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How do Hours Worked Vary with Income? Cross-Country Evidence and Implications
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ABSTRACT

This paper builds a new internationally comparable database of hours worked to measure how hours vary with income across and within countries. We document that average hours worked per adult are substantially higher in low-income countries than in high-income countries. The pattern of decreasing hours with income holds for both men and women, for adults of all ages and education levels, and along both the extensive and intensive margin. Within countries, hours worked per employed are also decreasing in the individual wage for most countries, though in the richest countries, hours worked are flat or increasing in the wage. Our findings imply that aggregate productivity and welfare differences across countries are larger than currently thought.

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1. Introduction

One of the most basic facts in macroeconomics is that aggregate income per capita varies greatly across countries (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Caselli, 2005). Much less is known about how aggregate hours worked vary across countries. Consider the basic question: are average hours worked higher for adults in high-income countries or for adults in low-income countries? Due to data limitations, the economics literature does not have an answer to this question. This is unfortunate, because if hours enter directly into preferences, then measures of average hours worked at the country level are a key input to understanding welfare differences across countries (Jones and Klenow, 2016).

In this paper, we create a new database of average hours worked using recent household survey data from 80 countries of all income levels. Unlike several other existing databases on hours worked, our data are internationally comparable and allow for rich disaggregate comparisons across and within countries. The surveys we employ are nationally representative and cover workers in all sectors, including the self-employed, which represent the majority of the workforce in low-income countries. We focus most of our analysis on a set of 48 *core countries*, for which international comparability of hours data is as high as possible. In particular, we require that the data from these core countries satisfy three basic criteria. First, the surveys cover the entire calendar year (rather than, say, one month of the year). This is necessary to prevent any bias induced by seasonality in labor demand. Second, hours worked are measured in a consistent way: actual (rather than usual) hours in all jobs (not just the primary job), and in the week prior to the interview. Finally, hours worked cover the production of goods or services counted in the National Income and Product Accounts (NIPA). Thus, our hours measures cover unpaid work in agricultural or non-agricultural businesses, as well as wage employment, but do not cover home-produced services, such as child care.[1]

Our main finding is that average hours worked per adult are substantially higher in low-income countries (the bottom third of the world income distribution) than in high-income countries (the top third). In low-income countries, adults work 28.5 hours per

[1]For a smaller set of countries, we document that hours spent on home production of services in low- and high-income countries follow the same pattern as hours spent on producing goods and services counted in NIPA; we present these findings in Section 4.4.

week on average, compared to 18.9 hours per week in high-income countries. This difference is both statistically and economically significant, with cross-country differences in average hours per adult (9.6 hours per week) being twice as large as the decline in hours per adult in the United States over the twentieth century (4.7 hours per week) (Ramey and Francis, 2009). In percentage terms, adults in low-income countries work about fifty percent more hours per week than adults in high-income countries. As one simple summary statistic, the slope coefficient from a regression of log hours per adult on log GDP per hour is -0.15. We also decompose average hours per adult into an extensive margin (employment rate) and intensive margin (average hours per worker). We find that cross-country differences in hours per adult are shaped by both margins. Employment rates are higher in the poorest third than in the middle third, and similar between the middle and top third of the world income distribution. Average hours per worker increase between the poorest and the middle third, and then decrease substantially for the richest third. Overall, employment rates account for about three quarters of the decline in hours per adult between low- and high-income countries, while hours per worker account for about one quarter.

After having documented the facts on the aggregate level, we compute average hours by sex, age group, and educational attainment. We find that the pattern of higher hours in low-income countries is quite broad-based, being present in each of the disaggregated categories. We also decompose average hours per worker into three broad sectoral aggregates: agriculture, manufacturing, and services. Hours per worker in agriculture are similar across the world income distribution, while manufacturing and services workers work 8.5 and 13.7 more hours per week in the low- than in the high-income countries. The results from the sectoral breakdowns are reassuring if one has the prior that hours worked are measured more accurately in manufacturing and services. We show that the differences in aggregate hours across countries are not driven by different compositions in age, education, or sectors across countries.

We next ask how hours vary with income within countries, and to what extent the within-country patterns help account for the aggregate patterns we document thus far. Our main measure of individual income is the hourly wage from paid employment, which we compute for all workers who are employed as wage workers.[2] We find that when

[2]We also look at wages plus self employment earnings for a broader set of workers, but with the caveat that self-employment earnings are less well measured than earnings from paid employment.

pooling individuals across all core countries, hours per worker fall with wages, just as they do in the aggregate: the slope of log hours on log wages is -0.09, compared to a slope of log hours on log GDP per hour of -0.12. When regressing log hours on both log wages and log country GDP per hour together, the slope on log wages falls only modestly, while the coefficient on GDP per hour becomes substantially smaller in absolute terms and insignificant. Even with country fixed effects, the coefficient on log wages remains similar in magnitude. This suggests that residents of poor countries work more hours on average mainly because of their low wages, rather than because of aggregate factors prevalent in poor countries. We find that this effect is stronger for men than for women, for whom both country effects and individual wages play important roles.

Finally, we explore how the elasticity of hours to wages varies country by country. We find that individual slopes are negative for the majority of countries in our database. Interestingly, these slopes are systematically lower in countries with lower GDP per capita than in richer countries like the United States, where hours are increasing in individual wages. This is consistent with historical evidence showing that hours-wage slopes for employed workers used to be decreasing or flat but are nowadays increasing in the United States (Aguiar and Hurst, 2007; Costa, 2000) and in other OECD countries (Huberman and Minns, 2007). The results for the extensive margin are in line with the intensive margin evidence. Using education as a proxy for the permanent income of non-working individuals we find that employment rates are flat by education in poor countries, but increasing by education in richer countries. Our findings suggest that the change from a decreasing hours-income slope to a positive one within countries may be a fundamental feature of the development process.

We conclude by discussing implications of our findings for cross-country differences in aggregate labor productivity and welfare. In the absence of data on hours worked, development accounting typically relies on GDP per worker as a measure of labor productivity, which implicitly treats hours per worker as identical across countries (see e.g. Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010). Across our core countries, GDP per worker is a factor 19.9 times larger in the richest third than in the poorest third of countries, while GDP per hour is 23.5 times as large. Thus, after taking hours into consideration, cross-country TFP differences are even larger than previously thought. Our findings also have implications for welfare differences across countries. Building on the work of Jones and Klenow (2016), we construct a flow measure of utility from consumption and disutility of work. Using our hours data, plus standard measures of consumption per capita, we calculate that welfare differs by a factor of 19 between high-income and low-income countries, compared to a factor of 12 when we ignore differences in hours worked. To put it succinctly, residents of low-income countries are not just consumption poor, but also leisure poor.

The rest of this paper is structured as follows. Section 2 highlights the paper's contribution relative to the literature. Section 3 describes our underlying data sources, and our efforts to construct internationally comparable data on hours worked. Section 4 documents that aggregate hours worked per adult are decreasing in the country income level, compares the data to U.S. time-series, and provides some evidence that hours on home services are also decreasing in income. Section 5 presents hours worked differences across countries by gender, education, age, and sector, and shows that differences in aggregate hours are not driven by differences in the demographic composition across countries. Section 6 then analyzes how hours vary with income at the individual level within our sample countries. Section 7 quantifies implications of the aggregate results for the measurement of labor productivity and welfare differences across poor and rich countries. Section 8 concludes.

2. Related Literature

Our study is the first to measure how hours worked vary with income across and within countries of all income levels. Prior studies of aggregate hours worked across countries have almost exclusively focused on rich countries, and in particular on the United States and European countries (e.g., Bick et al., 2016). Explanations of the U.S.-Europe gap in average hours have focused largely on differences in taxation (e.g., Prescott, 2004; Rogerson, 2006; McDaniel, 2011; Bick and Fuchs-Schündeln, 2017), institutions (Alesina et al., 2005) and social security systems (Erosa et al., 2012; Wallenius, 2013; Alonso-Ortiz, 2014). Other studies have focused on understanding changes in hours worked over time, though these have also concentrated on rich countries. For example, McGrattan and Rogerson (2004) and Ohanian et al. (2008) measure changes in hours among OECD countries over time, while Ramey and Francis (2009), and Francis and Ramey (2009) focus on the long-run decline in hours worked in the United States. Aguiar and Hurst (2007) and Costa (2000) study how hours vary with income within the United States historically, and Huberman and Minns (2007) focus on these patterns for a number of OECD countries.

The existing evidence on hours worked from developing countries is quite limited. The study by Lee et al. (2007) presents some evidence on hours from largely non-representative establishment surveys covering wage earners in manufacturing. Their data thus excludes the self-employed and those working in agriculture, which together form the vast majority of all workers in the developing world. Caselli (2005) considers hours worked data for 28 countries from the International Labor Organization (ILO), though just two of these countries are in the bottom half of the world income distribution. Gollin et al. (2014) compare average hours worked among workers in the agricultural and non-agricultural sectors of a large set of countries using nationally representative surveys. Their data are comparable across sectors within each country, though not necessarily comparable across countries. Bridgman et al. (2017) provide evidence on household and market production hours from time use surveys covering 43 countries of all income levels, including richer data than in our study on hours of home production. Jones and Klenow (2016) consider hours worked in their study of welfare differences across countries. Their micro data cover however only 3 middle- and 3 low-income countries, and of these 6 only 2 qualify as core countries in our study. For their extended analysis, they rely on hours data from the Penn World Tables (PWT). None of these studies analyzes how hours worked vary with wages on the individual level.

The Total Economy Database, run by the Conference Board, recently released data on annual hours worked per worker, in addition to employment rates, for an unbalanced panel of countries, with the earliest data coming from 1950. These data are also included now in the PWT. Many of these data points are however interpolated or extrapolated, especially for the low- and middle-income countries. Of the data points that have an actual source available, the quality is highly questionable in terms of consistency of hours measurement, activity coverage, and potential biases from seasonality. We detail some of these data quality issues in Online Appendix Section A.4.[3]

[3]To give some concrete examples, from the 304 country-year observations that come from country-years in which the country's GDP would place it into the lowest tercile of the world income distribution today, 89, i.e. almost one third, are inter- or extrapolated. Of the remaining data points, the vast majority,

3. Data

In this section, we describe the survey data underlying our analysis. We then introduce the criteria that we use to define the set of core countries, which are those that have the most scope for international comparability. Next, we describe how we measure hours per adult, employment rates, and hours per worker.

3.1. Data Sources

Our analysis draws on nationally representative household surveys. The key advantage of using household surveys, as opposed to firm surveys or administrative records, is that our measures of labor supply are not restricted to activities for which individuals receive a wage, but also include self-employed and unpaid family work. As is well known, the self-employed form an important fraction of the workforce in all countries, and particularly so in developing countries, see e.g. Gollin (2008).

All of the surveys we employ are publicly available for researchers, mostly via an application through national statistical agencies or similar institutions. We were able to collect nationally representative data for 80 countries with a population of at least one million. For 33 of our countries we can draw from harmonized data sets, for which efforts have already been made to standardize questions across countries. These comprise the European Labor Force Survey (ELFS; 26 countries) and the International Public-Use Microdata Project (IPUMS; 7 countries). For the remaining 47 countries, we draw on country-specific censuses, household or labor force surveys, including 20 surveys conducted as part of the World Bank's Living Standards Measurement Studies (LSMS).[4]

When multiple years of appropriate data are available, we choose the year closest to 2005. Most of our data are within a few years of 2005; exact years, data sources, and

namely 196, come from data provided by the Asian Productivity Organization (APO). For 83 of the 196 APO data points, there is no information available regarding the original data source, and for a further 71 the original data source does not contain any information on hours per worker. Hence, only for 42 data points from 4 countries is there any information on hours per worker in the original data, but the quality is still unclear. Some of the other low-income data points in the Total Economy Database come from either Hofman (1998) or Maddison (2001), which in turn often extrapolate data or impute average hours per employed using only the number of statutory public holidays and vacation days.

[4] Note that this does not imply that these standardized surveys are all in our sample of core countries. All ELFS countries are core countries, while none of the IPUMS countries and only 9 of the LSMS countries are core countries.

sample sizes for all countries are given in Online Appendix Table C.1. Our sample sizes range from 5,000 to over 700,000 individuals. We focus on all individuals of at least age 15, whom we refer to as "adults".[5]

3.2. Core Countries

The key measurement challenge we face is that not all of our surveys are conducted in the same way, and more specifically, not all surveys collect hours information in the same way. To ensure that international comparability is as high as possible, we focus our main analysis on a set of *core countries* which we define to be those that satisfy the following three criteria.

1. Activity Definition: We restrict attention to hours worked in the production of output that is counted in NIPA. These include hours worked in wage employment as well as hours in own-account agricultural or non-agricultural work, whether or not that output is sold or used for own consumption (see e.g. Gollin et al., 2014). This is important if we want to maintain a nationally representative sample of workers, particularly in the poorest countries, where agricultural work and self-employment are widespread. Not included in our definition of hours worked are hours spent on non-market services, such as cleaning or home-provided child care; we return to the issue of home-produced services in Section 4.4.

2. Hours Worked Information: We focus on actual hours worked, rather than usual hours worked, since individuals may work more or less than usual in a given week, due to e.g. over-time or sickness. We also focus on all jobs, rather than just the primary job, since many individuals have multiple jobs. Finally, we focus only on surveys that ask respondents about hours worked in the last week or in a recent reference week, since longer time periods may lead to recall bias.

3. Time Coverage: We restrict attention to surveys that cover the entire calendar year. While all of our surveys are nationally representative in terms of the covered population, some are conducted over the entire year, and others are conducted over only a few months or weeks. Using these partial-year surveys creates potentially biased estimates of hours worked unless the survey period happens to be representative of the entire year. This bias may be more pronounced in developing countries, which are largely agricul-

[5] The United States is an exception here as the youngest available age is 16.

tural and hence seasonal. Online Appendix A.1 provides a detailed explanation of how we determine the time coverage of each survey and which surveys qualify as covering the entire year according to our definition.

Out of the 80 countries in our sample, 48 qualify as core countries. All the non-core countries satisfy the first criterion on the activity definition but have either non-standard hours worked information or cover less than the full calendar year (or both).

3.3. Measuring Employment and Hours Worked

Our measures of employment rates and hours worked rest on two key variables: the self-reported employment status and actual hours worked in all jobs in the last week. We measure the employment rate as the fraction of all adults that report being employed or have positive hours worked. We measure hours per worker as the average hours worked in all jobs in the reference week among all those who are employed. Both measures are calculated with the individual survey weights. We measure hours per adult as the product of the employment rate and average hours per worker. We provide more details on our calculations in Online Appendix Section A.2. Since the surveys of the core countries cover the entire year, vacations, sick leave, or other reasons for seasonality should in principle be covered, and multiplying the reported numbers by 52 gives an estimate of annual hours worked per adult (see our discussion of potential biases in Online Appendix Section A.5).

Our definition of whether a country in our sample is a low- (bottom third of the world income distribution), middle- or high-income (top third of the world income distribution) country is based on GDP per capita in the year 2005 for all countries in the Penn World Tables version 9.0 (see Feenstra et al. (2015) for a detailed description of the PWT). Specifically, we use expenditure-side real GDP at chained PPPs in 2011 US $ (*rgdpe*). We find similar levels of average GDP per capita when comparing each of these terciles in our core and full set of countries to all countries in the PWT; see Online Appendix Table C.2. When plotting aggregate hours worked against GDP per capita, we use GDP per capita for each country from the same year for which we have the hours data.

4. Aggregate Hours by Income Across Countries

In this section, we document that average hours worked per adult are substantially higher in low-income countries than in high-income countries, and that the same holds true for both the extensive and the intensive margins of labor supply. Last, we provide suggestive evidence that also hours spent on the production of home services are decreasing by development.

4.1. Average Hours Worked Per Adult

Figure 1 plots average weekly hours per adult against log GDP per capita for our core countries. Vertical lines separate the three terciles of the world income distribution; 11 countries fall in the bottom tercile, 15 in the middle tercile, and 22 in the top tercile. The figure shows that average hours per adult are downward sloping in income per capita. The poorest countries in the world range from a low of around 24 hours per week in Malawi, Rwanda, and Uganda to a high of almost 40 hours per week in Cambodia. The richest countries average between a low of around 16 hours in Italy, Spain, Belgium, and France and a high of 24.4 hours in the United States. Iraq has the lowest hours per adult in our sample, which is driven entirely by women, as discussed in Section 5.1.

Panel A of Table 1 reports in the first row the average hours per adult by income tercile in our core countries. In these countries, average hours per adult are 28.5 hours per week in low-income countries, compared to 22.2 hours in middle- and 18.9 hours in high-income countries. In terms of economic significance, the 9.6 higher weekly hours in the low-income group correspond to 50 percent higher hours than in the high-income group.[6] Regressing the logarithm of hours on the logarithm of GDP per hour worked yields a slope coefficient of -0.15.[7]

Given that the number of core countries is relatively small, particularly in the lower end of the income distribution, we conduct statistical tests of the hypothesis that average

[6] In the main analysis, we take unweighted averages across countries. When weighting by population, hours differences between the bottom and top thirds of the world income distribution are similar: averages in the low-, middle- and high-income groups are 28, 23.6, and 20.7 hours per week.

[7] We regress on the logarithm of GDP per hour worked rather than GDP per capita, because GDP per hour worked is an aggregate productivity measure analogous to the individual wage, which we use as a regressor in a similar regression in Section 6. Figure C.2 in the Online Appendix shows the corresponding scatter plot of the logarithm of average hours worked per adult and the logarithm of GDP per hour worked.

hours worked in all countries are drawn from the same distribution. We do so using permutation tests, which have more favorable small-sample properties than other commonly used tests, such as t-tests (Lehmann and Romano, 2005). Panel B of Table 1 reports the results of these permutation tests. For the core countries, shown in the first row, the observed difference in mean hours between the low- and high-income groups is 9.6 hours per week, between the low- and middle-income group 6.3 hours per week, and between the middle- and high-income group 3.3 hours per week. All p-values are well under one percent. We conclude that the decreasing average hours over the income terciles are unlikely to be a coincidence.

Rows 2 and 3 of Table 1, Panel A, report average hours per adult by income tercile in two broader sets of countries: (i) the core plus those countries having a survey that covers only part of the year, and (ii) all countries in our data set, regardless of how hours are measured. Covering more countries comes however at the cost of lower international data comparability. Across the 73 core plus partial-year survey countries, average hours worked are 26.7 in the low-, 22.4 in the middle-, and 19.4 in the high-income countries. Thus, within the low-income countries average hours worked are slightly lower in this group than in the core, while hours worked in the middle- and high-income groups are similar to the core. Going to the full set of 80 countries, average hours per adult rise by 0.2 weekly hours in all income groups (see also Figure C.1 in the Online Appendix.) As Panel B of Table 1 shows, all differences across the income groups are significant at the one percent level in the broader set of countries. We conclude that our finding of higher hours per adult in poor countries than in rich countries holds in a broader set of countries as well as in our core countries. From here on we focus on the core countries due to their higher degree of international comparability.[8]

4.2. Comparison to Time-Series Data from the United States

Our research is motivated by the question of how hours worked vary with income in the cross-section of countries. Complementary evidence on the relationship between income and hours worked comes from time-series data. With time series data, one can ask how hours looked like in the currently rich countries back when they were poor.

[8]We conclude that potential biases from seasonality, measurement of vacation days and public holidays, and child labor would all likely increase measured hours worked differences between rich and poor countries; see Online Appendix Section A.5.

Comprehensive and reliable historical data on hours worked are unfortunately hard to obtain, and the discussion on the complications of constructing reliable hours worked data in Section 3 makes clear why this is the case. However, for the United States, data spanning over 100 years are available from Ramey and Francis (2009). Yet, even 100 years ago, the United States was as rich as current middle-income countries, so these time series data do not span as large an income range as our data does.

Figure 2 plots Ramey and Francis (2009)'s U.S. time series of average hours worked per adult (individuals aged 14+) from 1900 to 2005 (gray line), and average hours per adult from our data (black dots). Average adult hours per week in the United States decreased from 27.7 hours per week in 1900 to 23.0 hours in 2005, corresponding to a decline of 4.7 hours per week. Interestingly, the patterns for hours in the cross-section of countries is quantitatively similar over the range of GDP per capita spanned by the United States in the last century, only with slightly higher overall hours in the United States.

4.3. Extensive and Intensive Margins

Differences in hours worked per adult stem from differences in employment rates, which represent the extensive margin, and average hours per worker, which represent the intensive margin. Figure 3 plots employment rates (top panel) and average hours per worker (bottom panel) for our core countries. The figure shows that employment rates are decreasing for much of the income distribution, with a modest increase for the richest countries, while hours per worker follow more of a hump-shaped pattern.

Table 2 reports the average employment rates and hours per worker in each country income group. In the low-income countries, the average employment rate is 75.3 percent. In middle- and high-income countries, employment rates are 53.7 and 54.9 percent, respectively. Along the intensive margin, workers in low-income countries average 38.4 hours per week, compared to 41.2 hours and 34.5 hours in the middle- and high-income countries; thus, on average there is a mild hump-shape in hours per worker among the three income groups. For employment rates, the large difference between the low- and middle-income countries (21.6 percentage points) is statistically significant at the one-percent level, while the (negative) difference between the middle- and high-income countries is not significant. For hours per worker, the opposite is true. The small low-middle difference is statistically insignificant, while the large middle-high difference (6.7 hours per week) is significant at the one-percent level. Thus, average hours per adult are shaped by the two margins differently, with employment rates accounting for the decline in hours per adult between low- and middle-income countries, and hours per worker accounting for the decline between middle- and high-income countries. Overall, we calculate that employment rates account for around three quarters of the cross-country differences in hours per adult, while hours per worker account for around one quarter; see Online Appendix A.3 for details.

4.4. Time Spent on Production of Home Services

Until now, we have focused attention entirely on hours worked in the production of output counted in NIPA. A large literature has emphasized broader notions of work, however, including hours spent on home production of services (Parente et al., 2000; Aguiar and Hurst, 2007; Ngai and Pissarides, 2008; Ramey, 2009; Ngai and Pissarides, 2011; Aguiar et al., 2012, 2013; Rendall, 2015; Duernecker and Herrendorf, 2016). In this section, we consider hours of home production using a smaller set of countries for which we have data.

Hours spent producing home services are notoriously hard to measure. The two most important reasons are the difficult differentiation between leisure and home production of services in some categories, and the possibility of multi-tasking. Both difficulties apply especially when it comes to child care, but can also arise in other categories like cooking (see Aguiar and Hurst (2007) and Ramey (2009) for excellent discussions of the difficulties of measuring leisure and home production hours in general). Questions covering time spent on home production of services are therefore not usually included in labor force surveys or censuses. However, a few of the surveys we use do in fact ask about time spent on some categories of home production of services. We complement these surveys with data from the Multinational Time Use Study (MTUS).[9]

We provide evidence on average weekly hours spent in five aggregated service categories, namely cooking (including preparing food and washing dishes), cleaning, child care, shopping, and collecting water and firewood. These data should be considered

[9] For each country, we use the year closest to 2005. Online Appendix Table C.3 provides an overview of the countries with data on time use by income terciles. All data from the bottom and middle terciles, except South Africa, and data from Russia come from our main data source for the respective country. All other data come from the MTUS.

suggestive evidence: we do not apply the same standards to ensure comparability across countries that we apply when calculating hours worked in the market or in the production of home produced goods. The MTUS covers all five categories except collecting water and firewood. The other individual country surveys often cover only a subset of the categories. For each category and each income tercile, we have data from at least four countries, with the exception of hours spent on collecting water and firewood, which has minimal data outside the bottom tercile.

Table 3 presents the average hours spent on each of the time use categories by income group, with the number of countries for each category and group in parentheses. Average hours are lowest for the high-income countries in every single category except shopping. The totals amount to 25.3 weekly hours in the bottom tercile, 25.8 hours in the middle tercile, and 18.2 hours in the top tercile. We conclude that our main finding of higher hours worked in low-income than in high-income countries is still present once we consider time spent on broader categories of work, at least using these data. Our findings here are consistent with those of Bridgman et al. (2017). Using richer data on broader time use categories from 43 countries, they find that home production hours decrease in GDP per capita.

5. Hours Worked by Income for Different Demographic Groups

So far, we document that aggregate hours worked are decreasing in GDP per capita. We now turn our attention to potential heterogeneity related to this fact. We document hours worked per adult by sex, education, and over the life cycle, and hours worked per worker by sector across our core countries. We show that the finding that average hours worked per adult are substantially higher in low-income countries than in high-income countries is quite broad-based. The positive hours difference between low- and high-income countries is statistically significant for both sexes, all education groups, and all sectors except agriculture. Moreover, the decline of aggregate hours by income is not driven by different compositions of the population across countries.

5.1. Average Hours per Adult by Sex

We start by analyzing average hours worked for both sexes across our set of core countries. As Table 4 shows, for both men and women hours per adult are decreasing by development. For the low-income countries, men average 32.7 hours per week, while in the middle- and high-income countries they average 28.4 and 23.5 hours per week, for a difference of 9.2 hours per week between low and high. Women work fewer hours than men in all income groups, but show the same pattern of higher hours in poorer countries, with a very similar difference of 9.8 hours between low- and high-income countries.[10]

5.2. Average Hours by Education Group

Patterns of hours worked have been shown to differ systematically by education group within the United States, see e.g. Aguiar and Hurst (2007). Do similar patterns arise in countries in other parts of the world income distribution? Our data allow us to consistently define three broad education groups: those with (1) less than secondary school, (2) secondary school completed (but not more), and (3) more than secondary school. We restrict attention in this exercise to adults aged 25 and above, so as to focus on those who have most likely completed schooling.

Table 5 reports average hours per adult by education group; see Figure C.4 of the Online Appendix for the plots. All three education groups feature higher hours in the poorer countries. Among individuals with less than secondary school, average hours are 31.8 in the low-income countries compared to 19.8 in the middle- and just 12.2 in the high-income countries. Thus, for the lowest education group the difference between hours in low- and high-income countries amounts to 19.6 hours.[11] Individuals in low-income countries with secondary school completed work 13.9 more hours per week on average than their counterparts in high-income countries, and for individuals with more than secondary education the difference between low- and high-income countries falls to 12.6 hours. Within each country group, average hours are higher for more educated individuals than for the less educated, though less so for the low-income countries. We return to this evidence in Section 6.4 below.

[10] Online Appendix Figure C.3 plots average hours per adult for men (top panel) and women (bottom panel) for each country. A notable feature of the graphs by sex is that female hours are substantially lower for countries with large Muslim populations, such as Iraq, Pakistan, and Turkey.

[11] This dramatic difference is partly caused by an age-composition effect, because individuals with less than secondary education are most prevalent among the old in high-income countries. Focusing on individuals aged 25 to 54 (instead of all individuals aged over 25) reduces the hours difference between high- and low-income countries of the lowest education group from 19.6 hours to 12.0 hours.

5.3. Hours Worked over the Life Cycle

In this subsection, we document hours worked over the life cycle for the three country income groups. Figure 4 plots average hours for five year age groups, starting at age 15-19 and ending at age 85-89. Since we do not have panel data, we cannot distinguish between cohort and age effects. We interpret the data as age effects, but one should keep in mind the caveat that we could be capturing cohort effects at least to some extent. The well-known hump-shape of hours over the life cycle is present for all three country income groups. Most importantly, the pattern of decreasing hours by country income is present at each single age group. The largest differences arise for older individuals. Starting at the age group 55-59, the differences in hours worked between low- and high-income countries are increasing up to age 65-69, at which point they start decreasing again. This points to the absence or existence of social security programs as an important driver of hours worked differences around the retirement age. On average, individuals aged 55+ work 21.8 hours per week in the low-income countries, compared to 12.3 and 7.6 hours in the middle- and high-income countries. Among individuals younger than 55, the average hours difference between low- and middle-income countries amounts to 4.5 hours, and between middle- and high-income countries to 0.8 hours.[12]

5.4. Hours Per Worker by Sector

Which sectors contribute most to the patterns of hours per worker that we document? To answer this question, we compute average hours per worker by three broad sectoral aggregates, which we can define consistently across countries. These are agriculture (including forestry and fisheries), manufacturing (including mining and utilities), and services. We assign each worker to one of these sectors based on their primary sector of employment (though their hours cover all jobs). We focus on hours per worker (rather than hours per adult), since industry is only well defined for those currently working.

Table 6 presents the average hours per worker by industry. Among agricultural workers, differences in average hours are statistically insignificant across the three country groups, with the low-, middle- and high-income countries working 36.0, 37.7 and 39.9 hours per week, respectively. Manufacturing workers work longer hours in the low-income countries, at 44.9 hours per week, compared to 42.7 in the middle-income and

[12] De Magalhães et al. (2017) find similar patterns for several African countries.

36.4 in the high-income countries. The differences are even more substantial for services, where workers in the low-income countries average 47.7 hours, compared to 41.6 and 34.0 hours per week in the middle- and high-income countries. It is reassuring that the hours differences are so pronounced in manufacturing and services, if one has the prior that hours worked in these two sectors are measured more accurately since the prevalence of paid employment is higher. In contrast to age and education, the country income groups do not share a common pattern of hours worked differences across sectors.

5.5. Compositional Effects on Aggregate Hours

Given that we document substantial differences in hours worked by age, education, and sector in all three country income groups, the question arises whether the differences in aggregate hours by income arise due to substantial different compositions of the population by development. To gauge how important the composition of the population by country is for determining the aggregate hours differences, we conduct several counterfactual exercises. Starting with the age composition, we first compute in each country average hours per person for 5 year age groups. We then calculate hypothetical average weekly hours per adult in each country by multiplying U.S.-population weights for the age groups with average hours of the corresponding age group in each country, and then summing up over all age groups. We do a similar counterfactual exercise for the educational composition relying on the three education groups, and another one combining the age-education composition. Last, we conduct the same exercise for hours per worker, imposing the U.S. sectoral composition.

The results are shown in Table 7. The first two rows relate to the age structure. Average weekly hours per adult essentially do not change when the U.S. age structure is imposed. Imposing the U.S. age structure on poor countries shifts weight from the older population to the younger one; since both work similarly fewer hours than prime-aged individuals, the shift has on net a minimal effect. Rows 3 and 4 focus on the educational composition (and thus on the population 25+). The hypothetical hours difference between low- and high-income countries imposing the U.S. education composition is somewhat larger than the actual hours difference. By imposing the U.S. education composition, the share of higher educated individuals in the low-income countries rises, increasing the hypothetical hours there. However, since the hours gradient in education is smallest in the low-income countries, the difference in hypothetical hours is still relatively close to the difference in actual hours. Row 5 then combines the age and education structure, and finds a very similar difference in hypothetical hours as in actual hours between high- and low-income countries. The hypothetical values for hours per worker if the U.S. sectoral composition is imposed in all countries are presented in the last row of Table 7. What we find, not surprisingly, is that the hypothetical hours per worker would be even higher in low-income countries if those countries had the U.S. industry composition, given the small share of agriculture in the United States and the low average hours in the agricultural sector in low-income countries.

Summarizing, we unequivocally find that differences in the population composition across countries are not the main driver of the aggregate hours worked differences by development.

6. Individual Hours Worked and Wages

So far, we have provided evidence that hours are decreasing in income at the country level. In this section, we look at how hours vary with income within countries. We first pool all our individual data for our core countries and compute an hours-wage elasticity using individual-level wage data, and ask whether the aggregate hours-income relationship we document thus far is accounted for mostly by the individual elasticity, or whether there are aggregate features particular to poor countries that lead to higher hours there, such as a lack of social security programs. Finally, we compute the hours-wage slopes country by country, and ask how these slopes vary across countries.

6.1. Constructing Individual Wages

There are two major challenges in constructing wages on the individual level. First, we observe individual earnings only for individuals who are currently working. Thus, we focus on the intensive margin of labor supply, i.e. hours per worker. Second, while constructing hourly wages is relatively straightforward for individuals in paid employment, it is a challenging task for self-employed individuals, who make up the majority of the work force in developing countries. We thus construct two wage rates: the first is an individual hourly wage from paid employment, which we only construct for workers in paid employment; the second is an hourly wage including earnings from self-employment, which we construct for all individuals working positive hours. We exclude Namibia and Laos because of missing earnings data. We briefly summarize the construction of the two measures here, and more details as well as a validity check can be found in Online Appendix Section A.6.

Wage from Paid Employment For individuals in paid employment, we construct an hourly wage (expressed in 2011 PPP-adjusted US $) by dividing monthly earnings from paid employment by actual weekly hours worked from paid employment in the reference week multiplied by 4.33. We only include individuals who are paid employees in the main job. If they also report being paid employees in any additional jobs, we sum up earnings and hours over all relevant jobs, if available. The European Labor Force Survey, which is our main data source for European countries, does not include individual earnings, and thus in this analysis we use the European Union Statistics on Income and Living Conditions (EU-SILC) for the European countries. Moreover, we have to recur to usual rather than actual hours for the European countries and the United States. The main caveat concerning evidence from the group of wage earners in paid employment is that they are a selected set of all employed, particularly in lower income countries (see Table A.1 in the Online Appendix).

Figure 5 presents a simple way of summarizing our individual-level data across all sample countries for which we can construct an individual wage. We sort individuals into wage deciles within each country, and calculate for each decile the average wage and average hours worked. We then plot these against each other for all 46 core countries, and connect all deciles within a given country with a line. Notably, there is substantial overlap of individual wages between countries of different income levels. While there appear to be significant country fixed effects, especially among the low-income countries, the decrease of hours by wages seems to hold both within and across countries.

Wage from Paid Employment Plus Self-Employment We also construct an alternative hourly wage which includes earnings from self-employment for a broader set of individuals, encompassing all those who are working and have non-missing earnings data. In most of our surveys, self-employment income is reported at the individual level, and so we construct an individual wage by summing all wage and self-employed earnings and dividing by total hours worked at all jobs. An important caveat is that although self-employment income is reported at the individual level, it is still possible that other family members supply hours of work in order to help earn the reported income. Furthermore, self-employed income is reported in different ways across countries, and there are limits to how well we can standardize self-employment income. Fortunately, as we show below, our overall findings are similar with and without self-employment earnings.

Online Appendix Figure C.6 plots average hours against average wages for the deciles of the wage distribution in each country. As in Figure 5, there is substantial overlap in wages across countries. The overall pattern is still a negative relationship between hours and wages, though substantially flatter than the pattern for wage earners, particularly in the poorer countries.

6.2. Individual vs. Country Income

Our findings thus far of a negative relationship of hours and GDP per capita at the country level raise a natural question: do individuals in poor countries work more hours because they themselves have low income, or because they live in a poor country? If it is the former, this points to a strong role for preferences in which income effects outweigh substitution effects (see e.g. Boppart and Krusell, 2016). If country effects dominate, this points to institutional features of poor countries that raise labor supply relative to rich countries.

To answer this question, we build a world data set containing all individual observations from all 46 core countries, and regress hours worked of individual i living in country c on the individual wage (w) and country GDP per hour worked ($GDPph$), including as controls age and age squared, and clustering standard errors at the country level:

$$log\left(h_{ic}\right) = \alpha + \beta_w log\left(w_{ic}\right) + \beta_{GDP} log\left(GDPph_c\right) + \delta_1 age_{ic} + \delta_2 {age_{ic}}^2 + \varepsilon_{ic}. \qquad (1)$$

The results are shown in Table 8. Each column is a different regression specification. Panel A shows our findings for both sexes. In the first two columns, we show results if either only GDP per hour or only the individual wage are included as regressors. In this case, both turn out to have negative and highly significant coefficients of -0.12 and

-0.09, respectively. When both regressors are included at the same time (third column), the coefficient on the individual wage drops slightly to -0.08, but the coefficient on country GDP per hour drops more substantially to -0.03, and becomes insignificant. In the last column, we replace GDP per hour with country fixed effects, and the coefficient on the individual wage remains again largely unchanged at -0.10. We thus conclude that a low individual wage correlates significantly with high hours worked per worker across the entire world income distribution. On top of this effect, individuals living in poorer countries tend to work more hours, though that effect is more modest.

The next two panels of Table 8 show the estimation results separately for men and women. The main difference between both is that, once both GDP per hour or country fixed effects and individual wages are included, the coefficient on the individual wage is more negative for men than for women, while the coefficient on GDP per hour worked even turns slightly positive for men, but remains negative for women. The positive coefficient on country productivity for men is driven by variation within the group of low-income countries (see Figure C.7 in the Online Appendix).

We find similar regression results for the sample including earnings from self-employment (see Table C.5 in the Online Appendix). The only substantive difference is that the negative coefficient on GDP per hour is smaller in an absolute sense in the specification without individual wages as regressors, and turns positive for both men and women once individual wages are added. Thus, even more so than in the sample of wage workers, high hours seem to be driven by low individual wages rather than low country income.

6.3. Individual Hours-Wage Elasticities by Country

How does the hours-income elasticity vary from country to country? To answer this question, we follow Costa (2000) and regress within each country the logarithm of individual hours worked on the log wage and age and age squared, separately for men and women:

$$log\left(h_i\right) = \alpha + \beta_w log\left(w_i\right) + \delta_1 age_i + \delta_2 {age_i}^2 + \varepsilon_i. \quad (2)$$

Figure 6 plots the country-specific coefficients β_w against log GDP per capita, for men in Panel (a) and for women in Panel (b). It shows a negative coefficient for low- and middle-income countries, which increases towards zero starting with the richer end of the middle-income countries, and turns positive for the richest countries. Thus, in the majority of countries hours are decreasing with the individual wage, while only in the richest countries this relationship is reversed. This cross-country evidence is in line with the historical evidence by Huberman and Minns (2007) for a subset of OECD countries, and the time-series evidence for the United States. Costa (2000) runs the same regression on U.S. data from different time periods, and finds a negative coefficient in the 1890s, which increases over time and turns positive in the female sample by 1973 and in the male sample by 1991. Her estimates are included in Figure 6 and are in line with the values we find in the respective stages of development in the cross-section.[13]

Thus, in line with the cross-country evidence of a decline in hours worked per worker with income, in the majority of countries hours per worker are also declining in the individual wage. Only for the richest countries does the relationship between hours and individual wages turn positive. The same holds true in the sample including earnings from self-employment; see Figure C.8 in the Online Appendix.[14]

6.4. Variation of Employment Rates by Education

For non-working individuals, wage information is not present, so we use education as a proxy for permanent income. Table 9 shows employment rates by education for the age group 25 to 54 in the upper panel, and for the age group 55+ in the lower panel, and separately for men and women. Employment rates are essentially flat by education in the low-income countries for all four age-gender groups. By contrast, in the middle-income countries, and even more so in the high-income countries, employment rates are strongly increasing in education for all age-gender groups.

Of course, this evidence is only suggestive, as education is only a rough proxy for permanent income. However, the pattern of a positive relationship between employment rates and education in rich countries, and a flat relationship in poor countries, is in line with the patterns we find above between hours worked per worker and wages. This relationship is also positive in rich countries, but negative in poor countries.

[13] Costa restricts the sample to individuals aged 25 to 64. If we do the same, our coefficient for the United States falls from 0.09 to 0.07 for men, and from 0.12 to 0.10 for women.

[14] Note that measurement error in hours induces a negative bias in the coefficient β_w, because wages are constructed as earnings divided by hours. We provide some evidence on the scope of this division bias in Online Appendix Section A.6.5, which leads us to conclude that the division bias might be present, but is unlikely to substantially alter our findings.

One potential explanation for the diverging evidence from rich and poor countries could be the size of the welfare state: more generous welfare states in rich countries might create disincentives for low-productivity workers to participate in the labor market or work long hours. Another common pattern that we find is that both the gradient of employment rates in education, and the gradient of hours worked per worker in wages are more positive in high-income countries for women than for men. This points to within-household specialization and insurance in richer countries. In the low-income countries, by contrast, both gradients are similar for men and women.

7. Implications

Summarizing our findings thus far, we establish a robust negative relationship between hours worked and income on the aggregate level, for different demographic subgroups, and also on the individual level for the majority of countries. In this section we discuss two aggregate implications of these findings. The first is about development accounting, which tries to account for cross-country income differences using observable factors of production like physical and human capital. Our aggregate findings for average hours imply that labor productivity differences, and hence total factor productivity (TFP) differences, are even larger across countries than previously thought. The second implication is about welfare differences across countries. Our finding of higher hours worked for poorer countries, and poor individuals more generally, imply that welfare differences across countries are even larger than previously thought.

7.1. Development Accounting

What are the implications of the fact that hours per adult are higher in low-income countries than in high-income countries for the measurement of labor productivity differences? The literature on development accounting attempts to explain cross-country differences in output per worker using aggregate stocks of human and physical capital per worker. One basic piece of information missing from this literature has been hours worked per worker, which has limited the ability of researchers to accurately measure labor productivity (Klenow and Rodríguez-Clare, 1997; Hall and Jones, 1999; Caselli, 2005; Hsieh and Klenow, 2010). In the absence of data on hours worked, virtually all previous studies in this literature have measured labor productivity as GDP per worker.

Our data suggest that GDP per worker underestimates the true labor productivity differences across countries. To investigate this quantitatively, Table 10 shows two different measures of labor productivity: GDP per worker and GDP per hour. The first three columns report the respective values for our three core country income groups, normalizing the value of the high-income countries for each measure to 100, and the last column presents the ratio of the respective variable for high- to low-income countries. Focusing on this ratio, GDP per worker is 19.9 times larger in high-income countries than in low-income countries. We can improve on this by adding our data on hours worked. Since workers in low-income countries work on average 3.9 hours per week more, the ratio of GDP per hour in high- over low-income countries is even higher than the ratio of GDP per worker, specifically amounting to 23.5 instead of 19.9. This corresponds to 18 percent larger labor productivity differences across countries than implied by GDP per worker. Middle-income countries are also less productive relative to high-income countries based on hours worked compared to based on employment alone.[15]

Our findings imply that development accounting rests even more on the residual TFP term once cross-country differences in hours are taken into consideration. This casts doubt on theories of development that operate through lower labor input in poorer countries. Landes (1999), for example, points to hot weather in the tropics as a cost of working there. In his theory, TFP differences across countries are in part explained by differences in labor effort, with high effort in economies with higher TFP.

7.2. Welfare Differences Across Countries

How do measured welfare differences between rich and poor countries change if differences in hours worked are taken into account in addition to consumption differences? To answer this question, we broadly follow the approach by Jones and Klenow (2016), who study welfare differences across countries taking into account a wide range of outcome variables. We focus on hours worked, since our data set has a broader coverage of hours in low- and middle-income countries than the data in Jones and Klenow (2016). We rely on the standard neoclassical growth model, as used in the literature analyzing U.S.-Europe hours differences, see e.g. Prescott (2004). The key modification is a non-homotheticity in preferences in the form of a subsistence consumption requirement $\bar{c}$,

[15] Feenstra et al. (2015) recommend using *rgdpo* rather than *rgdpe* for productivity comparisons across countries. Online Appendix Table C.6 shows that using *rgdpo* does not alter our conclusions.

as in Ohanian et al. (2008) and Restuccia and Vandenbroucke (2014). This subsistence consumption requirement implies that the income effect dominates the substitution effect. As consumption rises, this dominance becomes weaker, and in the limit the two effects cancel out.

Each country has a representative, infinitely lived household which maximizes life-time utility:

$$\max_{\{c_t,h_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \left(\log\left(c_t - \bar{c}\right) - \alpha \frac{1}{1+\frac{1}{\phi}} h_t^{1+\frac{1}{\phi}} \right), \tag{3}$$

where c_t is consumption, h_t are hours worked, utility is separable in consumption and leisure, α determines the relative disutility weight of work, and ϕ is the Frisch elasticity, which allows for a more flexible labor supply elasticity than does Prescott (2004). The household faces a standard inter-temporal budget constraint, and there is a representative firm with an aggregate Cobb-Douglas production function. Combining the intra-temporal first-order condition of the household and the first-order condition of the firm gives the following solution for optimal hours:

$$h_t = \left[\frac{1-\theta}{\left(\frac{c_t}{y_t} - \frac{\bar{c}}{y_t}\right)\alpha} \right]^{\frac{\phi}{1+\phi}}. \tag{4}$$

Taking aggregate consumption (*csh_c* in PWT 9.0) and aggregate output (*rgdpe* in PWT 9.0) from the data, we use this equation to calibrate the preference parameters. We set the Frisch elasticity equal to $\phi = 1$ (Keane and Rogerson, 2015), and the capital share equal to $\theta = 0.3224$ (Prescott, 2004). We then calibrate α to match average hours worked per adult in high income countries, and the subsistence consumption term $\bar{c}$ to match hours worked per adult in low income countries. The resulting annual subsistence consumption amounts to \$896 in 2011 US \$, which is close to the value of \$842, corresponding to 5 percent of the U.S. GDP per capita in 1956, chosen by Ohanian et al. (2008). Online Appendix Section B includes more details on the model setup, calibration, and fit.

We use the calibrated utility function to compute a simple welfare metric, building on the work of Jones and Klenow (2016). Conceptually, the welfare metric imagines giving the representative household of some country i a choice between two options: first, to work the average hours of individuals in high-income countries and to consume a fraction λ of the average consumption in these high-income countries. The second option is to stay in country i, and to work i's average actual hours and enjoy i's average consumption. Formally, the welfare metric in country i is the λ_i that solves

$$u(c_i, h_i) = u(\lambda_i \cdot c_{HI}, h_{HI}) \tag{5}$$

where c_{HI} and h_{HI} are the average consumption and hours of individuals in our sample of high-income countries.

Table 11 presents our average λ_is by income tercile, normalizing them to have an average of 100 for the group of high-income countries. In row one, we consider only cross-country differences in consumption, and ignore differences in hours worked. Countries in the bottom third of the world income distribution have 8.3 percent of the welfare level of the richest third. The middle third features 35.4 percent of the welfare of the richest third. The final column shows that the ratio of the top to bottom third is 12.1, meaning, as expected, very sizable differences in welfare coming through consumption alone.

The second row adds differences in hours worked to the differences in consumption. Average welfare in the low-income countries falls to 5.2 percent of welfare in the high-income countries, leading to a welfare ratio of 19.2 between top and bottom. Thus, considering differences in hours worked between low- and high-income countries in addition to differences in consumption increases measured welfare differences by almost 60 percent. Measured welfare differences between middle- and high-income countries increase by a smaller degree, but still by a sizable 30 percent. Measuring welfare differences across countries is not an exact science, and our calculations leave out a lot of elements of reality that certainly matter for welfare, such as life expectancy and inequality, as emphasized by Jones and Klenow (2016). Our calculations make however clear that, all else equal, including cross-country differences in hours worked leads to substantially larger welfare differences across poor and rich countries than when ignoring differences in hours.[16]

[16] Almas (2012) also argues that welfare of the poorest countries are overstated relative to the richest, though for a different reason, which is a bias in the PPP methodology used in the PWT.

8. Conclusion

In this paper, we document how hours vary with income across and within countries of all income levels. To do so, we compile and harmonize international survey data from countries of all income levels, focusing on a set of countries with the most scope for international comparisons. We document that, on average, adults in the developing world work about fifty percent more hours per week than adults in rich countries. Average hours worked are higher in developing countries both for men and for women, for all age and education groups, and along both the extensive and intensive margins. Within countries, hours are decreasing with income on average and particularly so in the poorest countries. In the richest countries, hours worked are flat or increasing in income. One implication of our findings is that aggregate labor productivity and TFP differences across countries are larger than previously thought. Moreover, ignoring hours worked also leads to misleading conclusions about the extent of welfare differences across countries. Put simply, residents of the poorest countries are not only consumption poor, but leisure poor as well.

Future work is needed to reconcile the patterns we document in a model that takes within-country heterogeneity seriously. The decrease in hours with income suggests preferences in which income effects dominate substitution effects. The flattening of the negative hours-income relationship within countries with GDP per capita points to subsistence preferences as a potential driving force. Replicating the fact that the hours-income relationship actually turns positive for the richest countries suggests additionally a role for a tax-transfer system that varies systematically with development.

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Tables and Figures

Table 1: Average Hours Worked Per Adult

Panel A: Means

	Country Income Group			
	Low	Middle	High	# Countries
Core Countries	28.5	22.2	18.9	
	(11)	(15)	(22)	(48)
Core + Partial-Year	26.7	22.4	19.4	
	(16)	(32)	(25)	(73)
All Countries	26.9	22.6	19.6	
	(18)	(35)	(27)	(80)

Panel B: Tests of Differences in Means

	Country Income Group		
	Low-High	Low-Middle	Middle-High
Core Countries	9.6***	6.3***	3.3***
Core + Partial-Year	7.3***	4.3***	3.0***
All Countries	7.3***	4.3***	3.0***

Note: Panel A reports average weekly hours worked per adult by country income group in the core countries, the core countries plus those with partial-year surveys, and in our full set of countries. The number of countries in each group is in parentheses. Panel B reports differences in mean hours among pairs of country income groups. The stars represent the *p*-values from a permutation test of the hypothesis that the distribution of hours worked is the same in the two groups in question: *** means a *p*-value less than 0.01, ** means a *p*-value less than 0.05, and * means a *p*-value less than 0.10.

Table 2: Employment Rates and Hours Per Employed

	Country Income Group		
	Low	Middle	High
Hours Per Adult	28.5	22.2	18.9
Employment Rate	75.3	53.7	54.9
Hours Per Worker	38.4	41.2	34.5

Note: This table reports average weekly hours worked per adult, average employment rates, and average weekly hours worked per worker in the core countries by country income group.

Table 3: Hours Spent in Production of Home Services

	Country Income Group		
	Low	Middle	High
Cooking	8.8	8.3	5.8
	(4)	(6)	(9)
Childcare	5.5	6.2	2.8
	(6)	(6)	(9)
Cleaning	6.0	7.2	5.8
	(5)	(6)	(9)
Collecting Water	3.0	2.1	–
	(7)	(4)	(0)
Shopping	2.0	2.0	3.8
	(5)	(6)	(9)
Total	25.3	25.8	18.2

Note: Average weekly hours for each activity are computed only over countries in which data have been collected. The number of countries is in parentheses.

Table 4: Average Hours Worked Per Adult by Sex

Sex	Country Income Group		
	Low	Middle	High
All	28.5	22.2	18.9
Women	24.4	16.3	14.6
Men	32.7	28.4	23.5

Note: This table reports average weekly hours worked per adult among the core countries by sex and country income group.

Table 5: Average Hours Worked Per Adult by Education Level

Education	Country Income Group		
	Low	Middle	High
All Ages	28.5	22.2	18.9
Ages 25+ (*Non-missing Educ.*)	33.0	25.7	20.7
Ages 25+			
Less than Secondary	31.8	19.8	12.2
Secondary Completed	37.3	29.3	23.4
More than Secondary	39.5	31.7	26.9

Note: This table reports average weekly hours worked per adult among the core countries by education and country income group. The sample is restricted to individuals aged 25 or more for whom the education status is known, and excludes Turkey, for which education data are unavailable. For comparison, the first row shows the data for all ages including also observations with a missing education status.

Table 6: Average Hours per Worker by Sector

Sector	Country Income Group		
	Low	Middle	High
All	38.4	41.2	34.5
All (*Non-missing Sec.*)	40.0	40.9	34.8
Agriculture	36.0	37.7	39.9
Manufacturing	44.9	42.7	36.4
Services	47.7	41.6	34.0

Note: This table reports average weekly hours worked per worker among the core countries by sector of main job and country income group. The sample is restricted to individuals for whom the sector of employment is known, and excludes Switzerland and Turkey, for which sectoral data are unavailable. For comparison, the first row shows the data including observations with a missing sector of employment.

Table 7: Hypothetical Hours with U.S. Composition

	Country Income Group		
	Low	Middle	High
Actual Hours per Adult	28.5	22.2	18.9
Hypothetical Hours: U.S. Age Composition	29.5	22.2	19.5
Actual Hours per Adult (*Ages 25+, Non-miss. Educ.*)	33.0	25.7	20.7
Hypothetical Hours (*Ages 25+*): U.S. Educ. Comp.	38.3	28.2	24.5
Hypothetical Hours (*Ages 25+*): U.S. Age & Educ. Comp.	34.9	25.2	22.8
Actual Hours per Worker (*Non-miss. Sec.*)	40.0	40.9	34.8
Hypothetical Hours: U.S. Sectoral Comp.	46.9	41.7	34.6

Note: This table reports hypothetical mean hours using the U.S. composition rather than the actual country-specific composition. The first row shows actual hours per adult, and the second hypothetical hours imposing the U.S. age structure (5 year age groups from 15-19 to 95+). The third row shows actual hours per adult aged 25 or older with education information, the fourth one hypothetical hours imposing the U.S. education structure, and the fifth hypothetical hours imposing the U.S. age-education structure (10 year age groups combined with three education groups). The sixth row shows actual hours per worker with sectoral information, and the seventh hypothetical hours imposing the U.S. sectoral structure.

Table 8: Elasticities of Hours to Aggregate and Individual Income

Panel A: Both Sexes

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.117^{***}	–	-0.031	–
ln (Hourly Wage)	–	-0.093^{***}	-0.076^{*}	-0.098^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.081	0.098	0.100	0.208
Obs.	812,406	812,406	812,406	812,406

Panel B: Men

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.093^{***}	–	0.025	–
ln (Hourly Wage)	–	-0.089^{***}	-0.104^{***}	-0.125^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.069	0.110	0.111	0.225
Obs.	485,159	485,159	485,159	485,159

Panel C: Women

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.132^{***}	–	-0.074^{*}	–
ln (Hourly Wage)	–	-0.092^{***}	-0.050	-0.088^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.087	0.086	0.094	0.206
Obs.	327,247	327,247	327,247	327,247

Note: This table reports the coefficients from an estimation of a variant of equation 2 on a data set containing individual observations from 46 countries. The dependent variable is the logarithm of individual hours worked per worker. The explanatory variables are the ones listed in each column, plus age and age squared. Standard errors are clustered at the country level. *** means a p-value less than 0.01, ** means a p-value less than 0.05, and * means a p-value less than 0.10.

Table 9: Average Employment Rates by Education Level and Age

Panel A: Prime Aged (25-54)

	Country Income Group					
	Low		Middle		High	
	Men	Women	Men	Women	Men	Women
Less than Secondary	94.9	80.5	77.5	51.3	73.9	54.7
Secondary Completed	92.9	74.3	85.0	63.4	87.0	73.4
More than Secondary	95.1	82.1	90.2	80.5	92.2	84.4

Panel B: Old (55+)

	Country Income Group					
	Low		Middle		High	
	Men	Women	Men	Women	Men	Women
Less than Secondary	77.3	63.1	42.2	22.2	22.7	11.7
Secondary Completed	77.4	60.7	48.1	24.8	35.9	24.1
More than Secondary	74.3	62.8	53.1	41.0	47.5	37.9

Note: Panel A reports average employment rates of prime aged men and women (25-54) among the core countries by education group and country income group. Panel B reports average employment rates of old men and women (ages 55+) among the core countries by education group and country income group. The sample is restricted to individuals for whom the education status is known, and excludes Turkey, for which education data are unavailable.

Table 10: Labor Productivity Differences Across Countries

	Country Income Group			
	Low	Middle	High	High/Low
GDP per Worker	5.0	36.0	100.0	19.9
GDP per Hour Worked	4.3	29.8	100.0	23.5

Note: Labor productivity is computed as the average labor productivity within each country income group relative to the average labor productivity of the high-income group, which is normalized to 100. Only core countries are included in the analysis.

Table 11: Consumption-Equivalent Welfare Differences Across Countries

	Country Income Group			
	Low	Middle	High	High/Low
Consumption	8.3	35.4	100	12.1
+ Hours	5.2	27.2	100	19.2

Note: Average consumption-equivalent welfare is depicted for each country income group relative to the welfare of the average high-income country, which is normalized to 100. The first row includes only consumption and ignores differences in hours. The second row includes differences in hours worked. Only core countries are included in the analysis.

Figure 1: Average Hours Worked per Adult in Core Countries

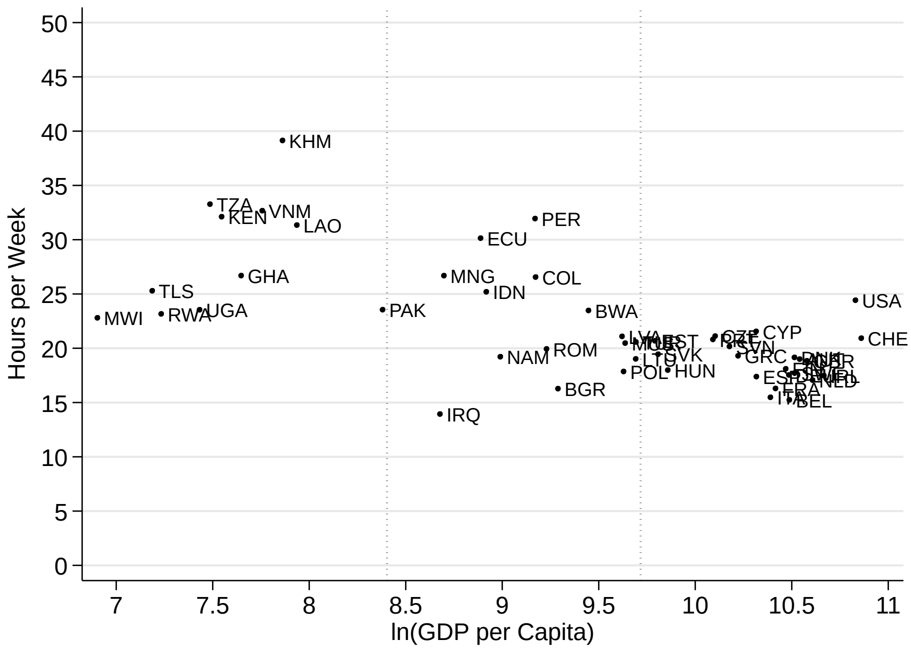
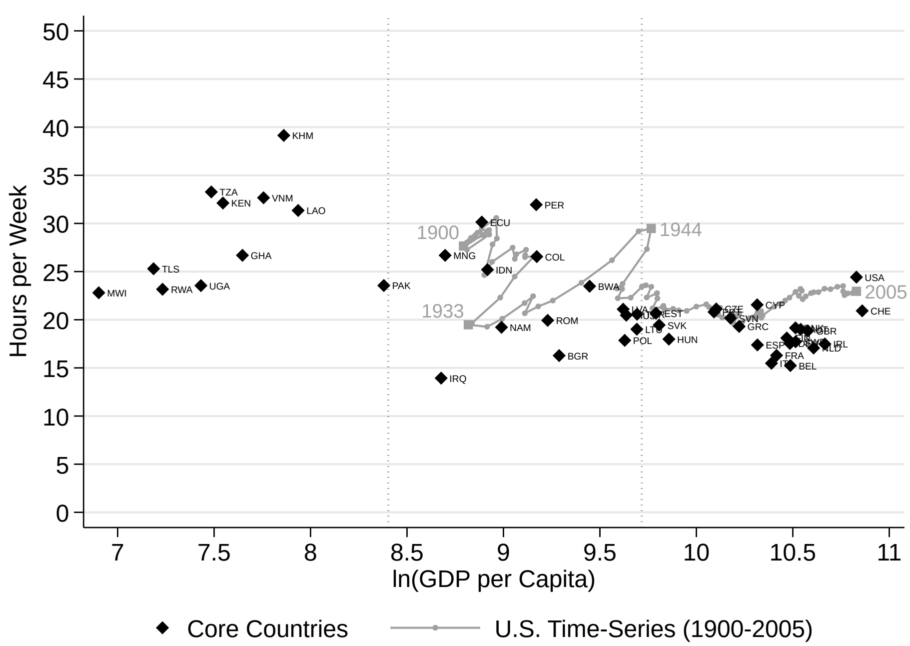


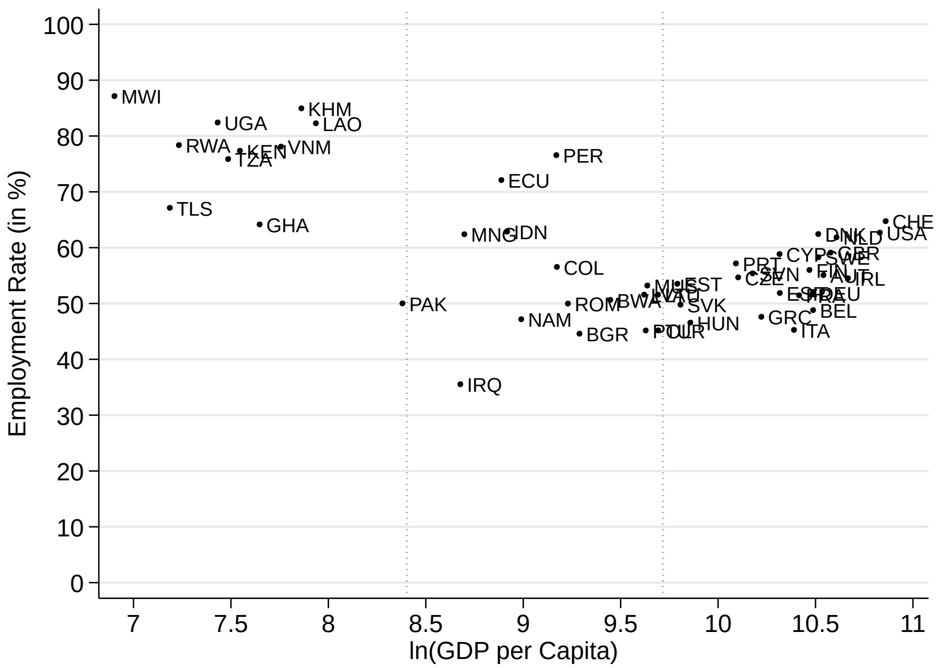
Figure 2: Average Hours per Adult – Core Countries vs. U.S. Time-Series



Note: The hours data for the U.S. Time-Series come from Ramey and Francis (2009).

Figure 3: Extensive and Intensive Margins in Core Countries

(a) Employment Rate



(b) Hours per Worker

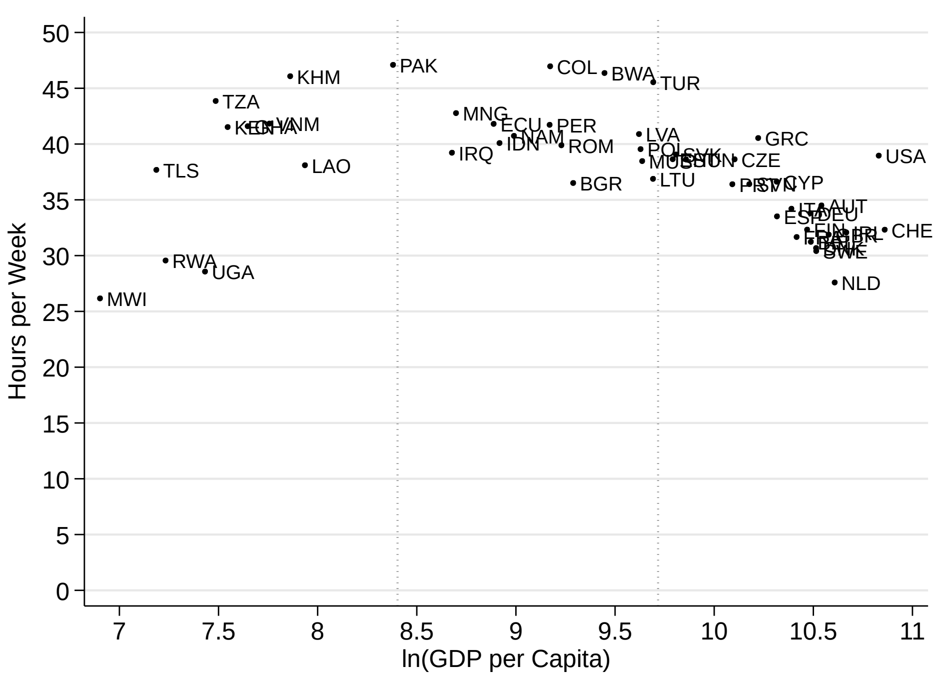


Figure 4: Average Hours per Adult over the Life Cycle

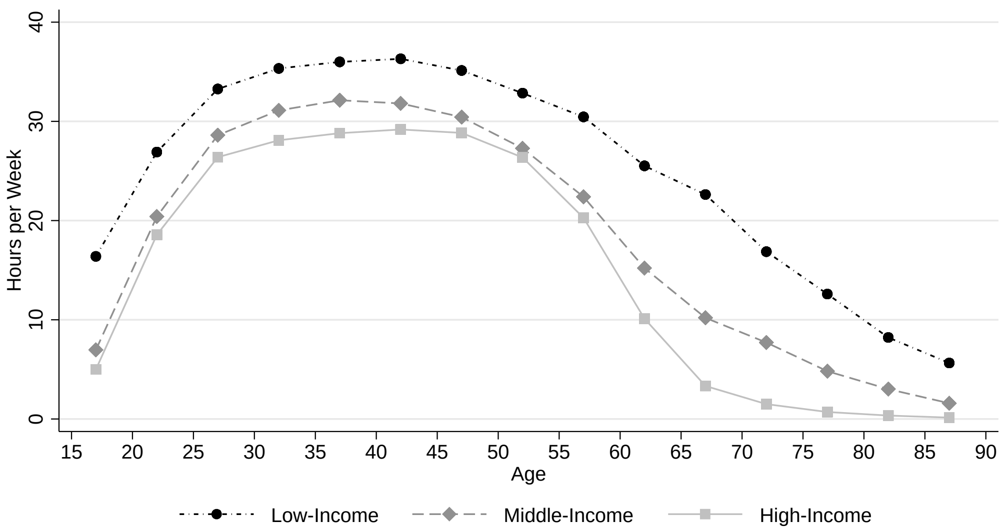


Figure 5: Hours By Wage Deciles For Paid Employees

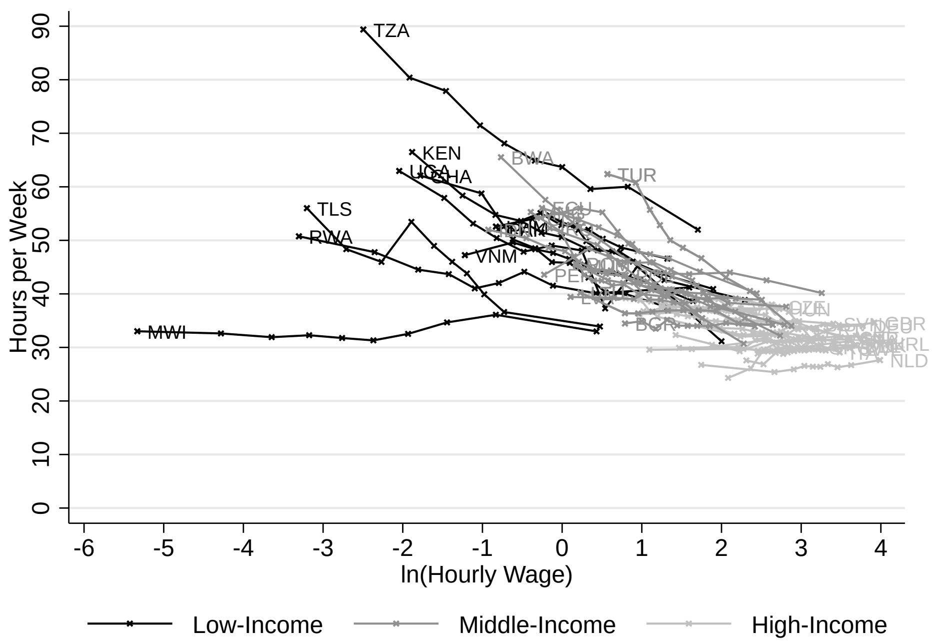
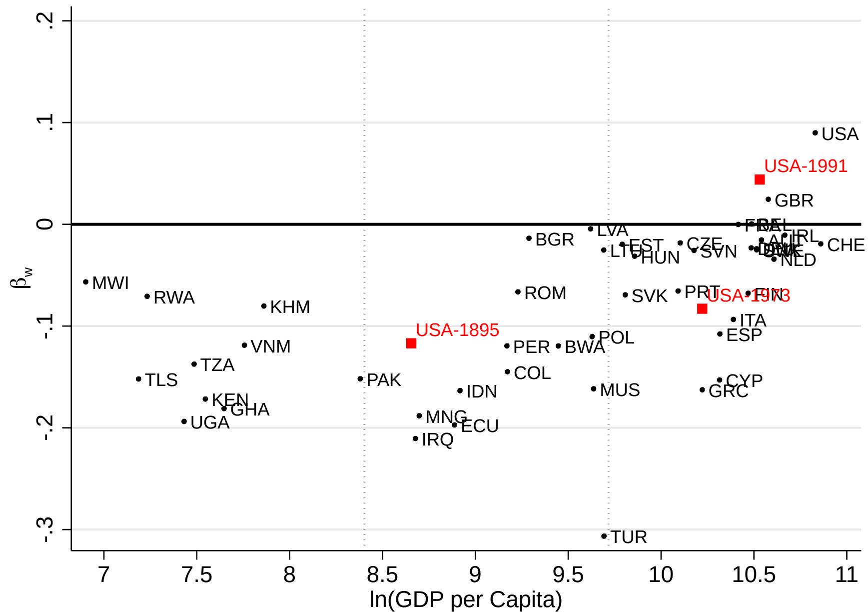
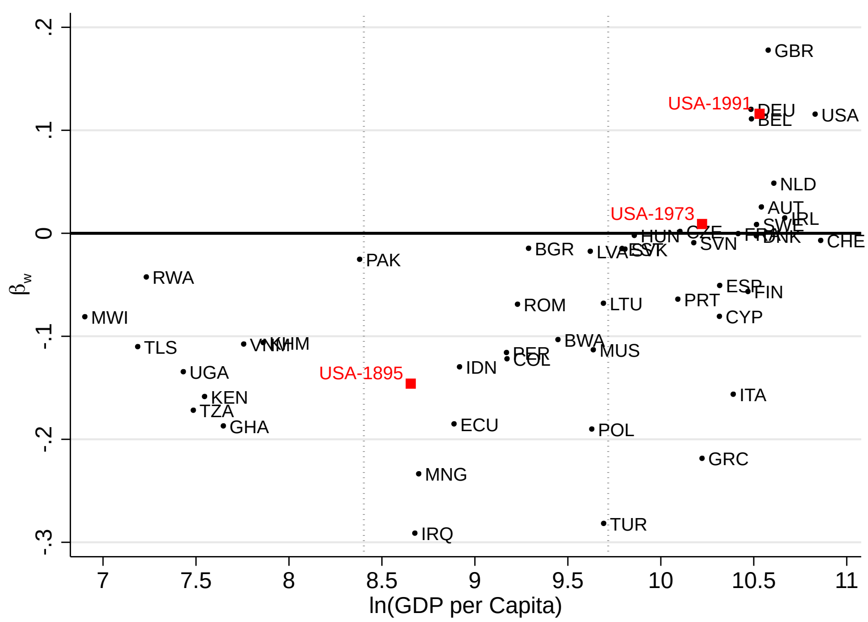


Figure 6: Country-Specific Elasticities of Hours to Wages

(a) Men



(b) Women



Note: The figures show the country-specific elasticities of hours to wages, represented by the coefficient β_w from a regression of individual hours worked on individual wages, controlling for age and age squared. The upper panel shows results for a sample of men only, and the lower panel of women only. The red (gray if printed in black and white) data points are corresponding coefficients from US samples of different years (1890s, 1973, and 1991) reported in Costa (2000).

Appendix (For Online Publication Only)

A. Data Appendix

A.1. Survey Time Coverage

Our core countries have the restriction that their surveys cover the entire calendar year. Because surveys are structured differently across countries, this classification is however not as straightforward as one may think. We categorize the surveys as follows, based on how much we know about the timing of household interviews:

(a) For any individual interview the week is known.

(b) For any individual interview the month is known, but not the week.

(c) Any individual interview falls within a period longer than a month and shorter than a quarter, but neither the week nor the month is known.

(d) Any individual interview falls within a quarter, but neither the week nor the month is known.

(e) Any individual interview falls within a period longer than a quarter, but neither the week nor the month is known.

Going from (a) to (e), the information about the individual interview date becomes less precise. In order to qualify as a core country, a country has to either

i. fall in category (a) or (b) and cover each month of the year

ii. fall in category (d) and cover each quarter

iii. fall in category (c) or (e) and cover the entire year.

To give a concrete example, the CPS in the US is conducted in each month but only covers one week (specifically, the reference week contains the 12th of a month). Hence, the US falls into category (a) and in our set of core countries. Brazil also falls in category (a) since we know the exact reference week. However, the Brazilian survey was conducted only in one week of the year, such that Brazil is not a core country. Except for case i, it may very well be that not each month is covered since we do not know for sure whether for countries in categories (c) to (e) interviews took place in each month. Of the 43 core countries four low-income and five middle-income countries fall in categories (c) to (e), though. Figures A.1 and A.2 split the countries by core and non-core countries, respectively, and show for each country the relevant category (a) to (e) and the covered weeks. Angola is not a core country despite covering the entire year since it misses information on actual hours worked.

Figure A.1: Survey Coverage – Core Countries

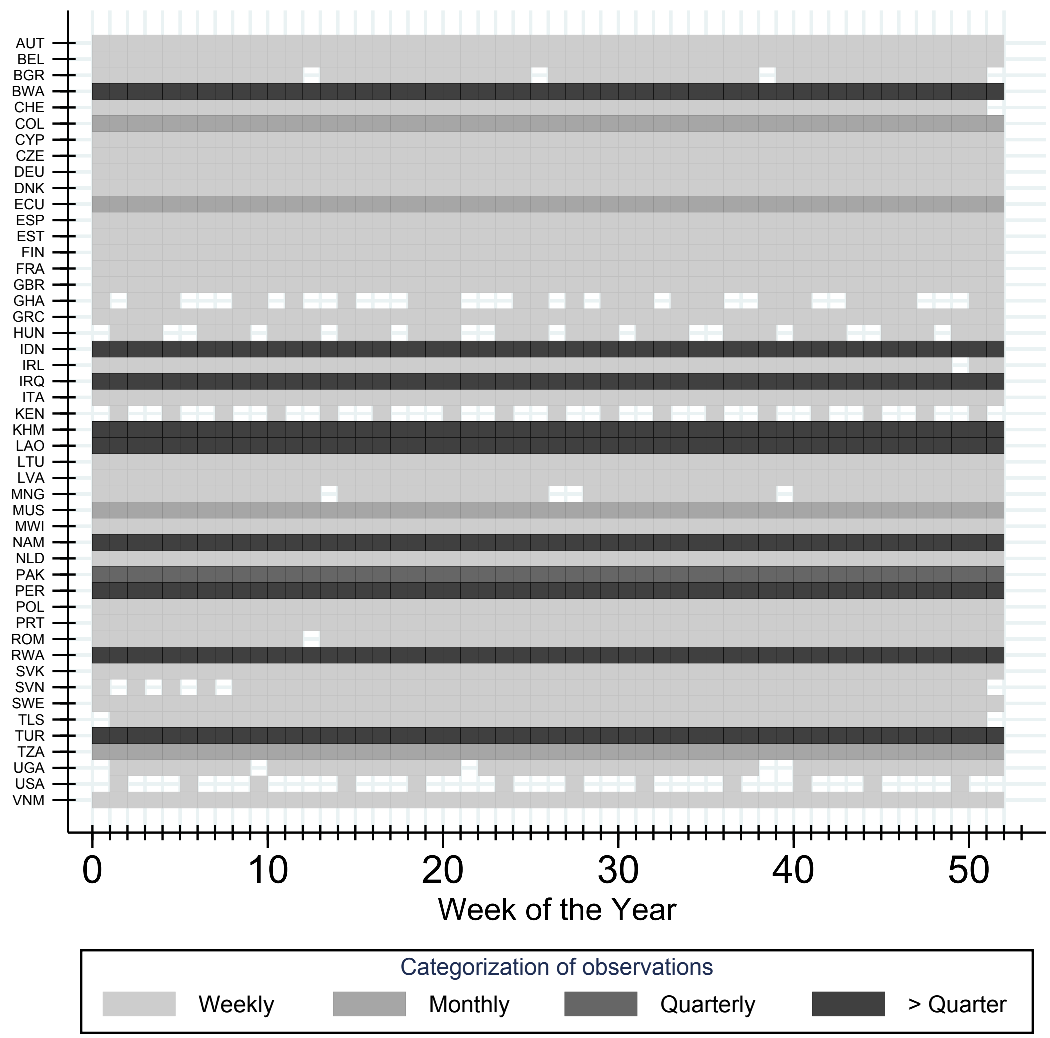
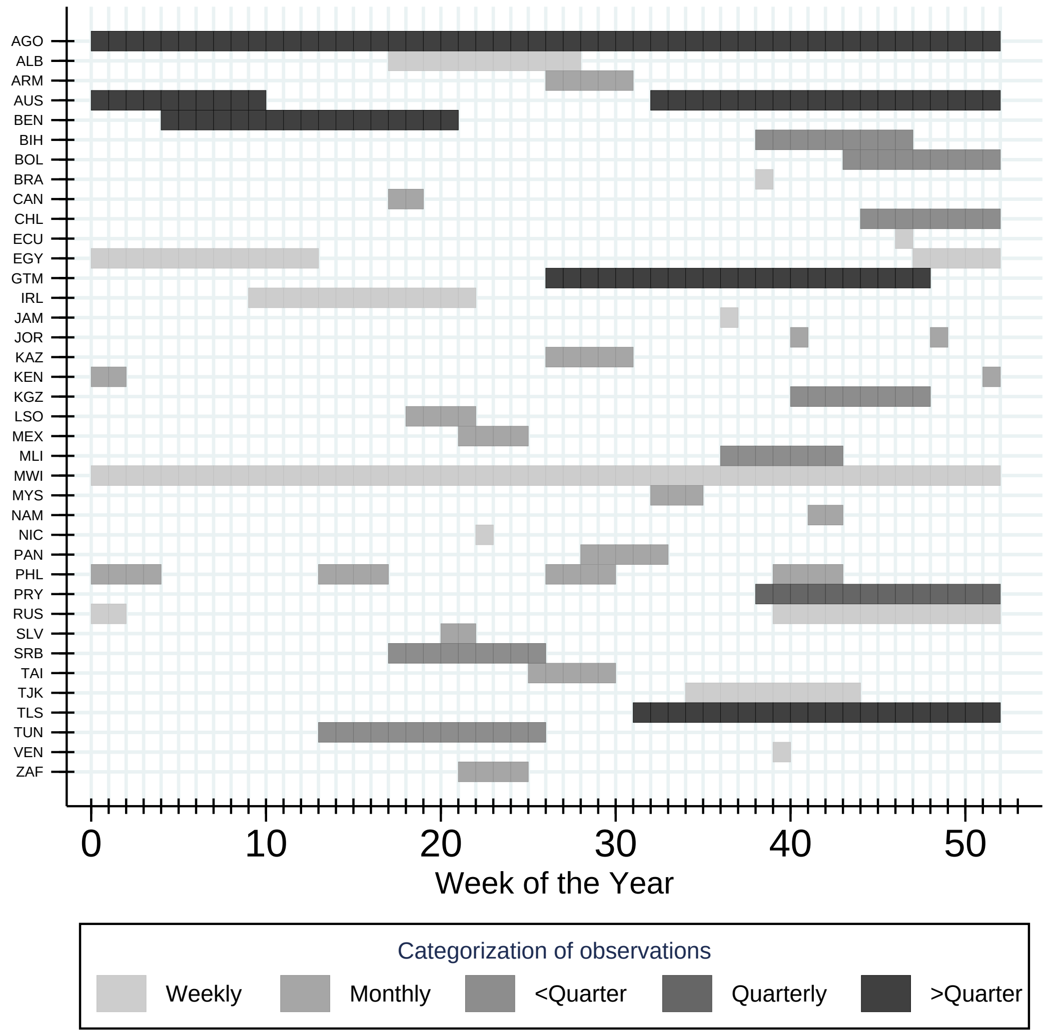


Figure A.2: Survey Coverage – Non-core Countries



A.2. Measuring Employment and Hours Worked

Our population of interest contains $i = 1,...,N$ individuals and may be only a subset of all individuals in our survey data (e.g., only men). For all our calculations, we use individual survey weights, but refrain from displaying them in the following paragraphs for the ease of notation. To measure employment, we use the self-reported employment status e_i of each individual i. e_i takes the value of 1 for anyone reporting to be employed, which includes self-employed and unpaid family workers, and 0 otherwise. We replace a missing employment status (including answers like "Don't know" and "Refuse to Answer") with 1 if positive actual hours worked are reported, and leave it missing otherwise. In general, missing employment status information is not very common in our data, with 38 of the 43 core countries having less than one percent of observations with missing employment status.

Letting the indicator $\mathbf{1_{e_i=nm}}$ (where nm stands for non-missing) take the value of 1 if the employment status is known and 0 otherwise, the employment rate (ER) is given by

$$ER = \frac{\sum_{i=1}^{N} e_i \mathbf{1_{e_i=nm}}}{\sum_{i=1}^{N} \mathbf{1_{e_i=nm}}}. \tag{A.1}$$

Our measure of hours per worker (H^e) is based on the actual number of hours worked in all jobs h_i in the reference period. This variable is directly available in some surveys, while in other surveys we add up actual hours in the main job and in all additional jobs. We assign zero hours to non-employed individuals. Employed individuals may have zero hours if they have been absent from work for the entire reference period, e.g. because of annual leave or sickness.

We impose a common cap of 112 weekly hours (7 days x 16 hours per day), though slightly lower country-specific caps may in fact be binding, since the maximum possible hours reported vary by survey. For example, for the United States, the reported number of actual hours worked in all jobs cannot exceed 99, while in the ELFS the reported actual hours in the main job are capped at 80 and in all additional jobs at 80 as well. In our data, the number of observations that are top-coded is small and exceeds 0.1 percent in only seven core countries, with the maximum being 0.87 percent in Tanzania. Bick et al. (2016) show that capping of hours in all jobs at 80 hours makes little difference for the United States and a subset of European countries from the ELFS.

Letting $\mathbf{1_{h_i=nm}}$ take the value of 1 if actual hours worked in all jobs are available, hours worked employed are given by

$$H^e = \frac{\sum_{i=1}^{N} e_i h_i \mathbf{1_{h_i=nm}}}{\sum_{i=1}^{N} e_i \mathbf{1_{h_i=nm}}}. \tag{A.2}$$

Our measure of hours per adult (H^a) is then obtained by multiplying the extensive (ER) with the intensive (H^e) margin of labor supply:

$$H^a = ER \times H^e = \frac{\sum_{i=1}^{N} e_i \mathbf{1_{e_i=nm}}}{\sum_{i=1}^{N} \mathbf{1_{e_i=nm}}} \times \frac{\sum_{i=1}^{N} e_i h_i \mathbf{1_{h_i=nm}}}{\sum_{i=1}^{N} e_i \mathbf{1_{h_i=nm}}}, \tag{A.3}$$

which is how Ramey and Francis (2009) measure hours per adult as well. For each country in our data we use (A.1), (A.2) and (A.3) to compute H^a, H^e and ER in the aggregate, and by sex, age and education groups, as well as H^e by sector. Note that an alternative approach is to drop all individuals with any missing data, and to compute H^a as the sum of hours over the sum of adults. We prefer our current approach since it drops fewer observations, though in practice the two approaches provide similar results, since missing observations are a small fraction of the total in our data.

A.3. Decomposing Hours per Adult

There are several ways to calculate the contribution of differences in the employment rate (ER) and hours per worker (H^e) to the differences in hours per adult (H^a) across country income groups. One possibility is as follows:

$$\begin{aligned}
\ln(H^a_{low}) - \ln(H^a_{high}) &= [\ln(ER_{low}) + \ln(H^e_{low})] - \left[\ln(ER_{high}) + \ln(H^e_{high})\right] \\
\ln(H^a_{low}) - \ln(H^a_{high}) &= \left[\ln(ER_{low}) - \ln(ER_{high})\right] + \left[\ln(H^e_{low}) - \ln(H^e_{high})\right] \\
1 &= \underbrace{\frac{\ln(ER_{low}) - \ln(ER_{high})}{\ln(H^a_{low}) - \ln(H^a_{high})}}_{ER \text{ Contribution}} + \underbrace{\frac{\ln(H^e_{low}) - \ln(H^e_{high})}{\ln(H^a_{low}) - \ln(H^a_{high})}}_{H^e \text{ Contribution}}
\end{aligned} \tag{A.4}$$

Using the averages for each country-income group yields a contribution of the log employment rate differences of 76.7% and of 25.5% of the log hours per worker differences. Note that the two numbers do not add up to 100% as suggested by Equation (A.4). This is because average hours per adult in country income group i are not equal to the product of the average employment rate in country group i and the average hours per worker in country group i:

$$H^a_i = \frac{1}{N_i}\sum_c^{N_i} H^a_c = \sum_c^{N_i} ER_c \times H^e_c \neq \frac{1}{N_i}\sum_c^{N_i} ER_c \times \frac{1}{N_i}\sum_c^{N_i} H^e_c \;\forall\; i = low, med, high.$$

If we would do this composition between two countries rather than country groups, the two contributions would add up to 100%. Obviously, this is not the only possible decomposition. An alternative to the log hours decomposition via the levels works as follows:

$$\begin{aligned}
H^a_{low} - H^a_{high} =& ER_{low} \times H^e_{low} - ER_{high} \times H^e_{high} \\
H^a_{low} - H^a_{high} =& ER_{low}\left(H^e_{low} - H^e_{high}\right) + H^e_{high}\left(ER_{low} - ER_{high}\right) \\
1 =& \underbrace{\frac{ER_{low}\left(H^e_{low} - H^e_{high}\right)}{H^a_{low} - H^a_{high}}}_{H^e \text{ Contribution}} + \underbrace{\frac{H^e_{high}\left(ER_{low} - ER_{high}\right)}{H^a_{low} - H^a_{high}}}_{ER \text{ Contribution}}
\end{aligned} \tag{A.5}$$

Using this specification, the contribution of the employment rate differences to the hours per adult difference is 73.2% and of the contribution of hours per worker is 29.2%. For the same reason as explained above the two fractions do not add up to 100%. Moreover, this decomposition is not unique. We weight the hours per employed difference by ER_{low} and the employment rate difference by H^e_{high}. Using as weights ER_{high} and H^e_{low} yields a contribution of the employment rate differences to the hours per adult difference of 81.3% and of hours per worker of 21.8%. Based on these three possible decompositions, we conclude that employment rates account for around three quarters of the cross-country differences in hours per adult, while hours per employed account for around one quarter.

A.4. Hours Data from Penn World Tables and Total Economy Database

Recently, the Penn World Tables (PWT, version 8.1 onwards) and the Total Economy Database (TED), run by the Conference Board, also released data on annual hours worked per worker, in addition to employment rates, for an unbalanced panel of countries, with the earliest data coming from the year 1950. The following comparison is based on PWT 8.1 and TED May 2015 Release. Data on hours worked per worker are missing much more often than data on employment rates. In the recent cross-section of countries, the hours data from both data sources cover less countries from the bottom third of the world income distribution than we do: compared to our 9 core countries and 20 total countries, the TED covers only 4 countries (Bangladesh, Pakistan, Sri Lanka, and Vietnam), and the PWT none. Moreover, the four countries in the TED have an average GDP per capita that is one third higher than the average GDP per capita in our bottom tercile countries. As such, both data sets are ill suited to answer the question of how hours worked in poor countries compare to the ones in rich countries nowadays.

Yet, going back in time, both data sources cover more countries that would qualify as low-income countries today. Several notable concerns arose from reading the documentation and the sources cited to construct these databases, however. The PWT report that hours worked are taken from the TED. Yet, the PWT apparently decided to include less observations and in many cases, the year-country observations between both data sets do not coincide, pointing to data revisions. TED itself reports the sources for each country-year observation. Many of these observations are either interpolated between two years (often spread a decade apart), or even extrapolated based on average growth rates from countries with available data in the same continent. Once we exclude these inter- or extrapolated observations, we are left with 215 observations from 14 countries (down from originally 304 observations from 17 countries) that would qualify as low-income countries today.

Looking further into the sources of these data, we still find extrapolated or interpolated values. For example, the value for Peru in 1950 is taken from Maddison (1995), who in turn reports that it is set to the average value of six other available Latin American countries. Most of the 215 observations, namely 196 observations from 8 countries, come from the Asian Productivity Organization (APO). The APO, while being generally very careful in constructing total hours worked, itself uses interpolations and extrapolations to get complete time series of hours for the Asian countries. From conversations with the APO,[1] we got some information on the sources of their data for five out of the eight countries (China, Indonesia, Sri Lanka, Thailand, and Vietnam). Only for 42 out of the 113 respective country-year observations do the original sources include any data on hours. Even for these, the sources might not necessarily use the same concept of hours across countries, and the hours measurement might not necessarily cover the entire year, but we have no further information on this. As an example for a richer country, namely Singapore, Nomura and Amano (2012) report for the APO construction of hours that, while in theory they would like to use actual hours, they have to rely on “mid-year estimates of usual weekly hours worked multiplied by 48 weeks per year as a crude assumption”.

Thus, we want to stress that the comparability over time and across countries of data from the TED is much more questionable than the comparability of our data. Moreover, there are much less independent observations in the country-year database than a first look suggests.

A.5. Potential Biases Resulting from Survey Methodology

No matter how carefully one tries to ensure comparability of different surveys across countries, there is still the potential for bias arising from limitations in the survey methodology. One such potential bias may arise from surveyors avoiding specific regions during periods of peak regional labor demand, such as harvest times, to maximize participation in the surveys. If anything, we argue that it would bias downward our measured average hours in low-income countries, which have higher shares of employment in agriculture. Thus, the actual difference between hours in low- and high-income countries would be even larger than the one we report above for our core countries. An indication for our prior is that hours in low-income countries fall if we add countries with partial-year surveys to the set of core countries, as shown in Table 1. This is much less pronounced in middle- and high-income countries, in which seasonality likely plays less of a role.

[1] We are extremely grateful to Koji Nomura for providing this information.

A second potential bias may arise from vacation periods, such as annual leave and public holidays. As Bick et al. (2016) show, hours lost due to vacation days and public holidays are likely underreported even in surveys that cover each week of the year. While data on vacation days across countries are not readily available, we suspect that vacation days are increasing in GDP per capita, which would imply that hours worked are likely overstated to a larger degree in high-income countries than in low-income ones.

A third possible bias comes from child labor, i.e. hours worked by individuals under our lower age bound of fifteen. Since child labor is more prevalent in low-income countries (Basu, 1999), this would mean that actual hours worked may be even higher in low-income countries compared to rich countries than our current calculations suggest. Thus, all these three potential biases indicate that our reported hours difference between low- and high-income countries is likely a lower bound of the true difference.

A fourth potential concern is that innumeracy among survey respondents in poor countries could lead to potential over- or underestimates of hours worked there. In this regard, it is reassuring that hours worked per adult are substantially higher in poor countries even for highly educated individuals.

A.6. Constructing Hourly Wages from the Micro Data

A.6.1. The European Union Statistics on Income and Living Conditions

We use the year 2005 for all countries from the EU-SILC, except for Hungary (2006), Romania and Latvia (2007), Bulgaria and the UK (2008), Ireland (2009), and Switzerland (2010). For UK and Ireland, these are the first years in which their ELFS surveys cover the entire year, so we use the same years here as in the main analysis. For the other countries, these are the first years in which the needed earnings measures are available in the EU-SILC. There are two earnings measures available in the EU-SILC, though not both for all countries. The first is a measure of annual earnings from the previous year, distinguishing between earnings from paid employment and from self-employment; the second is a measure of current monthly earnings in the main job from paid employment. The EU-SILC only contain a measure of usual weekly hours worked, not a measure of actual hours worked. Therefore, we use usual hours rather than actual hours as the variable to construct the wage rate. When we rely on monthly earnings from the main job, we divide by usual hours from the main job; when we rely on total earnings from all jobs, we divide by usual hours from all jobs. The question of usual hours refers to the current time period. Therefore, if available, we use the measure of current monthly earnings in the main job (this is the case for Austria, Belgium, Bulgaria, Greece, Hungary, Ireland, Italy, Poland, Portugal, Spain, Switzerland, and the UK); only if this variable is not available we recur to annual earnings. To correct for the use of usual hours rather than actual hours, we multiply individual hours with the country-specific ratio of average actual hours worked (from the ELFS) to average usual hours worked (from the EU-SILC). Thereby, we make sure that the average hours measure in each country is the same as in our aggregate analysis. Note that this correction has no effect on the estimation of individual hours on wages within each country, i.e. the estimation of equation 2.

A.6.2. Wage from Paid Employment

We exclude Namibia and Laos because of missing earnings data. For Namibia, the data set provides a measure of total household per capita income, which however amounts on average to almost twice GDP per worker and thus seems implausible.

Earnings refer to gross earnings whenever available, but in some countries to net earnings, and in many countries it is not clear whether reported earnings are gross or net. If earnings are provided at another frequency than monthly, we convert them to monthly earnings by multiplying with an appropriate factor (i.e. 4.33 for weekly earnings, 0.33 for quarterly earnings, etc.). For daily earnings, we multiply with days worked per week times 4.33 or days worked per month; if none of these are reported, we drop the observation from the sample, since we do not want to make an assumption how many days an individual works per month.

Calculating a wage is not always straightforward if an individual has multiple jobs. Our main priority is to calculate a wage by dividing earnings and hours referring to the same job(s). Both earnings and hours can in principle be available for (i) main job, (ii) all paid employment jobs, and/or (iii) all jobs, but the actual availability differs across countries. We proceed in five steps to calculate the best available wage rate for each individual (referring here always to individuals whose main job is from paid employment):

1. If an individual has only one job, we divide total earnings by total hours.
2. If an individual has multiple jobs, but all of them are from paid employment, we proceed the same way.
3. If an individual has multiple jobs, but not all of them from paid employment, we divide earnings from all paid employment jobs by hours from all paid employment jobs, i.e. excluding both earnings and hours from self-employment.
4. If an individual has multiple jobs, but either earnings or hours from a second (or further) job in paid employment are not available, we divide earnings from the main job by hours from the main job. Since for the US we know earnings only from the main job, the US falls in this category.
5. Last, for all other individuals, to whom we could not yet assign a wage rate because of missing information, we divide total earnings from paid employment jobs, or if not available earnings from main job, by total hours.

In the US we only have earnings in the main job (i.e. the fourth case above), but no actual hours worked in the main job (only in all jobs). Thus we construct a wage rate dividing earnings in the main job by usual hours worked in the main job as recommended by NBER in the documentation of the dataset. As for the European countries, we correct for the use of usual hours rather than actual hours by multiplying individual hours with the ratio of average actual hours worked to average usual hours worked.

Within each country, we omit the top and bottom one percent of the constructed wage observations. Table A.1 shows the share of workers in paid employment, as well as average hours of workers in paid employment, for the three country income groups. Workers in paid employment are clearly a positively selected sample in the low-income countries.

In the baseline regressions of hours on wages, we always use the same hours variable on the left hand side that we use to construct the wage rate on the right hand side. Table A.2 shows that our results from Table 8 are robust to including only individuals with exactly one job, and excluding the top and bottom decile of wages within each country.

A.6.3. Wage from Paid Employment Plus Self-Employment

For the majority of countries, we have a measure of self-employment earnings on the individual level. In this case, we calculate the hourly wage as the sum of total earnings from paid and self-employment divided by total hours in paid and self employment. We now go through the exceptions. In Cambodia, Iraq, Kenya, Malawi, Rwanda, Timor L'Este, Uganda, and Vietnam, self-employment earnings are only available at the household level. In Tanzania, agricultural self-employment earnings are available at the household level, but non-agricultural self-employment earnings (only from the main job) are available at the individual level, and we sum all self-employment earnings up at the household level. In these nine countries, we calculate total household earnings by adding all individual earnings from paid employment to the household earnings from self-employment. Total household earnings are then divided by the sum of the hours worked of all household members to get a household wage rate. Similarly, the sum of hours worked of all household members is divided by the number of employed household members to get average household hours conditional on working. Thus, in the end each household is represented with the same household wage rate and average household hours observation assigned to each working member. For Indonesia and Mauritius, self-employment earnings only refer to the main job, not all jobs. The surveys from Pakistan, Turkey, and the US do not include any self-employment earnings, and for these three countries total earnings are thus equal to earnings from paid employment. For self-employment from farming activities, we typically calculate earnings as revenues minus costs, which are often reported for individual crops, animals, etc., and then added up. The value of own consumption of self-produced goods is mostly explicitly asked for and then added to revenues. Self-employment earnings in the EU-SILC are sometimes gross and sometimes net earnings; if both are available in a country, we always take gross earnings. Since self-employment earnings in the EU-SILC are only available as annual earnings from the previous year, we also use annual earnings from paid employment from the previous year in this analysis, even if monthly earnings from paid employment in the current period are available. The only exception is if someone does not have any additional earnings apart from earnings from paid employment in the main job; in this case, we continue to work with monthly earnings, if available.

Within each country, we again omit the top and bottom one percent of the constructed wage observations. Table A.3 shows the share of workers from paid and self employment with missing wages, and the hours per worker conditional on observing a wage. The cross-country pattern in these hours resembles the one of hours per worker for the full sample.

A.6.4. Validity Check of Wage Measures

Given that clearly the earnings measures face shortcomings and the underlying data are sometimes of unclear quality, we conduct a validity check to gauge their general reliability. To do that, we construct a measure of average earnings per worker in each country, summing up all earnings from paid employment and dividing by workers in paid employment for the first earnings measure, and summing up all earnings (including self-employment earnings) and dividing by all individuals working positive hours for the second earnings measure. We then compare the respective average earnings per worker to GDP per worker reported in the Penn World Tables. Figure A.3 shows these two ratios. Focusing first on the earnings measure from paid employment, the ratio amounts on average to 0.57 in the low-income countries, 0.29 in the middle-income countries, and 0.34 in the high-income countries. This confirms positive selection into paid employment jobs in low-income countries. For total earnings, the ratios amount on average to 0.47, 0.27, and 0.38, respectively, for the low-, middle-, and high-income countries. Given that the labor share of GDP is roughly two thirds, but that the labor share also includes some components not measured in earnings (e.g. employer contributions to social security), these ratios are somewhat on the low side, but overall not too far off. While for some individual countries they raise some concerns about the measurement of earnings (e.g. in Kenia the ratio is over 1.2 for earnings from paid employment, but in Malawi just over 0.1), this validity check shows that our earnings measures are overall reasonable.

A.6.5. Some Evidence on Division Bias

Since individual hours worked are the dependent variable in our regressions, but also feature as a denominator on the right hand side of the regression equation in individual wages, any classical measurement error in hours leads to a spurious negative correlation between hours and wages, see e.g. Borjas (1980). To gain some insights into the potential size of this division bias, we conduct a number of robustness checks on a limited sample of countries for which we have an alternative hours variable available. The main strategy is to run regressions in which the measure of hours on the left hand side is replaced with an alternative measure (e.g. usual hours worked rather than actual hours worked, which are used to construct wages). Table A.4 shows results for the US, Turkey, Peru, Mongolia, and Uganda. In all six robustness checks (2 for Uganda), replacing hours with an alternative measure increases the coefficient β_w. Thus, there is robust evidence for the presence of a division bias. However, the coefficient change is generally relatively small: with the exception of Peru, the coefficient increases by on average one third, or 0.05 in absolute terms, and never changes sign. In the Peruvian sample, however, replacing actual hours worked with usual hours in all jobs increases the coefficient from -0.15 to 0.06.

Table A.1: Hours Worked and Shares of Workers in Paid Employment

	Country Income Group		
	Low	Middle	High
Hours per Worker: All Workers	38.4	41.2	34.5
Hours per Worker: Wage Workers (*Non-Missing Wages*)	48.2	43.1	33.3
Share of Wage Workers (in %)	23.4	61.2	83.9
Share of Workers w/ Missing Status (in %)	3.7	0.6	0.0
Share of Wage Workers w/ Missing Wage (in %)	16.1	5.8	2.9

Note: This table shows in row 1 hours per worker from our main sample, and in row 2 hours per worker from the sample of wage workers for whom we can construct a wage observation. Rows 3 gives the share of wage workers among all workers, and row 4 gives the share of workers for whom we don't know whether they are in paid employment or self-employed; thus, 100 minus the shares in rows 3 and 4 give the share of self-employed workers. Row 5 gives the share of wage workers for whom we do not observe a wage among all wage workers.

Table A.2: Robustness Exercises on Elasticities of Hours

Panel A: All Individuals with Only One Job

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.143^{***}	–	-0.004	–
ln (Hourly Wage)	–	-0.141^{***}	-0.139^{***}	-0.138^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.093	0.158	0.158	0.239
Obs.	569,433	569,433	569,433	569,433

Panel B: Excl. Individuals with Wage in 1st and 10th Decile in Each Country

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.118^{***}	–	-0.042	–
ln (Hourly Wage)	–	-0.093^{***}	-0.065	-0.100^{**}
Country Fixed Effects	No	No	No	Yes
R^2	0.092	0.098	0.100	0.225
Obs.	657,607	657,607	657,607	657,607

This table reports the coefficients from estimating equation 2 on a data set containing individual observations of both sexes but with different samples from 42 and 46 countries in Panels A and B, respectively. The dependent variable is the logarithm of individual hours worked per worker. The explanatory variables are the ones listed in each column, plus age and age squared. The first panel includes only individuals for which we know that they have exactly one job, which is a job in paid employment. The second panel excludes the top and bottom decile of individual wage observations within each country. *** means a p-value less than 0.01, ** means a p-value less than 0.05, and * means a p-value less than 0.10.

Table A.3: Hours Worked and Shares of Workers in Paid or Self Employment

	Country Income Group		
	Low	Middle	High
Hours per Worker: All Workers	38.4	41.2	34.5
Hours per Worker: All Workers (*Non-Missing Wages*)	39.3	43.5	34.3
Share of Workers w/ Missing Wage (in %)	2.7	9.4	0.3

Note: This table shows in row 1 hours per worker from our main sample, and in row 2 hours per worker from the sample of workers for whom we can construct a wage observation from paid or self-employment. Row 3 gives the share of workers for whom we do not observe a wage.

Table A.4: Evidence on Division Bias

	Dep. Var.: Hours	β_w	Obs.
Baseline - USA	Usual Main J.	0.125^{***}	162,283
Robustness	Usual Main J.	0.124^{***}	156,351
	Actual J.	0.125^{***}	
Baseline - Turkey	Actual	-0.303^{***}	88,138
Robustness	Actual	-0.303^{***}	88,138
	Usual Main J.	-0.211^{***}	
Baseline - Peru	Actual	-0.108^{***}	15,356
Robustness	Actual	-0.150^{***}	3,262
	Usual All J.	0.056^{***}	
Baseline - Mongolia	Actual	-0.212^{***}	1,223
Robustness	Actual	-0.212^{***}	1,223
	Usual Main J.	-0.188^{***}	
Baseline - Uganda	Actual	-0.176^{***}	671
Robustness	Actual	-0.155^{***}	360
	Usual All J.	-0.055^{*}	
	Usual Main J.	-0.070^{**}	

Note: This table reports the coefficient β_w from an estimation of the log of individual hours worked on the log of the individual wage in data from the US, Turkey, Peru, Mongolia, and Uganda, including age and age squared as explanatory variables. The first row for each country shows baseline results, in which the dependent hours variable corresponds to the one used to construct hourly wages. The second row for each country repeats the baseline estimation on a restricted sample of individuals for whom an alternative hours measure to the one used in the baseline estimation is available. The third row then shows results if the alternative hours measure is used as the dependent variable. For Turkey, Peru, Mongolia, and Uganda, the baseline hours measure is a measure of actual hours worked, while the alternative one is a measure of usual hours worked (either in the main job or in all jobs). For the US, it is the other way round. For Uganda, there are two alternative hours measures. *** means a p-value less than 0.01, ** means a p-value less than 0.05, and * means a p-value less than 0.10.

Figure A.3: Ratio of Income per Worker over GDP per Worker

Note: This figure shows the ratio of income per worker over GDP per worker from the Penn World Tables, plotted against the logarithm of GDP per capita. Income per worker is defined as earnings from paid employment divided by number of workers in paid employment for the black dots, and as earnings from paid employment plus earnings from self-employment divided by the total number of workers for the grey dots.

B. Model Appendix

In the following paragraphs, we first provide more details on the model setup. We then describe the calibration and model fit.

The household budget constraint amounts to $c_t + k_{t+1} = w_t h_t + (1 + r_t)k_t$, where w_t and r_t are the return to working and capital k_t. There is a representative firm with a Cobb-Douglas production function $y_t = A_t k_t^{\theta} h_t^{1-\theta}$, where y_t denotes output, A_t the efficiency of production, and θ the capital share. As is standard, household optimality implies that the marginal rate of substitution between leisure and consumption equals the price ratio. Profit maximization of the representative firm implies that the marginal product of labor equals the wage. Combining these two conditions yields the following Equation (4), which we restate here:

$$h_t = \left[\frac{1-\theta}{\left(\frac{c_t}{y_t} - \frac{\bar{c}}{y_t} \right) \alpha} \right]^{\frac{\phi}{1+\phi}} .$$

Rather than solving the full-dynamic model, Prescott (2004) interprets Equation (4) as the equilibrium value of hours worked given parameters and values for the consumption-output ratio. Our specification adds values for the subsistence consumption-output ratio as in Ohanian et al. (2008). The consumption-output ratio, directly taken from the data, captures the dynamic component of the neo-classical growth model. The difference between the consumption-output ratio and the subsistence consumption-output ratio in turn determines the size of the income effect. In the context of our data, the higher is output, y, the lower is the role of subsistence consumption for determining hours, holding everything else equal. This naturally generates a decreasing relationship between hours worked and output. Figure B.1 shows the model inputs for each country, evaluated at the calibrated value of $\bar{c}$, and Figure B.2 plots the data and model hours against GDP per capita. One key observation is that for Malawi the calibrated subsistence consumption exceeds actual consumption. As a consequence, Equation (4) does not predict hours for Malawi. This is however not a problem for our welfare analysis, in which the calibrated value of subsistence consumption cancels out as it is the same across countries. While we match on average hours per adult perfectly in low- and high-income countries, the model explains about half of the difference between middle- and high-income countries. Finally, Figure B.3 plots the ratio of welfare to consumption in each country.

As a last remark, it is worthwhile to mention that Prescott (2004) and Ohanian et al. (2008) use the above framework to quantify in how far cross-country differences in consumption taxes, labor income taxes, and government consumption can account for the differences in hours per adult across countries and over time in OECD countries. To keep the analysis focused, we abstract from these public policies. In a robustness exercise for a subset of countries for which we have information on these policies, we find that introducing them does not substantively change our main conclusions; results are available on request.

Figure B.1: Country-specific $\frac{c}{y} - \frac{\bar{c}}{y}$

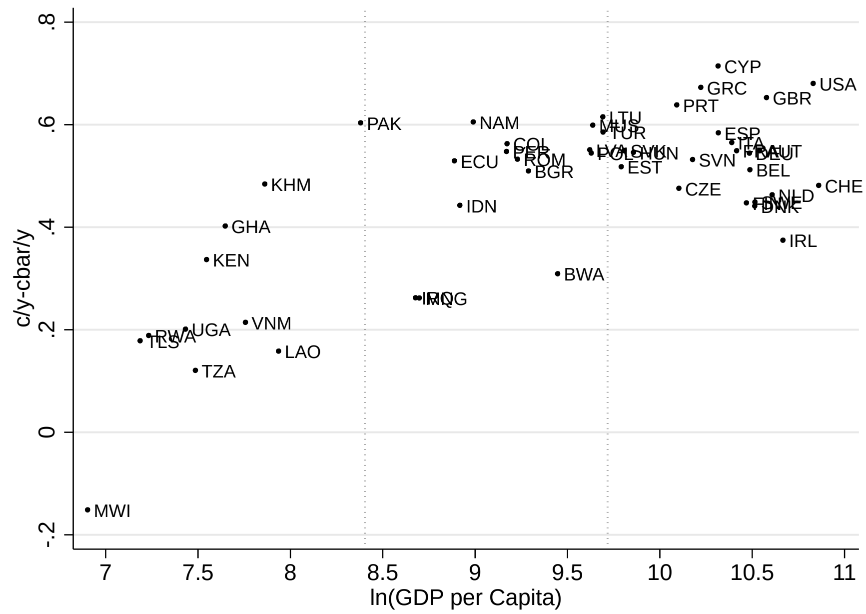


Figure B.2: Average Hours per Adult – Model vs. Data

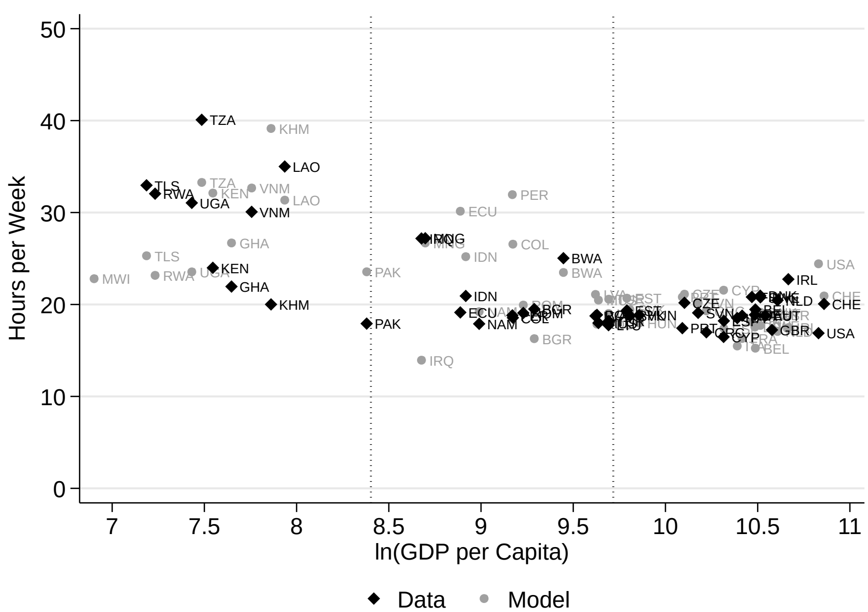
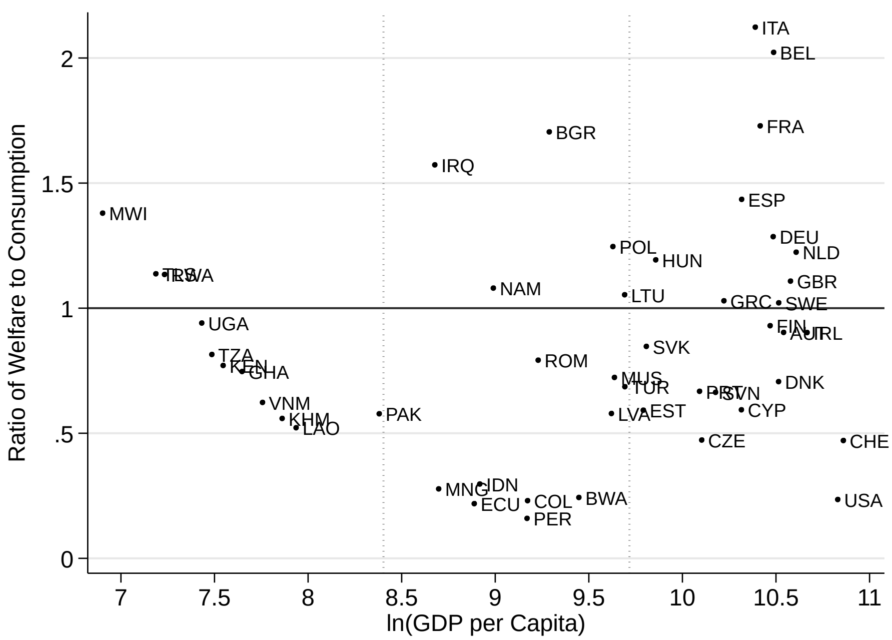


Figure B.3: Welfare vs. Consumption



C. Appendix Tables and Figures

Table C.1: Data Sources

Country	Source	Year	Tercile	Core	Sample Size
Albania	Living Standards Measurement Study (LSMS)	2005	2	No	12,979
Angola	Inquerito Integrado sobre o Bem-Estar da Populacao (IBEP)	2008	2	No	30,622
Armenia	Labour Force Survey	2008	2	No	6,065
Australia	Household, Income and Labour Dynamics in Australia (HILDA-CNEF)	2005	3	No	13,571
Austria	European Union Labour Force Survey	2005	3	Yes	168,399
Belgium	European Union Labour Force Survey	2005	3	Yes	88,670
Benin	Enquete Modulaire Integree sur les Conditions de Vie des Menages (EMICOV)	2010	1	No	41,515
Bolivia	Encuesta de Hogares (RIGA)	2005	1	No	10,436
Bosnia and Herzegovina	Living Standards Measurement Survey (LSMS)	2001	2	No	7,738
Botswana	Labour Force Survey	2005	2	Yes	19,390
Brazil	National Household Sample Survey (PNAD)	2009	2	No	300,734
Bulgaria	European Union Labour Force Survey	2005	2	Yes	123,108
Cambodia	Cambodia Socio-Economic Survey (CSES)	2011	1	Yes	11,542
Canada	Census of Canada (IPUMS)	2001	3	No	119,179
Chile	National Socioeconomic Survey (CASEN)	2009	3	No	193,231
Colombia	Integrated Household Survey (GEIH)	2008	2	Yes	593,287
Cyprus	European Union Labour Force Survey	2005	3	Yes	31,719
Czech Republic	European Union Labour Force Survey	2005	3	Yes	213,620
Denmark	European Union Labour Force Survey	2005	3	Yes	47,280
Ecuador	Encuesta de Condiciones de Vida (LSMS)	2005	2	Yes	35,947
Egypt	Labor Market Panel Survey	2006	2	No	25,661
El Salvador	VI Population and V Housing Census	2007	2	No	75,106
Estonia	European Union Labour Force Survey	2005	3	Yes	15,006
Finland	European Union Labour Force Survey	2005	3	Yes	36,544

Table C.1: Data Sources

Country	Source	Year	Tercile	Core	Sample Size
France	European Union Labour Force Survey	2005	3	Yes	278,613
Germany	European Union Labour Force Survey	2005	3	Yes	406,931
Ghana	Living Standards Survey (LSMS)	1998	1	Yes	15,003
Greece	European Union Labour Force Survey	2005	3	Yes	271,319
Guatemala	Encuesta Nacional Sobre Condiciones de Vida (ENCOVI) (LSMS)	2000	2	No	21,204
Hungary	European Union Labour Force Survey	2005	3	Yes	265,945
Indonesia	Sakernas (National Labour Force Survey)	2010	2	Yes	776,344
Iraq	Household Socio-Economic Survey (LSMS)	2007	2	Yes	75,500
Ireland	European Union Labour Force Survey	2009	3	Yes	211,337
Italy	European Union Labour Force Survey	2005	3	Yes	605,063
Jamaica	Population Census (IPUMS)	2001	2	No	111,153
Jordan	Population and Housing Census (IPUMS)	2004	2	No	95,908
Kazakhstan	Living Standards Measurement Survey (LSMS)	1996	2	No	5,141
Kenya	Kenya Integrated Household Budget Survey	2005	1	Yes	38,732
Kyrgyzstan	Living Standards Measurement Survey (LSMS)	1998	1	No	9,720
Lao PDR	Expenditure and Consumption Survey	2007	1	Yes	29,785
Latvia	European Union Labour Force Survey	2005	2	Yes	18,639
Lesotho	Integrated Labour Force Survey	2008	1	No	32,799
Lithuania	European Union Labour Force Survey	2005	2	Yes	40,232
Malawi	Integrated Household Survey (LSMS)	2004	1	Yes	27,526
Malaysia	Population and Housing Census (IPUMS)	1991	2	No	110,172
Mali	Permanent Household Survey (EPAM)	2010	1	No	9,383
Mauritius	Continuous Multi Purpose Household Survey (CMPHS)	2010	2	Yes	31,746
Mexico	Population and Housing Census (IPUMS) 2010	2010	2	No	80,761
Mongolia	Labour Force Survey	2006	2	Yes	10,371

Table C.1: Data Sources

Country	Source	Year	Tercile	Core	Sample Size
Namibia	Household Income and Expenditure Survey	2009	2	Yes	27,852
Netherlands	European Union Labour Force Survey	2005	3	Yes	359,045
Nicaragua	National Household Survey Measurements on Living Standards (EMNV) (LSMS)	2005	1	No	97,193
Pakistan	Labor Force Survey	2011	1	Yes	149,566
Panama	Encuesta de Niveles de Vida (ENV) (LSMS)	2008	2	No	18,493
Paraguay	Encuesta de Hogares (Household Survey)	2011	2	No	13,758
Peru	Encuesta Nacional de Hogares (ENAHO)	2010	2	Yes	61,695
Philippines	Labor Force Survey (Jan, Apr, Jul, Oct)	2010	2	No	540,352
Poland	European Union Labour Force Survey	2005	2	Yes	186,439
Portugal	European Union Labour Force Survey	2005	3	Yes	162,255
Romania	European Union Labour Force Survey	2005	2	Yes	234,399
Russia	Russia Longitudinal Monitoring Survey (RLMS)	2009	3	No	11,677
Rwanda	Enquete Integrale sur les conditions de vie des menages 2010-2011	2011	1	Yes	39,197
Serbia	Living Standards Measurement Survey (LSMS)	2007	2	No	14,925
Slovak Republic	European Union Labour Force Survey	2005	3	Yes	97,867
Slovenia	European Union Labour Force Survey	2005	3	Yes	62,173
South Africa	Census 2001 (IPUMS)	2001	2	No	75,796
Spain	European Union Labour Force Survey	2005	3	Yes	522,325
Sweden	European Union Labour Force Survey	2005	3	Yes	147,131
Switzerland	European Union Labour Force Survey	2010	3	Yes	67,121
Taiwan	Labor Force Survey	2011	3	No	682,792
Tajikistan	Living Standards Survey (LSMS)	2007	1	No	19,032
Tanzania	National Panel Survey (LSMS)	2009	1	Yes	9,519
Timor Leste	Living Standards Survey (LSMS)	2007	1	Yes	14,368
Tunisia	Enquete Nationale sur la Population et l'Emploi de 2010 (ENPE 2010)	2010	2	No	409,242

Table C.1: Data Sources

Country	Source	Year	Tercile	Core	Sample Size
Turkey	Household Labour Force Survey	2010	2	Yes	385,180
Uganda	National Panel Survey (LSMS)	2010	1	Yes	9,050
United Kingdom	European Union Labour Force Survey	2008	3	Yes	156,469
United States	Current Population Survey - Merged Outgoing Rotation Group (NBER)	2005	3	Yes	322,991
Venezuela	Population and Housing Census (IPUMS)	2001	2	No	76,502
Vietnam	Household Living Standards Survey (LSMS)	2002	1	Yes	92,718

Table C.2: GDP per Capita in 2011 US-Dollar, PPP-adjusted

Sample	Country Income Group		
	Low	Middle	High
Penn World Tables 9.0 (2005)	2,130	9,139	36,284
	(60)	(61)	(61)
Core Countries	2,113	11,030	33,059
	(11)	(15)	(22)
Core + All non-core Countries	2,228	9,143	32,590
	(18)	(35)	(27)

Note: The number of countries in each group is in parentheses. The last version of the PWT that includes Timor L'Este is version 7.1. We impute GDP per capita for Timor L'Este as follows. We use the ratio of GDP per capita (based on *rgdpch*) in Timor L'Este to GDP per capita in Indonesia for the year 2007 from PWT 7.1 and then multiply that ratio with GDP per capita (based on *rgdpe*) from Indonesia from PWT 9.0 for 2007.

Table C.3: Home Production Hours by Individual Country and Category

	cooking	cleaning	childcare	shopping	collwf	Tercile
BEN	–	6.9	–	3.9	–	1
GHA	6.9	1.9	8.0	2.8	3.1	1
KGZ	–	–	9.8	–	3.7	1
LSO	–	–	2.1	0.1	1.9	1
MLI	5.1	2.7	3.3	–	3.1	1
PAK	16.4	13.9	7.2	2.1	0.8	1
RWA	6.9	4.3	–	1.3	3.4	1
TLS	–	–	2.6	–	5.0	1
EGY	10.8	9.3	9.6	2.6	0.3	2
GTM	8.6	8.3	10.3	1.7	3.6	2
IRQ	7.3	5.7	3.2	2.1	–	2
KAZ	9.1	8.2	10.1	3.2	–	2
MNG	6.3	4.4	2.0	1.0	4.3	2
ZAF	7.7	7.2	2.2	1.4	0.0	2
AUT	6.6	7.8	3.0	4.4	–	3
DEU	5.5	6.1	2.3	3.7	–	3
ESP	7.3	6.5	2.1	3.3	–	3
FRA	6.4	6.0	2.1	4.4	–	3
GBR	4.8	4.9	3.8	3.9	–	3
ITA	7.6	7.8	1.9	3.9	–	3
NLD	5.9	3.6	2.9	3.8	–	3
RUS	4.6	4.4	3.7	2.4	–	3
USA	3.6	4.9	3.0	4.3	–	3

Table C.5: Elasticities of Hours to Aggregate and Individual Income (Incl. Earnings from Self-Employment)

Panel A: Both Sexes

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.033	–	0.062	–
ln (Hourly Wage)	–	-0.052^{**}	-0.086^{***}	-0.098^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.022	0.041	0.047	0.154
Obs.	1,289,548	1,289,548	1,289,548	1,289,548

Panel B: Men

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.022	–	0.092^{**}	–
ln (Hourly Wage)	–	-0.053^{**}	-0.102^{***}	-0.118^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.024	0.050	0.066	0.194
Obs.	770,727	770,727	770,727	770,727

Panel C: Women

	ln Hours	ln Hours	ln Hours	ln Hours
ln (GDP per Hour)	-0.044	–	0.039	–
ln (Hourly Wage)	–	-0.054^{**}	-0.075^{***}	-0.094^{***}
Country Fixed Effects	No	No	No	Yes
R^2	0.025	0.040	0.043	0.133
Obs.	518,821	518,821	518,821	518,821

Note: This table reports the coefficients from an estimation of a variant of equation 2 on a data set containing individual observations from 46 countries. The dependent variable is the logarithm of individual hours worked per worker. The explanatory variables are the ones listed in each column, plus age and age squared. Standard errors are clustered at the country level. *** means a p-value less than 0.01, ** means a p-value less than 0.05, and * means a p-value less than 0.10.

Table C.6: Labor Productivity Differences Across Countries Using *rgdpo* Instead of *rgdpe*

	Country Income Group			
	Low	Middle	High	High/Low
GDP per Worker	5.6	31.7	100.0	17.8
GDP per Hour Worked	4.8	26.3	100.0	20.7

Note: Labor productivity is computed as the average labor productivity within each country income group relative to the average labor productivity of the high-income group, which is normalized to 100. Only core countries are included in the analysis. In our baseline exercise, we use *rgdpe* to calculate GDP per hour and find 18 percent larger labor productivity differences across countries than implied by GDP per worker. Feenstra et al. (2015) recommend using *rgdpo* rather than *rgdpe* for productivity comparisons across countries. This implies 16 percent larger labor productivity differences across countries when relying on GDP per hour worked than implied by GDP per worker.

Figure C.1: Average Hours Worked per Adult: Core vs. All Non-Core Countries

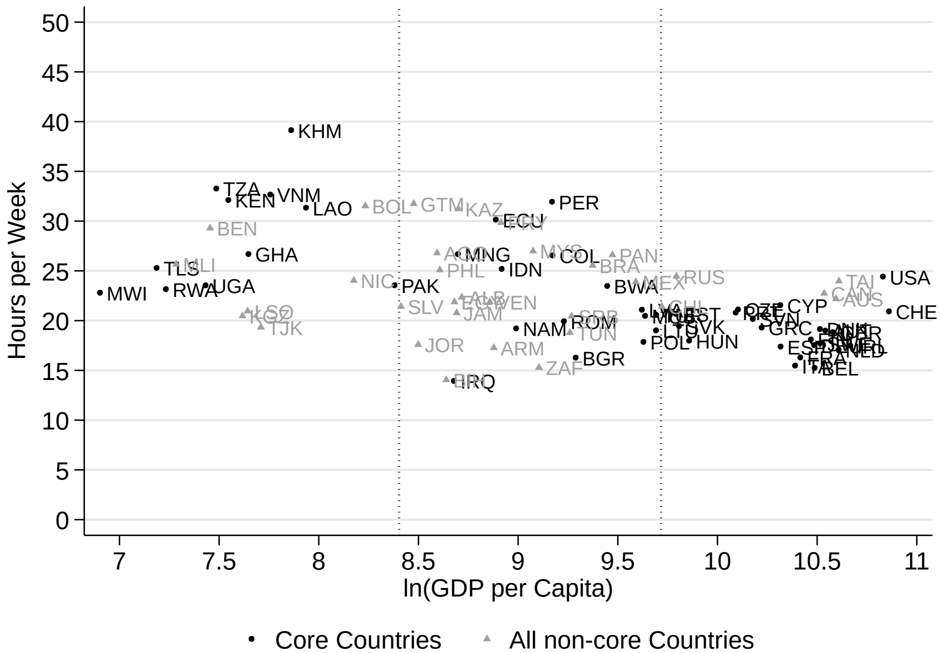


Figure C.2: ln(Hours per Adult) vs. ln(GDP per hour)

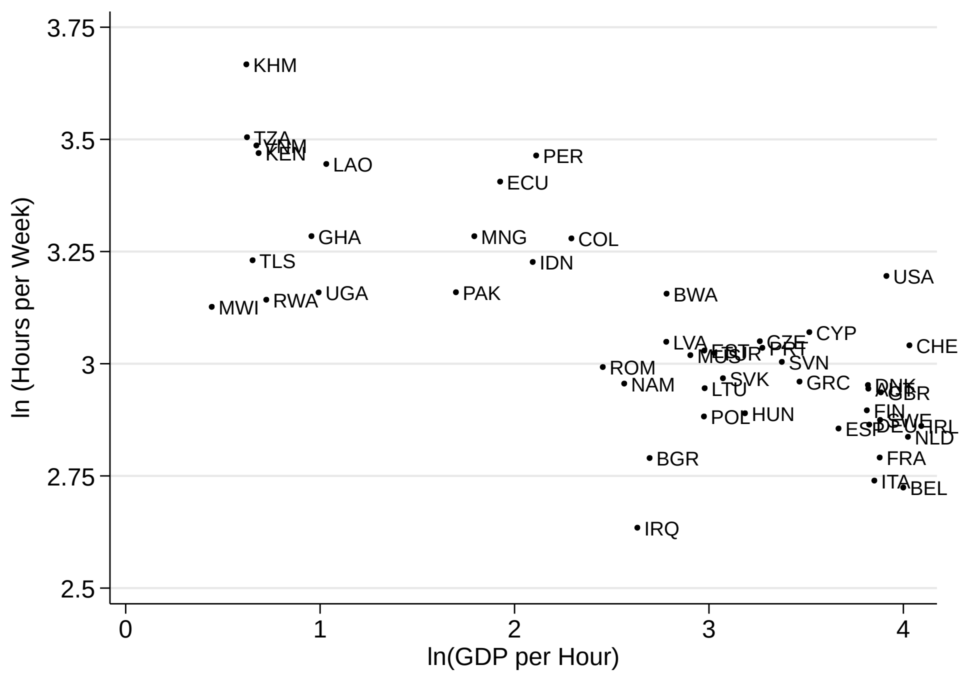
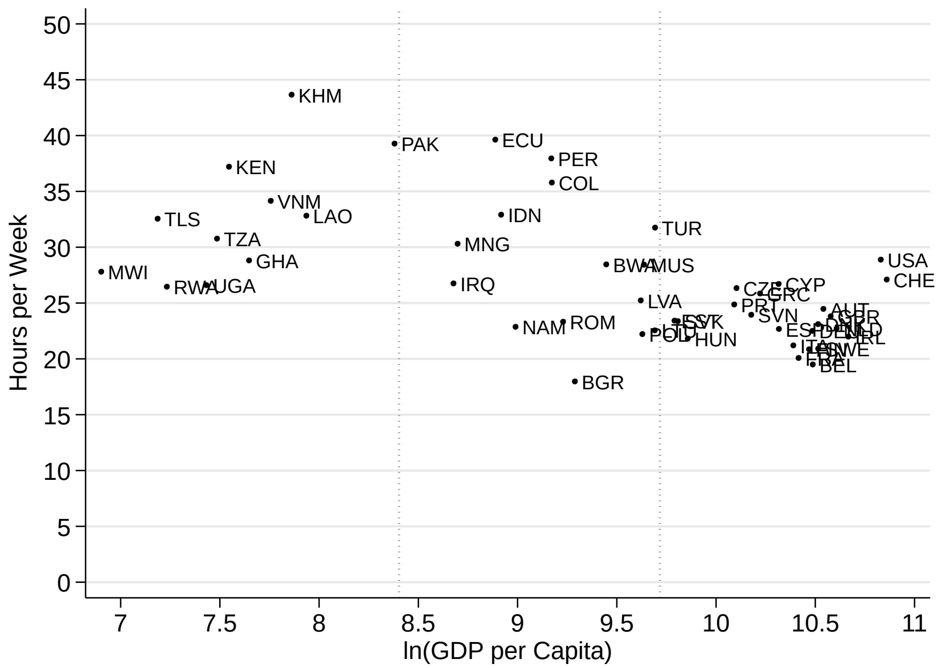


Figure C.3: Average Hours per Adult by Sex

(a) Men



(b) Women

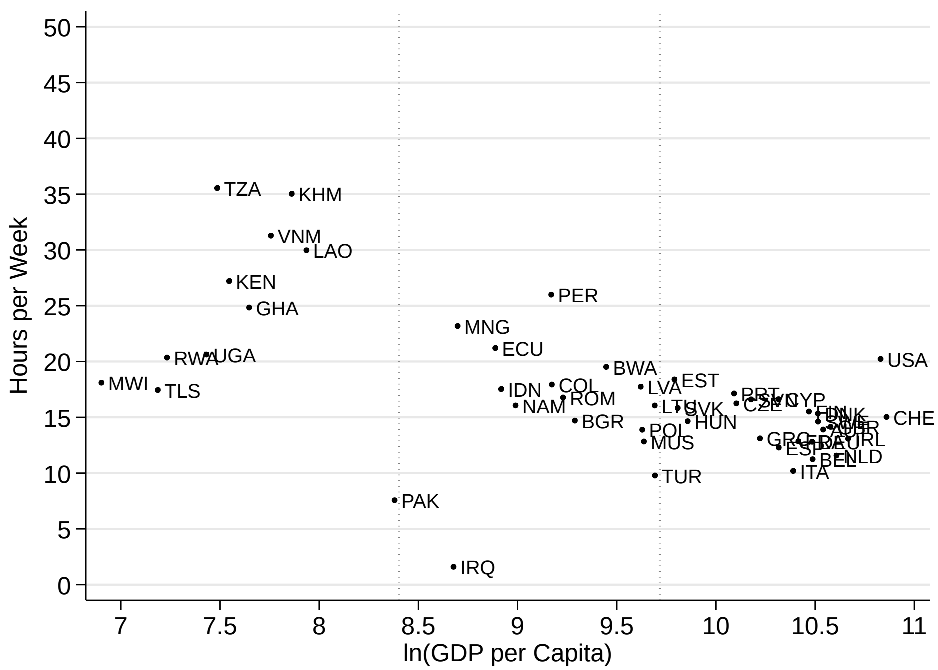
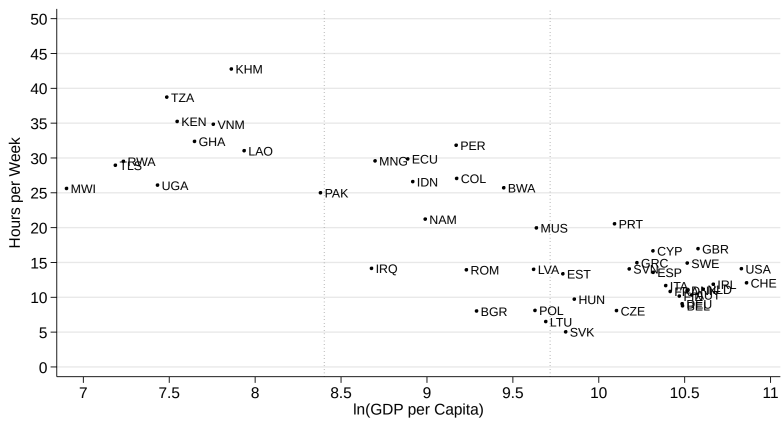
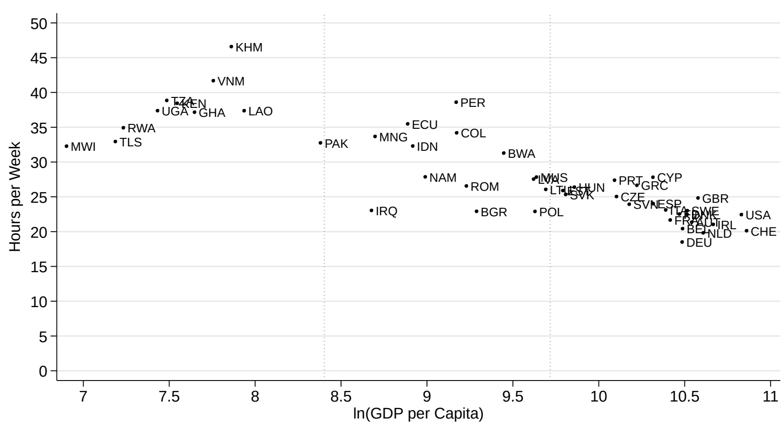


Figure C.4: Average Hours per Adult by Education (Ages 25+ only)

(a) Less than Secondary School



(b) Secondary School Completed



(c) More than Secondary School

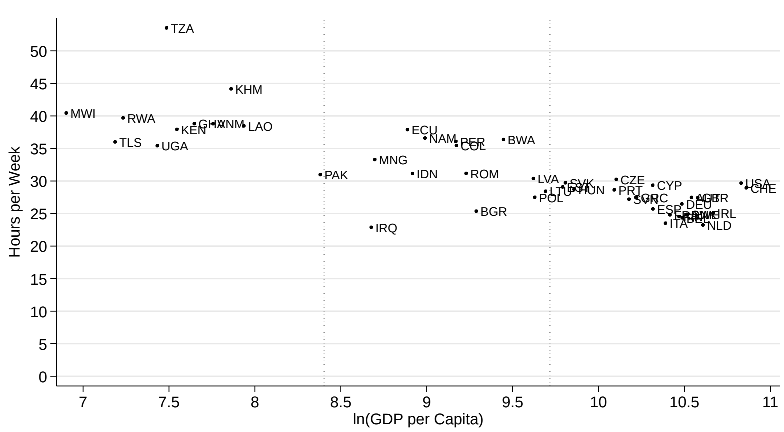
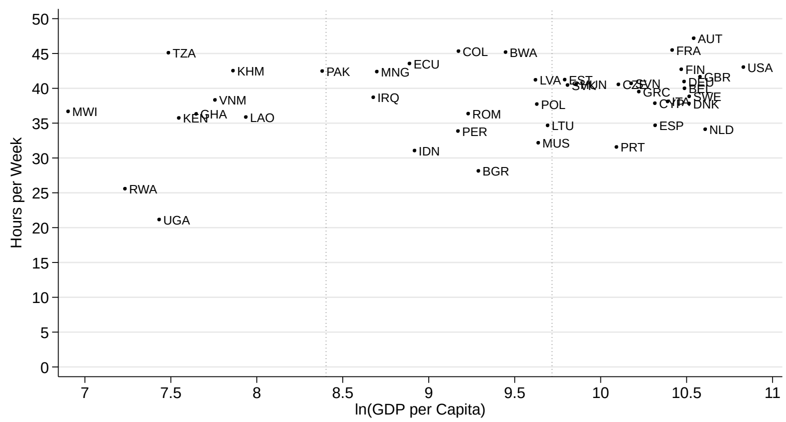
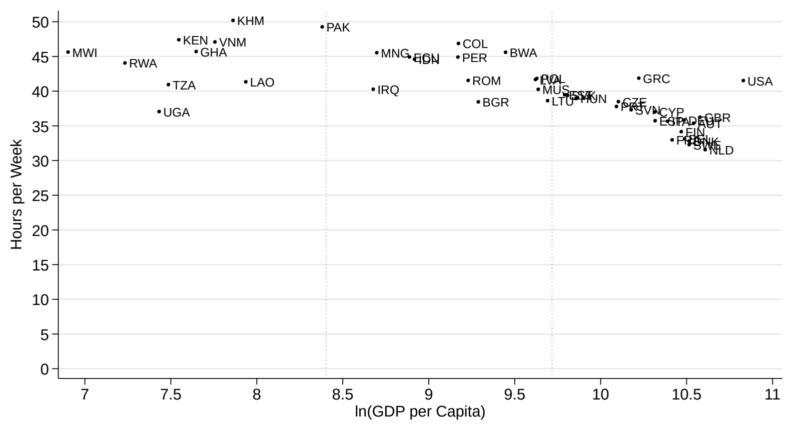


Figure C.5: Average Hours per Worker by Sector

(a) Agriculture



(b) Manufacturing



(c) Services

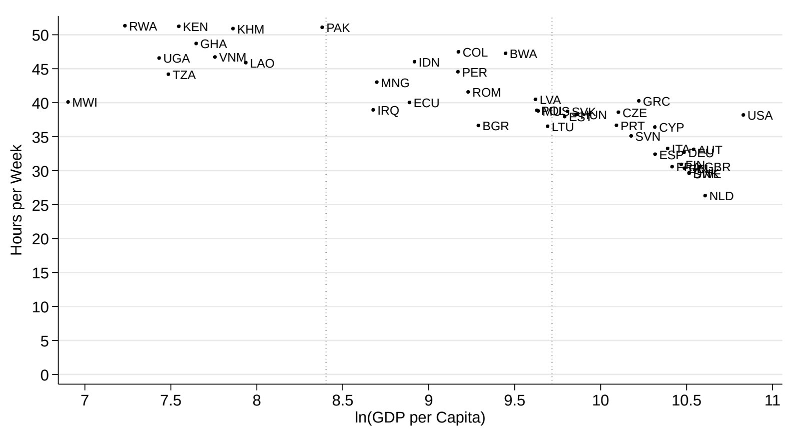


Figure C.6: Hours By Wage (Incl. Earnings from Self-Employment) Deciles For All Employees

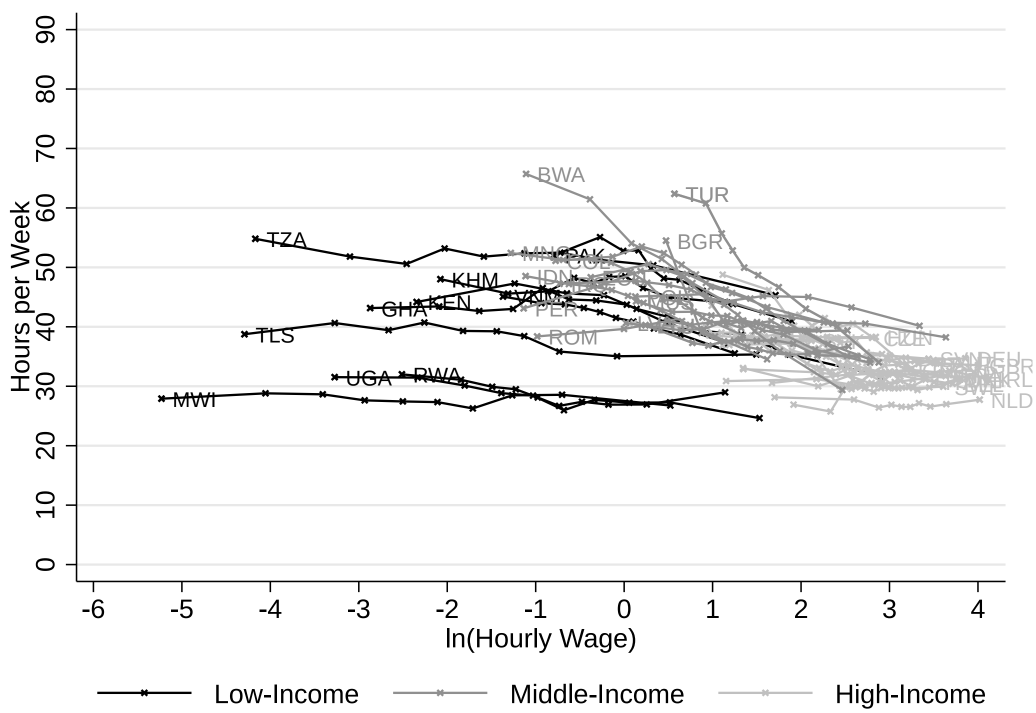
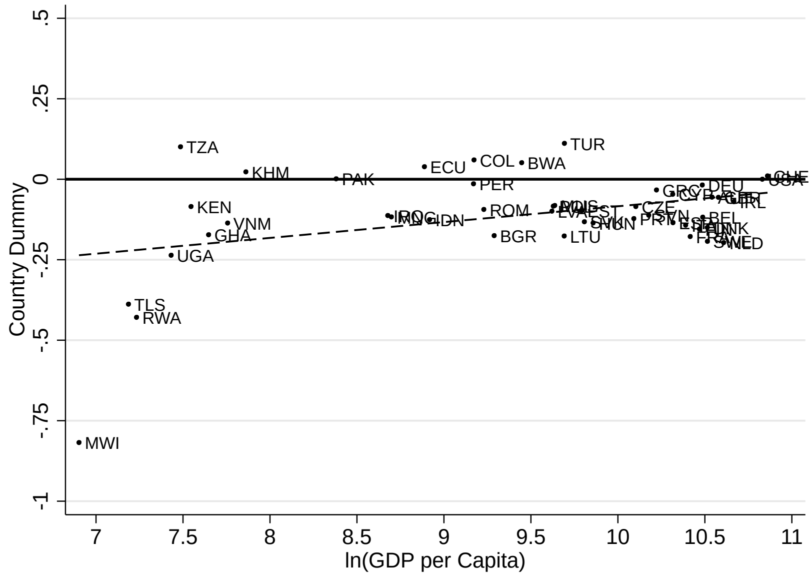
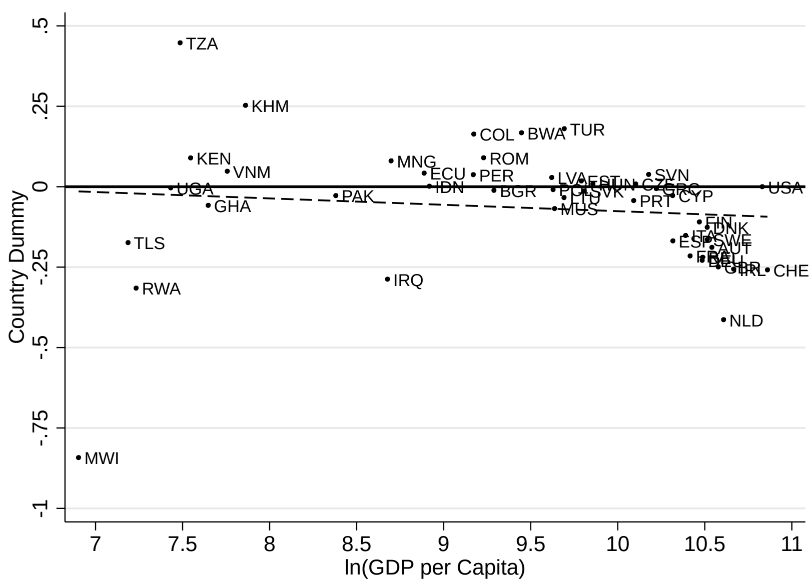


Figure C.7: Country Fixed Effects from Regression in Column 4 of Table 8

(a) Men



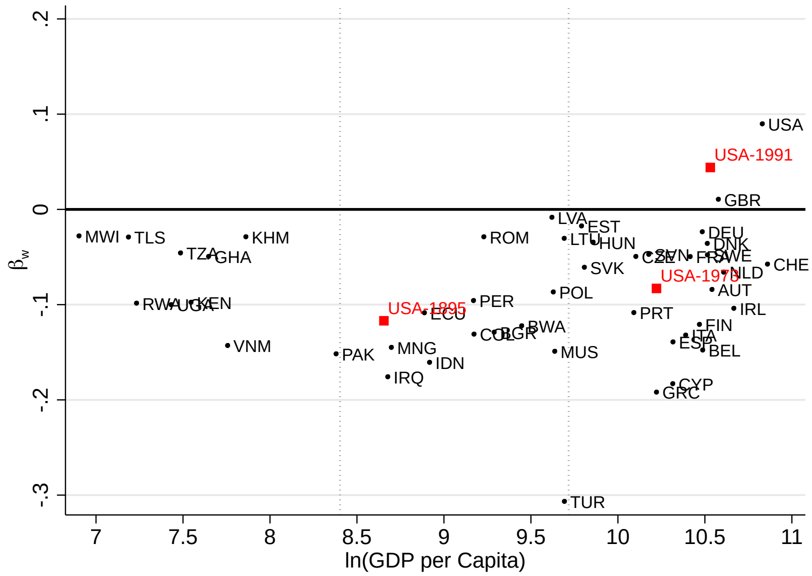
(b) Women



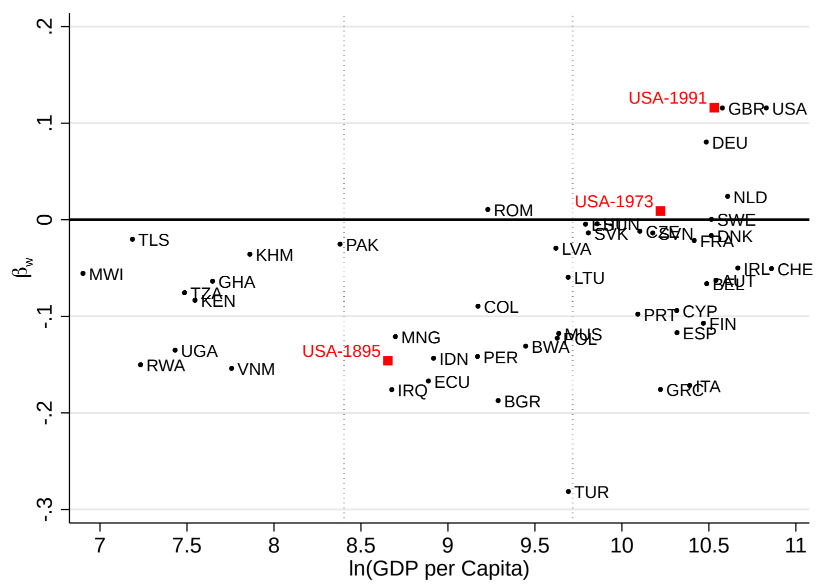
Note: The figure plots the country fixed effects from the regression in column 4 of Table 8 against the logarithm of GDP per adult in each country. The fixed effects for men come from Panel B of Table 8, and the fixed effects for women from Panel C. A linear fit is included.

Figure C.8: Country-Specific Elasticities of Hours to Wages (Incl. Earnings from Self-Employment)

(a) Men



(b) Women



Note: The figure shows the country-specific elasticities of hours to wages, represented by the coefficient β_w from a regression of individual hours worked on individual wages, controlling for age and age squared. Wages include earnings from self-employment. The upper panel shows results for a sample of men only, and the lower panel of women only. The red (gray if printed in black and white) data points are corresponding coefficients from US samples of different years (1890s, 1973, and 1991) reported in Costa (2000).

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