiji	1996	IPUMS-I	Worked for money	Not comparable
Ghana	2010	IPUMS-I	No text	No text
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
Slovenia	2002	IPUMS-I	Current	Registered as unemployed at the employment service of Slovenia

Spain	1991, 2001	IPUMS-I	7 Days	Unemployed, worked previously
South Africa	2001	IPUMS-I	4 Weeks	Could not find work
Switzerland	1990	IPUMS-I	Principal occupation	Current
Ukraine	2001	IPUMS-I	Status	Unemployment allowances, unemployed
Vietnam	2009, 1991	IPUMS-I	Earn income	4 Weeks

B Model Derivation and Proofs

B.1 Model Derivations

In this subsection, we develop the expressions of $U(x)$ and $w(x)$, and show the intermediate steps to develop Equation (8). We start y simplifying Equations (4) - (7) to

$$(1-\delta)U(x) = A_M bx + \delta\eta\theta^{1-\alpha}\big[E(x) - U(x)\big] \tag{B.1}$$

$$(1-\delta)E(x) = w(x) + \delta s\big[U(x) - E(x)\big] \tag{B.2}$$

$$J(x) = \frac{A_M x - w(x)}{1-\delta(1-s)} \tag{B.3}$$

$$\big(1 - G(x^*)\big)A_M c = \delta\eta\theta^{-\alpha}\int_{x^*}^{\bar{x}} J(x)g(x)dx. \tag{B.4}$$

It follows that the firm receives $(1-\beta)S(x) = (1-\beta)[E(x) - U(x) + J(x)] = J(x)$ when a vacancy is filled. Combining this division of surplus with equation (B.3) gives

$$E(x) - U(x) = \frac{\beta}{1-\beta}\frac{A_M x - w(x)}{1-\delta(1-s)}. \tag{B.5}$$

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

$$U(x) = \frac{1}{1-\delta}\Big(A_M bx + \delta\eta\theta^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x - w(x)}{1-\delta(1-s)}\Big). \tag{B.6}$$

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

$$w(x) = \frac{A_M bx}{1+k(\theta)} + \frac{k(\theta)}{1+k(\theta)}A_M x, \text{ with } k(\theta) = \frac{\beta(\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s)}{(1-\beta)(1-\delta+\delta s)}.$$

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

$$J(x) = \frac{A_M x(1-b)(1-\beta)}{\beta\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s} \tag{B.7}$$

$$U(x) = \frac{1}{1-\delta}\Big(A_M bx + \delta\eta\theta^{1-\alpha}\frac{\beta}{1-\beta}\frac{A_M x(1-b)(1-\beta)}{\beta\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s}\Big). \tag{B.8}$$

Equation (B.8) shows that $U(x)$ is increasing, as we asserted. Finally, substituting equation (B.7) into equation (B.4) and dividing both sides by $1 - G(x^*)$ yields the Equation (8) that determines θ for any given level of x^*:

$$c = \frac{(1-\beta)\delta\eta\theta^{-\alpha}}{\beta\delta\eta\theta^{1-\alpha} + 1 - \delta + \delta s}(1-b)\mathbb{E}(x|x > x^*).$$

B.2 Proof of Proposition 1

Recall that in the simple model outputs of the modern and traditional sectors are perfect substitutes, P_T is the unit price. Equations (8) and (9) then allow us to solve for unique values of θ and x^*. We first simplify equation (9) to

$$\theta^{1-\alpha} = \frac{(P_T A_T - A_M b x^*)(1-\delta+\delta s)}{\beta\delta\eta(A_M x^* - P_T A_T)}. \tag{B.9}$$

Substitute this expression into equation (8), yielding a single equation that determines x^*:

$$\frac{(P_T A_T - A_M b x^*)^{\frac{\alpha}{1-\alpha}} A_M x^* (1-b) c (1-\delta+\delta s)^{\frac{1}{1-\alpha}}}{(A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}}} = (1-\beta)(\delta\eta)^{\frac{1}{1-\alpha}} \beta^{\frac{\alpha}{1-\alpha}} (1-b)\mathbb{E}(x|x > x^*). \tag{B.10}$$

We assume that a solution $x^* \in (\underline{x}, \bar{x})$ to equation (B.10) exists. Since the existence of this solution implies that $A_M x^* - P_T A_T > 0$, it also implies the existence of a solution $\theta > 0$. Moreover, if the solution x^* is unique, then the solution θ is also unique.

To demonstrate uniqueness of the solution x^*, we first show that the left-hand side of equation (B.10) is decreasing in x^* for a given P_T. Inspection of equation (B.10) shows that a sufficient condition is that $A_M x^* / (A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}}$ is decreasing in x^*. We have

$$\begin{aligned} sign\left[\frac{d\frac{A_M x^*}{(A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}}}}{dx^*}\right] &= sign\left[(A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}} - \frac{x^*}{1-\alpha}(A_M x^* - P_T A_T)^{\frac{\alpha}{1-\alpha}} A_M\right] \\ &= sign\left[-P_T A_T - \frac{\alpha A_M x^*}{1-\alpha}\right], \end{aligned}$$

which is negative. Since the right-hand side of equation (B.10) is increasing in x^*, then the x^* that solves equation (B.10) must be unique.

Having demonstrated that the solution is unique, we turn to comparative statics of an increase in A_M. We want to show that the left-hand side of equation (B.10) is decreasing in A_M. It is sufficient to show:

$$sign\left[\frac{d\frac{A_M x^*}{(A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}}}}{dA_M}\right] = sign\left[(A_M x^* - P_T A_T)^{\frac{1}{1-\alpha}} - A_M \frac{1}{1-\alpha}(A_M x^* - P_T A_T)^{\frac{\alpha}{1-\alpha}} x^*\right]$$
$$= sign\left[(A_M x^* - P_T A_T) - \frac{A_M x^*}{1-\alpha}\right]$$
$$= sign\left[- P_T A_T - \alpha\frac{A_M x^*}{1-\alpha}\right]$$

Thus, we know that the sign of this derivative must be negative. We already know that the left- and right-hand sides of equation (B.10) are decreasing and increasing in x^*, respectively, so $dx^*/dA_M < 0$ follows.

B.3 Proof of Proposition 2

It follows from Proposition 1 that x^* decreases with A_M. As x^* decreases, we see from equation (8) that θ decreases. Inspection of equation (10) then shows that u must increase.

B.4 Proof of Lemma 1

We can solve for market tightness θ_h and θ_l and cutoff ability levels x_h^* and x_l^* using the equivalents of equations (8) and (B.9) for the high- and low-educated labor markets in the quantitative model:

$$c = \frac{(1-\beta)\delta\eta\theta_h^{-\alpha}}{\beta\delta\eta\theta_h^{1-\alpha} + 1 - \delta + \delta s_h}(1-b)\mathbb{E}_h(x|x > x_h^*) \tag{8h}$$

$$\theta_h^{1-\alpha} = \frac{(P_T A_T - A_M b x_h^*)(1-\delta+\delta s_h)}{\beta\delta\eta(A_M x_h^* - P_T A_T)} \tag{B.9h}$$

$$c = \frac{(1-\beta)\delta\eta\theta_l^{-\alpha}}{\beta\delta\eta\theta_l^{1-\alpha} + 1 - \delta + \delta s_l}(1-b)\mathbb{E}_l(x|x > x_l^*) \tag{8l}$$

$$\theta_l^{1-\alpha} = \frac{(P_T A_T - A_M b x_l^*)(1-\delta+\delta s_l)}{\beta\delta\eta(A_M x_l^* - P_T A_T)}, \tag{B.9l}$$

where $\mathbb{E}_h$ and $\mathbb{E}_l$ are computed using $g_h(x)$ and $g_l(x)$, respectively.

It follows that equation (B.10) that determines x^* can, with appropriate , determine x_h^* or x_l^*. We showed in the proof of Proposition 1 that the left- (right-) hand side of equation (B.10) is decreasing (increasing) in x^*. Inspection of the left-hand side of equation (B.10) shows that it is increasing in s, hence, any increase in s from s_h to s_l must increase x_l^* relative to x_h^*. Inspection of the right-hand side of equation (B.10) shows that it is increasing in $\mathbb{E}(x|x > x^*)$; thus, computing the expectation using $G_h(x)$ relative to $G_l(x)$ must decrease x_h^* relative to x_l^*.

C Figures and Tables

Table C1: 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).

Figure C1: Low-Education Share, λ, in Model and Data

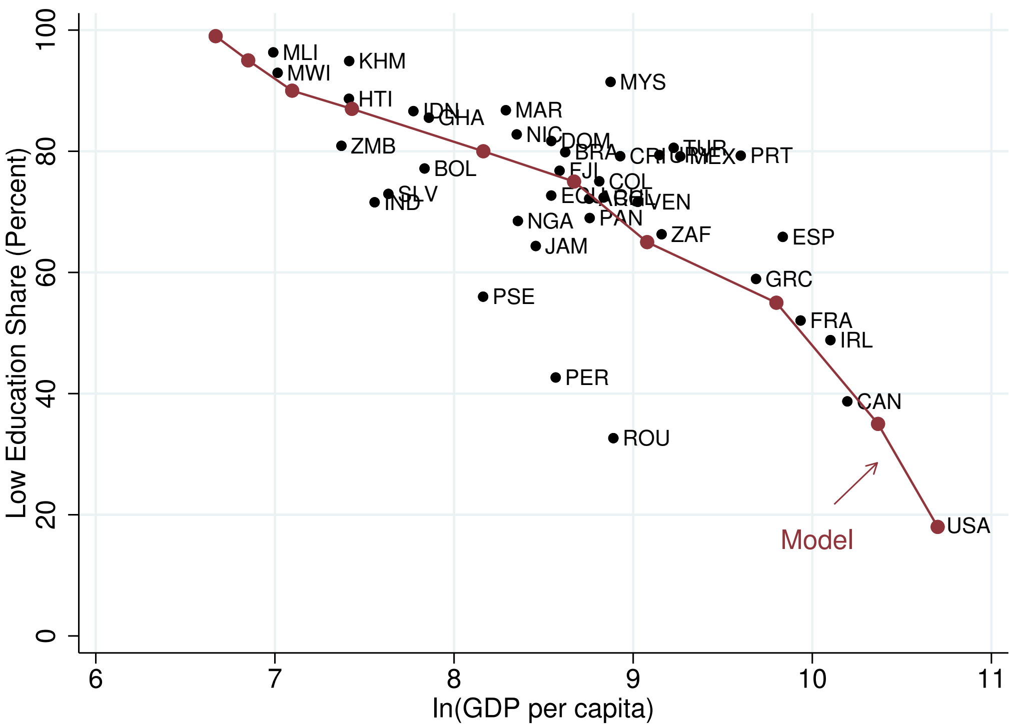

Table C2: U.S. Time Series Unemployment Rate and Traditional Sector

	Unemployment Rate				Traditional Sector share		
Decade	All	Low Edu.	High Edu.	Ratio	All	Low Edu.	High Edu.
1910	5.3						
1930	8.4						
1940	9.5	10.3	7.6	1.4			
1950	3.9	4.1	2.6	1.6			
1960	5.1	6.9	3.1	2.2	7.8	10.3	4.9
1970	4.3	5.9	3.2	1.8	5.2	7.8	3.5
1980	7.1	11.4	5.7	2.0	4.1	6.1	3.4
1990	6.2	12.9	5.0	2.6	4.6	7.3	4.1
2000	4.9	11.9	3.9	3.0	4.6	7.4	4.2
2005	7.2	15.9	6.2	2.5	4.5	7.8	4.1
2010	11.6	21.6	10.6	2.0	4.1	8.0	3.7

Note: The table reports the unemployment rate and the traditional sector share by each year available.