Unemployment and Development

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Abstract

This paper draws on household survey data from countries of all income levels to measure how average unemployment rates vary with income per capita. We document that unemployment is increasing with GDP per capita. This fact is accounted for almost entirely by low-educated workers, whose unemployment rates are strongly increasing in GDP per capita, rather than by high-educated workers, whose unemployment rates are not correlated with income. We interpret these facts in a model with frictional labor markets, a traditional self-employment sector, skill-biased productivity differences across countries, and unemployment benefits that become more generous with development. A calibrated version of the model does well in explaining the cross-country patterns we document. Counterfactual exercises using the model point to skill-biased productivity differences as being the most important factor in explaining the cross-country unemployment patterns, whereas changing unemployment benefits play a minor role.

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1 Introduction

No single measure of labor-market performance receives more attention in advanced economies than the unemployment rate. It is well known, for example, that average unemployment rates are higher in Western Europe than in the United States and Japan. Much less is known about unemployment outside the world's most advanced economies, and existing studies make contradictory claims about how average unemployment rates vary with income per capita across the full world income distribution.

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

We find, perhaps surprisingly, that unemployment rates are *increasing* in GDP per capita. This finding is present for men and for women, for all broad age groups, within urban and rural areas, and across all comparability tiers of our data. For prime-aged adults, a regression of the country average unemployment rate on log GDP per capita yields a statistically significant positive coefficient of 1.8 percent. In addition, we document that unemployment patterns across countries differ markedly by education level. Among high-educated workers (secondary school or more), unemployment rates *do not* vary systemically with GDP per capita. Among low-educated workers, in contrast, unemployment rates are substantially higher in rich countries. Regressing the country average high-educated unemployment on log GDP per capita yields an insignificant slope coefficient of 0.6 percent, whereas the slope coefficient for the low-educated is a significant 3.4 percent.

To interpret these patterns, we build a simple two-sector model with frictional labor markets, based on Diamond (1982) and Mortensen and Pissarides (1994), and heterogeneous workers that sort by ability as in Roy (1951). In the modern sector, labor markets are governed by search frictions, and worker productivity is determined by a worker's ability level. In the traditional sector, workers are self-employed with productivity that is independent of ability. Countries differ exogenously in their ratios of modern- to traditional-sector productivity. This latter assumption builds on the mounting evidence that cross-country productivity differences are skill-biased, as opposed to skill neutral (see, e.g., Caselli and Coleman, 2006; Hjort and Poulsen, 2019; Jerzmanowski and Tamura, 2019; Malmberg, 2016).

A natural explanation of why unemployment rates are higher in richer countries is that unemployment *benefits* are higher in richer countries as a fraction of worker income. To capture the increasing generosity of unemployment benefits with development in our model, we assume that unemployment benefits increase faster than productivity in the modern sector. Countries also differ in other ways that are empirically motivated, in particular in the the fraction of workers that are high-educated, the tax rate on labor income, and the search intensity of self-employed workers that are searching for wage jobs.

The main predictions of our simple model are qualitatively consistent with the facts we document. First, as modern-sector productivity increases, the aggregate unemployment rate increases. This occurs because workers can search more effectively for the increasingly attractive modern sector jobs when unemployed than when self-employed in the traditional sector. In addition, unemployment benefits become more generous when productivity increases, making job search – and potential unemployment spells – more attractive for workers. Second, as modern-sector productivity increases, unemployment rates rise faster for less able than for more able workers, since a greater share of less able workers are drawn out of the traditional sector. This prediction is consistent with the rising ratio of unemployment for low- to high-educated workers with GDP per capita that we document.

To assess the model's quantitative predictions, we calibrate the distributions of ability for high-educated and low-educated workers using moments of the U.S. wage distribution, and parameterize other aspects of the model to match key moments of the U.S. labor market—in particular the average unemployment rate and the ratio of the unemployment rate for low- to high-educated workers. Our main quantitative experiment lowers, from the U.S. levels, productivity in the modern sector relative to the traditional sector, unemployment benefits, the fraction of high-educated workers, and the tax rates on wage workers. It also increases the search intensity of the self-employed workers who are searching, to capture the fact that worker flows from self-employment to wage work tend to be larger in poorer countries (Donovan, Lu, and Schoellman, 2022). We then compute how the model's predictions for unemployment, in the aggregate and by education level, vary with GDP per capita.

The calibrated model predicts that unemployment rates are increasing in GDP per capita, as in the data, and with magnitudes that are comparable to the data. In both the model and data, there is around a 1.8 percentage-point increase in unemployment for an increase in one log point of GDP per capita. For unemployment by education, the model correctly predicts that the ratio of low- to high-educated unemployment is increasing in GDP per capita, though it slightly overpredicts the magnitude of the relationship, with a semi-elasticity of 0.48 in the data compared to 0.57 in the model.

To better understand the driving forces behind the higher unemployment rates in rich countries, we use the calibrated model to conduct a series of counterfactual experiments. We first compute how average unemployment rates would vary across the world income distribution under the assumption that countries only differ in modern- and traditional-sector productivity levels. This counterfactual leads to strongly increasing unemployment levels with income per capita, with magnitudes that are largely in line with the cross-country data. Our second counterfactual assumes that countries differ only in their generosity of unemployment benefits. In this counterfactual, unemployment rates are only somewhat lower in poor countries than rich ones, and the variation is only about one fifth as large as the actual variation in unemployment rates in the data. The counterfactual with countries differing only in productivity levels also gets the unemployment ratios largely correct, while the counterfactual with only unemployment benefits varying predicts – in contrast to the data – very little variation in unemployment by skill level. We conclude that rising unemployment with development is largely a consequence of skill-biased technological progress. The more generous unemployment benefits of richer economies contribute, but play a more minor role in explaining the cross-country unemployment patterns that we document.

We close the paper with a discussion of the broad policy implications of our analysis. To this end we solve the problem of a benevolent social planner and report the efficient allocations across the full range of country income levels. Just as in the competitive equilibrium, the planner's outcome features substantially higher unemployment in richer economies. We then simulate the effects of development policy aimed at raising worker productivity, which is meant to capture the wide range of policies aimed at increasing human capital levels in poor countries. In both the competitive equilibrium and planner's outcome, human capital accumulation leads to higher levels of unemployment in the model, while reducing levels of low-skilled self-employment. This result highlights how long-run increases in unemployment in developing countries can result from policy successes rather than policy failures.

Related Literature. Our work is most related to the literature that tries to document and understand cross-country patterns of labor market outcomes. Older studies did not have sufficient data points to draw firm conclusions about cross-country patterns but tended to find relatively low unemployment rates in poor countries, as in our study (e.g., Fields, 1980, 2004; Squire, 1981; Turnham, 1993). More recently, Poschke (2022) analyzes labor surveys from 68 countries and studies why wage employment forms such a small fraction of total employment in poor countries. His model focuses on cross-country differences in search frictions, whereas our theory emphasizes skill-biased technology differences. Banerjee, Basu, and Keller (2023) relate the high relative unemployment rates of more educated workers in poor counties to lower average school attainments. Donovan, Lu, and Schoellman (2022) use panel surveys from 42 countries to document high-frequency labor market patterns in the urban areas of middle and high income countries. Our paper covers more low income countries, whereas their study brings in repeated observations from the same individuals. Bick, Fuchs-Schuendeln, and Lagakos (2018) document how patterns of average hours worked vary across countries, and Bick, Fuchs-Schuendeln, Lagakos, and Tsujiyama (2022) attempt to explain these hours patterns using a model of skill-biased technical change, though neither study touches on unemployment either empirically or theoretically.

Our paper is closely related to the growing literature on structural change, though our two sectors do not fit neatly into the standard agriculture-manufacturing-services division (used by e.g. Duarte and Restuccia, 2010; Herrendorf, Rogerson, and Valentinyi, 2014; Mestieri, Comin, and Lashkari, 2018). In our modern and traditional sectors, we emphasize skilled wage employment versus unskilled self-employment, similar to the split between high-educated services and low-educated services taken by Buera, Kaboski, and Rogerson (2015). Rud and Trapeznikova (2021) study the role that firms play in worker transitions from self-employment to wage-employment in low-income economies. Bridgman, Duernecker, and Herrendorf (2018) show that the share of household production in total hours decreases with GDP per capita. None of these studies focuses on the link between unemployment and development, however.[1]

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

2 Data

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

[1] Our paper also builds on the macroeconomic literature on home production and its role in development (e.g. Gollin, Parente, and Rogerson, 2004; Parente, Rogerson, and Wright, 2000). The transition from home to market production with development is a key theme in the model of Ngai and Pissarides (2008), for example, as in our paper.

2.1 Data Sources

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

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

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

2.2 Unemployment Definition and Data Tiers

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

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

In Tier 1 and Tier 2 countries, employment specifically covers all economic activities that produce output counted in the National Income and Product Accounts (NIPA). In other

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

words, employment specifically comprises wage employment, self-employment or work at a family business or farm, whether or not the output is sold or consumed directly.[3] With regard to recent job search, Tier 1 includes surveys in which workers who searched did so either in the last week or the last four weeks. Tier 2 includes surveys in which workers are searching "currently" (without specifying a time frame) or in some time period other than the last week or last four weeks, such as the last two months.

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

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

2.3 Comparison to ILO and World Bank Data

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

Acknowledging the lack of international comparability in its full database, the ILO also publishes "ILO-comparable" unemployment rates from 30 countries, which are always based on a household labor force survey (Lepper, 2004). Unfortunately, the ILO-comparable unemployment rates have very limited coverage of the bottom half of the world income distribution, covering just one such country. Therefore, the ILO-comparable unemployment

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

dataset is ill-suited to answer the question of how average unemployment rates vary between poor and rich countries. In addition, it does not provide disaggregated unemployment rates, such as by education level, which we show are crucial to understanding the aggregate patterns.

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

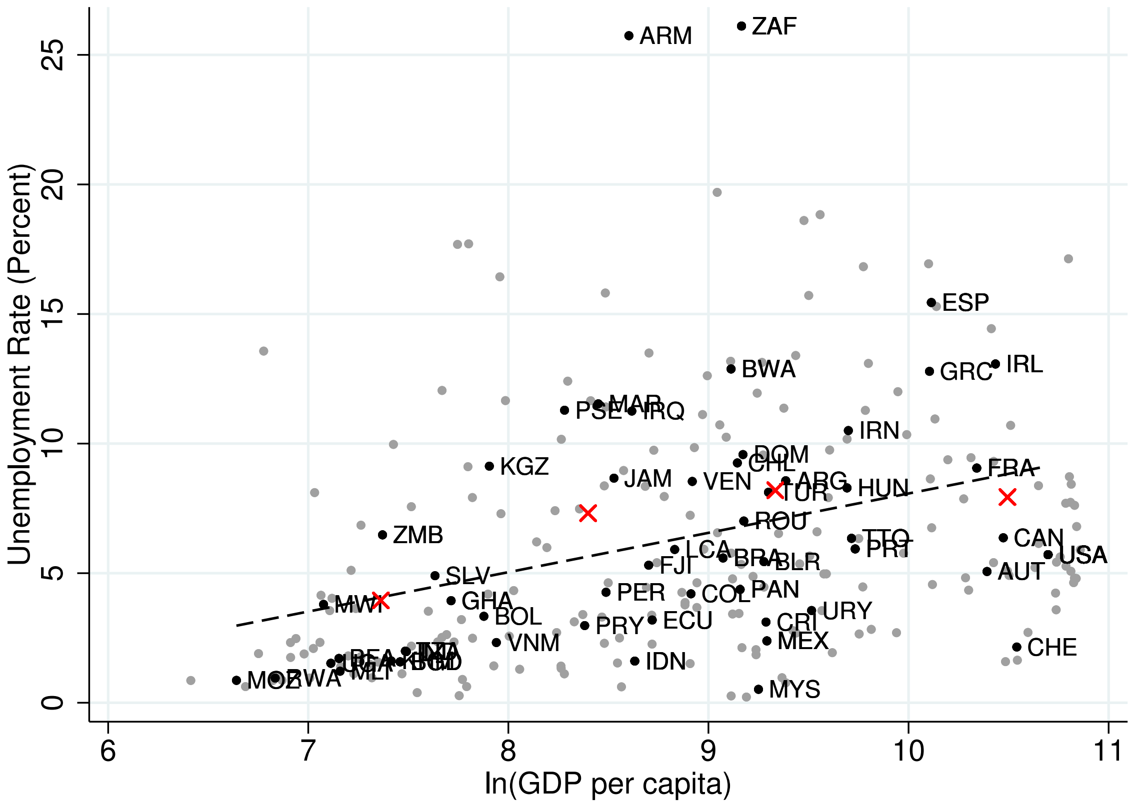
3 Empirical Findings

In this section, we report how average unemployment rates – and unemployment rates by education level – vary with GDP per capita. We first compare aggregate unemployment rates, and then look beneath the surface at unemployment by sex, by age group and by rural-urban status. We then provide historical evidence that unemployment rates have increased in the long run for the high-income countries of today that have available data, particularly for low-educated workers.

3.1 Aggregate Unemployment Rates

Figure 1 plots the country-year and country average unemployment rate for prime-aged adults against log GDP per capita. This figure adopts the common format we use throughout the paper. We plot all outcomes at the country-year level in grey against log GDP per capita. We also compute and plot the cross-year average for each country with at least two years of data in black, which we label with three-digit country codes. We then include in all scatter plots a best-fit line of a regression of the country-average data points against log GDP per capita. Finally, we plot in red the average of the country-year observations by quartile of the world income distribution.

Figure 1: Unemployment Rates by GDP per capita



Note: This figure plots the average unemployment rate for prime-aged adults in each country with at least two observations across all years of data from all tiers in black, all the country-year observations up to 25 percentage points in grey, the average of the country-year observations by quartile of the world income distribution in red, and a best-fit dashed line of a regression of the country-average data points against log GDP per capita.

In particular, Figure 1 includes countries from all three data tiers. The slope coefficient for the regression of the unemployment rate in natural units on log GDP per capita is 1.8 and is statistically significant at the one-percent level. Taking simple averages by country income quartile, the bottom (poorest) quartile has an average unemployment rate of 2.5 percent. By contrast, the top (richest) quartile has an average unemployment rate of 8.7 percent.

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

To help answer these questions, we report the slope coefficient of average unemployment on log GDP per capita using various alternative cuts of the data. The first data column of Table 1 reports these slopes. When considering all 199 country-year surveys separately, the slope is

1.2, compared to 1.8 for country averages shown in Figure 1. When using only Tier 1 surveys, the slope coefficient becomes 1.4, and with Tier 1 and 2 surveys, the slope becomes 1.3. All four slopes are statistically significant at the one percent level. We conclude that the pattern of increasing unemployment is not an artifact of our choice of countries in the main analysis.

3.2 Unemployment Rate by Education Level

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

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

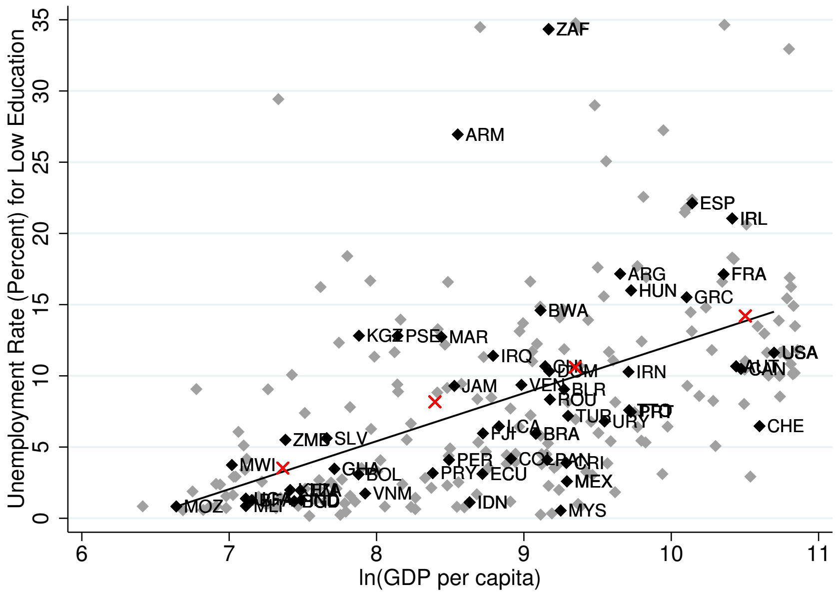
	All Workers	N	Low Education	High Education	Ratio
All surveys	1.15 (.29)***	199	3.03 (.36)***	-.20 (.32)	.51 (.03)***
Country average	1.82 (.46)***	55	3.39 (.56)***	.58 (.41)	.48 (.05)***
Only Tier 1 surveys	1.45 (.31)***	131	3.10 (.35)***	.40 (.28)	.46 (.03)***
Only Tier 1+2 surveys	1.35 (.31)***	168	3.08 (.39)***	.007 (.30)	.50 (.03)***

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

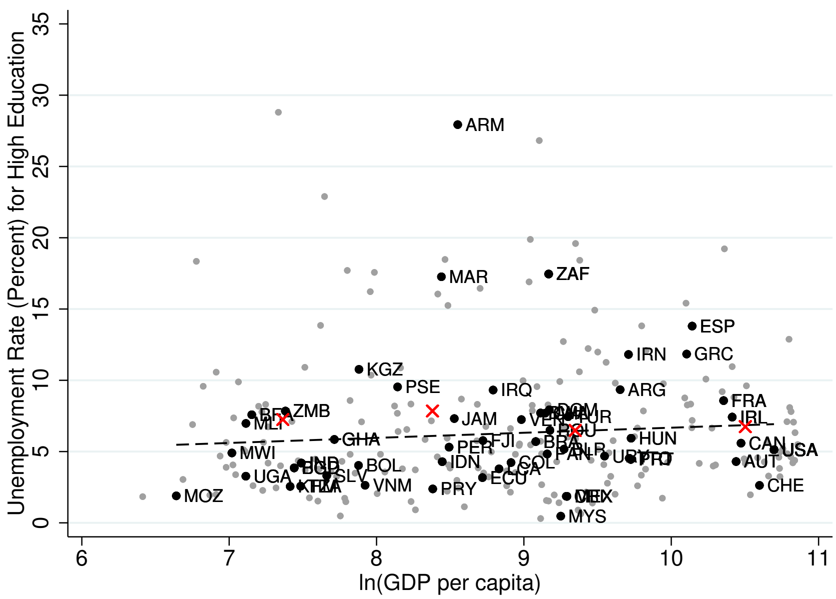
Figure 2 plots the unemployment rates for prime-aged adults by education group. As one can see, the patterns differ sharply by group. For the low-educated group, unemployment is strongly increasing in GDP per capita. For the high-educated group, unemployment rates are roughly constant across income levels. Again, there is quite a lot of variation in unemployment rates for each income level, though somewhat less than for the aggregate unemployment rates. Taking simple averages by income quartile, for the low-educated workers in the bottom

Figure 2: Unemployment Rates by GDP per capita and Education

(a) Low-Education Group



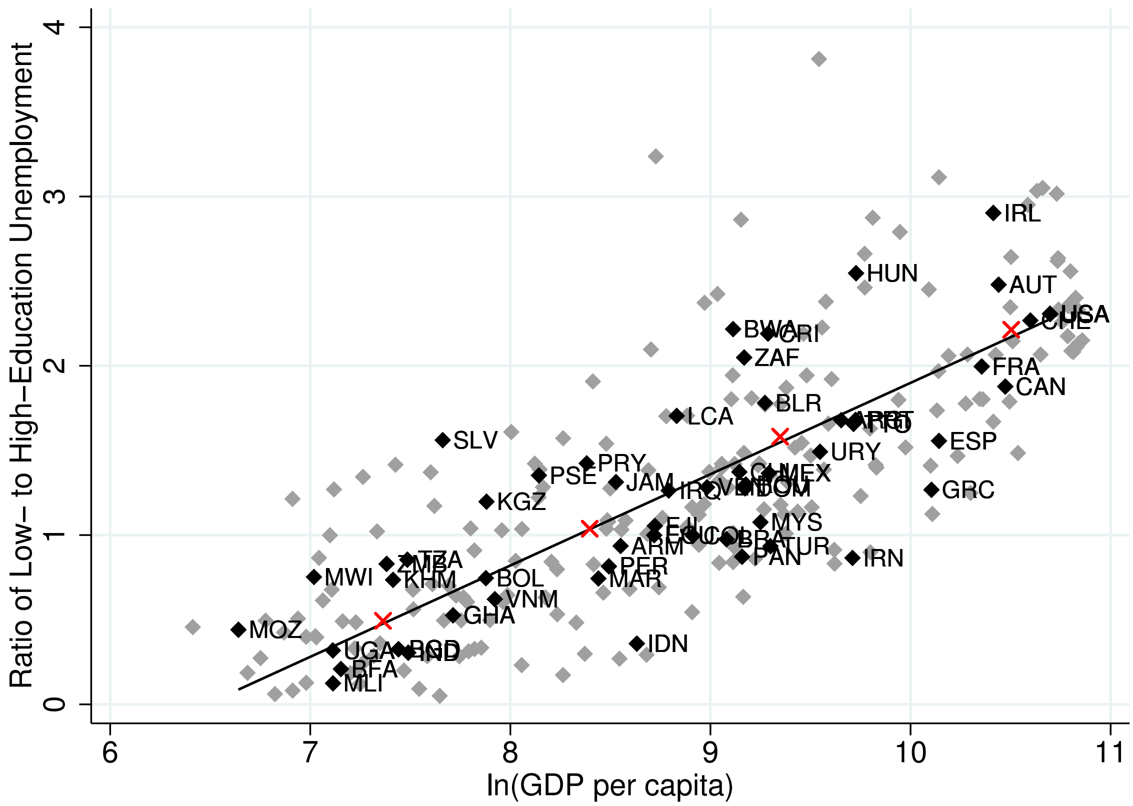
(b) High-Education Group



Note: This figure plots the average unemployment rate for prime-aged adults by education level in each country with at least two observations across all years of data from all tiers in black, all the country-year observations up to 35 percentage points in grey, the average of the country-year observations by quartile of the world income distribution in red, and a best-fit dashed line of a regression of the country-average data points against log GDP per capita. Low education means less than secondary school completed; high-education means secondary school completed or more.

quartile the average unemployment rate is 2.7 percent. This rises to 8.1 percent in the second quartile, 9.5 in the third and 14.3 in the richest quartile. For the high-educated, the average unemployment rate is not monotonically increasing in income per capita. It rises from 4.9 percent in the bottom quartile to 7.7 in the second, and then falls to 6.2 and 7.3 in the third and fourth quartiles.

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



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

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

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

3.3 Robustness of Unemployment-to-GDP per capita Patterns

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

The first row of Table 2 reports the slope for prime-aged males only. Across all surveys and country averages, low-educated prime-aged males have a statistically significant positive slope with GDP per capita, whereas high-educated ones have an insignificant slope. This pattern is replicated and even stronger in the full sample of households (second row), which includes household members aged 16 to 24, those above age 55, and both sexes. The patterns hold separately for males of all ages (third row) as well, whereas for females (fourth row), there is even a significant negative trend with GDP per capita among the high-educated. We conclude that our patterns hold for both sexes. We provide evidence that the patterns of employment rates and unemployment rates do not imply each other in Appendix B.

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

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

	All Surveys			All Country Averages		
	Low Edu.	High Edu.	N	Low Edu.	High Edu.	N
Prime males	2.51 (.36)***	-.25 (.29)	195	2.98 (.55)***	.43 (.35)	54
Full Sample	3.39 (.38)***	-.42 (.37)	197	3.55 (.62)***	.57 (.55)	54
Males	2.99 (.37)***	-.39 (.33)	197	3.19 (.59)***	.43 (.46)	54
Females	3.87 (.41)***	-.76 (.44)*	197	4.07 (.77)***	.52 (.75)	54
Age 16-24	6.42 (.65)***	-1.14 (.7)	196	6.47 (1.19)***	.41 (1.26)	54
Age 25-54	3.02 (.36)***	-.20 (.32)	195	3.38 (.56)***	.58 (.41)	54
Age 55+	2.12 (.33)***	.46 (.24)*	185	2.46 (.51)***	.71 (.39)*	51
Rural	2.87 (.55)***	.03 (.6)	113	3.4 (.99)***	1.67 (.96)*	30
Urban	2.71 (.79)***	-.88 (.57)	113	3.45 (1.19)***	.60 (.75)	30

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

3.4 Historical Unemployment Rates

In our main database, we have very short time series dimensions for most countries. Our cross-country data are not thus not suitable for studying how unemployment correlates with income levels over time within particular economies. In this section we partially address this limitation using historical evidence from countries that have high income per capita today to explore how 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 disaggregated evidence from the United States.

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 statistics for at least ten years before WWI started in 1914: Australia, France, Germany, the United Kingdom, and the United States. The recent period is then defined as 2004 - 2016 for Australia, 1998 - 2016 for France, 1990 - 2016 for Germany, 1984 - 2016 for the UK, and 1972 - 2016 for the U.S. The recent aggregate unemployment rate data are compiled from the World Bank, the U.K. office for National Statistics, and the U.S. BLS. Unemployment in all our sources is defined as the percent of the economically active adults of both sexes that are not working. The definition of an adult varies across countries, and is age 14+ in the United States, age 16+ in the United Kingdom, and "above the school-leaving age" in Australia, France and Germany.

Table 3: Historical Unemployment Rates

Country	Early Period (source)	Unemployment Early	Unemployment Recent	Difference (p-value)
Australia	1901 - 1913 (Mitchell, 1998a)	5.17	5.26	0.09 (.48)
France	1895 - 1913 (Mitchell, 1998b)	7.35	8.91	1.55*** (.00)
Germany	1887 - 1913 (Mitchell, 1998b)	2.37	7.55	5.18*** (.00)
United Kingdom	1881 - 1913 (Denman and McDonald, 1996)	4.71	7.29	2.57*** (.00)
United States	1869 - 1913 (Lebergott, 1957; Vernon, 1994)	5.11	6.38	1.27*** (.00)

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

Table 3 reports the average unemployment rates in the early and recent periods for these five countries, the difference between the recent and early periods, and a permutation test of the difference between the recent and early periods. The recent unemployment rate is larger than the early period for all five countries. Among them, Australia's unemployment rate is very similar in the two periods, and the difference is statistically insignificant. For the 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 historical evidence – at least for this small set of countries – is consistent with our cross sectional finding that the aggregate unemployment rate increases when GDP per capita increases.

One potential concern with these historical unemployment data is that they may be recorded somewhat differently in the early and later periods within each country. For this reason we turn next to historical micro data from the U.S. census. These data allow us to create our own unemployment rates in a consistent way over time by aggregating up from the micro data, either to the whole population or by education group. The data thus allow us to test whether unemployment rates rose over time particularly for the low-educated, as in our cross sectional data.

Table 4: Slope Coefficients for U.S. Time Series

		Worker Education Group		
	All Workers	Low	High	Ratio
Unemployment rate	3.3^{**} (1.6)	10.6^{***} (2.3)	3.8^{**} (1.6)	$.7^{**}$ (.3)

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

To do so, we draw on the U.S. census every decade from 1910 to 2010 from IPUMS International (Minnesota Population Center, 2017). To maintain consistency across years, we restrict attention to workers aged 16 and over in all states except Alaska and Hawaii. The first row of Table 4 reports the slope coefficients from regressions of the unemployment rates on log GDP per capita and a constant. As the table shows, unemployment rates rose with log GDP per capita on average, particularly for the less-educated. The estimated slope of the ratio of low-educated unemployment to high-educated unemployment is 0.7 using these data, compared with 0.5 in the cross-country data. We conclude that disaggregated unemployment rates from historical U.S. data are largely consistent our cross-country evidence.

4 A Model of Unemployment and Development

We now present a model to interpret the facts about average unemployment rates across countries and by education group that we document above. Because our empirical patterns are present for both sexes, all age groups and within both rural and urban areas, we abstract from demographics and regional considerations. In order to match the large decrease in the traditional sector that coincides with development, we allow for two sectors in our model. We relegate all derivations to Appendix C.

4.1 Environment

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

In the modern sector firms hire workers subject to matching friction and production displays constant returns to ability. In the traditional sector workers are self-employed without returns to ability. The technologies in the modern and traditional sectors, respectively, are given by:

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

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

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

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

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

$$W = \left[\gamma C_T^{\sigma} + (1-\gamma) C_M^{\sigma}\right]^{\frac{1}{\sigma}}, \tag{3}$$

where C_T and C_M denote consumption of traditional and modern sector output, respectively, and $\frac{1}{1-\sigma}$ is the elasticity of substitution in consumption. 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 utilities:

$$P_T = \frac{\partial W/\partial C_T}{\partial W/\partial C_M} = \frac{\gamma}{1-\gamma}\left(\frac{C_M}{C_T}\right)^{1-\sigma}. \tag{4}$$

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

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

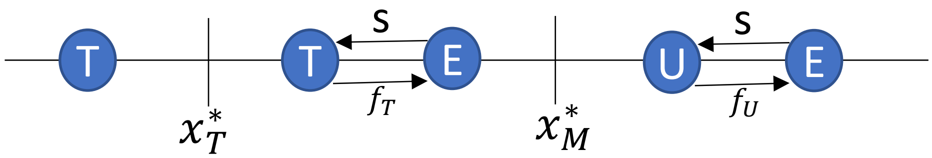
where $\psi_1 < 1$. In our quantitative exercise in Subsection 5.2 below we target the elasticity of the relative price of traditional goods with respect to GDP per capita to calibrate ψ_1. Differences in GDP per capita are driven by exogenous differences in A_M. The smaller is ψ_1 the more A_M/A_T increases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

Worker Sorting. Workers can search for jobs in the modern sector while self-employed in the traditional sector or while unemployed, but the former search is less intensive than the latter. Workers then sort as in Roy (1951) between self-employment in the traditional sector without search, self-employment in the traditional sector with search, and unemployment with search. The lowest ability workers earn less when employed in the modern sector than when self-employed in the traditional sector, hence do not search. Higher ability workers search because they earn more when employed in the modern sector than when self-employed in the traditional sector. This benefit of search is greatest for the highest ability workers, who therefore choose unemployment over self-employment in order to search more intensively.

Denote by x^*_{Ti} the efficiency units of the marginal high- or low-educated worker who is indifferent between self-employment and being employed in the modern sector; denote by x^*_{Mi} the efficiency units of the marginal high- or low-educated worker who is indifferent between searching from self-employment and searching from unemployment. In steady state, workers with $x \leq x^*_{Ti}$ prefer self-employment in the traditional sector, workers with $x \in (x^*_{Ti}, x^*_{Mi}]$ prefer searching for modern sector jobs while self-employed in the traditional sector, and workers with $x > x^*_{Mi}$ prefer searching for modern sector jobs while unemployed. Figure 4 illustrates worker sorting for the high- or low-educated workers.

Modern Sector. In order to hire a worker, a firm must post a vacancy at flow cost $A_M c$ in units of modern sector output. Since hiring skilled labor requires skilled labor, the cost

Figure 4: Worker Sorting



of posting vacancies should scale up with the productivity of skilled labor (and hence their wages). We follow Pissarides (1994) to let the flow of matches be given by the constant returns to scale function

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

where u_i is the endogenous measure of unemployed workers, t_i is the endogenous measure of self-employed workers who are also searching, v_i is the endogenous measure of vacancies in the labor market, and the parameter ϵ is the search intensity of the self-employed workers. We require that $\epsilon \in (0,1)$, meaning that self-employed workers do less job search than the unemployed. This is consistent with direct evidence on job flows in low-income countries, as we will argue below. It is also consistent with the observation that hours worked are high on average among self-employed workers, and similar to those of employed workers, leaving less time for job search.[4]

We define $\theta_i \equiv v_i/(u_i+\epsilon t_i)$ as market tightness. Because vacancies are undirected, the fraction of total matches going to unemployed workers is $m_{Ui}(u_i+\epsilon t_i, v_i) = \frac{u_i}{u_i+\epsilon t_i} m(u_i+\epsilon t_i, v_i)$ and the fraction of total matches going to self-employed and searching workers is $m_{Ti}(u_i + \epsilon t_i, v_i) = \frac{\epsilon t_i}{u_i+\epsilon t_i} m(u_i + \epsilon t_i, v_i)$. The job-finding rates are $f_{Ui}(u_i + \epsilon t_i, v_i) = \frac{m_{Ui}(u_i+\epsilon t_i, v_i)}{u_i} = \eta\theta_i^{1-\alpha}$ for unemployed workers and $f_{Ti}(u_i + \epsilon t_i, v_i) = \frac{m_{Ti}(u_i+\epsilon t_i, v_i)}{t_i} = \epsilon\eta\theta_i^{1-\alpha}$ for self-employed and searching workers, and the vacancy hiring rate is $q(u_i + \epsilon t_i, v_i) = \frac{m(u_i+\epsilon t_i, v_i)}{v_i} = \eta\theta_i^{-\alpha}$.

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

We let the unemployment flow payoff equal $A_M[b_0 + b_1(A_M)x]$, where $A_M b_0$ is home production and $A_M b_1(A_M)x$ is unemployment benefits, all in units of modern sector output. We show in Appendix C that wages are proportional to x in equilibrium, so that for any given A_M unemployment benefits are proportional to wages. One rationale for this choice is that unemployment benefits are typically indexed to wages. A second rationale is that job finding

[4] Bick, Fuchs-Schuendeln, Lagakos, and Tsujiyama (2022) measure average hours worked for adults in the "traditional sectors" of 48 countries of all income levels, defined (as in the current study) as own-account workers in low-skill occupations plus unpaid family workers. They find that traditional-sector workers average 37 hours of work per week, compared to 41 hours for the rest of the workforce.

rates are approximately constant across skill groups, which is consistent with a model where unemployment benefits scale with the expected wage (Hall and Mueller, 2018; Mincer, 1991; Mueller, 2017). We assume $0 \leq b_1(A_M) < 1$. In the special case where $b_1(A_M) = b$, a constant, unemployment benefits increase exactly in proportion to modern-sector productivity. However, our specification allows for a more general, nonlinear relationship between unemployment benefits and A_M. For example, for very poor countries with very low A_M we can have $b_1(A_M) = 0$, and we can allow $b_1'(A_M) > 0$ so that unemployment benefits increase faster than linearly with A_M.

Unemployment benefits are financed by taxes on modern sector wages. We allow the linear tax rate τ to vary across countries but suppress its dependence on A_M to save notation. Denoting by δ the rate of time discount for all agents, the values of self-employment and searching, unemployment, and employment for an individual with efficiency units x are given, respectively, by

$$T_i(x) = P_T A_T + \delta\big[f_{Ti}E_i(x) + (1 - f_{Ti})T_i(x)\big] \tag{7}$$

$$U_i(x) = A_M[b_0 + b_1(A_M)x] + \delta\big[f_{Ui}E_i(x) + (1 - f_{Ui})U_i(x)\big] \tag{8}$$

$$E_i(x) = \begin{cases} (1-\tau)w_i(x) + \delta\big[s_iT_i(x) + (1-s_i)E_i(x)\big] & \text{if } x \in (x^*_{Ti}, x^*_{Mi}] \\ (1-\tau)w_i(x) + \delta\big[s_iU_i(x) + (1-s_i)E_i(x)\big] & \text{if } x > x^*_{Mi} \end{cases} \tag{9}$$

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

$$J_i(x) = A_M x - w_i(x) + \delta\big[s_iV_i + (1-s_i)J_i(x)\big] \tag{10}$$

$$V_i = -A_M c + \delta\Big[\frac{\epsilon t_i q_i \mathbb{E}\big(J_i | x^*_{Ti} < x \leq x^*_{Mi}\big)}{u_i + \epsilon t_i} + \frac{u_i q_i \mathbb{E}\big(J_i | x > x^*_{Mi}\big)}{u_i + \epsilon t_i} + (1-q_i)V_i\Big] \tag{11}$$

where $\mathbb{E}\big(J_i | x^*_{Ti} < x \leq x^*_{Mi}\big) = \frac{\int_{x^*_{Ti}}^{x^*_{Mi}} J_i(x)g_i(x)dx}{G_i(x^*_{Mi}) - G_i(x^*_{Ti})}$ is the expected value of a job match conditional on the workers searching while self-employed and $\mathbb{E}\big(J_i | x > x^*_{Mi}\big) = \frac{\int_{x^*_{Mi}}^{\bar{x}} J_i(x)g_i(x)dx}{1 - G_i(x^*_{Mi})}$ is the expected value to the firm of a job match conditional on the workers searching while unemployed.

Because of the free-entry condition for firms, we have $V_i = 0$. Denote the total surplus of a match by:

$$S_i(x) = \begin{cases} E_i(x) - T_i(x) + J_i(x) & \text{if } x \in \big(x^*_{Ti}, x^*_{Mi}\big] \\ E_i(x) - U_i(x) + J_i(x) & \text{if } x > x^*_{Mi}, \end{cases} \tag{12}$$

and the Nash bargaining power of the worker by $\beta \in (0,1)$. The firm then receives $(1-\beta)S_i(x)$ when a vacancy is filled. Combining this division of the surplus with $V_i = 0$ and equations (7) to (10) allows us to solve for $w_i(x)$, $J_i(x)$, $E_i(x)$, $T_i(x)$, and $U_i(x)$ as shown in Appendix C.

Indifference Conditions. The value of always staying in the traditional sector is $\frac{P_T A_T}{1-\delta}$, since any traditional worker produces output with value $P_T A_T$ in every period. The high- or low-educated worker with efficiency units x^*_{Ti} is indifferent between always staying in the traditional sector and searching while self-employed when

$$\frac{P_T A_T}{1-\delta} = T(x^*_{Ti}). \tag{13}$$

The high- or low-educated worker with efficiency units x^*_{Mi} is indifferent between searching while self-employed and searching while unemployed when

$$T(x^*_{Mi}) = U(x^*_{Mi}). \tag{14}$$

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

$$\tilde{u}_i = \frac{s_i\big(1 - G_i(x^*_{Mi})\big)}{s_i + \eta\theta_i^{1-\alpha}}, i = h, l. \tag{15}$$

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

$$u = (1-\lambda)\tilde{u}_h + \lambda\tilde{u}_l. \tag{16}$$

Following the same steps, we can derive the shares of high- and low-educated workers that are searching while self-employed, and the share of all workers that is searching while self-employed:

$$\tilde{t}_i = \frac{s_i\big(G_i(x^*_{Mi}) - G_i(x^*_{Ti})\big)}{s_i + \epsilon\eta\theta_i^{1-\alpha}}, i = h, l, \tag{17}$$

$$t = (1-\lambda)\tilde{t}_h + \lambda\tilde{t}_l. \tag{18}$$

Goods-Market Clearing. All traditional sector output is available for consumption:

$$C_T = Y_T. \tag{19}$$

Modern sector output is produced by firms and at home, and some modern sector output is used to post vacancies. Modern sector output available for consumption is therefore given by

$$C_M = Y_M + A_M\big[b_0 u - c\big((1-\lambda)\theta_h(\tilde{u}_h + \epsilon\tilde{t}_h) + \lambda\theta_l(\tilde{u}_l + \epsilon\tilde{t}_l)\big)\big]. \tag{20}$$

4.2 Model Predictions

We consider two mechanisms by which development can affect unemployment in our model: skill-biased technological progress and changes in unemployment benefit rates. It is useful to first illustrate how, absent either mechanism, the model predicts that unemployment is unchanged across different levels of development. Specifically, shutting down the skill-biased nature of technological progress means setting $\psi_1 = 1$, so that A_M/A_T is constant by equation (5), and keeping a constant rate of unemployment benefits means setting $b_1(A_M) = b$, a constant. With these restrictions, the claim is that increases in A_M leave $\tilde{u}_i$ unchanged, and u unchanged for a given λ.

To see this, use $V_i = 0$ to rewrite equation (11) as

$$\theta_i^\alpha = \frac{\delta\eta\big[\epsilon t_i \mathbb{E}\big(J_i | x_{Ti}^* < x \leq x_{Mi}^*\big) + u_i \mathbb{E}\big(J_i | x > x_{Mi}^*\big)\big]}{A_M c(u_i + \epsilon t_i)}. \tag{21}$$

Next, provisionally assume that θ_i, x_{Mi}^*, x_{Ti}^*, and P_T are unchanged when A_M increases. Under this assumption, it follows from equations (15) and (17) that $\tilde{u}_i$ and $\tilde{t}_i$ are unchanged and therefore u_i, t_i, and aggregate unemployment are unchanged for a given λ. It is easily shown (see Appendix C) that, since $b_1(A_M)$ and P_T are constant and A_T scales with A_M, $\mathbb{E}\big(J_i | x_{Ti}^* < x \leq x_{Mi}^*\big)$ and $\mathbb{E}\big(J_i | x > x_{Mi}^*\big)$ scale with A_M. Equation (21) then confirms our provisional assumption that θ_i is unchanged. Similarly, equations (13) and (14) respectively confirm our provisional assumption that x_{Ti}^* and x_{Mi}^* are unchanged. Finally, it is then straightforward to show that Y_M/Y_T and C_M/C_T are unchanged and therefore P_T is unchanged by equation (4).

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

This leads to an increase in the unemployment rates for both high- and low-educated workers for two reasons. First, greater fractions of both types of worker now choose unemployment over self-employment in the traditional sector when separating from their modern sector jobs. Second, because the workers drawn into search for modern sector jobs are of lower ability than existing modern-sector workers, the expected value of a match to a firm falls. For the free-entry condition to hold, the job filling rate for a vacancy must rise. This means fewer vacancies per unemployed person, i.e., a smaller θ_i. Inspection of equation (15) shows that a lower x^*_{Mi} and a smaller θ_i imply a higher $\tilde{u}_i$.

Note that the aggregate unemployment rate u does not necessarily increase with A_M, despite increases in both $\tilde{u}_h$ and $\tilde{u}_l$. The aggregate unemployment rate is a weighted average of the unemployment rates of high- and low-educated workers, with weights $1 - \lambda$ and λ. In the data, as modern-sector productivity and thus GDP per capita increases, the share of low-educated workers λ tends to decrease. If the low-educated unemployment rate is greater than the high-educated unemployment rate, it is possible for the aggregate unemployment rate predicted by equation (16) to decrease with A_M and GDP per capita.

Skill-Biased Technological Progress and Unemployment by Education Level. Our model with skill-biased productivity growth also allows for a faster increase in the unemployment rate of low- than high-educated workers, as in the data. Suppose that participation of low-educated workers in the traditional sector is much greater than participation of high-educated workers at low levels of modern-sector productivity. As A_M increases, both participation rates approach zero. This generates a faster increase in the proportion of low- than high-educated workers that chooses unemployment over traditional sector self-employment when separating from their modern sector jobs, and a faster decline in their average ability in those jobs.

Traditional-sector participation in our model is greater for low- than for high-educated workers because the distribution of ability for low-educated workers is first-order stochastically dominated by the distribution of ability for high-educated workers, making the modern sector less attractive relative to the traditional sector for low-educated workers. Moreover, as noted in Subsection 5.1 below, data indicate a greater separation rate for low- than high-educated workers, further reducing the expected value of a modern sector job match.

Suppose that modern sector productivity were so low that nearly all workers participate in the traditional sector regardless of education level, so that traditional-sector participation by low-educated workers is only marginally greater than traditional-sector participation by high-educated workers. Our model then predicts that the ratio of low- to high-educated unemployment would actually decrease as A_M increases. The reason is that as A_M increases, high-educated workers would abandon the traditional sector and experience unemployment before low-educated workers. Which case is prevalent in our quantitative exercise below is determined by whether, even in the poorest countries, modern sector productivity is sufficiently high that participation in the traditional sector is much less for high- than for low-educated workers.

Rising Unemployment Benefits with Development. Our model predicts that greater unemployment benefits raise steady-state unemployment levels, which is standard in this class of models. It follows that if $b_1'(A_M) > 0$, unemployment benefits are an additional mechanism leading to higher unemployment as A_M and thus GDP per capita increases. We should note that in our model a higher b_1 increases unemployment not only by reducing market tightness θ_i, the standard mechanism, but also by reducing x^*_{Mi}, i.e., increasing the proportions of both types of workers that choose unemployment over self-employment in the traditional sector when separating from their modern sector jobs.

5 Quantitative Analysis

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

5.1 Parameterizing the Model

We begin by directly setting some parameters of our model. We set the quarterly discount factor, δ, to be 0.99, consistent with an annual interest rate of around four percent. We set the power on job searchers in the matching function, α, to be 0.7 in order to be consistent with the evidence summarized by Petrongolo and Pissarides (2001). We set the quarterly separation rate for the high-educated workers to $s_h = 0.045$, which is the value estimated in Wolcott (2018). We set the unemployment benefits replacement rate to be 45 percent in our calibrated economy, which is consistent with the range of estimates used in the literature (Chodorow-Reich and Karabarbounis, 2016; Krueger and Mueller, 2010; Shimer, 2005). We set the worker's bargaining weight, β, to be 0.7 following Fujita and Ramey (2012) and others in this literature. Finally, we assume log normal distributions for the workers' ability and normalize the mean of the ability for low-educated workers to be one.

Table 5: 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_0 - Home production efficiency	0.1
b_1^{US} - Unemployment benefit rate	0.45
A_T^{US} - U.S. traditional-sector productivity	1
m_l - Mean of ability for low-educated workers	1
Panel B: Calibrated Parameters	
m_h - Mean of ability for high-educated workers	1.67
v_l - Variance of ability for low-educated workers	0.44
v_h - Variance of ability for high-educated workers	1.22
c - Vacancy cost	0.27
η - Matching efficiency	1.04
γ - Traditional-sector share in utility function	0.028
s_l - Separation rate (quarterly) for low-educated workers	0.096
$max(A_M)$ - Modern-sector productivity for the richest country	0.23
$\frac{1}{1-\sigma}$ - Elasticity of substitution	3.97
ψ_1 - Elasticity of traditional-sector w.r.t. modern-sector productivity	0.023

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

We calibrate the remaining ten parameters to jointly match ten 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 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 utility function, γ; (vii) the quarterly separation rate for low-educated workers, s_l; (viii) the maximum value of A_M, which corresponds to the U.S. level;[5] (ix) the elasticity of substitution between traditional and modern goods $\frac{1}{1-\sigma}$; and, finally, (x) the elasticity of traditional-sector productivity with respect to modern-sector productivity, ψ_1.

The ten moments are: (i) the ratio of average modern-sector wages for the high- over low-educated that we calculated using the 2000 Census five-percent sample (1.60); (ii) and (iii) the variances of log wages for the high- and low-educated (0.34 and 0.28), using the same 2000 census; (iv) the vacancy cost of 17 percent of average output in the modern sector as used in Fujita and Ramey (2012); (v) the average U.S. unemployment rate of 5.71 percent in the United States among the 18 samples in our data from 1960 to 2014; (vi) the U.S. expenditure share in the traditional sector, which we conjecture to be smaller than two percent; (vii) the ratio of unemployment for the the low-educated to high-educated (2.31); (viii) an average employment share of two percent in the traditional sector (as we explain below); (ix) the slope of aggregate traditional sector employment share on log GDP per capita; and (x) the slope of log relative price of traditional sector output on log GDP per capita (as we specify later). We define the traditional sector as low-skilled own-account self-employed workers or unpaid family workers.[6]

Table 5 reports the value of each parameter used in the calibration. Our calibrated quarterly separation rate for the low-educated is 0.096, similar to the direct estimate of 0.06 - 0.12 during 1980 to 2010 computed by Wolcott (2018) for low-educated workers. Our estimate is also broadly consistent with the separation rate in low-skilled services in the United States. For example, according to the 2017 Job Openings and Labor Turnover Survey, the monthly separation rate in wholesale and retail trade, transportation and utilities is around 3.5 percent. This corresponds to a quarterly separation rate of around 10 percent. The parameter ψ_1 is calibrated to be 0.023, with the intercept ψ_0 in the equation $\ln(A_T) = \psi_0 + \psi_1 \ln(A_M)$ determined implicitly by our normalization of A_T to be one in the United States.

We report each moment and its model counterpart in Table 6. Overall, the model matches the desired moments quite well. Although all of the ten moments reported above jointly discipline all the parameters, it is useful to provide some intuition about which moments are

[5] Note that although the absolute value of A_M is smaller than A_T, the modern sector is more productive than the traditional sector in value terms. The traditional and modern sectors produce different goods, and the relative price of the traditional good, P_T, is around 0.06 in the United States in our calibrated model.

[6] Low-skilled occupations are defined as shop and market sales, agricultural and fishery workers, crafts and related trade workers, plant and machine operators and assemblers, and "elementary occupations." Unfortunately, the U.S. data after 1960 distinguish only between incorporated and unincorporated businesses among the self-employed, rather than between own-account workers and employers as in the countries in Figures 5 and Figure D3. Considering that the Canada samples have an average of 2.8 percent prime-aged employment in the traditional sector, which is defined consistently with the other countries, we conjecture that the United States has a smaller share of two percent. As with our benchmark unemployment measures, all traditional sector employment shares reported in this section are calculated for prime-aged workers.

Table 6: Moments Targeted in the Model vs Data

Moment	Target	Model
Ratio of average wage for the high- to low-educated	1.60	1.61
High-edu ln(wage) variance	0.34	0.34
Low-edu ln(wage) variance	0.28	0.28
U.S. vacancy cost as % of average output in modern sector	17	17.00
U.S. unemployment rate	5.71	5.71
U.S. % expenditure share of traditional sector	<2.0	0.34
U.S. ratio of unemployment rates u_l/u_h	2.31	2.31
U.S. traditional sector employment share	2	1.92
Slope of traditional sector employment share on log GDP per capita	-19.90	-19.91
Slope of log relative price on log GDP per capita	0.6	0.60

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

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 γ mostly informs the expenditure share of traditional-sector output. The quarterly separation rate for low-educated workers is most informative about the unemployment ratio of low- to high-educated workers. The maximum A_M value governs the traditional sector employment share in the richest country (the United States). Finally, the remaining two parameters are the elasticity of substitution between traditional and modern goods ($\frac{1}{1-\sigma}$) and the elasticity of the traditional sector productivity with respect to modern sector productivity (ψ_1). These two elasticities jointly determine the slope of traditional sector share and the slope of relative price on log GDP per capita.

Mechanically, we begin with values for σ and ψ_1 and then calibrate the model to match the eight moments from the United States. We then solve the model for poorer countries by lowering A_M, b_1 - the unemployment benefit rate, and τ - wage workers' effective tax rates, while increasing ϵ - search intensity of the self-employed who are searching, and λ - the fraction of workers that are low-educated. We lower b_1 from the U.S. level of 0.45 linearly to almost zero in the poorest model economy. We discipline τ directly by empirical evidence reported in Bachas, Fisher-Post, Jensen, and Zucman (2022) (see Appendix Figure D2) and

λ by using data on the fraction of workers with less than high school education across our set of countries (see Appendix Figure D1). As ϵ directly represents the ratio of job finding rate of the self-employed to the unemployed, we calibrate ϵ from Figure 2a in Donovan, Lu, and Schoellman (2022) so that ϵ decreases from 0.5 to 0.05 when we go from poor to richer economies. After solving each economy, we use the equilibrium prices P_T and sectoral outputs from each economy to compute the chained-type weighted indexes used by NIPA and the Bureau of Economic Analysis. We verify numerically that the government collects more than the unemployment benefits it pays out in equilibrium for each of the model economies. We then scale all output values such that the richest economy matches the U.S. GDP per capita of exp(10.7) or \$44,355. We iterate on σ and ψ_1 until we match the traditional-sector employment and relative price slopes.[7]

Table 7: Slope of Log Relative Prices on log(GDP) in Data

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

Note: Data come from the unpublished ICP 2011 disaggregated price data for the Global Core list of goods and services. See Appendix Table D1 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.

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

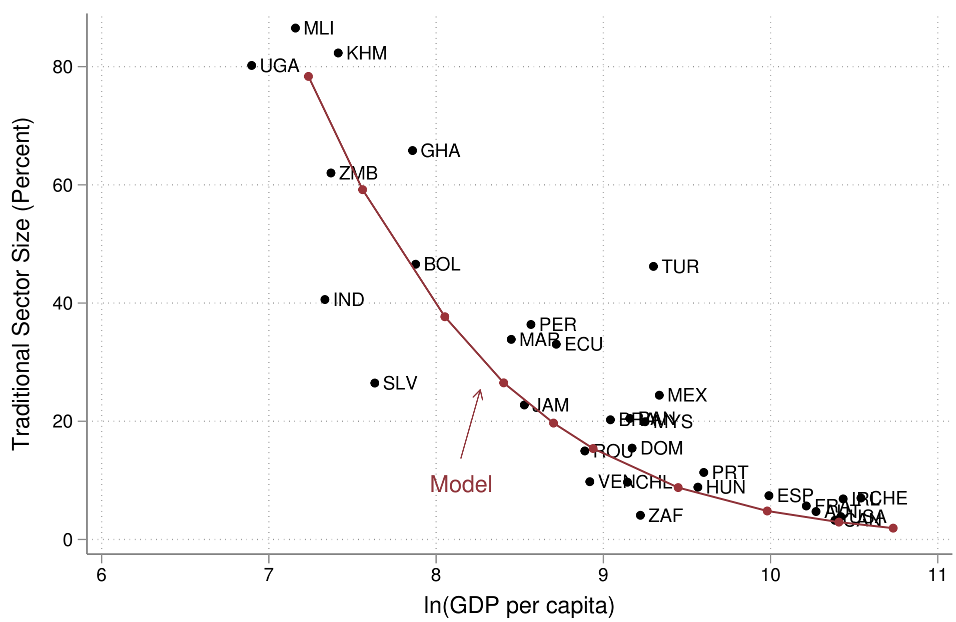
[7]From the poorest to the richest model economy, the A_M vector takes the values of $\{0.005, 0.01, 0.02, 0.03, 0.04, 0.05, 0.08, 0.13, 0.18, 0.23\}$, the $b_1(A_M)$ vector takes the values of $\{0.01, 0.06, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45\}$, and the vector of ϵ is $\{0.5, 0.5, 0.5, 0.5, 0.4, 0.3, 0.2, 0.1, 0.07, 0.05\}$. As the poorest economy in Figure 2a of Donovan, Lu, and Schoellman (2022) has a GDP per capita value of around \$4,000, we assume ϵ remains the same when we move to even poorer countries.

shoeshine; (iv) a 7 km taxi ride from the town center; (v) a men's basic haircut; (vi) a ladies haircut with curlers; (vii) a manicure; (viii) a ladies haircut, long hair. Appendix Table D1 provides the exact definitions of these eight traditional sector services. Since investment goods largely fit our definition of modern output, we take the aggregate price level of investment from the Penn World Table as a proxy for our modern sector price. For each traditional-sector service, we then compute the relative price of the service compared to investment goods in each country.

Table 7 reports the slope coefficient from a regression of the log of the item relative price on log GDP per capita and a constant. As shown in the table, the elasticity of the relative price ranges between 0.39 to 0.68. We target the median of these relative price elasticities, which is around 0.6.

5.2 Quantitative Predictions

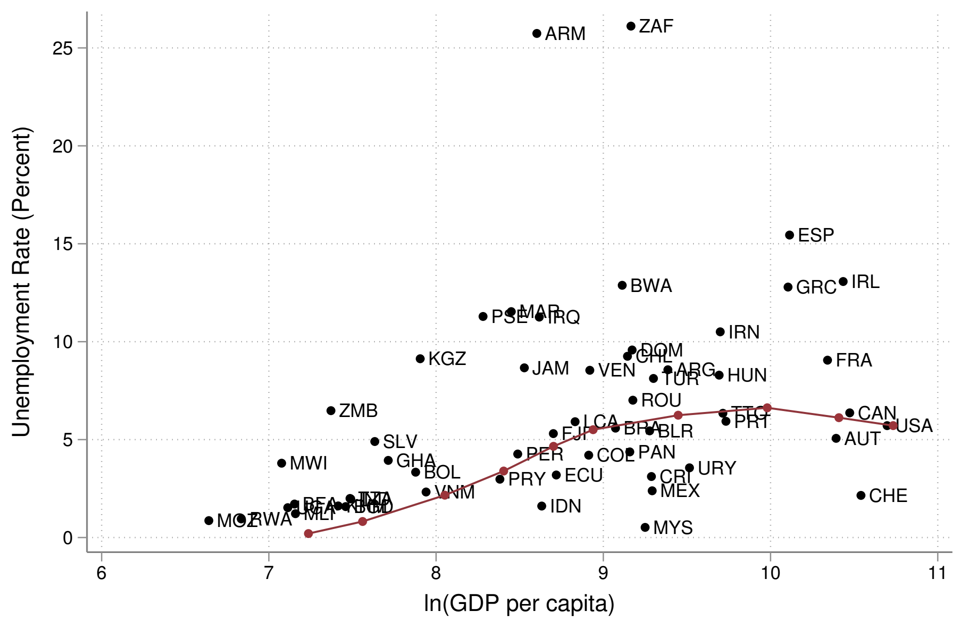
Figure 5: Traditional-Sector Share in Model and Data



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

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

Figure 6: Unemployment Rates in the Model and Data

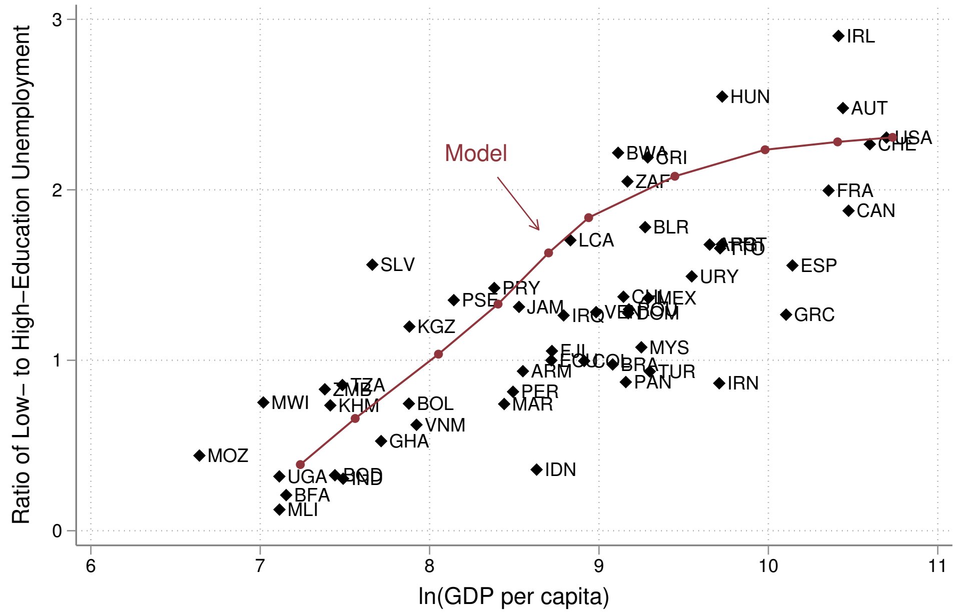


Note: This figure plots the aggregate unemployment rate against log GDP per capita. Each dot represents one country in our database as in Figure 1, and the solid line is the prediction of the quantitative model.

Figure 6 plots the aggregate unemployment level in the model and data. As GDP per capita increases, our model predicts that the unemployment rate will increase from 0.2 percent to the calibrated value of 5.7 percent, perfectly matching the steepness of the relationship. Further, consistent with the data, our model predicts a sharper increase when GDP per capita is lower. This is a result of the faster decrease in the traditional-sector share when GDP per capita is lower. For the richest countries, the model predicts that aggregate unemployment decreases because decreased weight on low-educated unemployment dominates any increases in unemployment within education group.

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

Figure 7: Unemployment Ratio in the Model and Data



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

Table 8: Slope Coefficients in Data and Quantitative Model

	Data	Model
Traditional-sector share for low educated	-21.04	-19.06
Traditional-sector share for high educated	-5.05	-10.13
Aggregate unemployment rate	1.82	1.80
Unemployment rate for low-educated	3.39	3.13
Unemployment rate for high-educated	0.58	1.08
Ratio of unemployment rates u_l/u_h	0.48	0.57

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

Table 8 reports the slope coefficients from regressions of the unemployment rate and other key variables for prime age workers on log GDP per capita and a constant, in our model and in the data. For the aggregate unemployment rate, the model yields a semi-elasticity of 1.80 compared to 1.82 in the data. Thus, the model accounts for almost all of the empirical relationship between unemployment and log GDP per capita. Unemployment rates for the low-educated have a semi-elasticity of 3.13 in the model, compared to 3.39 in the data. The high-educated semi-elasticities are 0.58 and 1.08, respectively, in the data and in the model. The semi-elasticity for the ratio of low- to high-educated unemployment rates is 0.48 in the data and 0.57 in the model.[8]

In our benchmark quantitative model, we allow five factors to vary across countries: A_M/A_T - relative sectoral productivity, b_1 - the unemployment benefit rate, τ - wage workers' effective tax rates, ϵ - search intensity of the self-employed who are searching, and λ - the fraction of workers that are low-educated. Among these factors, the first two (skill-biased technological change and b_1) are the two mechanisms affecting unemployment that are emphasized by our theory as described in Section 4.2, while the latter three are disciplined directly by the data to make the model more realistic. We now explore how much each individual mechanism alone contributes to our model predictions.

Table 9: Slope Coefficients: Effects of Varying One Parameter at a Time

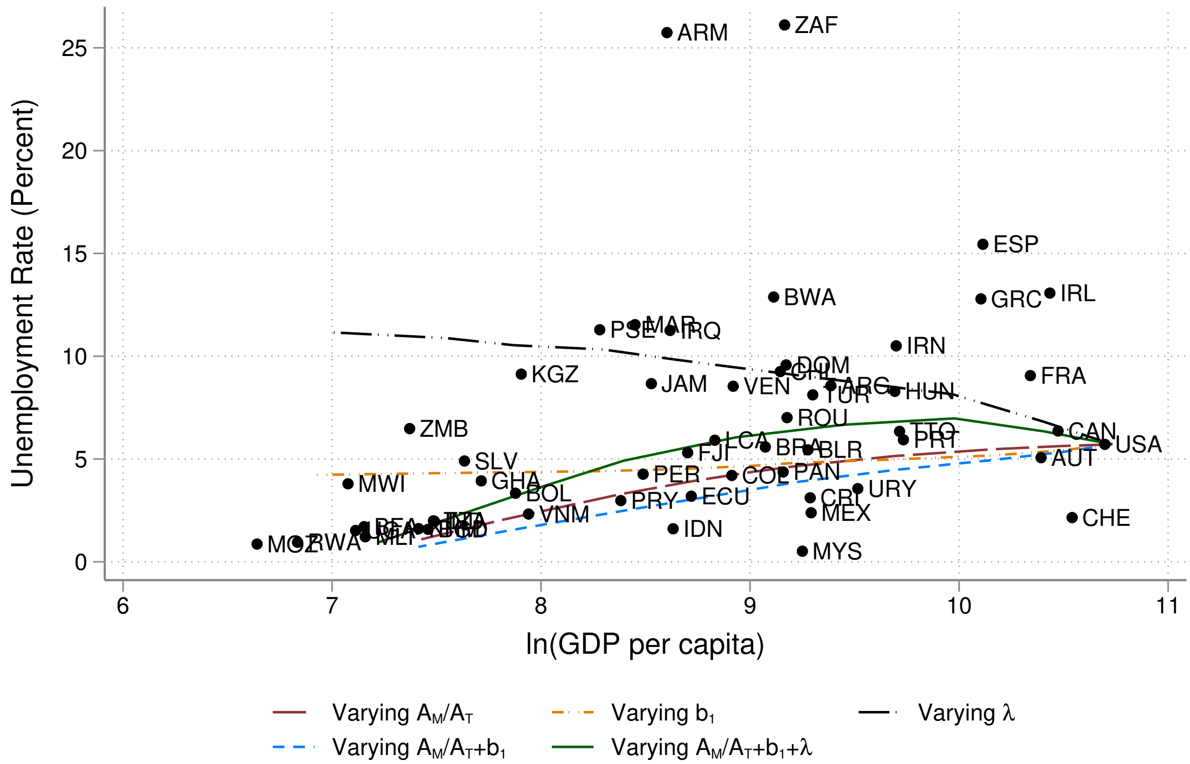
	Data	Model	A_M/A_T	b_1	τ	λ	ϵ
Traditional sector	-19.9	-19.9	-19.9	-0.1	0.1	-0.2	-0.0
Unemployment rate	1.8	1.8	1.4	0.4	0.2	-1.4	0.0
Ratio of u_l/u_h	0.48	0.57	0.53	0.02	-0.0	-0.02	0.0

Note: This table reports the slope coefficients from regressions of the traditional sector share, aggregate unemployment rate and unemployment ratio on log GDP per capita and a constant. The first column reports the values from our cross-country database. The second column reports the values from the benchmark model. Each of the next five columns reports the values from varying the parameter in the column heading across countries while holding the other four parameters at their U.S. levels: column A_M/A_T only varies relative productivity; column b_1 only varies the unemployment benefit rate; column τ only varies the tax rate for wage workers; column λ only varies the share of low-educated workers; column ϵ only varies the search intensity of the self-employed.

Table 9 reports the slope coefficients from regressions of the unemployment rate and unemployment ratio on log GDP per capita and a constant, in our benchmark model and in the alternative models, with only one mechanism varying across countries in each of the five right columns. Consistent with the model predictions, skill-biased technological change is the main driving force for model predictions of semi-elasticities for the traditional sector and for the unemployment ratio. For the increasing aggregate unemployment rate, skill-biased technical change alone can account for 76 percent (1.36/1.80) of the benchmark model semi-elasticity, unemployment transfers alone can account for 21 percent (0.38/1.80), and wage taxes alone can account for 9 percent (0.17/1.80).

[8]The reason our model slightly over-predicts the slope of u_l/u_h against GDP per capita, despite its over-prediction of the slope of u_h against GDP per capita, is that it under-predicts the levels of u_l, and this under-prediction is proportionately greatest for low levels of GDP per capita.

Figure 8: Unemployment Rates in the Counterfactual Models



Note: This figure plots the model predictions when we only allow selected mechanisms to vary across countries.

The one puzzle in Table 9 is that the negative contribution of λ, the share of low-educated workers, does not offset the positive contributions of the other mechanisms. To see why, note that λ does not directly affect either traditional sector participation or market tightness in the high- and low-educated labor markets. Variations in λ therefore tend to leave unemployment rates for both high- and low-educated workers at the U.S. levels to which they were calibrated. The aggregate unemployment rate then increases as GDP per capita is reduced and hence λ is increased because the weight on the low-educated unemployment rate increases, and the unemployment rate is greater for low- than for high-educated workers in the United States. We can see this in the line marked "varying λ" in Figure 8. Now combine increasing λ as GDP per capita falls with decreasing relative productivity A_M/A_T and decreasing benefit rates b_1. At high levels of GDP per capita, traditional sector participation remains small and unemployment rates of high- and low-educated workers remain near U.S. levels, so that increasing λ affects the aggregate unemployment rate similarly to when relative productivity and benefit rates were held constant. At middle levels of GDP per capita, falling relative productivity drives a rapid increase in traditional sector participation, especially by low-educated workers, reducing unemployment rates and sharply reducing the unemployment ratio, the latter negating the impact of increasing λ. At low levels of GDP per capita, u_l falls below u_h and rising λ reinforces the negative effects on the aggregate unemployment rate of falling A_M/A_T and b_1, as seen in Figure 8 by the increasing steepness of the curve combining the three mechanisms relative to the curves with only one or two of the mechanisms.

One important check on the quantitative predictions is whether our model has an empirically plausible response of unemployment rates to unemployment benefits. We calculate that the elasticity of the unemployment rate to benefits is 0.36 in our calibrated model, corresponding to the United States.[9] Schmieder and von Wachter (2021) summarize the empirical literature estimating how unemployment benefits affect unemployment rates. For studies based on U.S. data, they find a median estimated elasticity of unemployment rates to unemployment benefits of 0.38, with a range of 0.1 and 1.2, and all but two estimates below 0.7. Our model's estimate is very similar to their median estimate and well within the wide range of estimates reported in previous studies.

5.3 Sensitivity Analysis

In this section, we explore the sensitivity of our model's predictions to the value for the elasticity of substitution. Rather than targeting the slope of the traditional sector employment share on log GDP per capita, we use a more direct calibration strategy for this important parameter.

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

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

[9] Specifically, our model's estimate is calculated as 0.36=0.159/0.444, the percent change in the unemployment rate to the percent change in transfers b_1 when one compares the U.S. and the fifth richest economy in the counterfactual model where only b_1 varies across countries.

Weinstein (2006) estimate elasticities of substitution across a diverse set of goods varieties, finding median estimates of around 2.2 to 3.7 across goods categories.

Ex-post, our calibrated benchmark value of 3.97 is similar, though somewhat higher, than their estimates. Since there is not a more precise value suggested by the literature we explore a lower value of 3.5 and a higher value of 4.5. We compute the model's predictions while keeping all the other parameter values as in the benchmark.

We present the results in Table 10. Each row reports the slope coefficient from a regression of the variable on log GDP per capita. The second column is the data slope coefficients, and the third to fifth are the slope coefficients in the model with the lower, benchmark, and higher values of the substitution elasticities. For the lower value of 3.5, the model underpredicts the slope of the traditional sector shares on log GDP per capita. As a result, the aggregate unemployment rate varies slightly less with GDP per capita (1.67 versus 1.80 in the benchmark model), as do unemployment rates for low-educated workers (2.94 versus 3.13 in the benchmark) and high-educated workers (1.00 versus 1.08 in the benchmark). The ratio of low-to-high unemployment rates also varies slightly less with GDP per capita than in the benchmark (0.52 versus 0.57) and is closer to the slope of 0.48 in the data. The relative price varies slightly more than in the benchmark (0.63 versus 0.60).

For the higher value of 4.5, the model over-predicts the slope of the traditional sector share on log GDP per capita. The unemployment rate varies slightly more with GDP per capita than in the benchmark, both in the aggregate and by education level. The unemployment ratio has a slope of 0.61 compared to 0.57 in the benchmark. The relative price has a slightly smaller slope of 0.56 compared to 0.60 in the benchmark.

The intuition for these results is as follows. The change in the level of unemployment is driven by the exodus from the traditional sector, which, in turn, is driven by the increase in the ratio of marginal value products of labor: $\frac{A_M}{P_T A_T}$. The smaller is the elasticity of substitution, the less this ratio changes because the rise in P_T offsets the rise in A_M as we move from the poorest to the richest country. In the benchmark model, the slope of this ratio on log GDP per capita is 0.89, only 0.79 when the elasticity is 3.5, and 0.99 when the elasticity is 4.5. That is why the model predicts so much more change in unemployment when the elasticity is 4.5 than when it is 3.5.

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

Table 10: Sensitivity Analysis of Model Elasticity of Substitution

		Elasticity $\frac{1}{1-\sigma}$		
Slope Coefficients	Data	Lower (3.5)	Benchmark	Higher (4.5)
Aggregate traditional sector share	-19.90	-17.67	-19.91	-21.98
Traditional-sector share for low educated	-21.00	-16.63	-19.06	-21.30
Traditional-sector share for high educated	-5.10	-8.20	-10.13	-12.08
Aggregate unemployment rate	1.82	1.67	1.80	1.90
Unemployment rate for low-educated	3.39	2.94	3.13	3.30
Unemployment rate for high-educated	0.58	1.00	1.08	1.16
Ratio of unemployment rates u_l/u_h	0.48	0.52	0.57	0.61
Relative Price	0.60	0.63	0.60	0.56

Note: This table reports the slope coefficients from regressions of the statistics in each row on log GDP per capita and a constant. The second column (Data) reports the slopes from our cross-country database, the third column (Lower) is for an elasticity of substitution between modern and traditional output of 3.5, the fourth column (Benchmark) is the benchmark model with an elasticity of 3.97, and the fifth column (Higher) is for an elasticity of 4.5.

6 The Planner's Allocation and Policy

In this section we solve the problem of a benevolent social planner and characterize the Pareto optimal allocation across the full range of income levels. We find that unemployment levels are increasing in development in the planner's allocations, consistent with the equilibrium allocations. We then highlight the broad policy implications of our analysis by simulating the effects of human capital increases for less-educated workers in our model. The model predicts higher unemployment rates as the result of human capital increases in both the planner's problem and market equilibrium. We conclude that rising average unemployment levels are at least in part an efficient outcome following skill-biased productivity growth.

Planner's Problem. The planner's problem for our economy is to maximize the utility from consuming traditional and modern sector outputs as specified in equation (3), taking endowments, preferences, and technologies as given. Importantly, technologies include not only the production functions (1) and (2), but also the matching function (6), separation rates s_h and s_l, home production technology $A_M b_0$, and vacancy posting cost $A_M c$. Likewise, endowments include not only the measures of high- and low-educated labor $1-\lambda$ and λ but also the ability distributions G_h and G_l. The idea is that planner chooses the search strategies of the workers, through sorting by ability, and the firms, through vacancy postings, but not the employment outcomes directly.

Formally, the planner chooses $\theta_h, x^*_{Th}, x^*_{Mh}, \theta_l, x^*_{Tl}, x^*_{Ml}$ to maximize (3), subject to the constraints given by combining equations (2) and (19) and equations (1) and (20), respectively:

$$\max_{\substack{\theta_h, x^*_{Th}, x^*_{Mh},\\ \theta_l, x^*_{Tl}, x^*_{Ml}}} W = \big[\gamma (C_T)^\sigma + (1-\gamma)(C_M)^\sigma\big]^{\frac{1}{\sigma}}$$

$$\text{s.t. } C_T = A_T N_T,$$
$$C_M = A_M\big[X_M + b_0 u - c\big((1-\lambda)\theta_h(\tilde{u}_h + \epsilon \tilde{t}_h) + \lambda\theta_l(\tilde{u}_l + \epsilon \tilde{t}_l)\big)\big].$$

The labor inputs N_T and X_M in turn are given by:

$$N_T = (1-\lambda)G_h(x^*_{Th}) + \lambda G_l(x^*_{Tl}) + t, \text{ and}$$
$$X_M = (1-\lambda)\tilde{X}_{Mh} + \lambda \tilde{X}_{Ml}$$

where $\tilde{X}_{Mi}$ for $i = h, l$ represent the average abilities for high- and low-educated workers in the modern sector. These are given by:

$$\tilde{X}_{Mi} = \big(G_i(x^*_{Mi}) - G_i(x^*_{Ti}) - \tilde{t}_i\big)\mathbb{E}_i\big(x | x^*_{Ti} < x \leq x^*_{Mi}\big) + (1 - G_i(x^*_{Mi}) - \tilde{u}_i)\mathbb{E}_i\big(x|x > x^*_{Mi}\big),$$

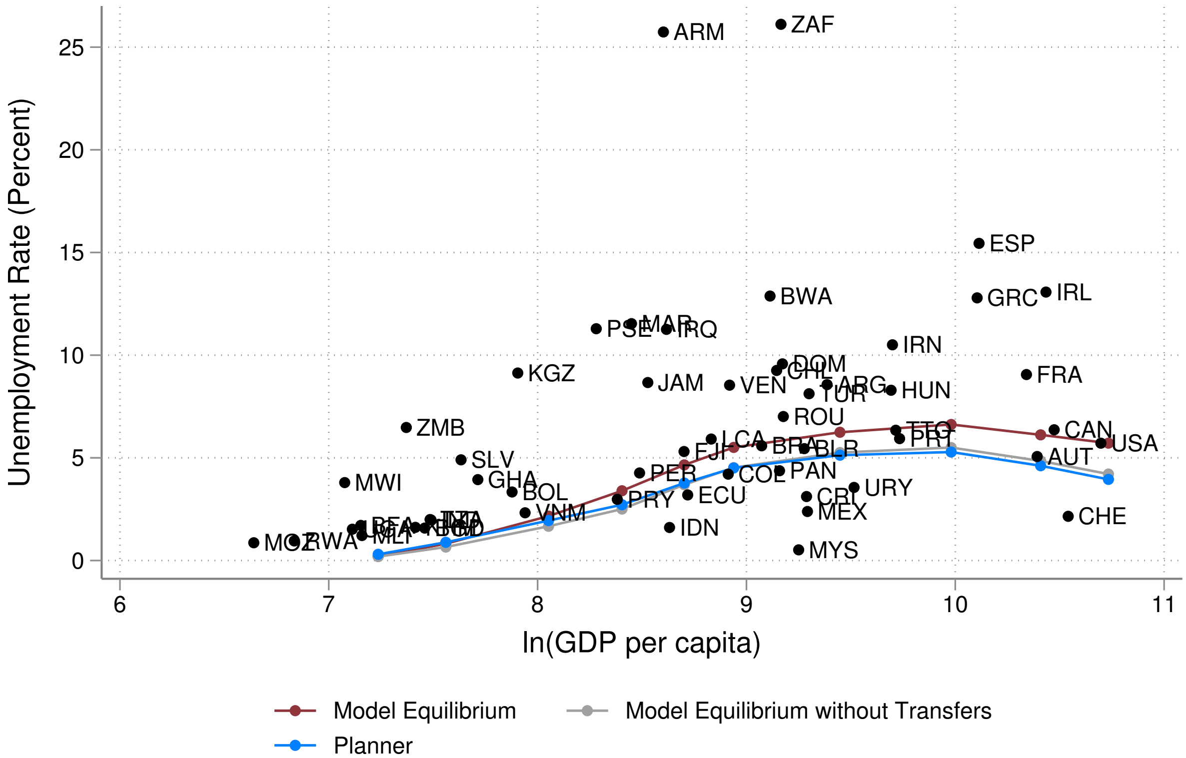
for $i = h, l$. Finally, $\tilde{u}_i, u, \tilde{t}_i$, and t are given by equations (15) to (18) above.

In this setup, the tools available to the planner are the posting of vacancies for the two types of labor and the allocations of the two types of labor to the traditional sector, the traditional sector with searching, and the modern sector. The planner controls vacancies by choosing the two market tightness values, θ_h and θ_l, and controls labor allocation by choosing the four ability cutoff values, x^*_{Mh}, x^*_{Ml}, x^*_{Th}, and x^*_{Tl}.

We solve the planner's problem numerically using the same calibrated parameter values as in the main analysis. Figure 9 plots the planner's solutions (in blue) of unemployment rates against the equilibrium solutions (in maroon). The two sets of solutions are almost the same for low-income countries, where the planner and market outcomes both feature very low unemployment rates. Importantly, both the planner and market outcomes also feature unemployment rates that are increasing in development. This highlights the point that greater unemployment levels in richer countries are, at least in part, efficient outcomes given search frictions in labor markets.

For the richest economies, the planner's outcome features moderately lower unemployment rates than the market outcome. The reason is that the planner internalizes the fact that unemployment benefits must be financed in general equilibrium using labor taxes. In the market outcome, households consider transfers as well as the home production value of unemployment in deciding whether to choose unemployment or self-employment in the traditional sector when separating from their modern sector jobs. As Figure 9 shows,

Figure 9: Unemployment Rates in the Equilibrium and Planner's Solutions



Note: This figure plots the aggregate unemployment rate against log GDP per capita. Each dot represents one country in our database as in Figure 1, and the solid lines are model predictions.

removing the unemployment transfers (setting $b_1 = 0$ for all countries) while keeping all other parameters at the calibrated values takes the equilibrium outcome very close to the planner's solution. With neither labor taxes nor unemployment transfers, the market outcome and planners solution essentially coincide over the full development spectrum.[10]

Effects of Human Capital Policy. The higher unemployment rates in richer economies suggest a lesson for policy making in low-income countries. These economies are faced with difficult decisions about how to spend scarce public resources on development goals of various types. To the extent that investments in development projects succeed in raising income levels, our paper implies that a side effect may be higher unemployment.

To make this point in a more specific context, we simulate the effects of human capital

[10] As shown in Mangin and Julien (2021), when the expected match output depends on market tightness, the classic Hosios (1990) condition does not restore efficiency. In our two-sector model, market tightness endogenously determines the ability distribution of the workers who are searching, thus affecting the expected match output. Therefore, the decentralized equilibrium presented in Section 5 in not necessarily efficient. In practice, absent labor taxes and unemployment transfers, the planner and market allocations are almost identical.

increases for less-educated workers, which may result from expansions in the number of public schools, improvements in primary schooling quality, improved attendance of primary school teachers, or other similar policies. Here, we simulate the effects of such policies, taking as given that they actually lead to human capital increases for less educated workers (meaning those not finishing secondary schooling). We do so for a model economy that has a GDP per capita level of $3,000, which is around the level of Vietnam or Bolivia. We assume that the less-educated workforce experiences an average productivity increase of 20 percent, which is like an increase in average schooling from 5 to 6 years.

Table 11: Effects of Human Capital Increases for Less-Educated Workers

Broad Policies	Wage Emp.	Unemployment	$\frac{\Delta\#\text{Unemployed}}{\Delta\#\text{100Wage}}$
Equilibrium	4.82	0.26	5.30
Planner	4.77	0.27	5.66

Note: This table reports the effects of increasing the productivity of the less-educated workers by 20 percent on wage employment (in percentage points), unemployment rates (in percentage points), and the change in unemployed workers for every 100 new wage workers.

Table 11 reports the results of this policy. In equilibrium, the modern sector expands at the expense of the traditional sector. After the policy change, the unemployment rate rises by 0.26 percentage points, which corresponds to an increase of 5.3 unemployed workers for every additional 100 wage workers. The reason is that, given their higher productivity, a greater share of less-educated workers wants to search with highest intensity for modern sector jobs. The bottom row of Table 11 reports the effects of the policy under the planner's solution. The planner's outcome responds in a nearly identical way to the market allocation in response to the policy. In particular, the planner's outcome features an almost identical increase in unemployment rates of 0.27 percentage points.[11]

The broad policy lesson is that increases in unemployment rates following a development policy, such as one that fosters human capital accumulation, may be a sign of success, rather than failure. Through the lens of our model, long-run increases in unemployment rates are an efficient response to greater economic opportunities given the search frictions that characterize wage employment. At the same time, we recognize that there is a great deal of variation in unemployment that is not explained by our model, suggesting a large scope for policies targeted more directly at improving the functioning of the labor market.

[11] The higher number of unemployed added per wage worker simply reflects the lower number of wage workers added by the planner. The percentage increase in utility is slightly greater in the planner's solution than in the market solution.

7 Conclusions

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

To interpret these facts, we build and calibrate a simple two-sector model that combines labor search, as in Diamond (1982) and Mortensen and Pissarides (1994), with a traditional self-employment sector, as in Parente, Rogerson, and Wright (2000). The proximate cause of development in the model is skill-biased technological progress, as emphasized by a growing literature in macroeconomics following Caselli and Coleman (2006). In spite of its simplicity, the model explains the bulk of the relationship between unemployment and development when parameterized to match plausible differences in the extent of cross-country differences in productivity by skill level. It also does well in matching the faster increase in unemployment for the low-skilled relative to the high-skilled, as in the data. We conclude that as long as development is itself the result of skill-biased productivity growth, then unemployment is a consequence of the development process, as progressively less skilled individuals move from self-employment into wage work.

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Online Appendices

A Data Appendix

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

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

Tier 1a: Searched for work last week

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

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

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

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

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

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

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

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

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

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

B Employment, unemployment, not in the labor force

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

Table B1: Employment, Unemployment and Not in the Labor Force

		Low Education			High Education		
		Q1	Q4	Difference	Q1	Q4	Difference
Male	Employed	86.51	72.83	-13.68***	82.72	86.28	3.57*
	Unemployed	1.99	11.22	9.23***	3.88	6.14	2.25**
	Not in labor force	11.50	15.95	4.45	13.40	7.58	-5.82**
Female	Employed	59.32	45.96	-13.36*	62.74	69.67	6.93
	Unemployed	1.19	9.13	7.93***	3.76	6.65	2.90*
	Not in labor force	39.49	44.92	5.43	33.51	23.68	-9.83

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

Table B1 reports the average percent of prime aged adults – by sex and education level – that are employed, unemployed, and not in the labor force, for countries in the bottom (Q1) and top income (Q4) quartiles. For low-educated males, employment rates are substantially lower in the richest quartile than in the poorest. This reflects a substantially higher percent of low-educated males not in the labor force in the richest quartile, as well as their higher unemployment rates in the richest quartile. A similar pattern also holds for women, though with lower employment levels in both quartiles.

Among high-educated males, employment rates are modestly higher in the richest quartile than in the poorest quartile (though the difference is statistically insignificant). Yet the percent of high-educated males that are unemployed is also modestly higher in the richest quartile. The reason that both are higher in the richest quartile is that, as Table B1 shows, the percent not in the labor force is substantially *lower* for high-educated males in the richest quartile. A similar pattern again holds for females, though with larger increases in employment rates and labor force participation rates than for the males. In sum, although cross-country differences in unemployment rates reflect cross-country differences in employment rates for the low-educated, the same is not true for the high-educated. We conclude that one cannot in general infer cross-country unemployment patterns by looking solely at data on employment rates, which reflect a margin of labor force participation as well.

C Model Derivations

In this appendix, we solve for $w_i(x)$ as a function of the model parameters and θ_i, and solve for $T_i(x)$, $U_i(x)$, and $E_i(x)$ as functions of the model parameters, θ_i, and $w_i(x)$.

Using the free-entry condition $V_i = 0$, we can simplify equation (10) to

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

Combining equations (7) to (9) and using the expressions for f_{Ti} and f_{Ui} yields

$$E_i(x) - T_i(x) = \frac{(1-\tau)w_i(x) - P_T A_T}{1-\delta(1-\epsilon\eta\theta_i^{1-\alpha} - s_i)} \qquad \text{for } x \in \left(x^*_{Ti}, x^*_{Mi}\right] \tag{C.2}$$

$$E_i(x) - U_i(x) = \frac{(1-\tau)w_i(x) - A_M[b_0 + b_1(A_M)x]}{1-\delta(1-\eta\theta_i^{1-\alpha} - s_i)} \qquad \text{for } x > x^*_{Mi}. \tag{C.3}$$

The firm receives

$$J_i(x) = (1-\beta)S_i(x) = \begin{cases} (1-\beta)[E_i(x) - T_i(x) + J_i(x)] & \text{if } x \in \left(x^*_{Ti}, x^*_{Mi}\right] \\ (1-\beta)[E_i(x) - U_i(x) + J_i(x)] & \text{if } x > x^*_{Mi} \end{cases} \tag{C.4}$$

when a vacancy is filled. Combining this division of surplus with equations (C.1), (C.2) and (C.3) yields

$$w_i(x) = \begin{cases} \frac{P_T A_T}{1-\tau+k_{Ti}(\theta)} + \frac{k_{Ti}(\theta)}{1-\tau+k_{Ti}(\theta)} A_M x \text{ with } k_{Ti}(\theta_i) \equiv \frac{\beta(\delta\epsilon\eta\theta_i^{1-\alpha}+1-\delta+\delta s_i)}{(1-\beta)(1-\delta+\delta s_i)} & \text{if } x \in \left(x^*_{Ti}, x^*_{Mi}\right] \\ \frac{(b_0+b_1 x)A_M}{1-\tau+k_{Mi}(\theta_i)} + \frac{k_{Mi}(\theta_i)}{1-\tau+k_{Mi}(\theta_i)} A_M x \text{ with } k_{Mi}(\theta_i) \equiv \frac{\beta(\delta\eta\theta_i^{1-\alpha}+1-\delta+\delta s_i)}{(1-\beta)(1-\delta+\delta s_i)} & \text{if } x > x^*_{Mi} \end{cases}$$

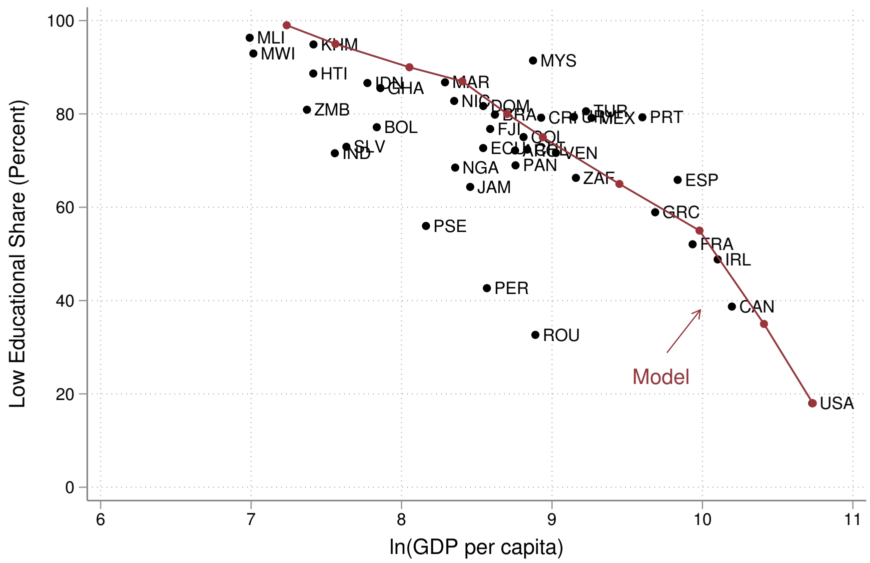
$$T_i(x) = \frac{P_T A_T}{1-\delta} + \frac{\delta\epsilon\eta\theta_i^{1-\alpha}\beta[A_M x - w_i(x)]}{(1-\delta)(1-\beta)(1-\delta+\delta s_i)} \text{ if } x \in \left(x^*_{Ti}, x^*_{Mi}\right]$$

$$U_i(x) = \frac{(b_0+b_1 x)A_M}{1-\delta} + \frac{\delta\eta\theta_i^{1-\alpha}\beta[A_M x - w_i(x)]}{(1-\delta)(1-\beta)(1-\delta+\delta s_i)} \text{ if } x > x^*_{Mi}.$$

$E_i(x)$ can then be obtained from equations (C.2) or (C.3).

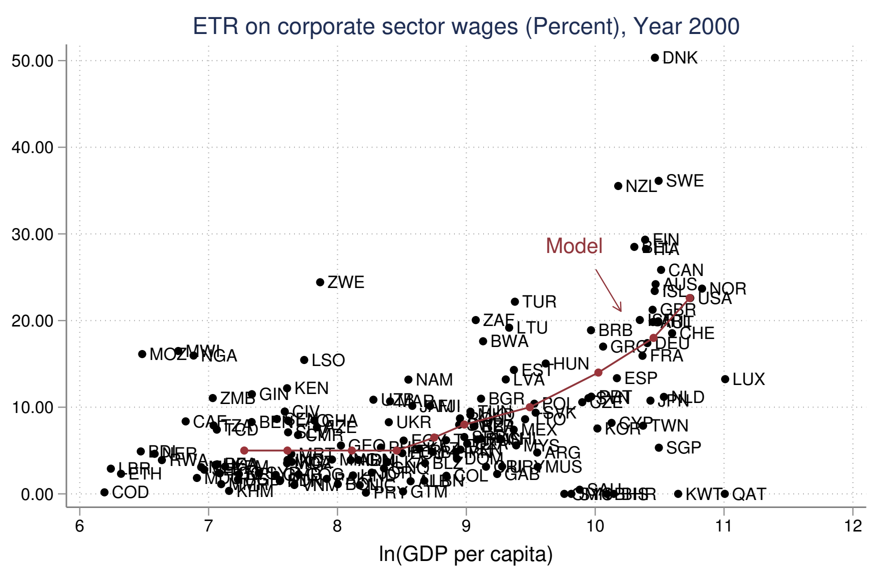
D Appendix Figures and Tables

Figure D1: Low-Education Share, λ, in Model and Data



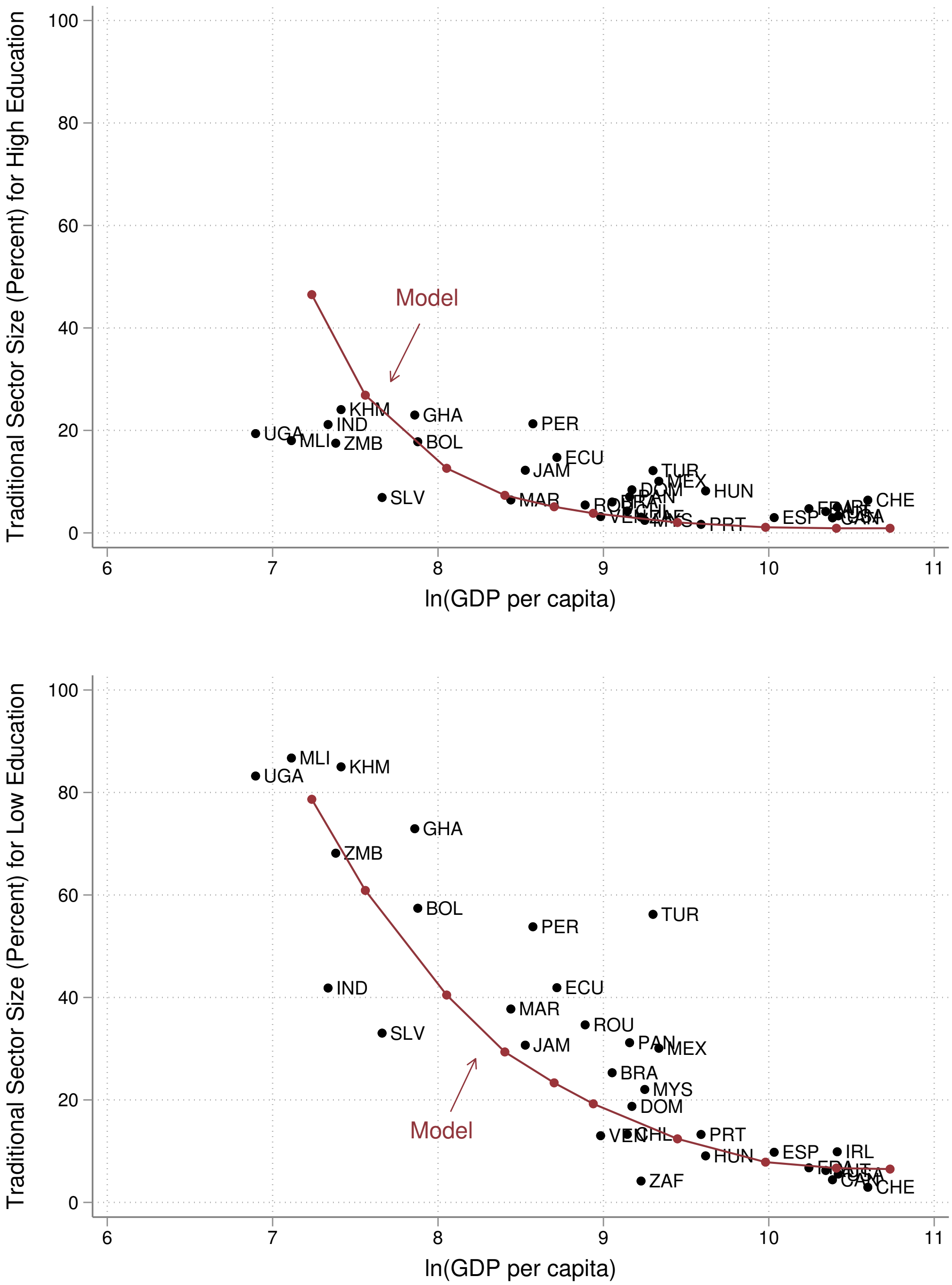
Note: This figure plots the values of λ used in the quantitative experiments of Section 5 (solid line), and the percent of the labor force that is low-educated in each of our countries (dots with identifiers). The data come from IPUMS. Low-educated individuals are defined to be those with less than a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

Figure D2: Effective Tax Rates of the Wage Workers in 2000, τ, in Model and Data



Note: This figure plots the values of τ used in the quantitative experiments of Section 5 (solid line), and the effective tax rates of wage workers across countries in year 2000 (dots with identifiers). The data come from Bachas, Fisher-Post, Jensen, and Zucman (2022).

Figure D3: Traditional-Sector Share by Education



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

Table D1: Definition of Traditional Sector Goods

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

Note: The table reports the definitions of each ICP traditional service used in Table 7, and described in Section 5.1. The services come from the unpublished ICP 2011 Global Core list of goods and services.