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Why Do Americans No Longer Work So Much More Than Non-Americans?*

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Abstract

In the 1990s, Americans used to work much more than non-Americans. Nowadays, about half of the gap in hours worked has reversed. To evaluate the convergence of working hours, we develop a tractable model of labor supply enriched with multiple sources of heterogeneity across individuals, an extensive margin of participation, multi-member households, and an elaborate system of taxes and benefits upon non-employment. Using detailed measurements from micro-level and aggregate datasets, we identify model parameters and sources of heterogeneity across individuals for various countries. We run a horse race between competing explanations and find that U.S. hours per person declined after 2000 owing mainly to the rise of government health benefits provided to the non-employed. Non-U.S. countries have generous benefits for the non-employed, but this generosity has not changed as much over time as in the United States, and public health coverage does not depend on employment status or income levels. For these countries, the rise of labor supply is generally accounted for by a mix of factors, such as the rise of wages and the falling disutility of work.

JEL Classifications: E24, E60, H53, J22.
Keywords: Employment, Hours, Wages, Benefits.

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1 Introduction

Prescott (2004) wrote an influential paper observing that whereas Americans and Europeans were working roughly the same hours in the early 1970s, by the mid 1990s, Americans were working much more than Europeans. We update Prescott's observations on hours worked for advanced economies and document that about half of the hours gap in the 1990s has reversed by the end of the 2010s. While the decline in the U.S. hours is well documented in the literature, the increase in non-U.S. hours in the past two decades, both relative to the United States and in absolute levels, has not yet been analyzed systematically. The convergence in hours worked is concentrated on the extensive margin and is observed for both men and women. We offer a comparative study on the convergence of hours worked, and paraphrasing Prescott's title, we ask, "Why do Americans no longer work so much more than non-Americans?"

To answer our question, we develop a parsimonious and tractable model of labor supply, along with detailed measurements from various micro-level and aggregate datasets. Our model includes four additional elements relative to textbook treatments of labor supply. First, we allow for substantial heterogeneity across individuals. It is important to model heterogeneity in a comprehensive way, because feeding in average changes is not necessarily informative for aggregate responses of labor supply. Second, we model both the intensive and the extensive margins of labor supply, given the prominence of the latter for the convergence of hours. Third, we consider multi-member households to examine the role of women's increasing labor force participation. Finally, we model an elaborate system of taxes and benefits upon non-employment to evaluate the role of government policies for hours worked across countries.

We use our model to run a horse race between various competing explanations and assess their quantitative importance for the post-2000 convergence in hours worked between non-U.S. countries and the United States. Labor demand forces, such as productivity growth or the disappearance of certain types of jobs due to technological change and globalization, are encoded in the evolution of wages, which we take as given from the data. We allow for variation in the variable costs of work (disutility of work) and the fixed costs of work, which capture developments such as changes in the occupational composition of the population, the changing productivity of certain leisure and home production technologies, or changes in social views and cultural norms about who ought to work and by how much. We model changes in non-labor income across countries which may have caused households in relatively richer countries to work less than households in relatively poorer countries. Regarding government policies, we consider changes in the level and progressivity of taxes and benefits. While we do not model explicitly, we also discuss and present evidence on alternative hypotheses such as changes in the aging of the population, schooling, retirement, living arrangements, and incarceration rates. We adjust our various estimates for compositional changes, which are important given the increasing educational attainment and aging of the population in advanced economies.

Our main finding is that U.S. hours per person declined after the 2000s owing to the rise of benefits provided to the non-employed. Among these benefits, we find the most important role for health benefits and, in particular, Medicaid. According to the official Medicaid and CHIP Payment and Access Commission (https://www.macpac.gov/), the number of Americans on Medicaid increased from roughly 20 million in the early 1970s to almost 100 million in the early 2020s. In our model, the increase in benefits mainly distorts the extensive margin of labor supply, as it raises the value of not working. While historically, non-U.S. countries offered more generous benefits for the non-employed, this generosity has not changed as much over time as in the United States, and core public health coverage does not depend on employment status or income levels. For non-U.S. countries, the increase in labor supply is generally accounted for by a combination of a rise of wages, a falling disutility of work along both margins, and in some cases changes in benefits, but no single factor stands out as prominently as the rise of health benefits in the United States. The rise in hours due to a falling disutility of work in non-U.S. countries is consistent with the U.S. rise of hours between the 1970s and the 1990s, which was driven partly by a declining disutility of work and partly by compositional changes.

Our analyses proceed in two steps. We begin with a detailed analysis of the United States. We use data from the Current Population Survey (CPS) and supplement these data with various other aggregate and micro-level datasets, such as the Survey of Consumer Finances (SCF). Individuals in our model are heterogeneous with respect to their wage, disutility of work on the intensive margin, benefit upon non-employment, non-labor income, and fixed costs of work. Given utility curvature and government policy parameters, we prove that the sources of heterogeneity across individuals are identified from cross-sectional data on wages, employment, hours, and benefits. We identify the sources of heterogeneity so that the model accounts perfectly for cross-sectional data on wages, employment, and hours of the employed and benefits of the non-employed, without imposing distributional assumptions on these sources of heterogeneity. Our procedure for imputing the wage and the disutility of work for the non-employed and the benefit upon non-employment for the employed resembles imputation-based methods that have been used previously in the literature. We also compare our procedure to alternative methods that correct for selection on wages using distributional assumptions and assumptions on instruments that affect wages indirectly through the probability of participation.

We estimate utility curvature parameters to match our cross-country evidence on the responsiveness of labor supply with respect to taxes. The median Marshallian elasticity of labor supply on the intensive margin is 0.06. We document substantial dispersion in elasticities of labor supply across individuals. Individuals with lower wages, lower hours, and higher benefits have a more responsive labor supply on the intensive margin. Our extensive margin elasticity is governed by the distribution of fixed costs. We non-parametrically identify bounds of these costs so that the employed prefer to work and the non-employed prefer not to work. The parametric distribution of fixed costs is then identified from these bounds with the requirement that the responsiveness of the extensive margin in our model is consistent with the responsiveness of the employment rate with respect to taxes in the cross section of countries. We estimate a Marshallian elasticity on labor supply on the extensive margin equal to 0.32. Both our intensive and extensive margin elasticity of labor supply fall in the range of estimates reported in the literature (Keen, 2011; Chetty, Guren, Manoli, and Weber, 2013).

We also estimate the level and progressivity of taxes and benefits. A new feature of our model is a parsimonious benefit function that maps gross labor income to benefits. For the United States, the benefits that we consider include welfare, unemployment insurance, workers' compensation, disability payments, veterans' benefits, food stamps, education benefits, health benefits, and housing, energy, and school lunch subsidies. We show that our measurement and various imputations of benefits in the CPS lead to levels and trends of benefits that are consistent with the levels and trends reported by national income and product accounts and administrative sources. The phase-out of benefits determines the responsiveness of labor supply on both the intensive and the extensive margin, and we estimate this phase out to match micro-level evidence on how benefits are related to income levels.

In the second step of our analysis, we extend our analyses to other countries. We begin by presenting aggregate summary statistics that show an increase in U.S. benefits relative to benefits in other countries after 2000. We also present reduced-form evidence that shows a negative correlation between benefit levels and hours worked across countries. This evidence is admittedly not causal, because other, unobserved factors that determine hours worked may correlate with benefits. Even if one interpreted this correlation as causal, this evidence is not necessarily informative about hours worked, because the incidence of who receives benefits and by how much varies over the income distribution, over time, and across countries in ways that aggregate correlations between benefits and hours cannot plausibly account for.

To overcome these issues, we implement our methodology of using micro-level data in our structural model for additional countries. For these analyses, we use the Luxembourg Income

Study (LIS) database and the Luxembourg Wealth Study (LWS). Although the LIS data on the United States is not identical to our CPS data, we show the consistency of the U.S. results from the CPS with the U.S. results from the LIS. The coverage and quality of the data for non-U.S. countries allows us to perform our analyses for Canada, Germany, France, Italy, Spain, Sweden, and the United Kingdom in the post-2000 period. For each country in our sample, we estimate utility parameters, the level and progressivity of taxes and benefits, and the sources of heterogeneity across individuals. While there is quite a bit of heterogeneity across countries, we find several consistent patterns. Similarly to the United States, compositional changes appear relatively unimportant for non-U.S. countries, with the exception of Southern European countries. But non-U.S. countries differ from the United States in that changes in wages, the disutility of work, and fixed costs of work increase their hours worked. With the exception of Sweden, we find a minor role for changes in tax rates. For Germany, Italy, and Sweden we find that changes in benefits increased their hours worked.

Following Prescott (2004), a large literature documented cross-country patterns of labor supply over time. Early examples include Rogerson (2006) and Ohanian, Raffo, and Rogerson (2008), who extended Prescott's analysis to consider more countries and data up to 2004, and McDaniel (2011), who used a model with home production to examine the role of taxes and sectoral productivity growth. Bick and Fuchs-Schundeln (2018) show the importance of modeling household labor supply, together with a more elaborate tax system, for accounting for differences in hours worked across countries. Bick, Lagakos, and Fuchs-Schundeln (2018) build a much broader and internationally comparable dataset of hours worked across the world and document that hours per person are decreasing in income. Boppart and Krusell (2020) take a much longer view of the evolution of work across countries than previous contributions to the literature and characterize utility functions that allow for a steady decline in hours over time. Kopytov, Roussanov, and Taschereau-Dumouchel (2023) also consider the evolution of work for a longer period of time and examine the role of changes in the price of leisure for trends in labor supply. Relative to these papers, our paper extends Prescott's analysis to more recent periods, enriches the labor supply choice to more sources of heterogeneity across individuals, and explores alternative mechanisms such as changes in benefits provided to the non-employed.[1]

There is also a large literature on the decline of hours worked in the United States since around 2000. Elsby and Shapiro (2012) relate the decline in male employment to slower productivity growth and reduced returns to experience. Autor, Dorn, and Hanson (2013) use a

[1]While the increase in hours after roughly 2000 in non-U.S. countries has not been noted or explored by the literature, it is visible in time series reported by some of these papers. For example, Figure 3 of Boppart and Krusell (2020) shows steady or increasing hours per person for every non-U.S. country after roughly 2000.

cross-sectional local labor markets approach to explore the role of globalization in the decline in U.S. aggregate and manufacturing employment. Acemoglu and Restrepo (2020) also use a cross-sectional approach to explore the effect of technological change due to robots on employment and wages. Aguiar, Bils, Charles, and Hurst (2021) examine the decline in labor supply of young men and show the importance of increasing leisure returns in accounting for this decline. Abraham and Kearney (2020) offer a thorough summary of the literature.

One difference with respect to the literature on U.S. labor supply is that our paper offers a more comprehensive modeling and measurement of government benefits provided to the non-employed alongside a horse race among competing explanations for the decline in hours worked within a unified framework. An important predecessor to our paper is Mulligan (2012), who besides examining various other government policies in housing, debt, and labor markets, also conducts careful measurements of how expansions in the social safety net between 2007 and 2011 raised effective marginal tax rates on labor supply and deepened the Great Recession in the United States.[2] In their normative analysis of the U.S. welfare state, Guner, Kaygusuz, and Ventura (2023) also measure the value of welfare programs that support low-income households. However, they exclude health benefits from their exercises. Our focus on health benefits is justified by the dramatic rise of the number of recipients over time.

Our paper also contributes to the literature that draws a distinction between individual and aggregate labor supply due to the extensive margin, such as Chang and Kim (2006), Pijoan-Mas (2006), Rogerson and Wallenius (2009), Guner, Kaygusuz, and Ventura (2012), and Erosa, Fuster, and Kambourov (2016). These papers consider dynamic models, whereas our model is static. This simplification allows us to identify in closed form a much richer set of primitives that drive heterogeneity across individuals.

Our procedure for imputing wages of the non-employed resembles imputation-based approaches, such as that of Juhn and Murphy (1997), who study how married women's labor supply affects married men's labor supply, that of Olivetti and Petrongolo (2008), who study

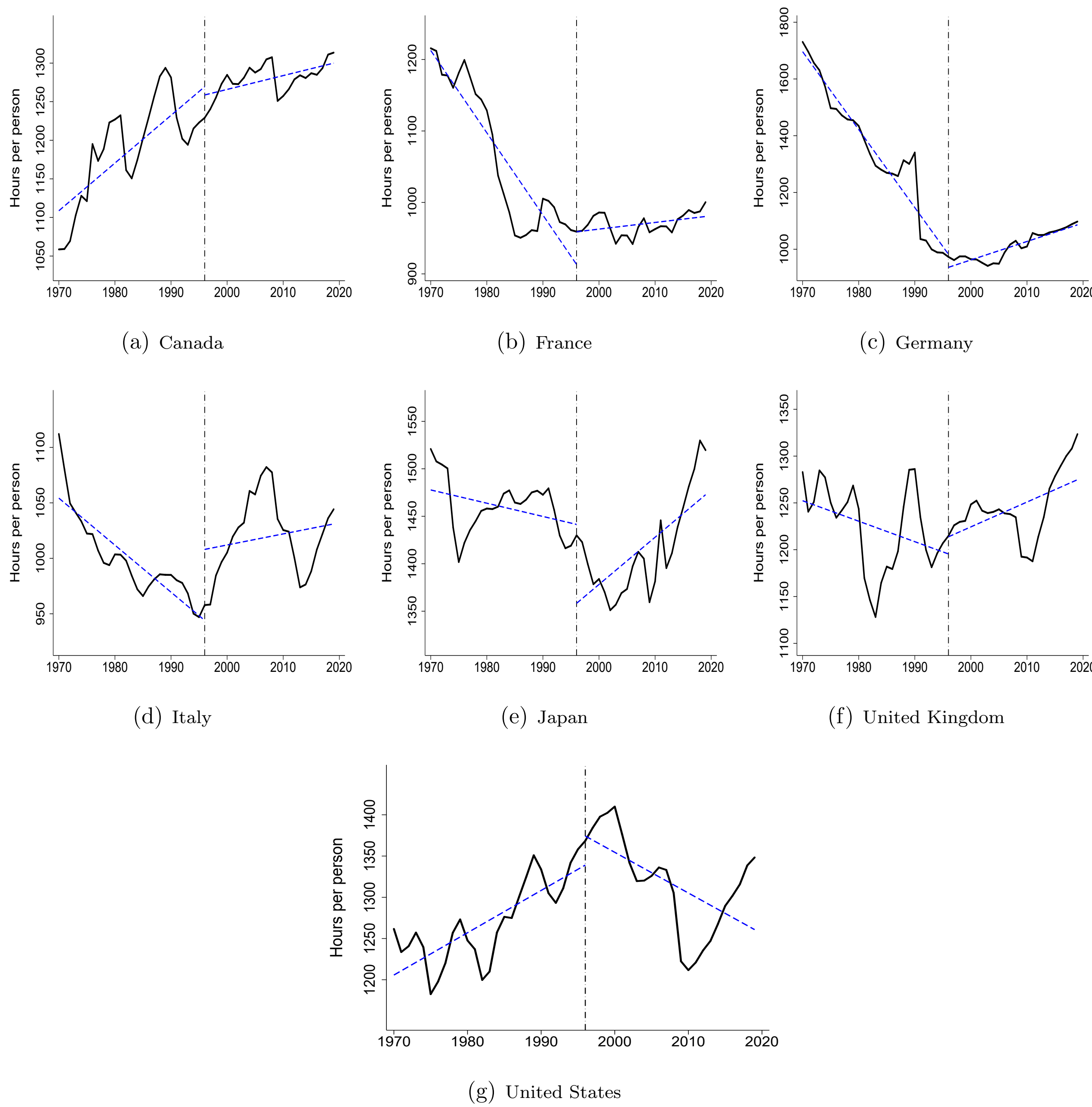
[2] Apart from our broader coverage in terms of years and countries, a difference with Mulligan is that our implicit taxes on labor supply are effective because we use micro-level measurements of benefits received, whereas Mulligan quantified implicit taxes on labor due to statutory changes in eligibility and benefits per recipient. In addition, we present cross-group and cross-country evidence on the effects of benefits on labor supply and compare our model estimates to reduced-form estimates, such as Baicker, Finkelstein, Song, and Taubman (2014) and Garthwaite, Gross, and Notowidigdo (2014). A parallel literature examines the effects of unemployment insurance extensions on the cyclicality of the unemployment rate, with mixed conclusions (Chodorow-Reich, Coglianese, and Karabarbounis, 2019; Karahan, Mitman, and Moore, 2025). Chodorow-Reich and Karabarbounis (2016) measure benefits other than unemployment insurance that workers may receive upon unemployment and conclude that they are small relative to average wages. We do not model movements in and out of unemployment in this paper, because the unemployment rate and vacancies do not display significant trends over time despite changing productivity and search frictions (Martellini and Menzio, 2020).

cross-country gender wage gaps, that of Blau, Kahn, Boboshko, and Comey (2024), who study selection bias and gender wage gaps, and that of Arellano-Bover, Bianchi, Lattanzio, and Paradisi (2024), who study the gender pay convergence and younger men's wage losses. Our methodology departs from these papers in two ways. First, in addition to wages, we consider other differences between the employed and the non-employed. Second, we are interested in the whole distribution of the sources of heterogeneity, and thus we add residuals to the imputed sources of heterogeneity. We demonstrate that shifting the whole distribution of sources of heterogeneity when performing counterfactuals gives different results than shifting, say, the mean or the median of the distribution. This justifies our interest in estimating the distribution of sources of heterogeneity, while imposing as few parametric assumptions as possible. A different procedure for inferring the wage of the non-employed is based on methods popularized by Heckman (1979). An influential example of this approach is the study of Mulligan and Rubinstein (2008), who document that selection of women into the labor force shifted from negative in the 1970s to positive in the 1990s. We also examine results using a Heckman selection model to infer the wages of the non-employed. With the exception of married spouses, we find that the selection is negative, which has the counterintuitive implication that the potential wages of the non-employed exceed the wages of the employed. However, even under the Heckman selection model, our conclusions regarding the drivers of hours do not change.

2 Observations on Hours Worked Across Countries

In this section, we use publicly available aggregate data to document patterns of hours worked across countries between 1970 and 2019. We use employment and population data from the Organization of Economic Cooperation and Development's (OECD) Labor Force Statistics and hours per worker data from the Penn World Tables (PWT, version 10.0). We begin our analyses by following the definition of aggregate hours worked used by Prescott (2004), and measure hours per person as the product of total employment with hours per worker divided by population between the ages of 15 to 64. Appendix A presents the data sources and the various adjustments we perform to impute some missing data.[3]

[3]Measuring hours per person using different populations in the numerator and denominator is common in the literature because of data availability constraints. For example, see Rogerson (2006), Ohanian, Raffo, and Rogerson (2008), McDaniel (2011), Ohanian and Raffo (2012), Boppart and Krusell (2020), and Kopytov, Roussanov, and Taschereau-Dumouchel (2023), who all adopt definitions similar or identical to the one in Prescott (2004). In results reported below for the analysis using aggregate data, we also consider consistent population measures for the numerator and the denominator of hours per person. Then we vary these population measures to examine the robustness of our results. Bick, Bruggemann, and Fuchs-Schundeln (2019) document substantial revisions in OECD's and PWT's measures of hours worked over time. For this reason, the OECD



(a) Canada (b) France (c) Germany

(d) Italy (e) Japan (f) United Kingdom

(g) United States

Figure 1: Hours per person in the G7 economies

Notes: The figure shows hours per person from the OECD/PWT data for G7 economies. The dashed vertical line signifies the last year covered by the analysis of Prescott (2004).

Figure 1 presents the evolution of hours per person for the G7 countries covered in the analysis of Prescott (2004). We plot a dashed vertical line in 1996 to signify the last year in Prescott's sample. For each of the two samples separated by the vertical line, we also plot a

recommends using the hours worked data for comparisons of trends over time, as opposed to levels which are sensitive to differences across countries in the way national labor force surveys define hours and employment. For our analyses in the rest of the paper, we use microdata from the LIS, which helps to standardize measures across countries and allows us to control for differential compositional changes over time across countries.

linear trend to better visualize the changes across the subperiods. Beginning with the United States at the bottom panel, we observe a secular increase in hours per person between 1970 and the early 2000s, followed by a decline after. While it is well known that U.S. hours per person have declined since their peak in the early 2000s, the literature has overlooked the fact that this is not the case for any of the other G7 economies. There is quite a bit of heterogeneity in the evolution of hours per person among non-U.S. countries. For example, Canada, France, and Germany experienced modest increases, whereas Italy, Japan, and the United Kingdom experienced larger increases. The figure also shows that with the exception of Canada, all these countries experienced decreases in their hours between 1970 and 1996.

Table 1 shows hours per person relative to the United States, for the expanded set of countries considered by Rogerson (2006) across subperiods (see Appendix Figure 1 for the time series of the non-G7 countries). The three columns present average hours per person for each country in the 1970s, 1990s, and 2010s, relative to the United States, which is normalized to 100. The last row presents the average across all countries. The average person in a non-U.S. country worked roughly the same hours as the average U.S. person during the 1970s. From a relative level of 99 percent in the 1970s, relative hours fell to 85 for the average non-U.S. person in the 1990s. By the 2010s, around half of the divergence in hours had disappeared, with the average non-U.S. person working 92 percent as much as the average U.S. person.

As a first pass to understanding the differential changes in hours per person across countries, we decompose changes in the gap between non-U.S. countries and the United States into a component due to differential changes in the extensive margin and a component due to differential changes in the intensive margin. Let e be the employment to population ratio and n be hours per worker, then $\mathrm{GAP}_{i,t} \equiv \frac{e_{i,t} n_{i,t}}{e_{\mathrm{US},t} n_{\mathrm{US},t}}$ is the gap in hours per person for country i relative to the United States. We can then write

$$\Delta \log \mathrm{GAP}_{i,t} = \underbrace{\Delta \log \left(\frac{e_{i,t}}{e_{\mathrm{US},t}} \right)}_{\text{extensive}} + \underbrace{\Delta \log \left(\frac{n_{i,t}}{n_{\mathrm{US},t}} \right)}_{\text{intensive}}. \tag{1}$$

Table 2 presents results from this decomposition. In the first panel, for the changes between the 1990s and the 1970s, we observe that for the average country, the extensive and the intensive margins play a roughly similar role in accounting for the decline in their hours per person relative to those of the United States. For the changes between the 2010s and the 1990s, however, only the extensive margin is important. The average country experienced an increase of 9 log points in their hours per person relative to the United States, with 11 log points being accounted for by the extensive margin. All countries except for Greece experienced an increase

Table 1: Hours per person relative to the United States

(US hours per person = 100)	1970s	1990s	2010s
Australia	104	93	103
Austria	90	92	93
Belgium	82	66	78
Canada	92	91	101
Denmark	94	80	83
Finland	107	83	90
France	95	72	77
Germany	127	76	83
Greece	98	88	86
Ireland	106	82	91
Italy	84	72	79
Japan	118	106	114
Netherlands	75	72	86
New Zealand	89	93	109
Norway	96	83	85
Portugal	105	95	103
Spain	95	65	80
Sweden	100	89	99
Switzerland	119	103	102
United Kingdom	102	91	99
Average	99	85	92

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table 2: Decomposition of hours gap between extensive and intensive margin

(log points	Change 1990s-1970s			Change 2010s-1990s		
relative to US)	Total	Extensive	Intensive	Total	Extensive	Intensive
Australia	-10	-10	-1	10	13	-3
Austria	2	5	-3	1	8	-7
Belgium	-21	-10	-11	17	14	3
Canada	0	3	-3	10	11	-2
Denmark	-16	-2	-14	3	1	1
Finland	-26	-17	-9	8	12	-4
France	-28	-13	-14	5	8	-3
Germany	-51	-34	-17	9	15	-6
Greece	-10	-12	2	-2	-2	-1
Ireland	-25	-14	-11	10	19	-9
Italy	-15	-14	-2	9	14	-4
Japan	-11	-5	-6	7	14	-6
Netherlands	-5	8	-13	18	19	0
New Zealand	5	4	1	15	16	-1
Norway	-14	-2	-12	2	6	-4
Portugal	-10	-2	-8	8	7	2
Spain	-38	-27	-11	21	21	0
Sweden	-11	-14	3	11	7	4
Switzerland	-14	-5	-9	-1	4	-5
United Kingdom	-12	-7	-5	9	9	-1
Average	-16	-8	-7	9	11	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

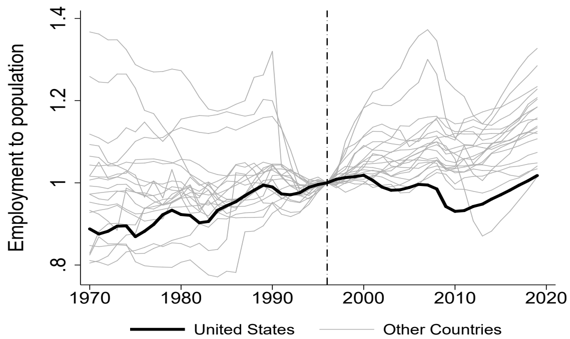
in their employment to population ratio relative to that of the United States.

Figure 2 presents changes in the employment-to-population ratio for the United States (solid, thick line) and all other countries in the sample (gray, thin lines) between 1970 and 2019. For all countries, the employment to population ratio is normalized to 1 in 1996, so that we can better visualize the relative changes before and after this year. The first panel repeats our baseline definition from Prescott (2004), in which the numerator has total employment and the denominator has population between the ages of 15 to 64. The other three panels use consistent definitions of the employment rate, in the sense that the numerator counts employment for the same subpopulation that appears in the denominator. In all cases, we observe that the United States begins close to or at the bottom of the distribution in 1970, which implies that its employment to population ratio grows by more than those of the other countries by 1996. In all cases, we also observe that the United States ends close to or at the bottom of the distribution by 2019. As the figure reveals, it is not only the case that other countries are converging to the Unites States in relative terms. Most non-U.S. countries experience growth in their employment rate in absolute terms between the late 1990s and the late 2010s.

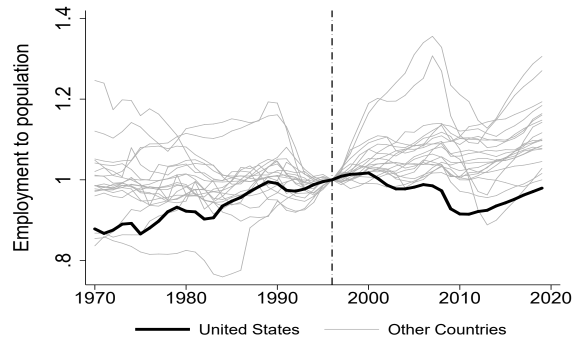
Appendix Tables A.1 to A.4 extend the analysis of Table 1 with population measures of hours per person that include workers between the ages of 15 to 64, or 15 to 54, or 25 to 64, or the total population, in both the numerator and denominator of the respective measure of hours. Appendix Tables A.5 to A.8 repeat the decompositions shown in Table 2 for these cases. As these tables document, our results are generally not sensitive to different definitions of hours worked. The implication of this finding is that the convergence in relative hours is not driven by differences in decisions close to retirement age, differences in decisions close to school age, or differences in the aging of the population.

Figure 3 shows employment to population ratios for persons aged between 15 and 64, separately for men and women. For men, in the left panel, we see a significant decline in the employment rate of non-U.S. countries between 1970 and the 1990s. After the 1990s, most countries experience growth in men's employment, with the United States experiencing a continued decline. For women, in the right panel, the United States experiences a larger employment growth in the first subperiod. However, U.S. women are the only women in the sample that have experienced declines in their employment rate between the late 1990s and the late 2010s. We conclude that the patterns of hours per person that we documented for the total population are qualitatively similar between men and women, but the convergence of hours per person after the 2000s is more pronounced for women.[4]

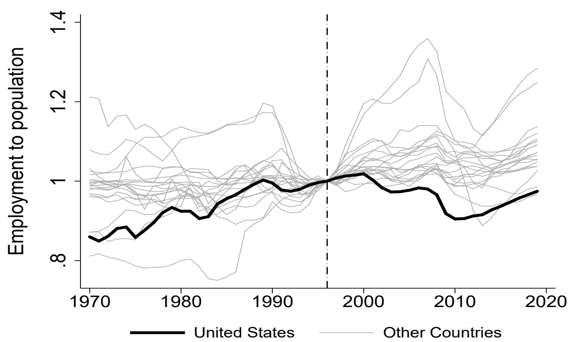
[4] Appendix Tables A.9 and A.10 repeat the analysis of Tables 1 and 2 for men, and Appendix Tables A.11



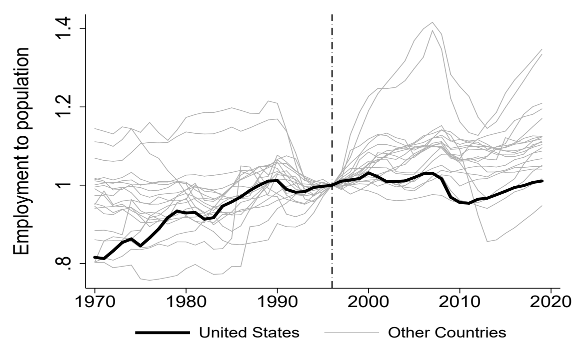
(a) (Total)/(15-64)



(b) (15-64)/(15-64)



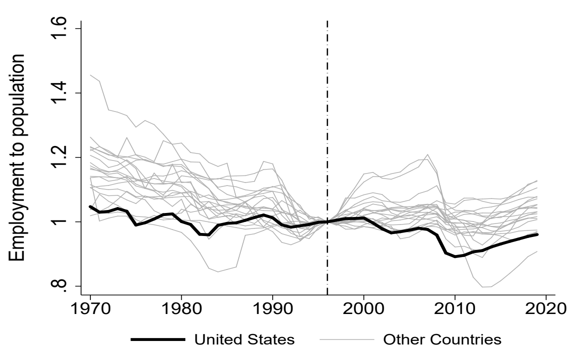
(c) (15-54)/(15-54)



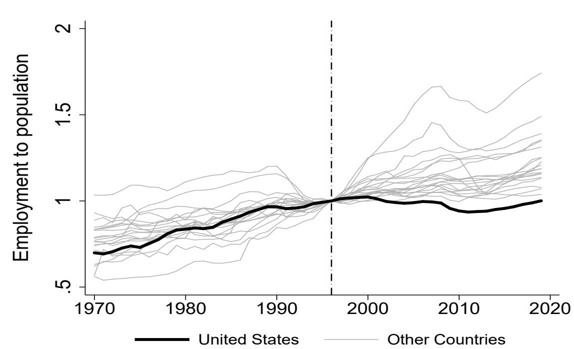
(d) (Total)/(Total)

Figure 2: Employment to Population across Countries

Notes: The figure shows the employment to population ratio for the United States (solid, black line) and the non-U.S. countries (thin, gray lines) presented in Table 1. All employment to population ratios are normalized to one in 1996, which is the last year covered by the analysis of Prescott (2004).



(a) (15-64)/(15-64), Men



(b) (15-64)/(15-64), Women

Figure 3: Employment to Population across Countries, by Sex

Notes: The figure shows the employment to population ratio by sex for the United States (solid, black line) and the non-U.S. countries (thin, gray lines) presented in Table 1. All employment to population ratios are normalized to one in 1996, which is the last year covered by the analysis of Prescott (2004).

3 Model of Labor Supply

We first describe the decision problem of a single individual. Then, we present the decision problem of a married household. The model is static, so we suppress the time subscript.[5]

3.1 Single Individuals

A single individual ι is characterized by a vector of sources of heterogeneity, $(\kappa, \chi, \theta, \beta_0, z)$, where κ is the fixed cost of working, χ is the variable disutility of working, θ is the potential wage, β_0 is the benefit under non-employment, and z is non-labor income. An individual chooses consumption c, employment $e \in \{0, 1\}$, and, if employed, hours of work n to maximize

$$\max_{c,e,n} V_\iota = \frac{c^{1-\gamma} - 1}{1-\gamma} - \left(\chi_\iota \frac{n^{1+1/\varepsilon}}{1+1/\varepsilon} + \kappa_\iota\right) \cdot \mathbb{I}(e=1), \tag{2}$$

where $\gamma > 0$ is the curvature of utility with respect to consumption and $\varepsilon > 0$ is the curvature of utility with respect to hours. The utility maximization problem is subject to the budget constraint

$$(1+\tau_c)c = y + b + (1-\tau_z)z_\iota, \tag{3}$$

where τ_c is the consumption tax rate and τ_z is the tax rate on non-labor income. Apart from non-labor income, individuals derive resources from after-tax labor income

$$y = (1-\tau_0)(wn)^{1-\tau_1}, \tag{4}$$

and from benefits provided by the government

$$b = \beta_{0\iota} \exp(-\beta_1 wn/\beta_{0\iota}). \tag{5}$$

In equation (4), w denotes the wage which equals the potential wage for those who choose to be employed; that is $w = \theta_\iota \mathbb{I}(e=1)$. Parameters τ_0, τ_1 characterize the tax function, as in Benabou (2002) and Heathcote, Storesletten, and Violante (2014). The upper panels of Figure 4 plot an example of after-tax labor income y as a function of the choice of hours n for various parameters. A higher τ_0 lowers after-tax labor income for all choices of hours. A higher τ_1

and A.12 repeat it for women. We caution readers that for these analyses, we use sex-specific data only for employment from the OECD, but for hours per worker, we apply the aggregate variable for both sexes due to data availability constraints. This is a drawback of analyzing hours trends using aggregate datasets. However, in the rest of our analyses, we use micro-level data from which we can measure employment and hours per worker at the individual level.

[5] To close the model, we assume that there exists a linear aggregate production function with exogenous productivity for each worker that equals their wage and a budget constraint for the government in which either spending or debt adjusts to absorb variations in taxes and benefits.

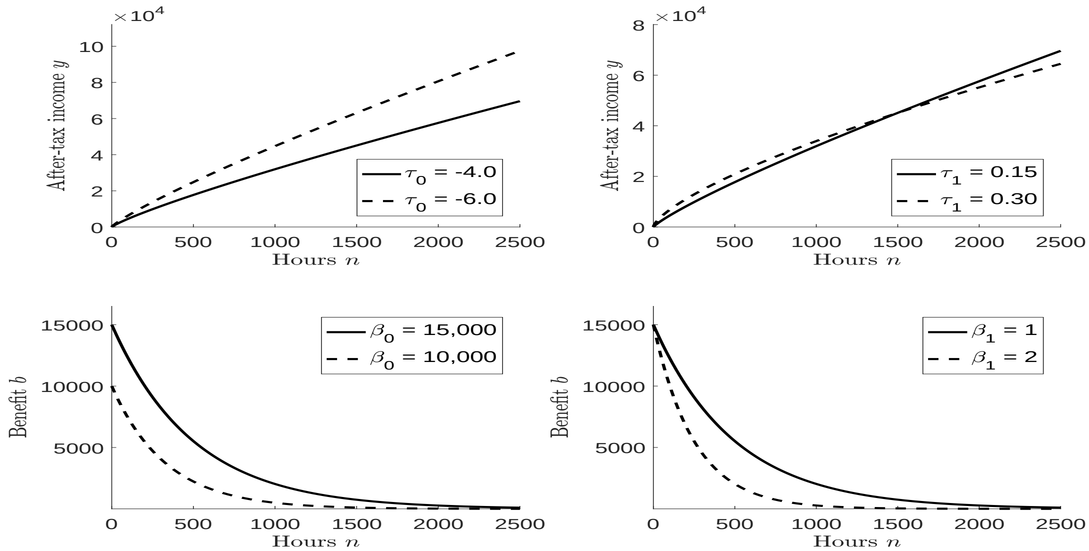


Figure 4: Tax and Benefit Function

Notes: The figure presents the tax function in equation (4) and the benefit function in equation (5) for various parameters.

implies a more progressive tax system, as after-tax labor income increases at the bottom of the hours distribution and decreases at the top.

The new feature of our analysis is the benefit function in equation (5). What we have in mind with this function is a parsimonious way to summarize the level and phase-out of benefits, similar to how the tax function in equation (4) parsimoniously summarizes the level and progressivity of taxes. The bottom left panel of Figure 4 shows that a higher β_0 shifts the benefit function upward for all levels of hours. Thus, a higher β_0 corresponds to more generous benefits provided by the government. The bottom right panel shows that a higher β_1 steepens the curve while maintaining the same level of benefits for the non-employed. Thus, a higher β_1 corresponds to a faster phase-out of benefits as individuals increase their working hours.

We present evidence for the convexity of the benefit function in our subsequent analyses. Here, we clarify that we separate taxes and credits in equation (4) from benefits in equation (5), because their incidence and levels close to non-employment are quite different. The credits that we include in our tax-and-transfer function in equation (4), such as the earned income tax credit (EITC) and the child tax credit, have work requirements. However, several of the benefits that we include in the benefit equation (5) do not have work requirements. In our quantitative analyses, the tax-and-transfer function includes federal taxes, state taxes, FICA taxes, the EITC, the child tax credit, and some stimulus transfers. The benefit function includes transfers such as welfare, unemployment insurance, workers' compensation, disability payments, veterans' benefits, food stamps, education benefits, health benefits, and housing, energy, and school lunch subsidies.[6] Various papers do not include benefits when they estimate the tax-and-transfer function in equation (4). For example, Heathcote, Storesletten, and Violante (2014) exclude all benefits in their after-tax-and-transfers y variable, because they are subsumed in what they call the "insurable shock." Like us, Ferriere, Grubener, Navarro, and Vardishvili (2023) also model taxes and benefits through different functions. Our approach differs from theirs in that we allow for heterogeneity in the shifter of the benefit function, $\beta_{0\iota}$, because we find that there is significant dispersion in the receipt of benefits even for the non-employed.

An individual chooses to work if the utility of employment exceeds the utility of non-employment:

$$\begin{aligned} W_\iota = & \frac{\left((y_\iota(n^*) + b_\iota(n^*) + (1-\tau_z)z_\iota)/(1+\tau_c)\right)^{1-\gamma} - 1}{1-\gamma} - \chi_\iota \frac{(n^*)^{1+1/\varepsilon}}{1+1/\varepsilon} - \kappa_\iota \\ & \geq U_\iota = \frac{\left((\beta_{0\iota} + (1-\tau_z)z_\iota)/(1+\tau_c)\right)^{1-\gamma} - 1}{1-\gamma}, \end{aligned} \tag{6}$$

where n^* is the optimal choice of hours conditional on working. The optimal choice of hours on the intensive margin is given by the equalization of the tax-adjusted marginal rate of substitution between labor and consumption to the slope of the budget constraint:

$$(1+\tau_c)\chi_\iota n^{1/\varepsilon} c^\gamma = \big((1-\tau_1)(1-\tau_0)(w_\iota n)^{-\tau_1} - \beta_1 \exp\left(-\beta_1 w_\iota n/\beta_0\right)\big)\, w_\iota \equiv p_\iota, \tag{7}$$

where we define the price of labor as p_ι. The price of labor is a wedge over the wage, with the wedge depending on the tax and benefit parameters and the labor earnings of the individual.

We first analyze labor supply choices on the intensive margin under the case of complete phase-out of benefits ($\beta_1 \to \infty$), or equivalently, the case of high earners with sufficiently low b that does not respond to labor supply. For this case, we calculate the responses of labor supply to changes in primitives as follows:

$$\eta_w \equiv \frac{\partial n}{\partial w_\iota}\frac{w_\iota}{n} = \frac{(1-\tau_1)(1-\gamma s_\iota)}{\frac{1}{\varepsilon} + \gamma s_\iota + \tau_1(1-\gamma s_\iota)}, \tag{8}$$

$$\eta_{1-\tau_0} \equiv \frac{\partial n}{\partial(1-\tau_0)}\frac{1-\tau_0}{n} = \frac{1-\gamma s_\iota}{\frac{1}{\varepsilon} + \gamma s_\iota + \tau_1(1-\gamma s_\iota)}, \tag{9}$$

$$\eta_z \equiv \frac{\partial n}{\partial(1-\tau_z)z_\iota}\frac{(1-\tau_z)z_\iota}{n} = \frac{-\gamma\left(1-s_\iota\right)}{\frac{1}{\varepsilon} + \gamma s_\iota + \tau_1(1-\gamma s_\iota)}, \tag{10}$$

[6] Supplemental income (SSI) does not have a work requirement, disability income (SSDI) and unemployment insurance (UI) require sufficient past earnings, Medicaid does not have a work requirement in general (although some states have one—for example, Alaska), welfare (TANF/AFDC) has a work requirement or a job search and training requirement, and food stamps (SNAP) have a general work requirement, but households with children are exempt from it.

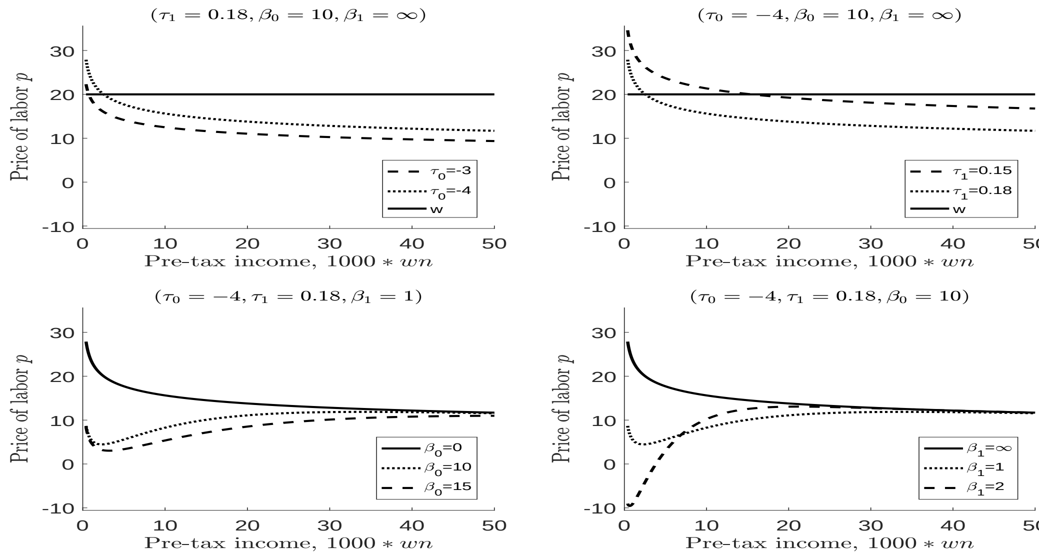


Figure 5: Price of Labor and Changes in Tax and Benefit Parameters

Notes: The figure presents the price of labor in equation (7) for various parameters.

where $s_\iota = \frac{y_\iota(n^*)}{(1+\tau_c)c_\iota(n^*)}$ is the labor share of total income. Equation (8) is the Marshallian elasticity of labor supply. Relative to standard expressions found in the literature (Keen, 2011), the elasticity here modifies the numerator to account for the effects of progressivity. The sign of the elasticity depends on the parameter that governs the curvature of utility with respect to consumption, γ, and the labor share, s_ι. When the labor share equals one and $\gamma < 1$, the substitution effect from a higher wage dominates the income effect from a higher wage and labor supply is increasing in the wage. With a labor share below one, the threshold for the γ that yields a positive Marshallian elasticity becomes higher. Equation (9) presents the elasticity of labor supply with respect to the after-tax parameter $1 - \tau_0$. This elasticity is the same as the elasticity with respect to the wage, except that the adjustment for progressivity, $1 - \tau_1$, does not appear in the numerator. Intuitively, with a progressive tax system, a higher wage tends to depress the return to labor at the margin, and thus labor supply responds less to a one percent change in the wage than to a one percent change in the after-tax parameter. Finally, equation (10) presents the income effect, which is negative because leisure is a normal good.

In equation (7), the price of labor p dictates the labor supply choices even when benefits phase out more slowly, but in this case, we no longer have tractable expressions for the elasticities of labor supply (see Appendix B for the formulas, which we use when we calibrate the model). To gain some intuition, Figure 5 presents comparative statics of the price of labor with respect to the tax and benefit parameters. The top left panel presents the price of labor for an individual who earns $w = 20$ dollars per hour when benefits phase out immediately after working ($\beta_1 \to \infty$). The price of labor is decreasing in earnings because of progressivity, $\tau_1 = 0.18$. Thus, for low hours, the price of labor exceeds the wage, and for high hours, the price of labor falls below the wage. As τ_0 increases, the price of labor falls. Similarly, the top right panel shows that the price of labor falls as progressivity τ_1 increases.

In the bottom panels, we present the comparative statics of the price of labor with respect to the benefit parameters, β_0 and β_1. Beginning with the left panel, we observe that a $\beta_0 > 0$ changes both the level and the slope of the price of labor. The price of labor is lower with benefits than without benefits, because workers forgo benefits by working an additional hour. Benefits completely phase out for sufficiently high levels of income. Thus, the price of labor with benefits asymptotes to the price of labor without benefits, which implies that the price of labor is upward sloping after some region of income. In the bottom right panel, we observe that for sufficiently high income, a slower phase-out of benefits (lower β_1) is associated with a lower price of labor as individuals forgo more benefits by working an additional hour. For sufficiently low income, the price of labor may become negative, and the model generates benefit cliffs in which working more reduces resources available for consumption. If benefits phase out fast enough, workers are better off either not working or working for sufficiently high hours. This is similar to the argument of Mulligan (2012), who showed that programs such as Medicaid create cliffs with effective marginal tax rates above 100 percent.

3.2 Married Couples

A married couple ι is characterized by a vector $(\kappa_1, \kappa_2, \chi_1, \chi_2, \theta_1, \theta_2, \beta_0, z)$, where we denote the head (generally a man) with a subscript of 1 and the spouse (generally a woman) with a subscript of 2. The fixed cost of working, the variable disutility of working, and potential wages are specific to individuals, while benefits under non-employment and non-labor income are household-level variables. A couple chooses consumption c, employment $e_1, e_2 \in \{0, 1\}$, and, if individual members are employed, hours of work n_1, n_2 to maximize

$$\max_{c,e_1,e_2,n_1,n_2} V_\iota = \frac{c^{1-\gamma} - 1}{1-\gamma} - \sum_{j=1,2} \left(\chi_{j\iota} \frac{n_j^{1+1/\varepsilon}}{1+1/\varepsilon} + \kappa_{j\iota} \right) \cdot \mathbb{I}(e_j = 1), \tag{11}$$

subject to the budget constraint

$$(1+\tau_c)c = y + b + (1-\tau_z)z_\iota, \tag{12}$$

where after-tax labor income is

$$y = (1-\tau_0)\Big(\sum_j w_j n_j\Big)^{1-\tau_1} \tag{13}$$

and benefits are

$$b = \beta_{0\iota} \exp\Big(-\beta_1\Big(\sum_j w_j n_j\Big)/\beta_{0\iota}\Big). \tag{14}$$

In equation (13), we modeled joint taxation, which is the relevant case for the United States. We modify this equation for non-U.S. countries with individual or income-splitting taxation. Similarly, in equation (14), the phase-out of benefits depends on the total income of both members, because several transfers in our data depend on household income.

The household decides which members work by comparing the utilities of four cases:

$$\begin{aligned}
W_\iota &= \frac{((y_\iota(n^*) + b_\iota(n^*) + (1-\tau_z)z_\iota)/(1+\tau_c))^{1-\gamma} - 1}{1-\gamma} - \sum_j \Big(\chi_{j\iota}\frac{(n_j^*)^{1+1/\varepsilon}}{1+1/\varepsilon} + \kappa_{j\iota}\Big), && (15)\\
W_{1\iota} &= \frac{((y_\iota(n_1^*,0) + b_\iota(n_1^*,0) + (1-\tau_z)z_\iota)/(1+\tau_c))^{1-\gamma} - 1}{1-\gamma} - \chi_{1\iota}\frac{(n_1^*)^{1+1/\varepsilon}}{1+1/\varepsilon} - \kappa_{1\iota}, && (16)\\
W_{2\iota} &= \frac{((y_\iota(0,n_2^*) + b_\iota(0,n_2^*) + (1-\tau_z)z_\iota)/(1+\tau_c))^{1-\gamma} - 1}{1-\gamma} - \chi_{2\iota}\frac{(n_2^*)^{1+1/\varepsilon}}{1+1/\varepsilon} - \kappa_{2\iota}, && (17)\\
U_\iota &= \frac{((\beta_{0\iota} + (1-\tau_z)z_\iota)/(1+\tau_c))^{1-\gamma} - 1}{1-\gamma}, && (18)
\end{aligned}$$

where n_1^* and n_2^* are the optimal choice of hours conditional on working. Similarly to single individuals, the optimal choice of hours on the intensive margin for member j is given by the equalization of the tax-adjusted marginal rate of substitution between labor and consumption to the slope of the budget constraint (the price of labor, $p_{j\iota}$):

$$(1+\tau_c)\chi_{j\iota} n_j^{1/\varepsilon} c^\gamma = \left((1-\tau_1)(1-\tau_0)\Big(\sum_j w_{j\iota} n_{j\iota}\Big)^{-\tau_1} - \beta_1 \exp\Big(-\beta_1 \sum_j w_{j\iota} n_{j\iota}/\beta_0\Big)\right) w_{j\iota}. \tag{19}$$

For the case of complete phase-out of benefits ($\beta_1 \to \infty$) or, equivalently, the case of a high-earning household with sufficiently low b that does not change labor supply, we calculate the responses of labor supply for member j to changes in primitives as follows:

$$\begin{aligned}
\eta_{jw} &\equiv \frac{\partial n_j}{\partial w_{j\iota}}\frac{w_{j\iota}}{n_j} = \frac{1 - \varphi_{j\iota}(\tau_1 + (1-\tau_1)\gamma s_\iota)}{\frac{1}{\varepsilon} + \varphi_{j\iota}(\gamma s_\iota + \tau_1(1-\gamma s_\iota))}, && (20)\\
\eta_{j1-\tau_0} &\equiv \frac{\partial n_j}{\partial(1-\tau_0)}\frac{1-\tau_0}{n_j} = \frac{1-\gamma s_\iota}{\frac{1}{\varepsilon} + \varphi_{j\iota}(\gamma s_\iota + \tau_1(1-\gamma s_\iota))}, && (21)\\
\eta_{jz} &\equiv \frac{\partial n_j}{\partial(1-\tau_z)z_\iota}\frac{(1-\tau_z)z_\iota}{n_j} = \frac{-\gamma\,(1-s_\iota)}{\frac{1}{\varepsilon} + \varphi_{j\iota}(\gamma s_\iota + \tau_1(1-\gamma s_\iota))}, && (22)\\
\eta_{jk} &\equiv \frac{\partial n_j}{\partial w_{k\iota}}\frac{w_{k\iota}}{n_j} = \frac{-\varphi_{k\iota}(\tau_1 + (1-\tau_1)\gamma s_\iota)}{\frac{1}{\varepsilon} + \varphi_{j\iota}(\gamma s_\iota + \tau_1(1-\gamma s_\iota))}, && (23)
\end{aligned}$$

where $\varphi_{j\iota} = w_{j\iota}n_{j\iota}/\sum_j(w_{j\iota}n_{j\iota})$ is the share of j's labor income in household-level labor income. Comparing these expressions to their analogs for single individuals, we see that they coincide only when $\varphi_{j\iota} = 1$. When both spouses are contributing to household income, $\varphi_{j\iota}$ modifies the elasticities of labor supply to account for the fact that income effects from changes in the labor income of a spouse are weaker than they are for a single individual. Equation (23) presents the cross-elasticity of labor supply of household member j with respect to the wage of member k. The cross-elasticity is always negative, both because a higher wage for spouse k generates an income effect for the other spouse and because a higher wage for spouse k lowers the other spouses' marginal return from working under a progressive tax function.[7]

4 Identification

In this section we explain theoretically our strategy for identifying the sources of heterogeneity across households and for estimating parameters of the model. We observe micro-level data on employment, hours and wages if employed, benefits, and non-labor income, $(e_j, n_j, w_j, b, z)_\iota$, where ι is a single individual or a married couple and j is the member of the household. Our model is static, and thus, cross-sectional data are sufficient for identification. We will apply our methodology to different cross-sectional datasets over time and across countries, but we suppress the time and country subscripts whenever no confusion arises.

4.1 Inference of Sources of Heterogeneity

Taking as given model parameters, we first explain our inference of the sources of heterogeneity. Our strategy is to infer the sources of heterogeneity, $(\theta_j, \beta_0, \chi_j, \kappa_j)_\iota$ so that the model accounts perfectly for the employment, hours, and wage of every household ι and member j in the dataset.

Single individual, non-employed, $e_\iota = 0$. For non-employed single individuals, we directly observe their benefit upon non-employment, thus $\beta_{0\iota} = b_\iota$. We infer their potential wage, θ_ι, and disutility of work, χ_ι, if they had worked by imputing them according to observationally similar employed individuals and a draw of an error term. For each year and country separately,

[7] We still do not have tractable expressions for the elasticities of labor supply when benefits phase out more slowly (see Appendix B for the formulas, which we use when we calibrate the model). We note that the price of labor in equation (19) is similar to the one for singles in equation (7), except for the fact that the wedge between the price of labor and the wage depends on household labor earnings instead of individual earnings.

in a sample of employed single individuals, we run regressions of the form

$$\log w_\iota = \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \text{ if single}_\iota = 1, e_\iota = 1, \tag{24}$$

$$\log \chi_\iota = \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \text{ if single}_\iota = 1, e_\iota = 1, \tag{25}$$

where X_ι is a vector of external variables to the model that affect the wage and the disutility of work directly and Z_ι is a vector of external variables to the model that affect the wage and the disutility of work indirectly through the probability of employment, $\mathbb{P}(Z_\iota)$. The external variables in X_ι include age, age squared, sex, education, and the generosity of the U.S. state of residence in terms of benefits. The external variables in Z_ι include the variables in vector X_ι and the number of children, the presence of a child with age below or equal to six, and unemployment status. The probability of employment is estimated in a first stage with a Probit regression, $\mathbb{P}(e_\iota = 1|Z_\iota) = \Phi(\gamma_z Z_\iota)$, where Φ is the cumulative distribution function of the standard normal distribution.

Given estimates of the δ coefficients in equations (24) and (25), we impute θ_ι and χ_ι using the observed predictors X_ι, Z_ι for every single non-employed individual and a draw of the residual $\hat{u}_\iota$ from the empirical distribution of residuals generated by these regressions. As we explain below, we add residuals to our imputations so that the potential wage and disutility of work among the non-employed have roughly the same dispersion as those among the employed.[8]

Finally, for non-employed single individuals, we estimate a *lower bound* for the fixed cost of work, $\underline{\kappa}$. Since these individuals prefer not to work, we know that their value when employed, evaluated at their fixed cost, is lower than their value when non-employed. Thus, their fixed cost must exceed the lower bound at which these individuals are indifferent between working and not working:

$$\kappa_\iota \geq \underline{\kappa}_\iota, \quad \text{such that} \quad W_\iota(\underline{\kappa}_\iota, ...) = U_\iota, \tag{26}$$

where the value of employment W_ι is evaluated under the optimal choice of hours, n_ι, that an non-employed individual would choose under the imputed θ_ι, χ_ι if that individual were to work. The value of non-employment, U_ι, uses the observed benefit and non-labor income of the individual. The two values are defined in equation (6).

[8] Our regressions are in logs, and thus we adjust the imputed levels of variables to target the average difference between groups. Let y_ι^0 be the unadjusted level of a variable for an individual we are imputing for (for instance, the wage of a non-employed) and y_ι^1 be the level of the variable for an individual belonging to a group we are imputing from (for instance, the wage of an employed). The adjusted level of the variable is $x_\iota^0 = \nu y_\iota^0$, where $\nu = \frac{\bar{x}^1/\bar{x}^0}{1+\overline{\log x^1}-\overline{\log x^0}}$ and bars denote sample averages. Thus, the adjusted ratio of means of variables equals $\bar{x}^1/\bar{y}^0 = 1 + \overline{\log x^1} - \overline{\log x^0}$.

Single individual, employed, $e_\iota = 1$. For employed single individuals we directly observe their wage; thus, $\theta_\iota = w_\iota$. Following a methodology analogous to the one we used for the non-employed, we impute the benefit upon non-employment for the employed based on observationally similar non-employed individuals and a draw of an error term. For each year and country separately, in a sample of non-employed single individuals, we run regressions of the form

$$\log \beta_{0\iota} = \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \ \text{ if single}_\iota = 1, e_\iota = 0. \tag{27}$$

To impute $\beta_{0\iota}$ for an employed, we use the estimates of the δ coefficients, the employed's observed predictors X_ι, Z_ι, and a draw of the residual $\hat{u}_\iota$ from the empirical distribution of residuals generated by these regressions.[9]

We infer the disutility of work by inverting the first-order condition for optimal hours conditional on working:

$$\chi_\iota = \frac{(y'(n_\iota) + b'(n_\iota))(1+\tau_c)^{\gamma-1}}{(n_\iota)^{1/\varepsilon}(y(n_\iota) + b(n_\iota) + (1-\tau_z)z_\iota)^\gamma}, \tag{28}$$

where the functions $b'()$ and $b(.)$ use the imputed $\beta_{0\iota}$ for every employed individual and our estimate of the phase-out parameter β_1 for single individuals described below.[10]

We estimate an *upper bound* for the fixed cost of work, $\overline{\kappa}$, so that employed individuals are indifferent between working and not working:

$$\kappa_\iota \leq \overline{\kappa}_\iota, \quad \text{such that} \quad U_\iota = W_\iota(\overline{\kappa}_\iota, ...), \tag{29}$$

where the value of non-employment, U_ι, uses the imputed benefit upon non-employment and the observed non-labor income of an employed individual.

Married couple, both members employed, $e_{1\iota} = e_{2\iota} = 1$. For married couples with both members working, we have $\theta_{j\iota} = w_{j\iota}$. For the benefit upon non-employment, in a sample of non-employed married couples, we run regressions of the form

$$\log \beta_{0\iota} = \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \ \text{ if married}_\iota = 1, e_{1\iota} = 0, e_{2\iota} = 0. \tag{30}$$

[9] We also impute $\beta_{0\iota}$ for a small share of non-employed individuals and married couples that have $b_\iota = 0$ in the data.

[10] Because of the convexity of the benefit function, the first-order condition for optimal hours potentially characterizes more than one local optimum. Thus, using the inferred χ_ι to solve for the optimal hours of an individual globally may not necessarily recover the global optimum for that individual. Similarly, the model-generated optimal choice of hours may be zero for some individuals, even if they work positive hours in the data. We drop observations from our results for which their observed hours differ significantly from their model-generated optimal hours. For example, in the U.S. CPS data, we drop around 4 percent of these inconsistent households.

To impute $\beta_{0\iota}$ for an employed couple, we use the estimates of the δ coefficients, the couple's observed predictors X_ι, Z_ι, and a draw of the residual $\hat{u}_\iota$ from the empirical distribution of residuals generated by these regressions.

We infer the disutility of work by inverting the first-order condition for optimal hours conditional on working for every spouse:

$$\chi_{j\iota} \;=\; \frac{(y'(n_{1\iota}, n_{2\iota}) + b'(n_{1\iota}, n_{2\iota}))(1+\tau_c)^{\gamma-1}}{(n_{j\iota})^{1/\varepsilon}(y(n_{1\iota}, n_{2\iota}) + b(n_{1\iota}, n_{2\iota}) + (1-\tau_z)z_\iota)^{\gamma}}, \tag{31}$$

where the functions $b'()$ and $b(.)$ use the imputed $\beta_{0\iota}$ for an employed couple and our estimate of the phase-out parameter β_1 for married couples.

We estimate upper bounds for the fixed cost of work so that employed individuals are indifferent between working and not working. In the first step, the bound for the fixed cost is computed by requiring indifference between both members of the household working and spouse j deviating to non-employment while keeping the other spouse employed at their observed hours:

$$\kappa_{1\iota} \;\leq\; \overline{\kappa}_{1\iota}, \quad \text{such that} \quad W_{2\iota} = W_\iota(\overline{\kappa}_{1\iota}, ...), \tag{32}$$

$$\kappa_{2\iota} \;\leq\; \overline{\kappa}_{2\iota}, \quad \text{such that} \quad W_{1\iota} = W_\iota(\overline{\kappa}_{2\iota}, ...). \tag{33}$$

The deviation values, $W_{j\iota}$, are given by equations (16) and (17), which recompute the disutility of work, $\chi_{j\iota}$, using equation (31) but at the new employment bundle with one spouse not working. In the second step, we compute the value of non-employment for married couples, U_ι, using the imputed benefit upon non-employment and the observed non-labor income of the couple in equation (18). If $U_\iota > W_\iota$ under our upper bounds in the first step, we decrease $\overline{\kappa}_{j\iota}$ proportionally between the two members of the household until $W_\iota = U_\iota$.

Married couple, one member employed, $e_{j\iota} = 1, e_{k\iota} = 0$. For the member who is employed, we have $\theta_{j\iota} = w_{j\iota}$. We run regressions of the form

$$\log \beta_{0\iota} \;=\; \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \;\; \text{if married}_\iota = 1, e_{1\iota} = 0, e_{2\iota} = 0, \tag{34}$$

$$\log w_{k\iota} \;=\; \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \;\; \text{if married}_\iota = 1, e_{k\iota} = 1, \tag{35}$$

$$\log \chi_{k\iota} \;=\; \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \;\; \text{if married}_\iota = 1, e_{k\iota} = 1. \tag{36}$$

When one member is working and the other is not, we impute the benefit upon non-employment for the household based on the married couples who are non-employed, and we impute the wage and the disutility of work for the non-employed member based on observationally equivalent married couples whose same member works. As we did before, we also add draws of residuals $\hat{u}_\iota$ from the empirical distribution of residuals generated by these regressions.

We infer the disutility of work for the employed member by inverting the first-order condition for optimal hours:

$$\chi_{j\iota} \;=\; \frac{(y'(n_{j\iota},0)+b'(n_{j\iota},0))(1+\tau_c)^{\gamma-1}}{(n_{j\iota})^{1/\varepsilon}(y(n_{j\iota},0)+b(n_{j\iota},0)+(1-\tau_z)z_\iota)^{\gamma}}, \tag{37}$$

where the functions $b'()$ and $b(.)$ use the imputed $\beta_{0\iota}$ for every couple and our estimate of the phase-out parameter β_1 for married couples.

We estimate an upper bound for the fixed cost for the member who works and a lower bound for the member who does not:

$$\kappa_{j\iota} \;\leq\; \overline{\kappa}_{j\iota}, \quad \text{such that} \quad U_\iota = W_{j\iota}(\overline{\kappa}_{j\iota}, ...), \tag{38}$$

$$\kappa_{k\iota} \;\geq\; \underline{\kappa}_{k\iota}, \quad \text{such that} \quad W_{j\iota} = W_\iota(\underline{\kappa}_{k\iota}, ...), \tag{39}$$

where the deviation value W_ι is evaluated under the optimal choice of hours, $n_{k\iota}$, that the non-employed member would choose under the imputed $\theta_{k\iota}, \chi_{k\iota}$ if that member were to work. If $W_{k\iota} > W_{j\iota}$ under our initially calculated bounds, we increase $\underline{\kappa}_{k\iota}$ until $W_{k\iota} = W_{j\iota}$.

Married couple, no member employed, $e_{1\iota} = e_{2\iota} = 0$. For this type of household, we directly observe their benefit upon non-employment; thus, $\beta_{0\iota} = b_\iota$. We impute the wage and the disutility of work from the sample of the married couples whose corresponding member is working:

$$\log w_{j\iota} \;=\; \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \;\; \text{if married}_\iota = 1, e_{j\iota} = 1, \tag{40}$$

$$\log \chi_{j\iota} \;=\; \delta_0 + \delta_x X_\iota + \delta_{z_1}\mathbb{P}(Z_\iota) + \delta_{z_2}\mathbb{P}^2(Z_\iota) + u_\iota, \;\; \text{if married}_\iota = 1, e_{j\iota} = 1. \tag{41}$$

We calculate initial lower bounds of fixed costs for both members:

$$\kappa_{1\iota} \;\geq\; \underline{\kappa}_{1\iota}, \quad \text{such that} \quad U_\iota = W_{1\iota}(\underline{\kappa}_{1\iota}, ...), \tag{42}$$

$$\kappa_{2\iota} \;\geq\; \underline{\kappa}_{2\iota}, \quad \text{such that} \quad U_\iota = W_{2\iota}(\underline{\kappa}_{2\iota}, ...), \tag{43}$$

where the deviation value $W_{j\iota}$ is evaluated under the optimal choice of hours, $n_{j\iota}$, that the non-employed member would choose under the imputed $\theta_{j\iota}, \chi_{j\iota}$ if that member were to work. If $W_\iota > U_\iota$, we decrease $\underline{\kappa}_{j\iota}$ proportionally between the two members of the household until $W_\iota = U_\iota$.

Values for fixed costs. The model accounts perfectly for a given cross-sectional data on employment, wages, and hours, for any values of the fixed costs that respect the lower bounds for the employed and the upper bounds for the non-employed. For our counterfactuals, we will need to draw specific values for these costs. We assume that fixed costs are drawn from uniform distributions that respect the lower and upper bounds that we estimated:

$$\kappa_{\iota j} \sim U[\underline{\kappa}_{\iota j}, \underline{\kappa}_{\iota j} + \alpha], \quad \text{for } e_{\iota j} = 0, \tag{44}$$

$$\kappa_{\iota j} \sim U[\overline{\kappa}_{\iota j} - \alpha, \overline{\kappa}_{\iota j}], \quad \text{for } e_{\iota j} = 1. \tag{45}$$

Parameter $\alpha \geq 0$ determines the dispersion of fixed costs around individuals' reservation value.

4.2 Other Parameters

We now discuss how we estimate the remaining parameters of the model, $(\tau_c, \tau_z, \tau_0, \tau_1, \beta_1, \gamma, \varepsilon, \alpha)$. For the consumption tax rate, τ_c, and the non-labor income tax rate, τ_z, we use the time-varying consumption and income tax rates from the updated effective tax rates series of McDaniel (2011). Separately by year and country, we estimate τ_0 and τ_1 using equations (4) and (13) for the United States and the corresponding equations given in Appendix E for other countries using data on taxes paid and gross earnings. Separately by country and family status, we estimate β_1 using equations (5) and (14) using data on benefits received and gross earnings. We have also allowed for time variation in parameter β_1, but it is relatively stable over time.

We identify the three parameters that govern the responsiveness of labor supply, $(\gamma, \varepsilon, \alpha)$, by targeting the Marshallian elasticity of labor supply with respect to a proportional change in the wage induced by changes in taxes on the intensive margin, the Frisch elasticity of labor supply on the intensive margin, and the Marshallian elasticity of labor supply on the extensive margin. For the Frisch elasticity, we use the target of 0.54 for the intensive margin from the meta-analysis of Chetty, Guren, Manoli, and Weber (2013). For the other two elasticity targets, we use the same OECD/PWT data that we used in Section 2 and effective labor income and consumption taxes from McDaniel (2011) to estimate

$$\begin{aligned}
\log n_{ct} &= d_c + d_t + 0.06 \times \log((1-\tau_\ell)/(1+\tau_c))_{ct} + \phi z_{ct} + u_{ct}, \\
\log e_{ct} &= d_c + d_t + 0.32 \times \log((1-\tau_\ell)/(1+\tau_c))_{ct} + \phi z_{ct} + u_{ct}, \\
\log(en)_{ct} &= d_c + d_t + 0.38 \times \log((1-\tau_\ell)/(1+\tau_c))_{ct} + \phi z_{ct} + u_{ct}.
\end{aligned} \tag{46}$$

Our independent variables are hours per worker, the employment rate, and total hours per person for country c in year t. We include in the regressions country and time fixed effects. We also include a measure of non-labor income, z_{ct}, calculated as one minus the labor share times real GDP per capita from the PWT. Thus, the coefficient on the after-tax term in the first regression yields the Marshallian elasticity of labor supply on the intensive margin and the coefficient on the after-tax term in the second regression yields the Marshallian elasticity of labor supply on the extensive margin. In the third regression, we obtain the Marshallian elasticity of total labor supply, which is the sum of the two elasticities.[11]

Our elasticity estimates are consistent with other estimates reported by the literature. For example, the meta-analysis of Keen (2011) reports a 0.06 Marshallian elasticity of labor supply on the intensive margin, which exactly coincides with our estimate. Our extensive margin Marshallian elasticity is 0.32. Attanasio, Levell, Low, and Sanchez-Marcos (2018) estimate a median Marshallian elasticity on the intensive margin of 0.18 and a median Marshallian elasticity on the extensive margin of 0.54.

We will estimate $(\gamma, \varepsilon, \alpha)$ separately for each country by targeting the same three elasticity estimates for all countries. The reason for estimating $(\gamma, \varepsilon, \alpha)$ separately for each country is that the parameters are informed by the elasticities, but are not identified by these elasticities without additional information. For example, parameter γ is related to the income effect that shapes the Marshallian elasticity on the intensive margin. However, this elasticity is also affected by the labor income share that varies across individuals and countries. Parameter ε is related to the Frisch elasticity of labor supply, but the Frisch elasticity is also affected by the degree of progressivity τ_1, which varies across countries. Parameter α governs the responsiveness of the extensive margin of labor supply. However, this responsiveness is also affected by the dispersions of wages, disutility of work, and benefits across individuals, which, in turn, are encoded in the dispersion of the bounds in the fixed costs.

4.3 Discussion of Identification Strategy

Before proceeding with our results, we pause to comment on our identification strategy and to compare our approach with other approaches in the literature. Our approach to identifying the sources of heterogeneity is so that the model accounts perfectly for cross-sectional data on employment, wages, and hours. A merit of our approach is that with the exception of the draws of the fixed costs—which are not needed to account for the cross-sectional data, but only for the counterfactuals—we do not impose parametric assumptions on the joint distribution that generates the sources of heterogeneity. In their analysis of labor supply and consumption, Heathcote, Storesletten, and Violante (2014) choose moments in order to estimate parameters using the method of moments. Our approach is different because it does not require restrictions on which moments are more informative for the identification of the sources of heterogeneity.

[11] We cluster standard errors at the country level. The p-value for the first regression is 0.623; for the second regression, it is 0.097; and for the third regression, it is 0.041.

Attanasio, Levell, Low, and Sanchez-Marcos (2018) adopt flexible preferences that generate substantial heterogeneity in elasticities of labor supply and use variation in taxation to estimate preference parameters. Similar to them, we also use variation in taxation to estimate the parameters $(\gamma, \varepsilon, \alpha)$ and show that our model also generates substantial heterogeneity in elasticities of labor supply. Closest to the spirit of our exercise is the identification strategy in the home production model of Boerma and Karabarbounis (2021). Relative to them, we add the extensive margin of labor supply.

Our procedure for imputing the wage and the disutility of work for the non-employed and the benefit upon non-employment for the employed resembles imputation-based methods that have been used previously in the literature (Juhn and Murphy, 1997; Olivetti and Petrongolo, 2008; Blau, Kahn, Boboshko, and Comey, 2024; Arellano-Bover, Bianchi, Lattanzio, and Paradisi, 2024). There are two differences between our methodology and those of these papers. First, in addition to demographic characteristics, our imputations hold constant predicted participation rates from a first stage. Second, and most importantly, we are interested in the whole distribution of the sources of heterogeneity, and thus we add residuals to the imputed sources of heterogeneity. Had we not added residuals, we would have obtained counterintuitive results; for example, the wage of the employed would have been more dispersed than the potential wage of the non-employed. We present examples below that show that shifting the whole distribution of sources of heterogeneity when performing counterfactuals gives different results than shifting the mean of the distribution. This justifies our interest in estimating the distribution of sources of heterogeneity, while imposing as few parametric assumptions as possible.

A different procedure for inferring the wage of the non-employed is based on methods popularized by Heckman (1979). We first clarify that our wage imputations that hold constant predicted participation rates from a first stage are not equivalent to a Heckman selection model, because we do not impose a parametric assumption on the error of the second stage and we do not exploit an assumed correlation structure of the errors from the two stages. Mulligan and Rubinstein (2008) is a well-known application of Heckman's two-stage estimator, documenting that selection of women into the labor force shifted from negative in the 1970s to positive in the 1990s. In robustness checks reported below, we also examine results using a Heckman selection model to infer the potential wages of the non-employed. Similar to Mulligan and Rubinstein (2008), we find that selection becomes more positive over time for married spouses. However, for other groups, selection is generally negative throughout the sample, which has the counterintuitive implication that the potential wages of the non-employed exceed the wages of the employed. Further, estimates of the coefficient on the inverse Mills ratio are quite volatile over time, which leads to unrealistically volatile time series of potential wages for the non-employed.

Thus, we favor our approach, which leads to more intuitive selection on observables regarding the wage, the disutility of work, and the benefit upon non-employment. Our baseline approach effectively loads all selection on unobservables on the fixed cost. We find this approach reasonable. There is one extensive margin choice in our model, and therefore we can load selection on unobservables without further assumptions on only one source of heterogeneity. Among them, the fixed cost of work is the source about which we know the least. The fixed cost includes parts of the monetary costs incurred from work due to transportation expenses, clothing, food at work, and child care costs, but also non-monetary, typically unobserved, costs such as commuting time, the utility of having a career, or the stigma of not working. By contrast, we know more about wages and benefits, such as that wages depend predictably on age and education and that benefits depend predictably on income and the location of residence.

5 U.S. Results

We first discuss the U.S. data. Next, we present our parameter estimates and inferred sources of heterogeneity. Finally, we perform counterfactuals to assess the evolution of hours worked.

5.1 U.S. Data

Our main source of data is the Annual Social and Economic Supplements of the CPS, downloaded from IPUMS. We use the consumer price index to convert all nominal amounts to constant 2019 dollars. The sample covers the years between 1978 and 2023 and includes heads and spouses between the ages of 15 and 64.[12] Our population is the civilian population and excludes members of the military who answer the survey and those who are incarcerated, who do not participate in the survey.[13] Appendix C details how we clean the data.

[12] We do not keep other people of the household in the sample, because, for example, a single adult who is living with their parents is not economically similar to a single adult who is living alone. Appendix Figure A.2 presents statistics on the living arrangements and employment of U.S. households. The employment rate of those aged between 18 and 29 and living with their parents is around 30 percentage points lower than the employment rate of those aged between 18 and 29 and living alone. The share of those aged between 18 and 29 and living with their parents has increased after the 2000s and spikes after the Great Recession, which is consistent with the cyclicality of moving back home reported by Kaplan (2012). However, the trend in coresidence is relatively muted, and the share of adults living with their parents is small. Comparing observed hours per person to those when we hold constant the share of those aged between 18 and 29 and living with their parents reveals a minor role of the increasing coresidence for aggregate hours worked after the 2000s.

[13] Given the lower propensity of incarcerated individuals to work post-incarceration, it is useful to estimate how much of the decline in U.S. hours after the 2000s is accounted for by rising incarceration rates. Appendix Table A.13 presents some back of the envelope calculations. We use data from the Prison Policy Initiative (https://www.prisonpolicy.org/). We estimate a rise of the share of incarcerated individuals from 5 to 9 percent between the 1990s and the 2010s when the duration of incarceration is roughly three years or a rise

Hours worked, n, are defined as usual hours per week times weeks per year. We define an individual as employed, $e = 1$, if they work more than 800 hours per year. We choose this threshold so that the generated employment rate from the CPS matches the roughly 73 percent employment rate for the United States between 1978 and 2019 in the OECD data that we used for our aggregate cross-country analyses. We define the wage w as the sum of salary, two-thirds of business income, and fringe benefits divided by hours worked.[14]

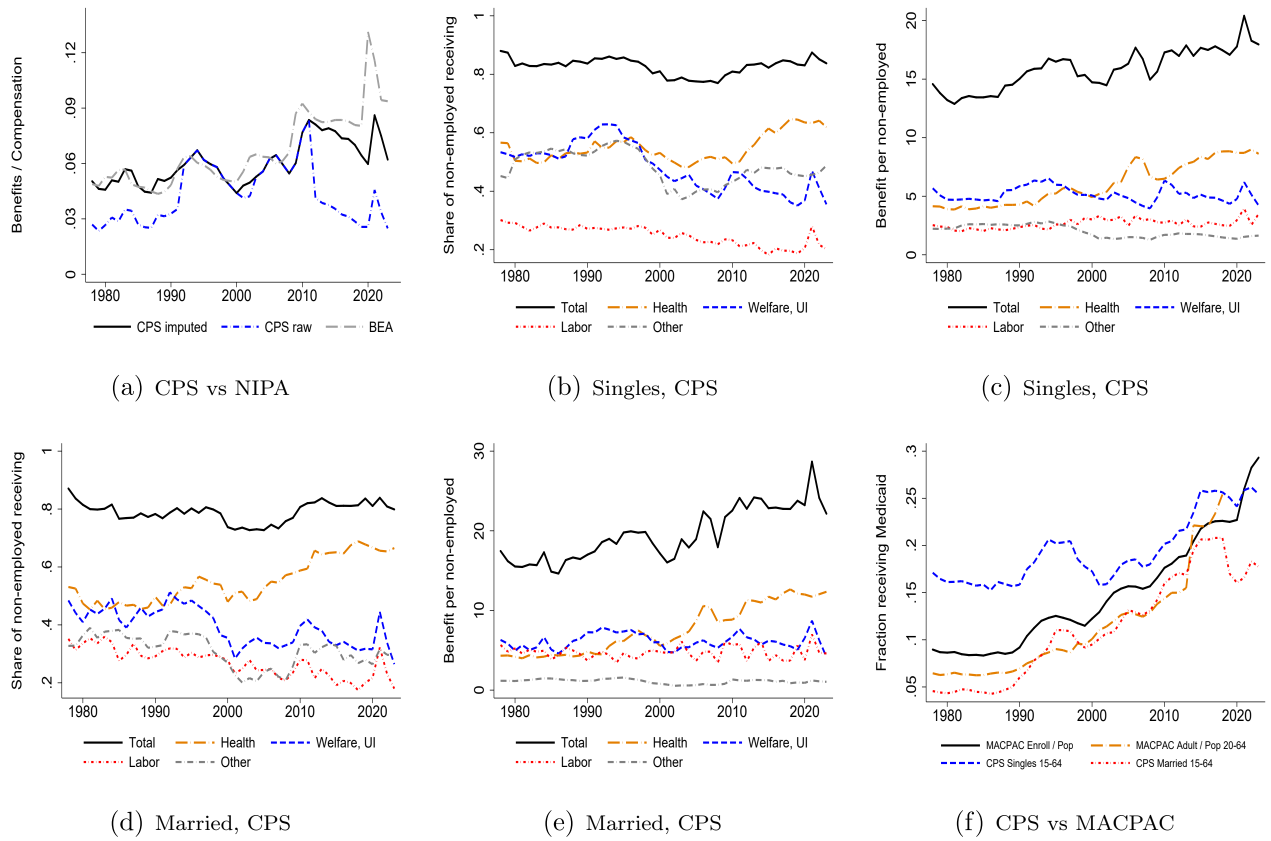
For non-labor income, z, we add non-labor income from the CPS to imputed non-labor income from the SCF; see Appendix Table A.14 for the variable names in the CPS and the SCF that are included in our measurement. Non-labor income in the CPS equals the remaining one-third of business income, survivor benefits, child support, alimony, and assistance from friends or relatives. Non-labor income in the SCF refers to returns generated by net liquid wealth, retirement, pensions, and real estate investments. We impute returns from the SCF to the CPS using demographic and income variables and historical data on rates of return. It is important to impute non-labor income from the SCF into our measure of z, as the level of the labor share of income governs the strength of income effects on labor supply. Summing up our labor income, wn, and non-labor income, z, across all households in the survey, we calculate that the labor share of household income averages around 85 percent during our sample period and exhibits a decline of roughly 6 percentage points between the early 1980s and the end of our sample. We find this result sensible, because our non-labor income excludes imputed rents from primary residences and the depreciation of fixed capital. Assuming that these categories account for 25 percent of GDP, we obtain a labor share of GDP equal to roughly 65 percent, in line with typical measurements of the labor share (Karabarbounis, 2024).

Our benefits variable, b, includes welfare (TANF/AFDC), unemployment insurance, workers' compensation, disability payments, veterans' benefits, food stamps (SNAP), health insurance from Medicaid and Medicare (since some individuals below the age of 65 may qualify under disability), educational assistance, and housing, energy, and school lunch subsidies; see Appendix Table A.15 for the CPS variable names that are included in our benefits. To these variables, we add unaccounted labor income, defined as any positive labor income reported by those who work fewer than 800 hours per year. Appendix Tables A.16 and A.17 present summary statistics of all variables for single and married individuals by employment status.[15]

from 6 to 12 percent when the duration is two years. Using estimates of the employment effects of conviction from Waldfogel (1994), we find that the rise of incarceration accounts for between 0.4 and 0.6 percentage point of the decline in the aggregate employment rate.

[14]See Appendix Figure A.3. We add fringe benefits to the wage because our model is static, and thus employer contributions for workers' pensions, insurance, Social Security, and Medicare would otherwise not be valued.

[15]We find that roughly 10 percent of single individuals and 5 percent of married couples have consumption



(a) CPS vs NIPA
(b) Singles, CPS
(c) Singles, CPS
(d) Married, CPS
(e) Married, CPS
(f) CPS vs MACPAC

Figure 6: The Evolution of Benefits in the United States

Notes: The figure shows statistics of benefits. In the first panel, the numerator for the BEA variable comes from NIPA Table 3.12 and includes unemployment insurance, veterans' benefits, workers' compensation, food stamps, Supplemental Security Income, disability, and Medicaid. The denominator is compensation of employees from NIPA Table 1.12, Line 3. In the last panel, MACPAC stands for Medicaid and CHIP Payment and Access Commission official statistics. The denominators for the MACPAC lines come from the OECD. For the solid, black line the numerator is the total enrollees in Medicaid as reported by MACPAC. For the dashed, orange line, the numerator includes adults, disabled people and a fraction of the beneficiaries that MACPAC designates as "unknown." The fraction equals the fraction of adults and disabled people in the total enrollees excluding those with unknown status.

It is well known that surveys such as the CPS underestimate the recipients of benefits and the amounts received (Meyer, Mok, and Sullivan, 2009). In Appendix C, we detail the various imputations to the benefits data that we perform in the CPS to fill in missing benefits information. Here, we show that our imputations perform well, in the sense that our CPS data with the imputations come close to measuring the level and trend of benefits observed in administrative datasets. The first panel of Figure 6 compares the ratio of total benefits (excluding unaccounted labor income) to total compensation (to which we add back unaccounted labor

expenditures (which we equate to $y + b + z$) below the federal poverty level. We also find around 1 to 2 percent of households have negative consumption, since z can become negative because of credit card and other debt that is included in our imputations. Whenever consumption is below its federal poverty level, we adjust z so that individuals or couples attain consumption equal to their corresponding federal poverty levels.

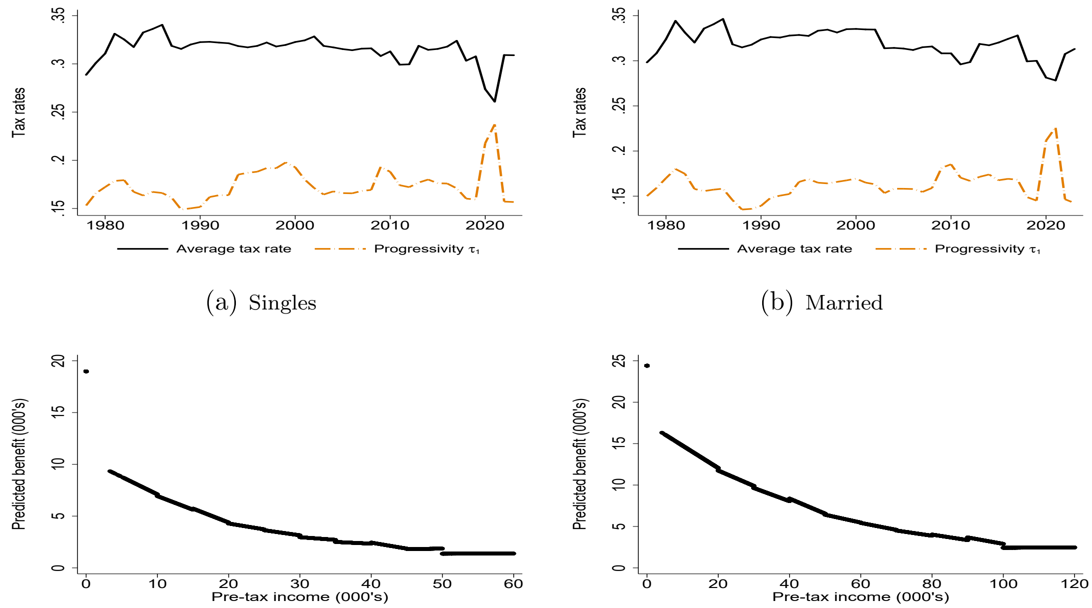
income) in the CPS to the corresponding ratio calculated using data from the National Income and Product Accounts from the Bureau of Economic Analysis (BEA). Without our imputations (dashed, blue line), the CPS ratio is as low as about half of the BEA ratio in some years. With our imputations (solid, black line), the two ratios are much closer in levels and in trends. The exception is during the COVID period, likely because we have excluded from our sample the self-employed, who received unemployment insurance during that period.

The second and third panels of Figure 6 present the share of non-employed single individuals who receive benefits and the benefit amount per non-employed single individual in thousands of 2019 dollars, respectively. The various lines break down total benefits into four categories: health (mostly Medicaid, with a few individuals also being covered by Medicare because of disability), welfare and UI (this category also includes disability, supplemental security income, and veterans' benefits), other (food stamps and various subsidies), and unaccounted labor income. The figure shows a large increase in benefits per non-employed individual, which is entirely accounted for by the rise of health benefits over time. The fourth and fifth panels repeat the same statistics for married couples. We again observe an increase in benefits per non-employed couple, which similarly reflects the rise of health benefits.

Given the prominence of health benefits in accounting for the trends in total benefits, the sixth panel compares statistics regarding Medicaid benefit receipt in our sample to administrative statistics from MACPAC. The solid, black line from MACPAC shows that the fraction of the total population that receives Medicaid benefits has increased from roughly 10 percent to roughly 30 percent over the past 40 years. The dashed, orange line tabulates the fraction of the working-age population that receives Medicaid benefits, a line that excludes children. This fraction has also dramatically increased over time. The other two lines present the fractions of single individuals and married couples that receive Medicaid in our CPS data with the imputations. An average of these two lines comes close to roughly matching both the level and the trend observed in the fraction of recipients from the administrative data.

5.2 Parameter Estimates

Figure 7 presents estimates of the parameters of the tax and benefit functions. Beginning with the top panels, we estimate parameters of the tax functions in equations (4) and (13) in each year by inputting our CPS data on labor earnings, $w_{j\iota}n_{j\iota}$, age, marital status, state of residence, and age of children into the TAXSIM software developed by the National Bureau of Economic Research. Taxes paid include both employee and employer contributions to FICA, state and local taxes, and federal taxes minus the earned income tax credit, the child tax credit, and some



(a) Singles

(b) Married

(c) Singles, $\beta_1 = 1.23$

(d) Married, $\beta_1 = 0.54$

Figure 7: Estimates of Tax and Benefit Parameters

Notes: The upper panels of the figure show our estimates of the average tax rate and progressivity parameter τ_1 for single individuals and married couples. The lower panels show the relationship in the CPS between benefits and pre-tax income for single individuals and married couples.

types of transfers such as the ones enacted by the CARES Act in 2020. Given the information we have from the CPS, our labor income measure is gross wages and salaries, which include imputed fringe benefits, and is not adjusted gross income. Thus, as observed in the top panels of Figure 7, our average tax rate is higher than the actual one because we do not deduct income for retirement, medical insurance, and other potential expenses. This is appropriate, because in our static model, labor earnings include fringe benefits, and thus all income earned in a period should be taxed. In terms of trends, we observe a small decline over time in the average tax rate on labor income, for both single individuals and married couples. The declines are concentrated in key episodes, such as the Bush tax cuts, the Trump tax cuts, and the COVID period. The progressivity parameter τ_1 increases somewhat over time, with the increases also being concentrated in key episodes, such as the expansion of the earned income tax credit and the introduction of the child tax credit in the 1990s and the elevated transfers during the COVID period. In each period t, we choose the parameter τ_0 so that our average tax rate in the model matches the average tax rate calculated from TAXSIM.

The bottom panels of Figure 7 present estimates of the benefit function for single individuals and married couples. We do not impose convexity of the function a priori. In the figure, we fit piecewise linear functions throughout the income distribution. As the figure shows, the benefit

Table 3: Marshallian Elasticities of Labor Supply

	With respect to $1-\tau_0$			With respect to w		
	$p25$	$p50$	$p75$	$p25$	$p50$	$p75$
Singles	0.00	0.04	0.14	0.01	0.07	0.30
Married Head	0.03	0.07	0.21	0.13	0.23	0.34
Married Spouse	0.03	0.07	0.20	0.25	0.33	0.41
Singles	Low 1/3	Middle 1/3	High 1/3	Low 1/3	Middle 1/3	High 1/3
By w	0.08	0.04	0.03	0.20	0.07	0.04
By n	0.05		0.03	0.08		0.04
By z	0.00	0.02	0.06	0.10	0.05	0.07
By b	0.01	0.03	0.27	0.01	0.08	0.53
Married Head	Low 1/3	Middle 1/3	High 1/3	Low 1/3	Middle 1/3	High 1/3
By w	0.14	0.07	0.06	0.31	0.23	0.16
By n	0.08	0.08	0.06	0.25	0.24	0.19
By z	0.09	0.06	0.08	0.27	0.23	0.20
By b	0.03	0.06	0.34	0.13	0.20	0.39
Married Spouse	Low 1/3	Middle 1/3	High 1/3	Low 1/3	Middle 1/3	High 1/3
By w	0.11	0.07	0.06	0.39	0.33	0.27
By n	0.07	0.07	0.06	0.39	0.31	0.28
By z	0.08	0.05	0.07	0.35	0.33	0.32
By b	0.02	0.05	0.31	0.27	0.31	0.43

Notes: The first panel presents distributional statistics of the Marshallian elasticity of labor supply with respect to after-tax income $1-\tau_0$ and the wage w. The second, third, and fourth panels present the median Marshallian elasticity of labor supply with respect to after-tax income $1-\tau_0$ and the wage w by different subgroup and variable. Subgroups are defined by tertiles. For single individuals, we split hours n to two groups due to the discreteness of hours in the data.

function is convex in earnings, because benefits decline rapidly at low income levels and phase out more gradually at higher earnings. The phase-out at a level above zero in the data is explained by the fact that even high income households are eligible to receive unemployment insurance in case of an unemployment spell. The point at zero earnings corresponds to the average β_0. The rate of decline in benefits through the pre-tax income distribution yields an estimate of the parameter β_1. We estimate one parameter for the whole period, because splitting estimates by subperiods yields quite similar β_1 estimates.[16]

We estimate parameters $(\gamma, \varepsilon, \alpha)$ by requiring that our model generates the elasticity of labor supply estimates presented in Section 4.2. We obtain $\gamma = 1.07$, $\varepsilon = 0.51$, and $\alpha = 0.68$.

[16]The average β_1 estimate for single individuals across years is 1.3 before 1996 and 1.2 after 1996. The average β_1 estimate for married couples across years is stable at 0.5 before and after 1996. Appendix Figure A.4 reports estimates of the benefit function by different subcategories of benefits and similarly reports a convex function.

Table 3 presents various summary statistics of the Marshallian elasticities of labor supply. The top panel presents the 25th, 50th, and 75th percentile of the elasticity of labor supply with respect to after tax income, $1 - \tau_0$, and the wage, w. The latter elasticity exceeds the former, because an increase in the wage tends to lower benefits, thereby increasing labor supply by more than a lowering of the average tax rate. Married couples have higher elasticities than single individuals, because income effects from a change in the wage are smaller for members of a household with a working spouse than for single individuals. Similarly, married spouses have higher elasticities with respect to their wage than married heads, as their labor earnings contribute less on average to household earnings than the earnings of the heads do. There is quite a bit of dispersion in the elasticities of labor supply. For example, single individuals at the 25th percentile have an elasticity with respect to the wage that is close to zero, whereas single individuals at the 75th percentile have an elasticity of 0.3.

Separately for each family status, the three bottom panels of Table 3 shows how the elasticities of labor supply vary by observables. Higher-wage earners and individuals who work longer hours have lower elasticities, because income effects tend to be stronger for groups with higher earnings. Individuals with higher benefits have higher elasticities of labor supply. This result is explained both by the stronger income effect induced by higher share of non-labor income and by the faster phase-out of benefits for those with higher benefits. For individuals with benefits at the top one-third of the benefit distribution, we obtain elasticities of labor supply with respect to the wage that range between roughly 0.4 and 0.5.[17]

5.3 Sources of Heterogeneity

Figure 8 presents the evolution of the mean values of the sources of heterogeneity over time. Beginning with potential wages, we observe their steady increase over time for both single individuals and married couples and for both employed and non-employed individuals. Our procedure for imputing potential wages for non-employed individuals yields a potential wage for the non-employed that is roughly 20 percent lower for single individuals and roughly 15 percent lower for married individuals. As explained in Section 4, our imputation of potential wages for the non-employed is based only on observables with the addition of draws of residuals (see

[17]We also calculate cross-wage elasticities of labor supply, defined as the change in hours of a member of the household when the other member of the household experiences a one percent increase in their wage. We obtain both mean and median cross-wage elasticities of labor supply equal to -0.11 for heads and -0.19 for spouses. These estimates are consistent with the estimates of Blau and Kahn (2007), who document roughly zero cross-wage elasticities for men and cross-wage elasticities that range from roughly -0.1 to -0.2 for women. Our low cross-wage elasticities are also consistent with the analysis of Fukui, Nakamura, and Steinsson (2022), who find that women's labor supply does not significantly crowd out men's labor supply across U.S. states.

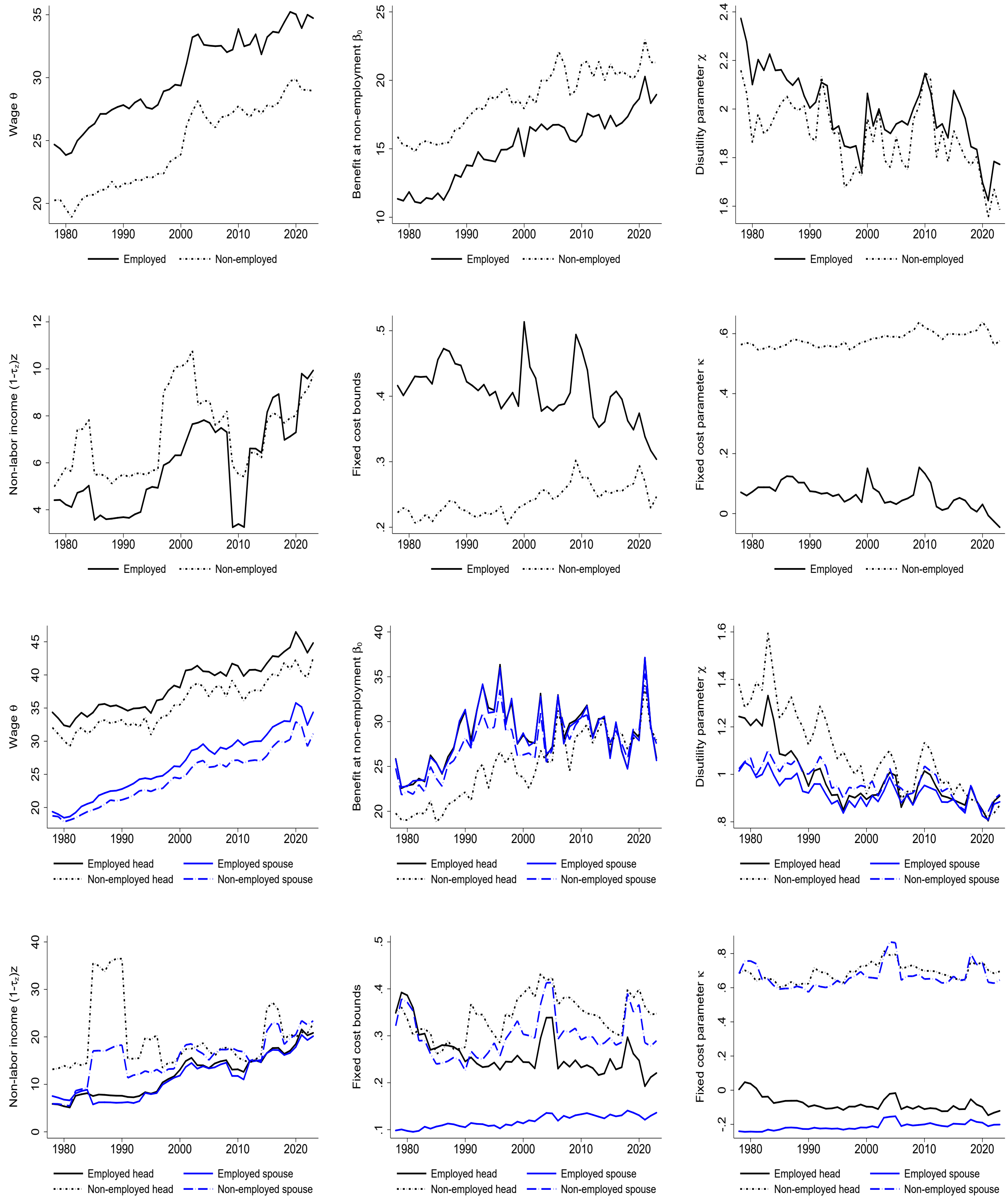


Figure 8: Means of Sources of Heterogeneity: U.S. CPS

Notes: The figure shows means of sources of heterogeneity over time, separately by employed and non-employed and single individuals, married heads, and married spouses.

Appendix Table A.18 for the imputations of potential wages and other sources of heterogeneity).

The benefit upon non-employment is also rising over time, but more strongly for single individuals and married heads than for other groups. The disutility of work is decreasing over time for most groups, with the largest share of this decline being observed during the early part of the sample. The evolution of the disutility of work is consistent with several previous findings in the literature. Kaplan and Schulhofer-Wohl (2018) analyze time use data to show that the occupational shift toward less manual and tiring jobs has lowered the non-pecuniary costs of work. Aguiar, Bils, Charles, and Hurst (2021) examine the role of the declining relative price of leisure goods for labor supply after the 2000s. For earlier periods, Greenwood, Seshadri, and Yorukoglu (2005) argue that the consumer durable goods revolution liberated women from home production, and Fogli and Veldkamp (2011) argue that increased information diffusion helped to increase female labor force participation. Our estimates of the disutility of work capture in a reduced-form way these deeper forces analyzed by the literature. Our estimates of after-tax non-labor income are generally noisy because they use imputations of net worth that vary with the stock market. Nonetheless, we generally find that mean non-labor income is increasing over time and that the non-employed have higher non-labor income than the employed.

Figure 8 also presents our estimates of the bounds for the fixed costs, $\underline{\kappa}$ and $\overline{\kappa}$. Beginning with single individuals, we observe an increase in the lower bound for the non-employed and a decline in the upper bound for the employed. These changes have opposing effects on labor supply, as more non-employed individuals would work in the absence of the increase in their lower bound, whereas fewer employed individuals would work in the absence of the decline in their upper bound. The patterns for married individuals are somewhat different. We observe increases in the lower bound for the non-employed during the 1990s and the 2000s and a decline in the upper bound for employed heads in the early part of the sample. However, the upper bound of the fixed cost for employed spouses increases over time.[18]

Table 4 presents the means of the sources of heterogeneity by education, age, and family status. The patterns are intuitive across groups, lending further credibility to our inference

[18] The mean fixed cost across all individuals is 7 percent of average consumption. This is generally lower than other estimates in the literature, partly because we take into account that upon non-employment, individuals earn more benefits. For example, Cogan (1981) estimates a mean fixed cost value of 28 percent of annual earnings for women. In French (2005), fixed costs represent 65 percent of labor earnings without tied wage-hours offers, but 12 percent with tied wage-hours offers. Rogerson and Wallenius (2009) calibrate a value of 19 percent, whereas Bick, Lagakos, Fuchs-Schundeln, and Tsujiyama (2022) calibrate a value of 26 percent. Erosa, Fuster, and Kambourov (2016) calibrate a value of 37 percent with linear earnings and a value of 10 percent with non-linear earnings. Closer to our estimate is the calibrated value of 6 percent in Attanasio, Levell, Low, and Sanchez-Marcos (2018) and the more direct measurements of Aguiar and Hurst (2013), indicating that around 9 percent of work-related expenses would have been saved were individuals not to work.

Table 4: Means of Sources of Heterogeneity by Group: U.S. CPS

	θ_1	θ_2	χ_1	χ_2	κ_1	κ_2	β_0	$(1-\tau_z)z$
Educ: no high-school	20.0	14.6	1.7	1.1	0.3	0.3	21.0	3.9
Educ: high-school	31.2	23.2	1.4	0.9	0.1	0.1	23.6	8.1
Educ: college	47.9	39.4	1.3	0.8	0.1	0.0	22.6	18.4
Age: 15-29	24.2	19.8	1.8	1.1	0.1	0.1	21.1	3.9
Age: 30-49	35.9	26.8	1.3	0.9	0.1	0.1	25.4	7.5
Age: 50-64	37.1	27.0	1.4	0.9	0.2	0.2	20.8	17.6
Married	38.0	25.8	1.0	0.9	0.0	0.1	28.1	13.0
Married: $e_1 = 1, e_2 = 1$	36.9	27.0	0.8	0.8	-0.2	-0.2	28.9	12.0
Married: $e_1 = 1, e_2 = 0$	40.7	24.1	1.3	1.0	0.1	0.7	27.9	11.6
Married: $e_1 = 0, e_2 = 1$	37.1	26.5	1.0	1.5	0.8	0.0	26.9	10.4
Married: $e_1 = 0, e_2 = 0$	35.3	23.3	1.1	1.0	0.6	0.6	24.6	27.5
Singles	28.7	.	2.0	.	0.2	.	16.4	6.3
Singles: $e = 1$	30.4	.	2.0	.	0.1	.	15.3	6.0
Singles: $e = 0$	24.9	.	1.9	.	0.6	.	19.0	7.2

Notes: The table presents means of sources of heterogeneity for the entire sample period for different groups defined by education, age, and family status. Means of θ_1 and θ_2 are in 2019 dollars. Means of χ are normalized relative to the mean value of χ for married which equals one. Means of κ_1 and κ_2 are in utility terms, but given our estimated value of $\gamma = 1.07$ they can be interpreted as roughly in terms of consumption units. Means of β_0 and $(1-\tau_z)z$ are in thousands of 2019 dollars.

strategy. Less educated individuals have a higher disutility of work, higher fixed cost of work, and lower non-labor income than more educated individuals. Older individuals display lower disutility of work, but higher fixed cost. Single individuals have a higher disutility and fixed cost of work and lower non-labor income than married individuals.[19]

5.4 Counterfactuals

Our model accounts perfectly for hours worked of every individual observed in the data by construction. Our counterfactuals change the primitive sources of heterogeneity and policy parameters to recalculate endogenous variables of every individual under different scenarios.

[19] Appendix Table A.19 presents the dispersion of the sources of heterogeneity. The disutility of work and the fixed cost of work are generally more dispersed across individuals than potential wages and benefits upon non-employment. Appendix Table A.20 presents correlations between the sources of heterogeneity. We find that potential wages are relatively uncorrelated with all sources of heterogeneity except for non-labor income, which displays a correlation of roughly 0.4 to 0.5 with potential wages. We also find that the benefit upon non-employment is negatively correlated with the fixed cost of work, which is intuitive because a higher benefit upon non-employment necessitates a lower fixed cost to rationalize why the non-employed do not work. Appendix Figure A.5 presents the inferred distributions of the sources of heterogeneity.

For each source of heterogeneity, $x = \{\theta, z, \chi, \overline{\kappa}, \underline{\kappa}, \beta_0/\theta\}$, we replace $x_{\iota t}$ with

$$\tilde{x}_{\iota t} = x_{\tilde{\iota}\tilde{t}}: \quad F_g(x_t \leq x_{\iota t}) = F_g(x_{\tilde{t}} \leq x_{\tilde{\iota}\tilde{t}}), \tag{47}$$

where $\tilde{t}$ is a reference period, g denotes the group of the individual defined by the combination of education, age, and family status, and F_g denotes the empirical distribution of variable x_t in group g. As an example, consider the potential wage. We replace the potential wage of individual ι in period t, $\theta_{\iota t}$, which is the factual, with a counterfactual potential wage $\tilde{\theta}_{\iota t}$ that equals the potential wage of an individual $\tilde{\iota}$ in the reference period $\tilde{t}$ who is positioned in the same rank of the group distribution as the rank of individual ι in the factual. In effect, we replace the distribution of potential wages and of other sources of heterogeneity in period t with the distribution observed in the reference period $\tilde{t}$. The reference period is the average of years between 1978 and 1999 when we wish to understand the drivers of the boom of U.S. hours and the average of years between 1998 and 2019 when we wish to understand the drivers of the bust of U.S. hours. Finally, for the tax parameters $\tau_{ct}, \tau_{zt}, \tau_{1t}$, we replace their observed values with the average values in the reference years, and we change τ_{0t} using the change in the average tax rate, $\tilde{\tau}_{0t} = \tau_{0t} + \text{ATR}_{\tilde{t}} - \text{ATR}_t$. Appendix D describes further implementation details of our procedure for performing counterfactuals.[20]

Table 5 presents our results. Beginning with the upper panel, in the data we observe an increase of 5.2 percentage points in the employment rate, an increase of 9.9 log points in hours worked, an increase of 10 log points in the wage, and an increase of 11.7 log points in the price of labor between the 1980s and the 1990s.[21] We adjust for compositional changes by fixing the shares of group g in the population to their average values in the boom and the bust. The compositional effects observed in the boom period are quite substantial, as the U.S. population became more educated during this period, and more educated individuals work more and have higher wages. The third line shows the composition-adjusted changes, which equal roughly half of the changes that we observe in the unadjusted data. Correspondingly, in our counterfactuals, we also fix the shares of the population so that we compare composition-adjusted changes in the model to composition-adjusted changes in the data.

Beginning with changes in potential wages in line 4, we find that changes in potential wages

[20] For benefits, we find natural to change the "replacement rate," β_0/θ, as opposed to the level of the variables. We have also changed the levels, with small difference in the results, as individuals at the bottom half of the distribution, who are more likely to receive benefits, have not experienced large changes in their potential wages. For married individuals, we use the sum of potential wages. We calculate the counterfactual benefit upon non-employment $\tilde{\beta}_0$ as the counterfactual replacement rate times the factual potential wage.

[21] These changes are calculated as the difference between mean outcomes in the 1990s and mean outcomes between 1978 and 1982. For the bust, we take differences between the 2010s and the period between 1998 and 2002. Taking differences across longer periods of time avoids sensitivity to choices of starting and ending points.

Table 5: Drivers of Hours Worked: U.S. CPS

	(p-points)		(log-points)	
Period: 1980-1990s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	5.2	9.9	10.0	11.7
Composition	3.0	5.1	3.2	7.1
Composition-Adjusted	2.2	4.8	6.8	4.6
Wages, θ	-0.4	-0.7	7.1	5.1
Non-labor income, z	-1.2	-2.5	0.0	0.1
Disutility of hours, χ	0.5	8.2	-0.2	0.2
Fixed cost, κ	1.3	1.8	-0.1	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.2	-0.2	0.0	0.1
Health replacement, β_0/θ	-1.6	-3.7	0.3	-1.7
Period: 2000-2010s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	-4.5	-6.8	9.2	13.0
Composition	-0.2	0.1	5.9	5.7
Composition-Adjusted	-4.3	-6.9	3.3	7.2
Wages, θ	-0.1	0.0	3.5	2.8
Non-labor income, z	0.6	1.6	0.7	0.0
Disutility of hours, χ	-0.1	-1.8	0.0	0.0
Fixed cost, κ	1.9	2.8	0.2	0.1
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.2	0.6	-0.1	1.0
Health replacement, β_0/θ	-3.2	-6.3	0.5	-2.9

Notes: The upper panel of the table presents results for the period between 1978 and 1998 and the lower panel presents results for the period between 1998 and 2019. In the first panel, changes of variables are calculated as the difference between mean outcomes in the 1990s and mean outcomes between 1978 and 1982. In the second panel, changes of variable are calculated as the difference between mean outcomes in the 2010s and mean outcomes between 1998 and 2002. The first row of each panel calculates the change of each variable in the raw data. The second row calculates the effects of composition. The third row calculates the compositionally-adjusted change in the data, which is the difference between the first two rows. The adjustment for composition holds fixed the share of each group in their respective average values, where groups are defined by the interaction of education, age, and family status. The other lines present the model-generated effects of keeping the distribution of primitives of the model fixed at their average distributions per sample period.

do not contribute to the rise of the employment rate and total hours during the boom. By contrast, we find that feeding into our model the average distribution of potential wages during the boom period lowers the employment rate by 0.4 percentage point and total hours by 0.7 log point relative to the factual. This result may appear counterintuitive, given the significant rise of mean potential wages documented previously in Figure 8 and our positive Marshallian elasticities of labor supply. However, it is important to realize that the increase in the mean potential wage masks significant heterogeneity across groups. Table 6 documents the drivers of total hours by subgroup. We note that potential wages increase hours only for highly educated individuals and for single and married women. For all other groups, potential wages either did not change significantly or decreased.[22] We observe significant declines in labor supply for the less educated, the young, and for married heads of households. The mapping between potential wages and wages is theoretically less than perfect, because of selection along the extensive margin. However, changes in potential wages account almost perfectly for the increases in the average wage and the price of labor during the boom.

To illustrate the importance of modeling heterogeneity, we perform a simple calculation. In Figure 8, wages and potential wages grow by roughly 20 percent. The sum of the estimated intensive and extensive elasticities of labor supply is 0.38. Had we feeded the mean change in wages into a representative worker model, we would have concluded that hours increase by roughly 8 log points. By contrast, hours per worker fall slightly in our model that explicitly considers the heterogeneous changes in wages in the cross section of workers.

After adjusting for composition, quantitatively the most important factor driving the boom of U.S. hours is the decline in the disutility of work, previously documented in Figure 8. To give a back-of-the envelope calculation, in the absence of taxes and with log preferences, hours are related to the disutility of work according to $n = (1/\chi)^{\frac{\varepsilon}{1+\varepsilon}}$. With our estimate of ε of roughly 0.5, a 25 percent decline in χ generates a roughly 8 percent increase in hours. Health benefits are rising during the boom, as seen in Figures 6 and 8, and tend to lower total hours primarily by reducing the employment rate. However, the rise of benefits is dominated quantitatively by compositional factors and the decline in the disutility of work, which mostly account for the rise of hours between the early 1980s and the late 1990s. Changes in tax system do not contribute significantly to changes in U.S. labor supply. This result may appear to contradict the original analysis of Prescott (2004). However, Prescott's analysis concerned relative differences in taxes and labor supply across countries. Tax rates in the United States did not change dramatically during the boom in U.S. hours, as shown in Figure 7.

Moving to the bottom panel of Table 5 for the bust in hours, we note that adjusting for changing composition plays a minor role for the employment rate and hours. The rising educational attainment of the population tends to increase employment and hours, as in the early part of the sample. However, the U.S. population also became older, and older individuals tend

[22]When we change only women's potential wages while keeping constant men's potential wages, we find that women's wages generate a 0.8 percentage increase in aggregate hours during the boom period. See Appendix Figures A.6 and A.7, which present the evolution of the sources of heterogeneity for education, age, and family status groups in the boom and the bust.

Table 6: Drivers of Hours Worked by Group: U.S. CPS

	Hours, en			Price of Labor, p		
(log points)	$<$ HS	HS	$>$ HS	$<$ HS	HS	$>$ HS
Change 1980-1990s	-7.1	8.2	4.5	-7.7	4.4	15.3
Wages, θ	-5.7	-1.3	3.0	-7.9	2.5	14.6
Non-labor income, z	-4.2	-1.6	-4.6	-0.1	0.1	0.1
Disutility of hours, χ	6.3	8.7	7.7	0.2	0.3	-0.1
Fixed cost, κ	8.6	0.4	3.0	0.1	0.0	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.0	-0.2	-0.4	-0.1	0.2	0.2
Health replacement, β_0/θ	-4.0	-4.0	-2.4	-1.7	-2.0	-1.0
Change 2000-2010s	-14.0	-10.9	-6.2	4.9	6.3	10.2
Wages, θ	-0.1	-0.6	0.9	0.7	0.9	5.0
Non-labor income, z	1.4	1.7	1.3	0.2	0.0	0.0
Disutility of hours, χ	1.6	-0.6	-4.5	0.1	0.0	0.0
Fixed cost, κ	4.6	5.7	-2.1	0.1	0.1	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	1.5	0.8	0.2	1.2	0.9	0.8
Health replacement, β_0/θ	-13.8	-7.7	-2.1	-6.4	-3.9	-1.1

	Hours, en			Price of Labor, p		
(log points)	15-29	30-49	50-64	15-29	30-49	50-64
Change 1980-1990s	7.3	10.7	4.6	2.4	11.1	11.9
Wages, θ	-2.6	-0.1	-0.1	-1.5	7.0	4.3
Non-labor income, z	-2.7	-3.5	-0.9	0.0	0.2	0.1
Disutility of hours, χ	9.7	8.9	4.2	0.8	0.1	-0.1
Fixed cost, κ	-1.1	3.0	2.6	0.0	0.0	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.4	-0.4	-0.3	-0.1	0.2	0.1
Health replacement, β_0/θ	-4.0	-3.9	-2.3	-2.1	-1.8	-1.2
Change 2000-2010s	-6.8	-5.1	-1.6	12.3	12.8	11.3
Wages, θ	-0.5	-0.3	0.9	1.6	1.7	4.5
Non-labor income, z	1.0	2.2	1.2	0.2	0.0	0.0
Disutility of hours, χ	-5.0	-2.6	1.3	-0.4	0.0	0.1
Fixed cost, κ	1.0	4.7	1.0	0.1	0.1	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.6	0.5	0.4	1.2	0.9	0.9
Health replacement, β_0/θ	-5.5	-5.5	-7.2	-2.9	-2.6	-3.1

	Hours, en				Price of Labor, p			
(log points)	M-m	M-w	S-m	S-w	M-m	M-w	S-m	S-w
Change 1980-1990s	-0.9	33.7	1.5	10.7	5.8	23.1	3.2	17.0
Wages, θ	-4.5	6.8	-3.9	2.0	-0.7	14.0	-1.9	10.1
Non-labor income, z	-4.8	-1.4	-4.0	4.3	0.1	0.2	0.0	0.2
Disutility of hours, χ	10.2	2.8	9.9	7.4	0.1	0.1	0.2	0.6
Fixed cost, κ	6.1	-0.8	6.3	-12.6	0.0	0.0	0.0	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.3	0.6	-0.8	-1.0	0.7	0.7	-1.6	-1.9
Health replacement, β_0/θ	-3.4	-2.1	-7.0	-4.1	-1.5	-1.5	-2.2	-2.0
Change 2000-2010s	-8.1	-0.2	-13.6	-10.2	10.7	18.9	8.4	12.2
Wages, θ	-1.6	2.2	-0.3	0.5	0.2	6.4	1.7	3.8
Non-labor income, z	2.0	1.3	-4.3	5.7	0.0	0.0	-0.4	0.2
Disutility of hours, χ	-1.8	-1.9	-1.7	-2.2	0.1	0.1	-0.1	-0.2
Fixed cost, κ	6.7	-3.4	2.9	1.9	0.1	0.1	0.0	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.4	0.7	0.7	0.9	0.5	0.4	2.2	2.4
Health replacement, β_0/θ	-4.3	-3.3	-10.5	-13.9	-2.1	-2.2	-3.6	-5.6

Notes: The table presents changes in total hours and the price of labor by subgroup. In the first panel, changes are calculated as the difference between mean outcomes in the 1990s and mean outcomes between 1978 and 1982. In the second panel, changes are calculated as differences between mean outcomes in the 2010s and mean outcomes between 1998 and 2002.

to work less. These two forces roughly offset each other quantitatively. On the other hand, adjusting for composition makes a significant difference for the wage and the price of labor, because more educated and older individuals have higher wages than less educated and younger individuals.

The effect of potential wages on labor supply is quite similar to the one documented in the early part of the sample. For the groups that experienced growth in potential wages, such as the more educated and women, Table 6 shows an increase in their hours. However, for other groups, potential wages did not grow, so in the aggregate, potential wages did not contribute significantly to changes in U.S. employment and hours. Non-labor income also does not explain why U.S. employment and hours fall in the late part of the sample. The bottom half of the non-labor income distribution experiences a decline in their non-labor income during this period, and poorer workers tend to have a more elastic labor supply than richer workers. Thus, we find that non-labor income increases labor supply during the bust of U.S. hours. We also find a minor role for changes in the tax system during that period.

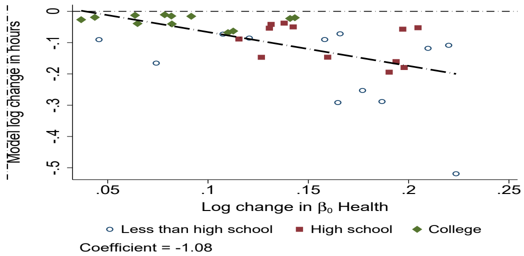
Changes in the disutility and fixed costs of work do not contribute significantly to the decline in aggregate employment and hours. However, we find that for workers between the ages of 15 and 29, the decline in the disutility of work plays a major role for the decline in hours, as shown in Table 6. This result echoes Aguiar, Bils, Charles, and Hurst (2021), who argue that the increase in the returns of leisure for young workers significantly lowered their labor supply.

Quantitatively, the most important factor driving the bust of aggregate U.S. employment and hours is the increase in health benefits.[23] To get some intuition on how benefits affect labor supply, we differentiate the price of labor in equation (7) with respect to the benefit upon non-employment β_0 and derive the elasticity

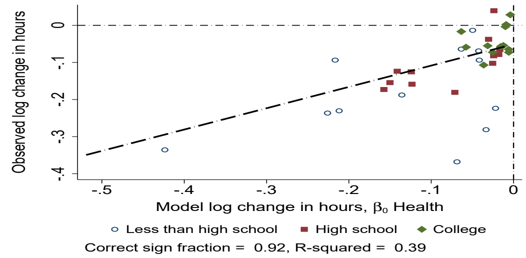
$$\frac{\partial p}{\partial \beta_0}\frac{\beta_0}{p} = -(\beta_1^2) \times \underbrace{\frac{w}{p}}_{\text{wedge}} \times \frac{\overbrace{b/\beta_0}^{\text{phase out}}}{\underbrace{\beta_0/wn}_{\text{replacement rate}}}. \tag{48}$$

The price of labor is more responsive to changes in the benefit upon non-employment the larger is the phase-out parameter β_1, the larger is the wedge between the wage and the price of labor, and the higher is benefit of the worker relative to their labor earnings. Consider, as an example, a single worker with earnings of $wn = 20,000$ dollars. This worker's wedge between the wage and the price of labor is 2.4, the phase-out term is 0.3, and the replacement rate is 0.9. The

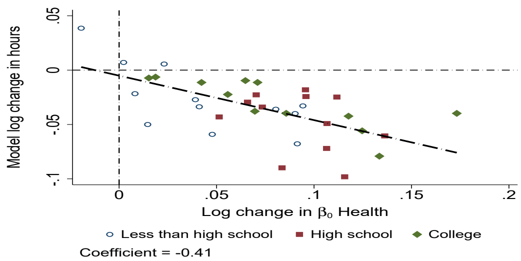
[23]In Tables 5 and 6 we present the effects of changes in health benefits as they are the most important quantitatively among all types of benefits. Appendix Table A.21 splits the effects of all taxes and all benefits on U.S. hours by subperiod and subcategory of tax and benefit.



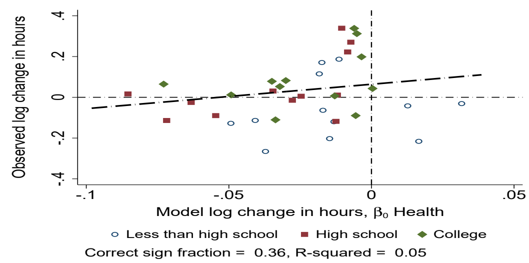
(a) Bust Period



(b) Bust Period



(c) Boom Period



(d) Boom Period

Figure 9: Health Benefits and Hours Worked Across Groups: U.S. CPS

Notes: The upper panels show the correlations across subgroups between changes in benefits due to health, model-generated changes in total hours worked, and observed changes in total hours worked for the period between 1998 and 2019. The lower panels show the correlations for the period between 1978 and 1998. Each dot represents a different group defined by the interaction of education, age, and family status, with the education groups being signified by circles, squares, and diamonds.

elasticity of the price of labor to a change in benefits is around -1. A single worker with earnings of $wn = 40,000$ dollars has a wedge of 1.8, a phase-out term of 0.1, and a replacement rate of 0.5. Thus, this worker has an elasticity of -0.4. In contrast, a single worker with earnings of $wn = 100,000$ has a zero elasticity as benefits have almost completely phased out.

Figure 9 relates the rise of health benefits to changes in total hours across groups. The upper left panel presents the relationship generated by our model during the bust of U.S. hours between 1998 and 2019. There are 24 groups in the figure, defined by their education, age, and family status. The figure signifies the groups defined by their education. As the figure shows, less educated individuals typically experienced larger changes in their health benefits than more educated groups. As is consistent with the analysis underlying equation (48), the figure also shows that, if we hold constant health benefits, less educated groups are more elastic and experience larger declines in their hours than more educated groups. Apart from education, Table 6 shows that the rise of health benefits affects single individuals more than married couples, because single individuals experienced larger increases in health benefits. The upper right panel of Figure 9 projects observed changes in hours in the data on model-generated changes in hours only due to changes in health benefits. We observe that the model predicts quite well the observed changes in hours in the data across groups, with changes in health benefits accounting for roughly 40 percent of the variation in hours observed in the data. The lower panels repeat these relationships during the boom of U.S. hours between 1978 and 1998. While health benefits also rose during that period, observed changes in hours worked do not correlate highly with model-generated changes in hours across groups, because observed changes in hours reflect many other factors that correlate with the rise of benefits.

Appendix Figures A.8 and A.9 repeat the analysis of Figure 9 for changes in other primitives of the model. Among them, only changes in potential wages during the early part of the sample have significant explanatory power in accounting for the observed cross-section of changes in total hours of demographic groups. However, as discussed above, potential wages do not account for the rise of aggregate hours in the early part of the sample. We conclude that the rise of health benefits during the late part of the sample is the only force in the model that accounts for both aggregate changes in hours worked and changes in hours worked across groups.

We present two types of evidence that relate benefits to labor supply outcomes. Figure 9 demonstrates that groups with larger changes in health benefits experience larger declines in hours than groups with smaller changes in health benefits. This type of evidence controls, through the structure of the model, for other determinants of labor supply, some of which are observed (for example, wages and non-labor income) and some of which are unobserved in typical datasets (for example, disutility and fixed costs of work). Figure 10 below shows a negative and sizable correlation between benefit replacement rates and labor supply across countries, controlling for country and time fixed effects.

How do our estimates of the effects of health benefits on labor supply compare to those found in the empirical literature? It is fair to say that the results in the literature vary considerably. To give two examples, Baicker, Finkelstein, Song, and Taubman (2014) find that low-income recipients of Medicaid in Oregon from winning a lottery decreased their employment rate by 1.6 percentage points relative to those who were on the lottery list and were not selected, but this decrease is not statistically significant. Meanwhile, Garthwaite, Gross, and Notowidigdo (2014) examine the loss in Medicaid coverage in Tennessee using a difference-in-differences strategy, and find that a 7.3 percentage points drop in public coverage for childless adults was associated with a 4.6 percentage points increase in their employment rate. Table 5 reports a 3.2 percentage points decline in the employment rate in response to the rise in health benefits between 2000 and the 2010s. To make more direct comparisons to the empirical literature, we calculate employment rates in our model when we entirely remove health benefits from recipients. The aggregate employment rate increases by 2.4 percentage points, with the employment rate increasing by 6 percentage points for single and 1 percentage point for married individuals. Removing health benefits for childless adults who are already receiving health benefits increases their employment rate between 8 (for married) and 32 (for single) percentage points. These responses are significantly lower than the 0.6 ratio of employment to disenrollment in Garthwaite, Gross, and Notowidigdo (2014), because the drop in public coverage in our case is 100 percentage points. Appendix Figures A.10 and A.11 present the detailed results.

We conclude this section by presenting two robustness exercises. First, we examine the sensitivity of our results to the way we imputed the wage of the non-employed. Appendix Figure A.12 shows the evolution of sources of heterogeneity when we implement a Heckman selection model to infer the wages of the non-employed. We find that the wage of the non-employed for single individuals and for married heads exceeds the wage of the employed, so that the correction for selection yields a negative selection on unobservables for these groups. For married spouses, the selection is typically positive, and thus in most years, the wage of the non-employed is lower than the wage of the employed. Appendix Figure A.13 presents estimates from the implementation of the Heckman model. Appendix Table A.22 is the analog of Table 5, using the Heckman model to infer the wages of the non-employed and new estimates of the fixed costs and parameter $\alpha = 0.70$. None of our conclusions about the drivers of U.S. hours change when using the Heckman model.[24]

The second exercise examines the sensitivity of our results to the way we measure health benefits. In our baseline results, Medicaid benefits are valued at the cost that the government faces to provide these benefits. We prefer this assumption to the alternative assumption adopted in some of the Census measurements that values health benefits at their fungible values, because fungible values are zero or low for low-income households.[25] However, we acknowledge that there are various reasons why government's spending on health benefits may deviate from the monetary value that households attach to these benefits. Some of these benefits may

[24] Alternatively, we have considered ad-hoc adjustments to the potential wages of the non-employed, so that some of the unobserved differences between the employed and the non-employed load on potential wages instead of fixed costs. Appendix Table A.23 repeats the results for the drivers of U.S. hours from the CPS when we lower the potential wages of the non-employed by 20 percent relative to the potential wages predicted based on observables in our baseline. We find that the results are indistinguishable from our baseline results, because this adjustment essentially shifts the potential wages and fixed costs of the non-employed by a constant proportion over time and does not affect changes in hours per person over time.

[25] Let cash income be the sum of earnings, food stamps, and housing subsidies. Only if cash income exceeds the sum of food costs, housing costs, and Medicaid or Medicare costs, does the Census equate the fungible value with the cost of health benefits. If cash income is below the cost of food and housing, the fungible value of health benefits is assumed to be zero. If the cash income exceeds the cost of food and housing but is below the cost of food and housing and the cost of Medicaid or Medicare, then the fungible value of health benefits is the excess income over the cost of food and housing. See https://tinyurl.com/3svc2u2b for more details of the measurements adopted by the Census.

indeed not be fungible, which means that households may not reduce their total consumption expenditure one-to-one with the reduction in health benefits. In addition, some of the value of providing health benefits may accrue indirectly to firms providing health services, because these firms would otherwise provide uncompensated services to uninsured individuals. Finally, health benefits may be more valuable than the cost of providing them by the government, to the extent that these benefits provide insurance in states of the world with poor health. For our robustness check, we adopt the assumption in Mulligan (2012) that the income value of health benefits is 50 percent of their cost to the government and multiply our original values for health benefits in b by 0.5.[26] Appendix Table A.24 is the analog of Table 5, when valuing health benefits at 50 percent of their cost to the government. This adjustment reduces somewhat the role of health benefits in the decline of hours after the 2000s. Applying a 50 percent discount generates a decline of 4.5 percentage points in total hours per person due to health benefits during the bust period, compared with our baseline estimate of 6.3 percentage points.[27]

6 International Results

We begin our international analyses by presenting some summary statistics and motivating reduced-form evidence that relate benefits to hours worked across countries. We then use cross-country micro-level data and our structural model to analyze the drivers of the convergence of hours between the United States and several non-U.S. countries.

6.1 Benefits and Labor Supply Across Countries

We combine the data on hours worked from the OECD, used previously in Section 2, with the OECD's database on social benefits and expenditures starting in 1980. The OECD's data on social benefits to households are broken down into social transfers in kind and social benefits other than social transfers in kind. The latter are typically in cash, whereas benefits in kind are related to the provision of certain goods or services and predominantly reflect health care and education. Cash benefits are further broken down into pensions and non-pension benefits. The OECD data are compiled according to the 2008 System of National Accounts (SNA).

[26]This estimate is also consistent with some of the estimates presented in Finkelstein, Hendren, and Luttmer (2019) for recipients' willingness to pay for Medicaid following the Oregon Health Insurance Experiment. Under their complete information model, the authors report a willingness to pay 116 percent of the net cost to the government, with the net cost to the government being around 40 percent of the total cost, as the majority of the cost accrues to health care providers.

[27]For this exercise, we reestimate parameters ($\gamma = 1.08, \varepsilon = 0.52, \alpha = 0.41$) and repeat our analyses of inferring the sources of heterogeneity using the adjusted values of b. The decline in the importance of health benefits is offset by an increasing importance of the disutility of work and fixed costs.

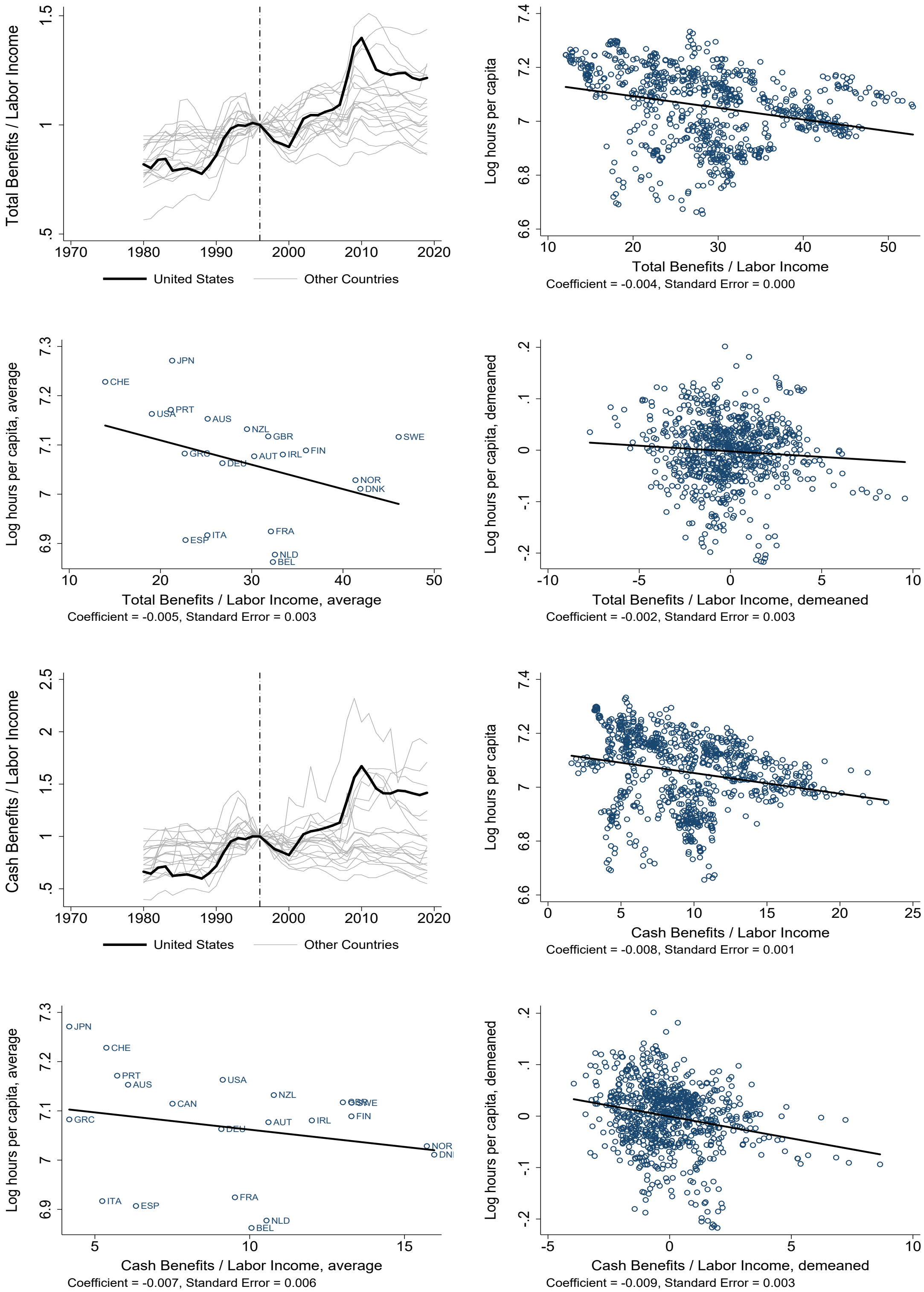


Figure 10: Benefits and Hours Worked Across Countries

Notes: The first panel shows the ratio of total benefits less pensions divided by labor income for the United States (solid, black line) and non-U.S. countries (thin, gray lines) presented in Table 1. All ratios are normalized to one in 1996, which is the last year covered by the analysis of Prescott (2004). The next three panels present the correlation between total benefits to labor income and hours worked, first in the raw data, then when we take averages for each country over time, and finally when we demean the data using country and time fixed effects. The next four panels repeat these statistics for cash benefits less pensions to labor income.

The first panel of Figure 10 presents the evolution of total benefits excluding pensions relative to labor income for the United States (solid, black line) and non-U.S. countries (thin, gray lines). Similar to our analysis in Section 2, we normalize the ratio to one in 1996. We observe that benefits to labor income have increased for most OECD countries in our sample. However, the increase is larger in the United States, especially after around 2000. The next three panels correlate benefits to labor income with total hours worked across countries and time. The second panel shows the total variation in the data, the third panel shows the between variation (averaged benefits to labor income and averaged log hours worked), and the fourth panel shows the within variation when we demean both variables using time and country fixed effects. We observe a negative—and, in the second and third panels, statistically significant—relationship between benefits and hours worked. A 5 percentage points increase in benefits relative to labor income is associated with a roughly 2 percent decline in hours worked.

The four lower panels repeat these analyses when we use cash benefits as opposed to total benefits (again, excluding pensions). Here, we also observe a larger increase in cash benefits relative to labor income over time for the United States. The statistical relationship between cash benefits and hours worked becomes stronger. A 5 percentage points increase in benefits relative to labor income is associated with a roughly 4 percent decline in hours worked.

The relationship between cash benefits and hours worked in Figure 10 is roughly consistent with the quantitative effects of benefits on labor supply estimated through our structural model for the United States in Section 5.4. For example, Figure 6 shows an increase in benefits to labor income of roughly 4 percentage points between 2000 and the late 2010s, and Table 5 reports a roughly 6 log points decline in total hours. However, the evidence presented in Figure 10 is correlational in nature, because other factors that determine hours worked correlate with benefits. Some of these factors, such as the disutility and fixed cost of work, are unobserved and inferred through the lens of our model. It is equally important to note that the empirical relationship between aggregate benefits and aggregate hours worked may not necessarily be that informative, because what matters for aggregate labor supply is the incidence of who receives the benefits, which cannot be measured without micro-level data. In the rest of this section, we use our structural model and micro-level datasets for various countries.

6.2 International Micro-Level Data

For wages, employment, hours, and benefits our main source data is the LIS. For our imputation of non-labor income, we use data from the LWS. The LIS and LWS acquire various micro-level datasets with income, wealth, employment, and demographic data from many countries and harmonize these data to allow researchers to conduct comparisons across countries. The coverage and quality of the LIS data allow us to perform analyses for Canada, Germany, France, Italy, Spain, Sweden, the United Kingdom, and the United States. Because of coverage issues in the LIS data, we present analyses on the evolution of hours for only the post-2000 period.[28]

Whenever feasible, we follow the same steps as in the U.S. CPS to clean the data and to measure or impute variables. In this section, we highlight some differences between the CPS and the LIS data. Appendix E presents additional details of our work to further harmonize the data and a country-by-country guide of the steps that we followed to construct our final dataset.[29] Hours worked and employment at the LIS are constructed similarly to those in the CPS. Wages are also constructed similarly, apart from farm income which is observed only at the household level and is therefore split equally between spouses. We follow country-specific hours thresholds to classify individuals as employed. The principle is that we try to match in the LIS the employment rate observed in the OECD data. For non-labor income, we sum one-third of business income, alimony, child support, and remittances to imputed non-labor income from the LWS.

The LIS includes seven categories of benefits: family benefits (child allowance, maternity and paternity payments), unemployment insurance, sickness and injury payments, disability, general assistance, housing benefits, and public in-kind benefits such as food benefits. As in the CPS, we also add unaccounted labor income into benefits for all countries in the data. A major difference between the LIS data and the CPS data for the United States is that the LIS does not measure health benefits, because in other countries, these benefits are financed universally by the government irrespective of employment status or income level. Our solution is to use the U.S. CPS data to relate receipt and benefit amount to various demographic and income variables, and then use this information to predict health benefits in the U.S. LIS data. Thus, in the LIS data, we split benefits into health benefits that exist only for the United States, welfare and UI (sum of LIS variables hi41 to hi45), other (sum of LIS variables hi46 to hi47),

[28]Our analyses require longer time series, and thus we cannot rely on the same sources used in recent work compiling and analyzing international datasets of hours worked for a larger number of countries, such as Bick, Lagakos, and Fuchs-Schundeln (2018) or Donovan, Lu, and Schoellman (2023). Appendix Table A.25 presents the yearly coverage of available data in the LIS and the LWS for each country in our sample and Appendix Table A.26 presents the subperiods. In Appendix Table A.27 we present summary statistics for the employment rate in the LIS data as compared to the OECD data.

[29]A difference between the U.S. CPS and the U.S. LIS is that the LIS uses the ASEC oversample with the additional State Childrens Health Insurance Program sample and the Hispanic sample. Because these samples typically have lower labor market attachment and basic employment statistics are derived from basic monthly files, we do not use ASEC oversamples in our CPS estimates. In the LIS, there is no way for us to identify individuals that belong to the oversample. The rest of the sample selection is identical to that in the CPS.

and unaccounted labor income.[30]

Comparing the LIS benefits relative to labor income to the same ratio reported from the OECD in Figure 10 we find that the LIS significantly underestimates benefits for some non-U.S. countries. To adjust benefits for underreporting in the LIS, for non-U.S. countries we use the ratio of OECD cash benefits over labor income to LIS benefits to labor income, and scale the categories of benefits, except for unaccounted labor income, proportionally for every individual in each year of the LIS survey. Appendix Figure A.14 shows LIS and OECD ratios of benefits to labor income, with the ratio of the two being our adjustment factor.

For taxes, we do not have consistent information across countries on social security taxes paid. For this reason, we estimate the average tax rate for each country by adding the social security taxes on labor income from the McDaniel (2011) dataset with the income taxes reported by households or individuals in the LIS dataset. Using the sum of these taxes, we then estimate the progressivity parameter τ_1 for each country, which depends on whether a country has individual taxation (Canada, Sweden, Italy, and the United Kingdom), income-splitting taxation (Germany), or joint taxation (France, Spain, and the United States). Parameter τ_0 is estimated so that, given estimates of τ_1, the in-sample average tax rate on labor income equals our estimate of the average tax rate, which includes the social security tax rates from McDaniel. For countries with individual taxation, we estimate a single τ_0 parameter by year to hit the same average tax rate in each year for all individuals, whereas for countries without individual taxation, we estimate separate τ_0 parameters for single and married individuals to hit their respective average tax rates.

6.3 The Drivers of Hours Across Countries

We feed in the international micro-level data to our model and repeat the steps we followed previously for the U.S. CPS data to estimate parameters and infer the sources of heterogeneity for each country.[31] In Figure 11, we present the changes in the employment rate and total hours worked for the post-2000 periods from the LIS data, alongside the U.S. CPS estimates for comparison. We present both unadjusted changes over time and changes adjusted for composition. For the United States, we note the similarity between the U.S. CPS trends and

[30]Effectively, for non-U.S. countries, we treat health insurance as a public good that enters separably into preferences. This is justified because health insurance does not create disincentives at the margin to work in non-U.S. countries. The same logic applies to other government expenditures such as public education or public infrastructure, and thus we do not model cross-country differences in these programs.

[31]Appendix Table A.28 presents our estimated parameters $\epsilon, \gamma, \alpha, \beta_1$ by country. Appendix Figures A.15 and A.16 report the average tax rate and the progressivity parameter τ_1 for single and married individuals by country. Appendix Figures A.17 to A.22 report the sources of heterogeneity for single individuals by country and Appendix Figures A.23 to A.28 report the sources of heterogeneity for married couples by country.

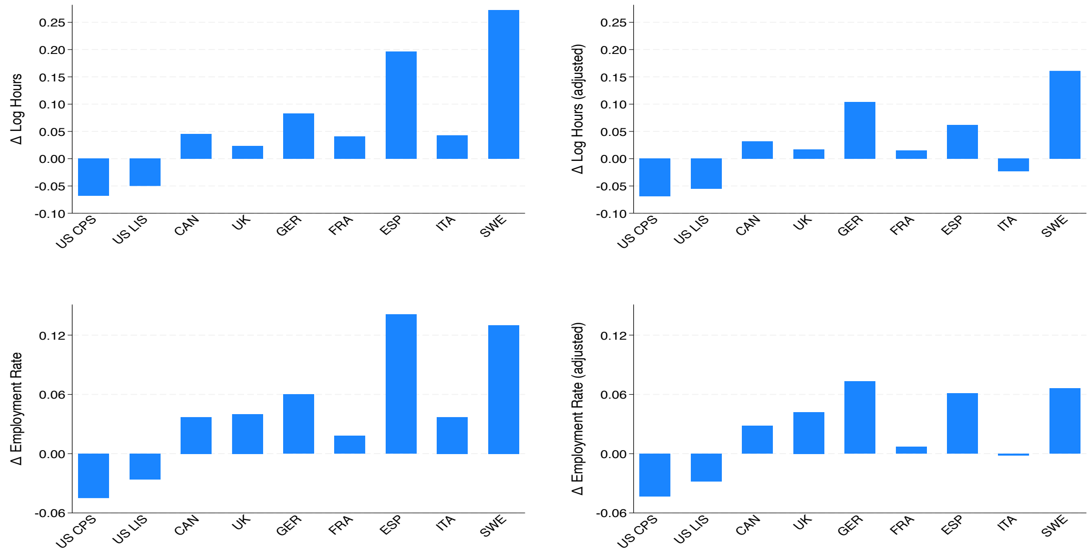


Figure 11: Changes in Hours Worked and Employment Across Countries, Post-2000 Period
Notes: The figure shows changes in total hours worked and the employment rate by country in the post-2000 period.

the trends calculated in the LIS, both in terms of the employment rate and for total hours worked. As is consistent with our analyses using aggregate OECD data in Section 2, all non-U.S. countries exhibit increases in the employment rate and hours worked in the post-2000 period. While composition plays a relatively larger role in both Italy and Spain, the two cases differ after adjusting for composition: hours worked decline slightly in Italy, whereas Spain continues to exhibit an increase in both hours worked and the employment rate.

Figure 12 summarizes our counterfactuals for the post-2000 period. Our methodology is similar to the one we followed previously for the data for the United States from the CPS. Each panel presents the effects of changes in a primitive on changes in log total hours worked in the LIS, alongside our previous results from the CPS for the United States for comparison. In the first panel, we observe that changes in potential wages do not contribute significantly to changes in hours worked for the United States (both in the CPS and in the LIS). On the other hand, changes in potential wages contribute to an increase in hours worked in all non-U.S. countries with the exception of Germany. With the exception of Germany and Italy, declines in either the disutility of work or fixed costs of working also contribute significantly into the increases of hours worked in non-U.S. countries. With the exception of Sweden, we do not find a significant role for changes in the tax system in any country. By contrast, we find a significant role for changes in benefits. In addition to the United States, the United Kingdom, France, and Spain experience significant declines in their hours worked due to the rise of the replacement rate

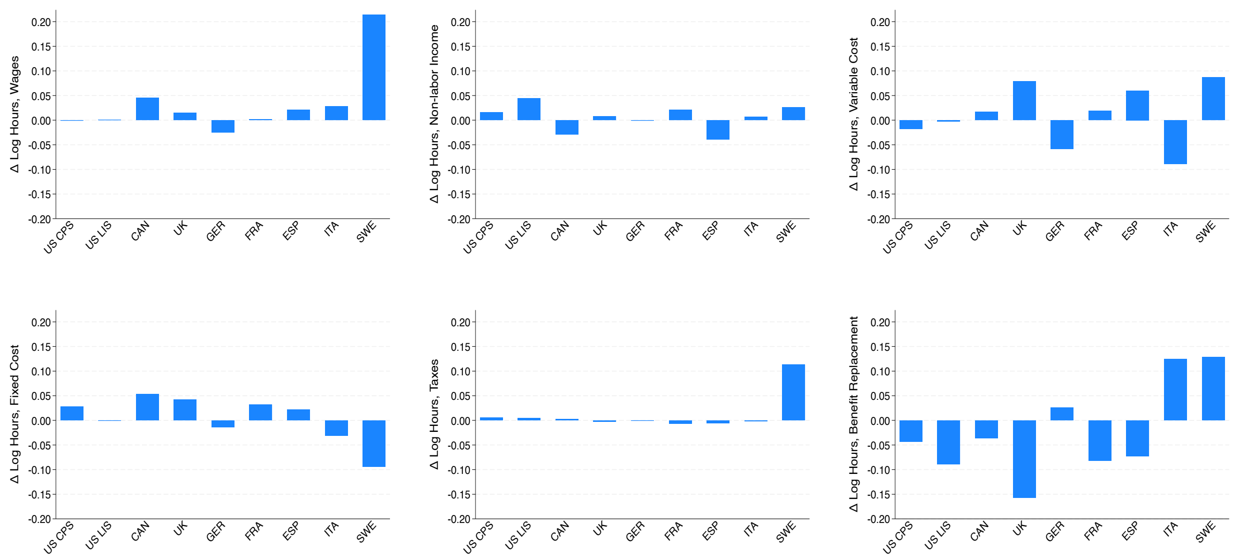


Figure 12: Drivers of Hours Worked Across Countries, Post-2000 Period

Notes: The figure shows the contribution of changes in primitives to total hours worked by country in the post-2000 period.

of benefits. Differently from the United States, however, for these three countries, changes in the disutility of work and fixed costs increase hours worked, mitigating the effects of changes in benefit replacement rates. Finally, we find that changes in the benefit replacement rates actually increase hours worked in Germany, Italy, and Sweden.

To summarize, with the exception of Germany, non-U.S. countries increase their labor supply owing to a broader mix of factors, including higher wages, declining disutility of work and fixed costs, and, in some cases, changes in benefits. However, different from the United States, there is no single driver of the increase in labor supply that stands out as prominently as benefits do in terms of the decline in the labor supply of the United States.

7 Conclusion

Though in the 1990s Americans used to work much more than non-Americans, twenty years later, roughly half of this gap has disappeared. In this paper, we document trends in hours worked across countries and offer a comparative study on the convergence of hours worked. We develop a parsimonious model of labor supply and estimate it with detailed measurements from various micro-level and aggregate datasets. We use our model to run a horse race between various competing explanations and assess quantitatively the convergence of hours worked between non-U.S. countries and the United States after the 2000s. Our main finding is that U.S. hours per person declined after the 2000s because of the rise of benefits provided to the non-employed.

Among these benefits, we find the most important role for health benefits and, in particular, Medicaid. For non-U.S. countries, the rise of labor supply is generally accounted for by a rise of wages and falling fixed costs and disutility of work. The latter is also consistent with the rise of hours in the United States between the 1970s and the 1990s, which was driven by compositional changes and a declining disutility of work.

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Why Do Americans No Longer Work So Much More Than Non-Americans?

Online Appendix

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Appendix A presents details of the data used for the aggregate cross-country analyses and additional results. Appendix B presents various model derivations. Appendix C provides details of the U.S. datasets and Appendix D presents additional results from the U.S. data. Appendix E provides details of the international datasets and Appendix F presents additional results from the international data.

A Aggregate Data

Data sources for aggregate data.

For our analysis using aggregate data, we perform some imputations to fill in missing data.

- We impute missing population variables in the OECD (total or by age group) using PWT total population.
- We impute missing employment variables in the OECD (total or by age group) using PWT total employment.
- We impute missing total hours per worker variables in the OECD using PWT total hours per worker.
- For sex-specific employment rates, we first impute few missing observations for total women's employment using the trend in the share of women's employment in other countries. We then impute missing observations for age groups using total employment by sex from the OECD.
- We impute cash benefits less pensions and total benefits less pensions using OECD's total social expenditure less pensions variable.

Additional results from aggregate data analysis.

- Appendix Table A.1 presents hours per person relative to the United States, using employment of persons between 15 and 64 divided by population of persons between 15 and 64.

- Appendix Table A.2 presents hours per person relative to the United States, using employment of persons between 15 and 54 divided by population of persons between 15 and 54.
- Appendix Table A.3 presents hours per person relative to the United States, using employment of persons between 25 and 64 divided by population of persons between 25 and 64.
- Appendix Table A.4 presents hours per person relative to the United States, using total employment divided by total population.
- Appendix Table A.5 presents the decomposition of the gap in hours per person relative to the United States, using employment of persons between 15 and 64 divided by population of persons between 15 and 64.
- Appendix Table A.6 presents the decomposition of the gap in hours per person relative to the United States, using employment of persons between 15 and 54 divided by population of persons between 15 and 54.
- Appendix Table A.7 presents the decomposition of the gap in hours per person relative to the United States, using employment of persons between 25 and 64 divided by population of persons between 25 and 64.
- Appendix Table A.8 presents the decomposition of the gap in hours per person relative to the United States, using total employment divided by total population.
- Appendix Table A.9 presets hours per person relative to United States, using men's employment of person between 15 and 64 divided by men's population of persons between 15 and 64.
- Appendix Table A.10 presents the decomposition of the gap in hours per person relative to the United States, using men's employment of persons between 15 and 64 divided by men's population of persons between 15 and 64.
- Appendix Table A.11 presets hours per person relative to United States, using women's employment of person between 15 and 64 divided by women's population of persons between 15 and 64.

- Appendix Table A.12 presents the decomposition of the gap in hours per person relative to the United States, using women's employment of persons between 15 and 64 divided by women's population of persons between 15 and 64.

B Model

Elasticity formulas with benefits, single individuals. The first-order condition for optimal hours conditional on working are:

$$\frac{c^{-\gamma}}{1+\tau_c}\underbrace{\left((1-\tau_0)(1-\tau_1)(wn)^{-\tau_1}-\beta_1\exp(-\beta_1 wn/\beta_0)\right)w}_{y_n+b_n}=\chi n^{1/\varepsilon}, \tag{A.1}$$

$$(1+\tau_c)c=\underbrace{(1-\tau_0)(wn)^{1-\tau_1}}_{y}+\underbrace{\beta_0\exp(-\beta_1 wn/\beta_0)}_{b}+(1-\tau_z)z. \tag{A.2}$$

We use the implicit function theorem to derive the Marshallian elasticities with respect to w and $1-\tau_0$ and the Frisch elasticities with respect to w and $1-\tau_0$:

$$\eta_w=\frac{\partial n}{\partial w}\frac{w}{n}=\frac{\frac{\gamma w}{(1+\tau_c)c}(y_n+b_n)(y_w+b_w)-(y_{nw}+b_{nw})w}{-\frac{1}{\varepsilon}(y_n+b_n)+(y_{nn}+b_{nn})n-\frac{(y_n+b_n)^2\gamma n}{(1+\tau_c)c}}, \tag{A.3}$$

$$\eta_{1-\tau_0}=\frac{\partial n}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n}=\frac{\frac{\gamma(1-\tau_0)}{(1+\tau_c)c}(y_n+b_n)y_t-y_{nt}(1-\tau_0)}{-\frac{1}{\varepsilon}(y_n+b_n)+(y_{nn}+b_{nn})n-\frac{(y_n+b_n)^2\gamma n}{(1+\tau_c)c}}, \tag{A.4}$$

$$\eta_{w|c}=\left.\frac{\partial n}{\partial w}\frac{w}{n}\right|_c=\frac{(y_{nw}+b_{nw})w}{\frac{1}{\varepsilon}(y_n+b_n)-(y_{nn}+b_{nn})n}, \tag{A.5}$$

$$\eta_{1-\tau_0|c}=\left.\frac{\partial n}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n}\right|_c=\frac{y_{nt}(1-\tau_0)}{\frac{1}{\varepsilon}(y_n+b_n)-(y_{nn}+b_{nn})n}, \tag{A.6}$$

where the derivatives are given by

$$\begin{aligned}
y_n &= (1-\tau_0)(1-\tau_1)(wn)^{-\tau_1}w,\\
b_n &= -\beta_1 w\exp\left(-\frac{\beta_1 wn}{\beta_0}\right),\\
y_w &= (1-\tau_0)(1-\tau_1)(wn)^{-\tau_1}n,\\
y_t &= (wn)^{1-\tau_1},\\
b_w &= -\beta_1 n\exp\left(-\frac{\beta_1 wn}{\beta_0}\right),\\
y_{nn} &= -\tau_1(1-\tau_0)(1-\tau_1)n^{-\tau_1-1}w^{1-\tau_1},\\
b_{nn} &= \frac{\beta_1^2 w^2}{\beta_0}\exp\left(-\frac{\beta_1 wn}{\beta_0}\right),
\end{aligned}$$

$$
\begin{aligned}
y_{nw} &= (1-\tau_0)(1-\tau_1)^2(wn)^{-\tau_1}, \\
y_{nt} &= (1-\tau_1)(wn)^{-\tau_1} w, \\
b_{nw} &= -\beta_1 \exp\left(-\frac{\beta_1 wn}{\beta_0}\right)\left(1-\frac{\beta_1 wn}{\beta_0}\right).
\end{aligned}
$$

Elasticity formulas with benefits, married couples. The first-order condition for optimal hours conditional on working for member j are:

$$
\frac{c^{-\gamma}}{1+\tau_c} \underbrace{\left((1-\tau_0)(1-\tau_1)(\sum_j w_j n_j)^{-\tau_1} - \beta_1 \exp(-\beta_1(\sum_j w_j n_j)/\beta_0)\right) w_j}_{y_{n_j}+b_{n_j}} = \chi_j n_j^{1/\varepsilon}, \tag{A.7}
$$

$$
(1+\tau_c)c = \underbrace{(1-\tau_0)(w_1 n_1 + w_2 n_2)^{1-\tau_1}}_{y} + \underbrace{\beta_0 \exp(-\beta_1(w_1 n_1 + w_2 n_2)/\beta_0)}_{b} + (1-\tau_z)z. \tag{A.8}
$$

We use the implicit function theorem to derive the Marshallian elasticities with respect to w and $1-\tau_0$, the Frisch elasticities with respect to w and $1-\tau_0$, and the cross-wage elasticity:

$$
\eta_w^j = \frac{\partial n_j}{\partial w_j}\frac{w_j}{n_j} = \frac{\frac{\gamma w_j}{(1+\tau_c)c}(y_{n_j}+b_{n_j})(y_{w_j}+b_{w_j}) - (y_{n_j w_j}+b_{n_j w_j})w_j}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.9}
$$

$$
\eta_{1-\tau_0}^j = \frac{\partial n_j}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n_j} = \frac{\frac{\gamma(1-\tau_0)}{(1+\tau_c)c}(y_{n_j}+b_{n_j})y_t - y_{n_j t}(1-\tau_0)}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.10}
$$

$$
\eta_{w|c}^j = \frac{\partial n_j}{\partial w_j}\frac{w_j}{n_j} = \frac{(y_{n_j w_j}+b_{n_j w_j})w_j}{\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) - (y_{n_j n_j}+b_{n_j n_j})n_j}, \tag{A.11}
$$

$$
\eta_{1-\tau_0|c}^j = \frac{\partial n_j}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n_j} = \frac{y_{n_j t}(1-\tau_0)}{\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) - (y_{n_j n_j}+b_{n_j n_j})n_j}, \tag{A.12}
$$

$$
\eta_{jk} = \frac{\partial n_j}{\partial w_k}\frac{w_k}{n_j} = \frac{\frac{\gamma w_k}{(1+\tau_c)c}(y_{n_j}+b_{n_j})(y_{w_k}+b_{w_k}) - (y_{n_j w_k}+b_{n_j w_k})w_k}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.13}
$$

where the derivatives are given by

$$
\begin{aligned}
y_{n_j} &= (1-\tau_0)(1-\tau_1)(w_1 n_1 + w_2 n_2)^{-\tau_1} w_j, \\
b_{n_j} &= -\beta_1 w_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right), \\
y_{w_j} &= (1-\tau_0)(1-\tau_1)(w_1 n_1 + w_2 n_2)^{-\tau_1} n_j, \\
y_t &= (w_1 n_1 + w_2 n_2)^{1-\tau_1}, \\
b_{w_j} &= -\beta_1 n_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right),
\end{aligned}
$$

$$
\begin{aligned}
y_{n_j n_j} &= -\tau_1(1-\tau_0)(1-\tau_1)(w_1n_1+w_2n_2)^{-\tau_1-1}w_j^2,\\
b_{n_j n_j} &= \frac{\beta_1^2 w_j^2}{\beta_0}\exp\left(-\frac{\beta_1(w_1n_1+w_2n_2)}{\beta_0}\right),\\
y_{n_j t} &= (1-\tau_1)(w_1n_1+w_2n_2)^{-\tau_1}w_j,\\
y_{n_j w_j} &= -\tau_1(1-\tau_0)(1-\tau_1)(w_1n_1+w_2n_2)^{-\tau_1-1}w_jn_j+(1-\tau_0)(1-\tau_1)(w_1n_1+w_2n_2)^{-\tau_1},\\
y_{n_j w_k} &= -\tau_1(1-\tau_0)(1-\tau_1)(w_1n_1+w_2n_2)^{-\tau_1-1}w_jn_k,\\
b_{n_j w_j} &= -\beta_1\exp\left(-\frac{\beta_1(w_1n_1+w_2n_2)}{\beta_0}\right)\left(1-\frac{\beta_1 w_jn_j}{\beta_0}\right),\\
b_{n_j w_k} &= \frac{\beta_1^2}{\beta_0}\exp\left(-\frac{\beta_1(w_1n_1+w_2n_2)}{\beta_0}\right)w_jn_k.
\end{aligned}
$$

Analysis of married couples under individual taxation. The only difference relative to the analysis in the main text is that after-tax household income in the budget constraint (12) becomes

$$
y=(1-\tau_0)\left((w_1n_1)^{1-\tau_1}+(w_2n_2)^{1-\tau_1}\right). \tag{A.14}
$$

Equations (20) to (23) are replaced by

$$
\begin{aligned}
\eta_{jw} &\equiv \frac{\partial n_j}{\partial w_{j\iota}}\frac{w_{j\iota}}{n_j}=\frac{(1-\tau_1)(1-\gamma s_{j\iota})}{\frac{1}{\varepsilon}+\gamma s_{j\iota}+\tau_1(1-\gamma s_{j\iota})}, && \text{(A.15)}\\
\eta_{j1-\tau_0} &\equiv \frac{\partial n_j}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n_j}=\frac{1-\gamma s_{j\iota}}{\frac{1}{\varepsilon}+\gamma s_{j\iota}+\tau_1(1-\gamma s_{j\iota})}, && \text{(A.16)}\\
\eta_{jz} &\equiv \frac{\partial n_j}{\partial(1-\tau_z)z_\iota}\frac{(1-\tau_z)z_\iota}{n_j}=\frac{-\gamma\,(1-s_{j\iota})}{\frac{1}{\varepsilon}+\gamma s_{j\iota}+\tau_1(1-\gamma s_{j\iota})}, && \text{(A.17)}\\
\eta_{jk} &\equiv \frac{\partial n_j}{\partial w_{k\iota}}\frac{w_{k\iota}}{n_j}=\frac{-(1-\tau_1)\gamma s_{k\iota}}{\frac{1}{\varepsilon}+\gamma s_{j\iota}+\tau_1(1-\gamma s_{j\iota})}, && \text{(A.18)}
\end{aligned}
$$

where $s_{j\iota}=(1-\tau_0)(w_{j\iota}n_j)^{1-\tau_1}/(1+\tau_c)c$ is individual j's labor income share.

These formulas apply only when $\beta_1\to\infty$, so that benefits complete phase out upon working positive hours. For the more general case with benefits that phase out slower, we obtain the first-order conditions for optimal hours conditional on working for member j

$$
\frac{c^{-\gamma}}{1+\tau_c}\underbrace{\left((1-\tau_0)(1-\tau_1)(w_jn_j)^{-\tau_1}-\beta_1\exp(-\beta_1(\sum_j w_jn_j)/\beta_0)\right)w_j}_{y_{n_j}+b_{n_j}}=\chi_j n_j^{1/\varepsilon}, \tag{A.19}
$$

$$
(1+\tau_c)c=\underbrace{(1-\tau_0)((w_1n_1)^{1-\tau_1}+(w_2n_2)^{1-\tau_1})}_{y}+\underbrace{\beta_0\exp(-\beta_1(w_1n_1+w_2n_2)/\beta_0)}_{b}+(1-\tau_z)z.
$$

$$(A.20)$$

We use the implicit function theorem to derive the Marshallian elasticities with respect to w and $1-\tau_0$, the Frisch elasticities with respect to w and $1-\tau_0$, and the cross-wage elasticity:

$$\eta_w^j = \frac{\partial n_j}{\partial w_j}\frac{w_j}{n_j} = \frac{\frac{\gamma w_j}{(1+\tau_c)c}(y_{n_j}+b_{n_j})(y_{w_j}+b_{w_j}) - (y_{n_j w_j}+b_{n_j w_j})w_j}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.21}$$

$$\eta_{1-\tau_0}^j = \frac{\partial n_j}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n_j} = \frac{\frac{\gamma(1-\tau_0)}{(1+\tau_c)c}(y_{n_j}+b_{n_j})y_t - y_{n_j t}(1-\tau_0)}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.22}$$

$$\eta_{w|c}^j = \frac{\partial n_j}{\partial w_j}\frac{w_j}{n_j} = \frac{(y_{n_j w_j}+b_{n_j w_j})w_j}{\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) - (y_{n_j n_j}+b_{n_j n_j})n_j}, \tag{A.23}$$

$$\eta_{1-\tau_0|c}^j = \frac{\partial n_j}{\partial(1-\tau_0)}\frac{(1-\tau_0)}{n_j} = \frac{y_{n_j t}(1-\tau_0)}{\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) - (y_{n_j n_j}+b_{n_j n_j})n_j}, \tag{A.24}$$

$$\eta_{jk} = \frac{\partial n_j}{\partial w_k}\frac{w_k}{n_j} = \frac{\frac{\gamma w_k}{(1+\tau_c)c}(y_{n_j}+b_{n_j})(y_{w_k}+b_{w_k}) - (y_{n_j w_k}+b_{n_j w_k})w_k}{-\frac{1}{\varepsilon}(y_{n_j}+b_{n_j}) + (y_{n_j n_j}+b_{n_j n_j})n_j - \frac{(y_{n_j}+b_{n_j})^2\gamma n_j}{(1+\tau_c)c}}, \tag{A.25}$$

where the derivatives are given by

$$\begin{aligned}
y_{n_j} &= (1-\tau_0)(1-\tau_1)(w_j n_j)^{-\tau_1} w_j,\\
b_{n_j} &= -\beta_1 w_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right),\\
y_{w_j} &= (1-\tau_0)(1-\tau_1)(w_j n_j)^{-\tau_1} n_j,\\
y_t &= (w_1 n_1)^{1-\tau_1} + (w_2 n_2)^{1-\tau_1},\\
b_{w_j} &= -\beta_1 n_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right),\\
y_{n_j n_j} &= -\tau_1(1-\tau_0)(1-\tau_1)(w_j n_j)^{-\tau_1-1} w_j^2,\\
b_{n_j n_j} &= \frac{\beta_1^2 w_j^2}{\beta_0}\exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right),\\
y_{n_j t} &= (1-\tau_1)(w_j n_j)^{-\tau_1} w_j,\\
y_{n_j w_j} &= -\tau_1(1-\tau_0)(1-\tau_1)(w_j n_j)^{-\tau_1-1} w_j n_j + (1-\tau_0)(1-\tau_1)(w_j n_j)^{-\tau_1},\\
y_{n_j w_k} &= 0,\\
b_{n_j w_j} &= -\beta_1 \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right)\left(1 - \frac{\beta_1 w_j n_j}{\beta_0}\right),\\
b_{n_j w_k} &= \frac{\beta_1^2}{\beta_0}\exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right) w_j n_k.
\end{aligned}$$

Analysis of married couples under split taxation. The only difference relative to the analysis in the main text is that after-tax household income in the budget constraint (12) becomes

$$y = (1-\tau_0)\left[2\left(\frac{w_1 n_1 + w_2 n_2}{2}\right)^{1-\tau_1}\right] = 2^{\tau_1}(1-\tau_0)\,(w_1 n_1 + w_2 n_2)^{1-\tau_1}. \tag{A.26}$$

The elasticity formulas when benefits phase-out immediately with positive hours ($\beta_1 \to \infty$) are identical to those under joint taxation, as given in Equations (20) to (23). For the more general case in which benefits phase out more gradually, we derive the first-order conditions for optimal hours, conditional on working, for household member j:

$$\frac{c^{-\gamma}}{1+\tau_c}\underbrace{\left(2^{\tau_1}(1-\tau_0)(1-\tau_1)(w_1 n_1 + w_2 n_2)^{-\tau_1} - \beta_1 \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right)\right) w_j}_{y_{n_j}+b_{n_j}} = \chi_j n_j^{1/\varepsilon}, \tag{A.27}$$

$$(1+\tau_c)c = \underbrace{2^{\tau_1}(1-\tau_0)(w_1 n_1 + w_2 n_2)^{1-\tau_1}}_{y} + \underbrace{\beta_0 \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right)}_{b} + (1-\tau_z)z. \tag{A.28}$$

We use the implicit function theorem to derive the Marshallian elasticities with respect to w and $1-\tau_0$, the Frisch elasticities with respect to w and $1-\tau_0$, and the cross-wage elasticity. Equations (A.21) to (A.25) remain the same but the derivatives are instead given by

$$\begin{aligned}
y_{n_j} &= 2^{\tau_1}(1-\tau_0)(1-\tau_1)\,(w_1 n_1 + w_2 n_2)^{-\tau_1}\, w_j, \\
b_{n_j} &= -\beta_1 w_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right), \\
y_{w_j} &= 2^{\tau_1}(1-\tau_0)(1-\tau_1)\,(w_1 n_1 + w_2 n_2)^{-\tau_1}\, n_j, \\
y_t &= 2^{\tau_1}\,(w_1 n_1 + w_2 n_2)^{1-\tau_1}, \\
b_{w_j} &= -\beta_1 n_j \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right), \\
y_{n_j n_j} &= -\tau_1\, 2^{\tau_1}(1-\tau_0)(1-\tau_1)\,(w_1 n_1 + w_2 n_2)^{-\tau_1-1}\, w_j^2, \\
y_{n_j n_k} &= -\tau_1\, 2^{\tau_1}(1-\tau_0)(1-\tau_1)\,(w_1 n_1 + w_2 n_2)^{-\tau_1-1}\, w_j w_k \qquad (k \neq j), \\
b_{n_j n_j} &= \frac{\beta_1^2 w_j^2}{\beta_0} \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right), \\
y_{n_j t} &= 2^{\tau_1}(1-\tau_1)\,(w_1 n_1 + w_2 n_2)^{-\tau_1}\, w_j, \\
y_{n_j w_j} &= 2^{\tau_1}(1-\tau_0)(1-\tau_1)\Big[(w_1 n_1 + w_2 n_2)^{-\tau_1} - \tau_1\, w_j n_j\,(w_1 n_1 + w_2 n_2)^{-\tau_1-1}\Big], \\
y_{n_j w_k} &= -\tau_1\, 2^{\tau_1}(1-\tau_0)(1-\tau_1)\, w_j n_k\,(w_1 n_1 + w_2 n_2)^{-\tau_1-1} \qquad (k \neq j),
\end{aligned}$$

$$b_{n_j w_j} = -\beta_1 \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right)\left(1 - \frac{\beta_1 w_j n_j}{\beta_0}\right),$$
$$b_{n_j w_k} = \frac{\beta_1^2}{\beta_0} \exp\left(-\frac{\beta_1(w_1 n_1 + w_2 n_2)}{\beta_0}\right) w_j n_k.$$

C U.S. Data

Our main source of data is the CPS-ASEC, downloaded from IPUMS, for the years between 1978 and 2023. We convert all nominal amounts to constant 2019 dollars using the consumer price index. We restrict attention to civilians, employees, and to the head and spouse of a household. We mostly follow the procedure of Heathcote, Perri, and Violante (2010) to clean the data. We drop observations, in order, for which: (i) sex, race, or age information are inconsistent across two consecutive ASEC samples; (ii) with self-employed individuals to increase comparability across countries, where we define an individual as self-employed if either the class of worker is self-employed, or their salary is less than 25 percent of their business and farm income; (iii) with head or spouse being members of the military; (iv) with missing age, education, or gender information for head or spouse; (v) with positive labor income but zero reported hours; (vi) with a wage below half of the minimum wage; (vii) with head or spouse below the age of 15; (viii) with heads above the age of 64. We only keep the head and relevant information of the spouse within each household and do not track the head or the spouse of other families that may reside within the household.

Definition of variables. We measure model variables as follows.

- Hours worked, n. Defined as usual hours per week times weeks worked per year.
- Employment, $e = 1$. We define an individual as employed if their hours satisfy $n \geq 800$. We pick the threshold of 800 hours so that the implied employment rate from the CPS matches the roughly 73 percent employment rate for the United States between 1978 and 2019 in the OECD data that we used for our aggregate cross-country analyses.
- Wage, w. We define the wage as the sum of salary, two-thirds of business and farm income, and fringe benefits divided by hours worked. We add fringe benefits to the wage, because our model is static and thus employer contributions for workers' pensions, insurance, social security, and Medicare would otherwise not be valued. To operationalize the addition of fringe benefits, we define the ratio of fringe benefits to wages and salaries from the National Income and Product Accounts in year t, ω_t, and then multiply wages

and salaries for every individual in the CPS with $1 + \omega_t$, with

$$\omega_t = \frac{\text{Supplements NIPA 1.12, Line 6}}{\text{Wages and Salaries, NIPA 1.12, Line 3}}.$$

According to data from the Bureau of Labor Statistics (2025), the value on non-wage benefits is quite stable across industries and occupations and thus we apply the same time-varying factor ω_t to every individual. Appendix Figure A.3 reports the evolution of ω_t over time.

- Non-labor income, z: This is the sum of non-labor income from the CPS and imputed non-labor income from the SCF. Non-labor income in the CPS equals one-third of business income, survivor benefits, child support, alimony, and assistance from friends or relatives. Non-labor income in the SCF refers to returns generated by net liquid wealth, retirement, pensions, and real estate investments. We use the SCF panels of 1983 and the panels between 1989 and 2020. For each panel, we calculate wealth as the sum of: (i) liquid wealth, which is the sum of the total amounts in checking and saving accounts, bonds, stocks, mutual funds, money market accounts, certificate of deposits, other financial assets (annuities, trusts, managed investment accounts, notes and land contracts) less than credit card debt; (ii) retirement accounts, which is the sum of total amount in all retirement accounts such as IRA/Keogh and net value (gross minus the outstanding loans) in pension accounts from current and past jobs; (iii) net equity in investment homes, that is homes other than the principal residence, which equals the gross value of all these homes minus the outstanding debt. All values are converted in 2019 dollars. To avoid absurd changes in non-labor income, we use a constant real rate of return on wealth of 6.6 percent, calculated over our sample period from the dataset of Jorda, Knoll, Kuvshinov, Schularick, and Taylor (2019).

  To impute from the SCF to the CPS, we first clean the SCF data to align with the CPS. Separately for six groups defined by family and employment status, we regress non-labor income in the SCF on members' age and age squared, gender of the head, education, household labor income and labor income squared, members' annual hours worked, a dummy for each member's unemployment status, and four dummies for the number of children in the household. We use the coefficients of these regressions to impute non-labor income in the CPS for surveys adjacent to the SCF panels.

  Appendix Table A.14 summarizes the variables we use from the CPS.

- Benefits, b: Our benefits variable includes welfare (TANF/AFDC), unemployment insurance, workers' compensation, disability payments (SSI and SSDI), veterans' benefits, food stamps (SNAP), education benefits, health benefits from Medicaid and Medicare, and housing, energy, and school lunch subsidies. Most health benefits are covered by Medicaid, with few individuals below the age of 64 being covered from Medicare due to disability (SSDI). To these variables we add unaccounted labor income, which is the labor income of those who work less than 800 hours per year and thus are classified as non-employed. We sum all the benefits data within the household. This includes members of the household that belong to a different family, because other families' transfers can be shared by the main family (head and spouse). Appendix Table A.15 summarizes the variables that we use from the CPS to measure benefits.

  We perform various imputations to the benefits data. We impute food stamps before 1980, energy subsidy before 1982, school lunch subsidy before 1992, housing subsidy before 1992 and after 2015, and Medicaid and Medicare before 1992 and after 2011. We do so in two steps. In the first step, we impute the probability of receiving a particular benefit for individuals in missing years and rank these individuals based on imputed probabilities. We assign a receipt status in missing years based on the average fraction of people who receive these benefits in the next five non-missing years and the ranking of individuals in missing years. We adjust the means between the last missing year and the first available year so that we avoid discrete jumps in the probability of receiving benefits. In the second step, we impute the amount of the benefit, again using the next five non-missing years. We implement these two imputations separately for six marital and employment status groups. The regressions we use to impute include members' age and age square, gender of person if the household consists of a single member, members' education, household total labor income and total labor income squared, members' hours worked, members' unemployment indicator, dummy for the presence of a child younger or equal to 6 years old, four dummies for the number of children, and three dummies for the state's overall generosity of benefits.

  For Medicaid and Medicare benefits, instead of predicting eligibility before 1992 and after 2011 based on these regressions, we use directly the dummy variables HIMCAIDLY and HIMCARELY for coverage that are available since 1980. We also note that the fraction of persons (or households) with positive values for receipt of Medicaid and Medicare (variables PMVCAID and FFNGCARE) changes implausibly in 2001 and 2002. To fix this problem, we change the amount of receipt in 2001 and 2002 with predicted estimates using a regression with the above regressors and the HIMCAIDLY and HIMCARELY dummies in 2001 or 2002. We do this separately for the six marital and employment status groups.

Additional statistics and calculations.

- Figure A.2 presents summary statistics on the living arrangements and employment of U.S. households. In the first panel, we plot the employment rate for different subgroups. The employment rate of those aged between 18 and 29 and living with their parents is around 30 percentage points lower than the employment rate of those aged between 18 and 29 and living alone. A similar pattern is observed in the second panel, which plots total hours. In the third panel, we plot the share of those aged between 18 and 29 and living with their parents. As we can see, this share has increased after the 2000s, but the magnitude of the increase is relatively small. The last panel does a simple decomposition exercise which compares observed hours per capita to hours per capita holding constant the share of those aged between 18 and 29 and living with their parents at its minimum value in the sample. As we can see, total hours do not change by much. This is because the share of those aged between 18 and 29 and living with their parents has not increased so much and this group is small to begin with as a share of the total population.

- Table A.13 presents back of the envelope calculations on the effects of rising incarceration on U.S. hours per person. Let X_t denote the number of individuals that are incarcerated in year t, which is available from the Prison Policy Initiative (https://www.prisonpolicy.org/). Let $\nu = 0.005$ be the death rate for working age individuals. Let p denote the exit rate from incarceration. We are interested in estimating the stock variable I_t, which is the number of individuals ever incarcerated

$$I_t = \underbrace{(1-\nu)I_{t-1}}_{\text{continuing}} + \underbrace{X_t - (1-p)X_{t-1}}_{\text{new entrants}}.$$

  The next input in our calculations is the decline in employment upon incarceration. Waldfogel (1994) reports that those with four convictions have roughly 15 percent lower employment than those without convictions. To make our estimates as large as possible regarding the effects of incarceration, we assume that the effect of incarceration on employment is permanent.

The first column of the table shows estimates under the assumption that the exit rate is $p = 0.37$, which is a duration of incarceration around 2.7 years. Under this parameter, our estimate of the share of ever being incarcerated in the population rises from 5 to 9 percent of the population. Using the Waldfogel (1994) estimate on the lower employment rate of the incarcerated, we obtain an effect of incarceration on aggregate employment of roughly 0.4 percentage points. This is an order of magnitude smaller than the decline in the employment rate observed in the United States after the 2000s. The second column repeats this exercise under $p = 0.50$, which yields an increase in the share of ever being incarcerated in the population from 6 to 12 percent of the population. The effect of incarceration on aggregate employment increases to 0.6 percentage points. The last column shows an extreme combination of parameters that would generate a decline in aggregate employment of the same magnitude as observed in the data. For this to happen we need to assume that $p = 0.60$, so that incarcerated individuals spend less than two years in prison, and that the employment rate of incarcerated is zero, so that incarcerated individuals do not ever work again.

- Appendix Table A.16 presents summary statistics of various variables of single individuals in the CPS sample, by employment status.

- Appendix Table A.17 presents summary statistics of various variables of married couples in the CPS sample, by employment status.

D Additional Results from the U.S. Data

- Appendix Figure A.4 reports estimates of the benefit function by different subcategories of benefits. We find that the benefit function is convex for all different subcategories.

- Appendix Table A.18 presents results for the imputations of the sources of heterogeneity.

- Appendix Table A.19 presents the dispersion in the sources of heterogeneity. Appendix Table A.20 presents the correlations between the sources of heterogeneity. Appendix Figure A.5 presents the distributions of the sources of heterogeneity.

- Adjustments in counterfactuals, χ. The value of χ affects both the intensive and the extensive margin of work. For our counterfactuals that change the value of χ, we adjust the fixed cost of working so that changes in χ affect the extensive margin only because of changes in hours conditional on working. To achieve this, we adjust κ to keep value of employment constant at initial allocations:

$$\tilde{W} = W \Longrightarrow \tilde{\kappa} = \kappa - (\tilde{\chi} - \chi)\frac{n^{1+1/\varepsilon}}{1+1/\varepsilon}.$$

- Adjustments in counterfactuals, $\overline{\kappa}$ and $\underline{\kappa}$. In our counterfactuals, we wish to change the bounds of the fixed costs, without changing the mean fixed cost. Beginning with the employed, let 0 denote the factual distribution and 1 denote the counterfactual distribution. We adjust the value of the parameter α so that we keep the same mean between the factual and the counterfactual

$$\begin{aligned}
\kappa_0 &\sim \text{Uniform}[\overline{\kappa}_0 - \alpha_0, \overline{\kappa}_0], \\
\kappa_1 &\sim \text{Uniform}[\overline{\kappa}_1 - \alpha_1, \overline{\kappa}_1], \\
\alpha_1 &= \alpha_0 + 2(\overline{\kappa}_1 - \overline{\kappa}_0), \\
\Delta \log e &= -\frac{\Delta\overline{\kappa}}{\alpha_0 + 2\Delta\overline{\kappa}}.
\end{aligned}$$

Similarly, for the non-employed, we set $\alpha_1 = \alpha_0 - 2(\underline{\kappa}_1 - \underline{\kappa}_0)$.

- Adjustments in counterfactuals, τ_1. Unlike parameters τ_0, β_0, β_1, the comparative statics with respect to τ_1 depends on units. We can see this by writing the price of labor for singles

$$p = \big((1-\tau_0)(1-\tau_1)(wn)^{-\tau_1} - \beta_1 \exp\left(-\beta_1 wn/\beta_0\right)\big)\, w.$$

The effect of τ_1 on the price in labor depends on units of measurements through the term signified with blue color. Thus, for the counterfactuals, we modify the tax functions to:

$$\begin{aligned}
\tilde{y} &= (1-\tau_0) w^{1-\tau_1} \tilde{n}^{1-\tilde{\tau}_1} n^{\tilde{\tau}_1 - \tau_1} \\
\tilde{y} &= y, \quad \text{when } \tilde{\tau}_1 = \tau_1, \\
p &= \left[(1-\tau_0)(1-\tilde{\tau}_1)(wn)^{-\tau_1}\left(\frac{n}{\tilde{n}}\right)^{\tilde{\tau}_1} - \beta_1 \exp\left(\frac{-\beta_1 w\tilde{n}}{\beta_0}\right)\right] w. \\
\tilde{y} &= (1-\tau_0)(w_1 n_1 + w_2 n_2)^{-\tau_1}\left(w_1 \tilde{n}_1^{1-\tilde{\tau}_1} n_1^{\tilde{\tau}_1} + w_2 \tilde{n}_2^{1-\tilde{\tau}_1} n_2^{\tilde{\tau}_1}\right), \\
\tilde{y} &= y, \quad \text{when } \tilde{\tau}_1 = \tau_1, \\
p_1 &= \left[(1-\tau_0)(1-\tilde{\tau}_1)(\sum w_j n_j)^{-\tau_1}\left(\frac{n_1}{\tilde{n}_1}\right)^{\tilde{\tau}_1} - \beta_1 \exp\left(\frac{-\beta_1 \sum_j w\tilde{n}}{\beta_0}\right)\right] w_1.
\end{aligned}$$

We denote the factual allocation and progressivity parameter by n, τ_1 and the counterfactual allocation and progressivity parameter by $\tilde{n}, \tilde{\tau}_1$. The modifications the are such that, at the initial progressivity parameter, we recover the factual after-tax earnings, that is when $\tilde{\tau}_1 = \tau_1$, we have $\tilde{y} = y$. As shown by the expressions for the price of labor, the modified tax function depends intuitively, in a unit-free way, on the change in the progressivity parameter.

- Appendix Figures A.6 and A.7 present the evolution of the sources of heterogeneity for education, age, and family status groups in the boom and the bust.
- Appendix Table A.21 presents the effects of taxes and benefits on U.S. hours by subperiod and subcategory of tax and benefit.
- Appendix Figures A.8 and A.9 present the correlations between changes in primitives, changes in model total hours, and changes in total hours observed in the data across education, age, and family status groups during the boom and the bust periods.
- Appendix Figure A.10 presents changes in the employment rate by year for the aggregate population and by demographic group when we remove health benefits from total benefits, while keeping all other parameters and sources of heterogeneity constant. Appendix Figure A.11 presents changes in employment rate by year by demographic group when we remove health benefits from total benefits, conditional on receiving health benefits, while keeping all other parameters and sources of heterogeneity constant..
- Appendix Figure A.12 reports the inferred sources of heterogeneity when we implement a Heckman selection model to impute the wage of the non-employed. The selection equation is

$$e_{j\iota} = \mathbb{I}(Z_{j\iota}\delta_z + \epsilon_{j\iota} > 0), \tag{A.29}$$

and the outcome equation conditional on working is

$$\ln w_{j\iota} = \delta_x X_{j\iota} + u_{j\iota}, \tag{A.30}$$

where the errors of the two equations are jointly normal. The correlation of the two errors is given by ρ, the variance of $\epsilon_{j\iota}$ is normalized to one, and variance of $u_{j\iota}$ is σ^2.

The first step of the estimation is a Probit model that yields the inverse Mills ratio for the employed, $\lambda^1_{j\iota} = \phi(\hat{\delta}_z Z_{j\iota})/\Phi(\hat{\delta}_z Z_{j\iota})$. The second step adds the inverse Mills ratio to the outcome equation that yields an estimate of $\rho\sigma$. We impute the wage of the non-employed as

$$\ln w^0_{j\iota} = \hat{\delta}_x X_{j\iota} + \hat{\rho\sigma}\lambda^0_{j\iota} + \eta_{j\iota}, \tag{A.31}$$

where the inverse Mills ratio for the non-employed is $\lambda^0_{j\iota} = -\phi(\hat{\delta}_z Z_{j\iota})/(1-\Phi(\hat{\delta}_z Z_{j\iota}))$ and the error term $\eta_{j\iota}$ is drawn from a normal distribution with mean zero and variance of $\hat{\sigma}^2(1-\hat{\rho}^2)$.

After imputing the wage of the non-employed, we repeat our inference of the other sources of heterogeneity. The only difference is our estimates of fixed cost bounds and the parameter α of the distribution of fixed costs. Parameters γ and ε do not change, because these are based on estimates of elasticities from the intensive margin. Similarly, the inferred χ does not change, because it is based on the first-order condition for optimal hours, conditional on working.

Appendix Figure A.13 presents our estimates of ρ, σ for single individuals, married heads of households, and married spouses of households.

Appendix Table A.22 repeats the results for the drivers of U.S. hours from the CPS using the Heckman selection model to infer the wages of the non-employed. In this exercise we use the new estimates of the fixed costs presented in Appendix Figure A.12 and corresponding estimate of $\alpha = 0.70$.

- Appendix Table A.23 repeats the results for the drivers of U.S. hours from the CPS when we lower the potential wages of the non-employed by 20 percent relative to the potential wages predicted based on observables in our baseline. For this exercise, we repeat the inference of the sources of heterogeneity and estimate of $\alpha = 0.64$ using the adjusted wages of the non-employed.

- Appendix Table A.24 repeats the results for the drivers of U.S. hours from the CPS adjusting health benefits to equal 50 percent of their cost to the government. For this exercise, we have reestimated the parameters, $\gamma = 1.08, \varepsilon = 0.52, \alpha = 0.41$, and we have repeated our analyses of inferring the sources of heterogeneity using the adjusted values of b.

E International Data

In this appendix we provide details on our measurement of model inputs using the international microdata.

Coverage, sample selection, and variable definitions. Table A.25 presents the yearly coverage of available data in the LIS and the LWS for each country in our sample. Table A.26 presents boom and bust subperiods for each country in our LIS sample. Our choice of these subperiods is guided by two objectives. First, we use the available data for each country and aim to be as close as possible to the subperiods in the U.S. LIS (and thus the U.S. CPS). Second, whenever the first objective yields changes in employment and hours worked that are inconsistent with the aggregate data, we modify the subperiods as little as possible to better match the observed changes in these moments in the aggregate data.

Variables in the LIS are defined in local currency, which we convert to constant 2019 dollars by using the country-specific consumer price index included in the LIS and the average exchange rate with the United States in 2019.

Our sample selection follows the same process as with the U.S. CPS data which we discussed above, subject to data availability which is discussed in detail below for each individual country. Variables are also defined following the definitions in the U.S. CPS data, again subject to data differences across individual countries. We first provide a broad discussion of some differences across countries and then proceed to describe finer details specific to each country in our sample.

- Hours worked, n. Defined as the total weekly hours worked times weeks worked per year.

- Employment, $e = 1$. An individual is considered employed if their annual hours exceed a country-specific threshold, which we choose in each country to approximate the average employment rate between 1978 and 2019 according to OECD data. We make an exception to this rule when the threshold required to match the aggregate employment rate becomes too low. In such cases, the implied hourly wages for some workers with very low annual hours would be unreasonably high. Therefore, whenever the threshold is less than 800 hours, we set it to the U.S. threshold of 800 hours, which may result in an average employment rate in our LIS sample that is lower than the OECD aggregate for some countries. Table A.27 presents the annual hours worked cutoffs for employment, as well as the average employment rate in the aggregate OECD data and in our LIS sample across countries.

- Wage, w. As in the U.S. CPS data, we define the wage as the sum of salary, two-thirds of business and farm income, and fringe benefits, divided by hours worked. However, the LIS provides information on farm income at the household level. For this reason, we split total farm income equally between spouses. Furthermore, we obtain data on our measure of fringe benefits across countries from the International Labor Comparisons (ILC) data provided by the U.S. Bureau of Labor Statistics (BLS).[1] Using these data, we compute

[1] These data are available at https://www.bls.gov/ilc/. Data collection was discontinued in 2013, and coverage

the time series of ω for each country as follows:

$$\omega = \left(\frac{\text{Direct benefits} + \text{Insurance and taxes}}{\text{Direct pay for time worked}} \right) /2,$$

where "Direct benefits" refer to pay other than pay for time worked, such as pay for vacations, holidays, and other leave; allowances for family events and commuting expenses; and the cash value of payments in kind; "Insurance and taxes" refer to employer social insurance expenditures and other taxes, such as retirement and disability pensions, health insurance, life and accident insurance, UI and other social insurance expenditures, and taxes on payrolls or employment; and "Direct pay for time worked" covers salary, overtime, and bonuses paid in each pay period. The denominator of ω divides the direct benefits and insurance and taxes by two, so that we allocate half of these expenditures to workers and the other half to employers.

- Benefits, b. The LIS includes seven categories of benefits: family benefits (child allowance, maternity and paternity payments), unemployment insurance, sickness and injury payments, disability, general assistance, housing benefits, and public in-kind benefits such as food benefits. As in the CPS, we also add unaccounted labor income into benefits for all countries in the data. Similar to the U.S. CPS, if a component of b is not available for a given year in the LIS data, we impute it using data from the next five available years. We adjust the means between the last missing year and the first available year so that we avoid discrete jumps in the probability of receiving benefits. Methodologically, this part is the same as in the CPS, except that we do not include generosity of state of residence in the list of regressors, as we do not observe state of residence in the LIS data. The LIS includes various tax credits, such as the EITC for the United States and the child tax credit for the United Kingdom, in family benefits. We cannot drop this variable from benefits, because it includes benefits such as welfare for the United States or the child allowance for the United Kingdom.

  A major difference between the LIS data and the CPS data for the United States is that the LIS does not measure health benefits, because in other countries these benefits are financed universally by the central government irrespective of employment status or income level. Our solution is to use the U.S. CPS data to relate receipt probability and benefit amount to various demographic and income variables and then use this information to predict health benefits in the U.S. LIS data. Thus, in the LIS data we split benefits

varies across countries. For each country, we use values from 2012 for all years after 2012, and values from the first available year for all earlier years.

into health benefits which exist only for the United States, welfare and UI (sum of LIS variables hi41 to hi45), other (sum of LIS variables hi46 to hi47), and unaccounted labor income. As discussed in the main text, we find that benefits relative to labor income are significantly lower for some non-U.S. countries than the ratio reported from the OECD in Figure 10. To adjust benefits for underreporting in the LIS, for non-U.S. countries we use the ratio of OECD cash benefits over labor income to LIS benefits to labor income and scale the three categories of benefits except for unaccounted labor income proportionally for every individual in the LIS survey. Appendix Figure A.14 shows LIS and OECD ratios of benefits to labor income, with the ratio of the two being our adjustment factor. For the United States in LIS, we scale using the ratio relative to the U.S. CPS data.

- Non-labor income, z. This is the sum of non-labor income from the LIS and imputed non-labor income from the LWS. Non-labor income in the LIS equals one-third of business income, inter-household cash transfers (alimony, child support, remittances, etc.), and other unearned income. Non-labor income in the LWS refers to returns generated by net liquid wealth, retirement accounts, pensions, and real estate investments, subject to data availability as discussed further below. For each country, we use a constant real rate of return on wealth, calculated over our sample period from the dataset of Jorda, Knoll, Kuvshinov, Schularick, and Taylor (2019). Then, similar to our imputations from the SCF to the CPS for the United States, we clean the LWS data to align with the LIS; we regress non-labor income in the LWS on the same set of household demographics, separately for six groups defined by family and employment status; and we use the coefficients of these regressions to impute non-labor income in the LIS for surveys adjacent to the LWS panels. We implement this process separately for each country.

- Taxes. For each country, we estimate parameters of the tax function following country-specific taxation rules (joint, individual, income-splitting), which are summarized in the last column of Table A.27. The LIS data provide information on income taxes paid. We use social security tax rates over time for each country from McDaniel (2011), together with gross labor income in the LIS, to obtain social security taxes paid. We then calculate the average tax rate using income and social security taxes paid.[2] Next, we estimate τ_1 by regressing the logarithm of net labor income on the logarithm of gross labor income.

[2] Our average tax rates in the LIS that do not adjust for social security taxes are relatively similar to the ones reported by Qiu and Russo (Forthcoming), who also used the LIS to estimate tax functions for a large cross-section of countries.

Finally, we back out τ_0 to match the average tax rates obtained above.[3]

For our estimation of tax parameters across countries, we take into account that countries differ in their tax system. For singles, we use the same tax function for all countries, $y = (1 - \tau_0)(wn)^{\tau_1}$. For married households, we have the following formulations:

- Joint taxation. $y = (1 - \tau_0)(w_1 n_1 + w_2 n_2)^{(1-\tau_1)}$. To estimate τ_1 we require information on gross and net labor income at the household level.
- Individual taxation. For countries with individual taxation, we estimate for every individual, irrespective of marital status, the same tax function, $y = (1 - \tau_0)(wn)^{\tau_1}$. To estimate τ_1 we require information on gross and net labor income at the individual level.
- Income splitting. $y = 2^{\tau_1}(1 - \tau_0)(w_1 n_1 + w_2 n_2)^{1-\tau_1}$. To estimate τ_1 we require information on gross and net labor income at the household level.

We estimate separate τ_0 and τ_1 for singles and married households under joint and income-splitting taxation systems, and uniform τ_0 and τ_1 for singles and married households under individual taxation.

- Minimum wages. One of our sample selection criteria requires information on the national minimum wage over time for each country, as we drop households when either the head or the spouse has a wage that is less than half of the minimum wage. We obtain information on minimum wages for each country using the statutory national minimum hourly wages from the OECD.[4]

Country-specific data details. Next, we discuss further details for each country in our LIS sample.

[3]For Spain, Italy, and Sweden, LIS information on income taxes paid is missing in some years, despite the presence of the general LIS data for those same years. For these cases, we take the sum of income and social security taxes paid from McDaniel (2011) and apply it to gross income in the LIS. We then take the ratio of the average tax rate obtained with the average tax rate calculated using available information on income taxes paid from LIS and social security taxes from McDaniel (2011). We use the average of this ratio to scale the average tax rate series obtained using income and social security taxes paid from McDaniel (2011). The target average tax rates for missing LIS tax years are then filled with this series.

[4]In Germany, the national minimum wage was introduced after 2015, but there were sector- and region-specific minimum wages before this period. As a result, the OECD data for Germany on minimum wages start only after 2015. There are similar issues in the UK, Italy, and Sweden, where OECD data on minimum wages are available for limited years, but there were sector-specific minimum wage rules. For these reasons, we do not use OECD data on minimum wages for these countries and instead use minimum wage values for the U.S., converted to the national currency of these countries.

- *United States.* We treat the U.S. LIS as a special case because our goal is to stay as close as possible to the U.S. CPS. As a result, the U.S. LIS data differs from the LIS data for other countries in several ways.
  - For fringe benefits ω, we use the series obtained from NIPA data, implemented in our analysis using the CPS. Thus, for the U.S. LIS, we do not use ILC data from the BLS, which we use for all other countries in our LIS sample.
  - For taxes in the U.S. LIS, we use our estimates of τ_0 and τ_1, obtained using TAXSIM together with CPS data.
  - For health benefits, as mentioned in the main text, we use CPS data to estimate group-specific regressions (based on marital status and employment), separately for Medicaid and Medicare, of eligibility and receipt amounts on demographics. We estimate these regressions for three separate time periods: 1992-1996, 1996-2006, and 2007-2011. These choices are based on the availability of Medicaid and Medicare data in the CPS. In this way, given demographics, we can impute whether a household is eligible for Medicaid or Medicare and how much it receives in these transfers. We use the estimated coefficients by group and time period to impute health benefits in the U.S. LIS data for each household, given their observables.
- *Germany.*
  - The LWS data for Germany do not provide information on the amount of assets in pensions and social security accounts or on the amount of credit card debt. As a result, our measure of non-labor income in the LWS (that is, returns generated by various sources of wealth) does not include these assets.
  - While Germany has data for 1973, 1978, and 1983 in the LIS, these years do not provide information on hours worked or self-employment income. In addition, we find that between 1984 and 1989, the employment-to-population ratio increases slightly in the LIS data for Germany, which is not the case in the aggregate OECD data. As a result, although the data are available starting in 1984, our LIS sample for Germany starts in 1989. This choice yields a decline in the employment-to-population ratio that is closer to the decline observed in the aggregate OECD data after the German reunification.
- *Canada.*

- The LWS data do not provide information on pensions. Thus, we cannot include them in our measure of wealth when calculating non-labor income in the LWS.
- The rate of return for Canada is not available in the dataset from Jorda, Knoll, Kuvshinov, Schularick, and Taylor (2019). For this reason, we instead use the U.S. rate of return.
- The unit of observation in the LWS data for Canada is the household head. It is not possible to determine who is married because the marital status variable and other related variables, which would help identify spouses, are not available. For this reason, we perform imputations only based on employment. This issue is present only in the LWS and not in the LIS data for Canada. We note that this data limitation in the LWS also implies that we cannot implement sample selection based on spousal information.
- The LWS data for Canada also do not provide information on hours worked. As a result, we cannot define the employment variable in the LWS using hours-worked information. We instead use self-reported employment variables to classify individuals as employed or non-employed. Relatedly, the LWS data also do not provide wage information, implying that we cannot implement sample selection based on wages, labor income, or business income. Again, these limitations are present only in the LWS data, not in the LIS data for Canada.
- The regressions for imputing non-labor income in the LWS are also implemented with a limited set of regressors due to data availability. The LWS data do not include information on children or hours worked, so these variables are excluded from the set of regressors.

- *Spain.*
  - The LWS data for Spain do not provide information on pensions. Thus, we cannot include them in our measure of wealth when calculating non-labor income in the LWS.
  - The LWS data for Spain also do not provide information on annual weeks worked. To impute this variable in the LWS data, we use information on annual weeks worked from the LIS data for Spain and calculate the distribution of weeks worked among the employed. We find that the 10th percentile is employed for 39 weeks, while the

rest are employed for 52 weeks. Then, in the LWS data for Spain in each year, we randomly assign 39 weeks to 10 percent of the employed and 52 weeks to the rest.

- In the LWS data, before 2017, the labor force status variable does not include a code for unemployment. The other variables or codes within this variable do not identify the unemployed. For this reason, we cannot use an unemployment dummy in the LWS regressions used to impute non-labor income in the LIS. That is, we do not use the unemployment dummy for non-labor income imputations in the LIS because we cannot estimate its coefficient in the LWS.
- For consumption taxes τ_c, the dataset from McDaniel (2011) does not provide information on consumption taxes for 2019 at the time we downloaded it. For 2019, we use the value from 2018.
- The LIS data for Spain provide information on the total income taxes paid by the household only after 2004. For this reason, we can estimate τ_1 only using data from after 2004. We then use the 2004 estimates of τ_1 (separately for married and single households) for all years before 2004 in the data.

- *France.*
  - The LWS data for France do not provide information on pensions. Thus, we cannot include them in our measure of wealth when calculating non-labor income in the LWS.
  - The LWS data for France do not provide information on annual weeks worked or hours per week. Thus, even if we can impute annual weeks worked using data from the LIS (as in the case of Spain), we still would not have hours per week. For this reason, we cannot use hours worked in the LWS regressions used to impute non-labor income in the LIS. In addition, we cannot implement sample selection based on wages (minimum wage). Similarly, because information on annual hours worked is not available, we define employment in the LWS based on self-reported employment status.
  - The LIS data for France provide annual weeks worked only starting in 2013. We calculate the distribution of annual weeks worked using pooled data starting in 2013 among the employed, assign the 10th percentile (39 weeks) randomly to 10 percent of the employed in each year, and assign 52 weeks to the remaining 90 percent. In addition, in 2012, weekly hours worked at all jobs in the LIS data become unavailable

for one year. In 2012, we instead use hours worked at the main job (instead of all jobs).

- *United Kingdom.*
  - The LWS data for the UK do not provide information on pensions. Thus, we cannot include them in our measure of wealth when calculating non-labor income in the LWS.
  - The LWS data for the UK do not provide information on hours per week at all jobs. We instead use information on hours per week at the main job, which is only available starting in 2009. For this reason, we do not use data from 2007.
  - In the LIS data for the UK, whenever annual weeks worked are not available, we impute them following the same procedure as above for Spain and France.
- *Sweden.*
  - The LWS data for Sweden are available only for 2002 and 2005. However, in 2005, information on weekly hours worked is not available. Thus, we use only data from 2002. In addition, information on annual weeks worked in the 2002 LWS is also not available. We impute this using LIS data for Sweden, as in the cases of France, Spain, and the United Kingdom.
  - The LWS data for Sweden do not provide information on pensions. Thus, we cannot include them in our measure of wealth when calculating non-labor income in the LWS. In addition, mortgage debt and consumer loans are also missing in the LWS data. Therefore, non-labor income in the LWS for Sweden is likely to be overstated.
  - The LIS data for Sweden are available for 1975, 1981, and 1987. However, the data for these years do not provide information on weekly hours worked. Thus, our sample for Sweden starts in 1992. In addition, the LIS data for Sweden do not provide information on weekly hours worked in 2000 or in any year between 2004 and 2012. As a result, we cannot use data from these years either. Finally, although data are available for 2001, 2002, and 2003, we drop these years from our analysis because they have substantially lower hours worked, potentially due to issues related to the hours-worked variable in the dataset in those years.
  - The LIS data for Sweden in 1992 and 1995 do not provide information on self-employment income at the individual level. However, self-employment income is

available at the household level. Therefore, for these years, we split it equally between the head and the spouse.

– In our estimation of tax parameters using the LIS data, we noticed that the average tax rate declines substantially. We find this unreasonable, given that the same decline is not observed in the McDaniel (2011) data. For this reason, we instead use the average tax rate from the OECD data to pin down τ_0, given the information on τ_1 estimated using the LIS data (based on information on income taxes paid and gross income) and social security tax rates from McDaniel (2011).

- *Italy.*
  - While the LWS data for Italy are available before 2008, they lack information on several important asset categories. For this reason, our LWS data for Italy start in 2008. After 2008, similar to other countries, the LWS data for Italy do not provide information on pensions.
  - The LIS data for Italy provide information on income taxes paid only in 2004, 2008, and 2010. Thus, we can estimate τ_1 only for these years. We then use our estimate from 2004 for all years before 2006, our estimate from 2008 for all years between 2006 and 2009, and our estimate from 2010 for all years after 2009. For τ_0, we require that our model matches OECD data on the average tax rate.
  - The Italian sample is small and this creates noise in the estimation of parameters and the results. To ameliorate this problem, we group nearby survey years together and treat them as common reference years.
  - The benefits data for Italy is of low quality, as a significantly larger number of observations for the non-employed have zero benefits than in other countries. To reduce the sensitivity of the results to this problem, we use the average β_1 from the other countries and winsorize the top 20 percent of β_0 observations.

F Additional Results from the International Data

In this section, we provide additional results and details on our estimation of the model and counterfactual analysis using the international micro-level data.

- Table A.28 presents estimates of the parameters ϵ, γ, α, and β_1 for each country in our sample. We estimate the first three parameters to match the same three target elasticities as in our analysis using the U.S. CPS in the main text and the β_1 coefficients by projecting benefits on labor income.

- Appendix Figures A.15 and A.16 present the average tax rate and progressivity parameter τ_1 by country for single and married individuals.

- Appendix Figure A.17 reports potential wages for singles by country. Appendix Figure A.18 reports the benefit upon non-employment for singles by country. Appendix Figure A.19 reports the disutility of work for singles by country. Appendix Figure A.20 reports non-labor income for singles by country. Appendix Figure A.21 reports the fixed cost value and Appendix Figure A.22 reports the bounds for the fixed costs for singles by country. Appendix Figure A.23 reports potential wages for married by country. Appendix Figure A.24 reports the benefit upon non-employment for married by country. Appendix Figure A.25 reports the disutility of work for married by country. Appendix Figure A.26 reports non-labor income for married by country. Appendix Figure A.27 reports the fixed cost value and Appendix Figure A.28 reports the bounds for the fixed costs for married by country.

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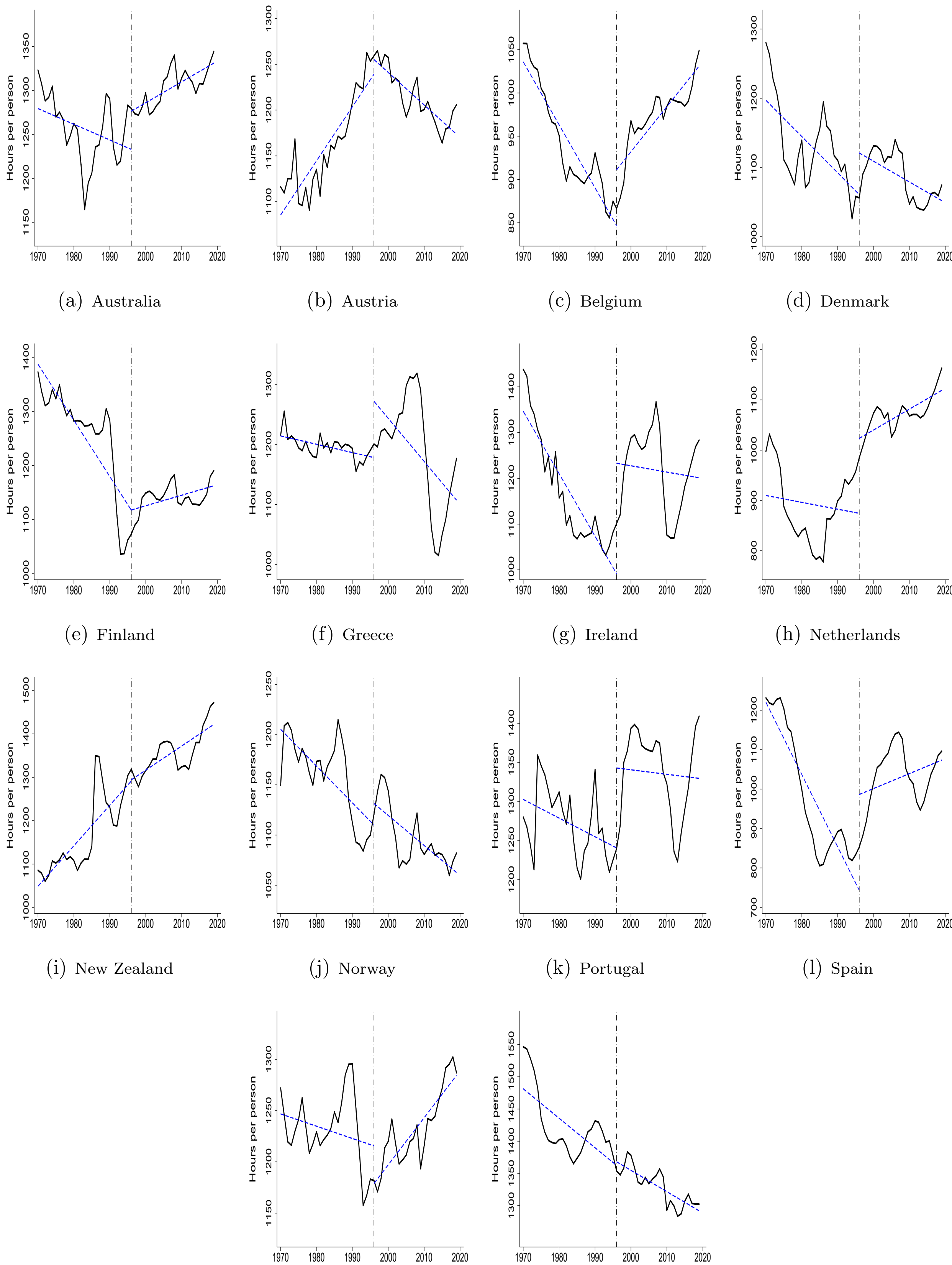


(a) Australia (b) Austria (c) Belgium (d) Denmark

(e) Finland (f) Greece (g) Ireland (h) Netherlands

(i) New Zealand (j) Norway (k) Portugal (l) Spain

(m) Sweden (n) Switzerland

Figure A.1: Hours per person in other advanced economies

Notes: The figure shows hours per person from the OECD/PWT data for other advanced economies. The dashed vertical line signifies the last year covered by the analysis of Prescott (2004).

Table A.1: Hours per person relative to the United States, population 15-64

(US hours per person = 100)	1970s	1990s	2010s
Australia	105	95	105
Austria	107	94	97
Belgium	84	68	82
Canada	96	93	103
Denmark	102	82	85
Finland	112	86	93
France	103	75	81
Germany	102	76	86
Greece	94	88	90
Ireland	103	82	94
Italy	84	74	82
Japan	117	102	106
Netherlands	79	74	89
New Zealand	107	95	109
Norway	95	84	87
Portugal	112	94	101
Spain	97	67	84
Sweden	101	92	101
Switzerland	118	102	104
United Kingdom	105	92	100
Average	101	86	94

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.2: Hours per person relative to the United States, population 15-54

(US hours per person = 100)	1970s	1990s	2010s
Australia	107	97	106
Austria	117	101	102
Belgium	91	74	86
Canada	99	94	104
Denmark	108	83	85
Finland	114	89	94
France	106	79	84
Germany	106	81	86
Greece	97	90	93
Ireland	103	82	94
Italy	85	78	84
Japan	115	100	105
Netherlands	80	78	90
New Zealand	110	95	106
Norway	95	84	85
Portugal	113	95	105
Spain	97	69	86
Sweden	102	91	99
Switzerland	122	101	104
United Kingdom	110	94	101
Average	104	88	95

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.3: Hours per person relative to the United States, population 25-64

(US hours per person = 100)	1970s	1990s	2010s
Australia	102	93	103
Austria	106	93	96
Belgium	90	73	87
Canada	95	93	101
Denmark	99	80	84
Finland	116	89	95
France	107	81	85
Germany	99	76	86
Greece	103	94	95
Ireland	105	87	96
Italy	88	79	86
Japan	121	107	108
Netherlands	78	72	86
New Zealand	107	95	110
Norway	98	86	87
Portugal	111	99	104
Spain	96	71	86
Sweden	100	95	105
Switzerland	116	100	101
United Kingdom	102	90	99
Average	102	88	95

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.4: Hours per person relative to the United States, total population

(US hours per person = 100)	1970s	1990s	2010s
Australia	108	98	107
Austria	101	97	98
Belgium	90	69	79
Canada	100	96	105
Denmark	105	85	84
Finland	119	87	90
France	101	76	77
Germany	106	80	86
Greece	98	89	84
Ireland	103	83	96
Italy	91	79	79
Japan	133	116	110
Netherlands	80	77	88
New Zealand	96	97	113
Norway	98	83	90
Portugal	112	101	104
Spain	94	67	83
Sweden	105	89	99
Switzerland	137	111	108
United Kingdom	108	90	99
Average	104	89	94

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.5: Decomposition of hours gap, population 15-64

(log points relative to US)	Change 1990s-1970s Total	Extensive	Intensive	Change 2010s-1990s Total	Extensive	Intensive
Australia	-10	-9	-1	10	14	-3
Austria	-12	-9	-3	3	10	-7
Belgium	-20	-9	-11	19	16	3
Canada	-4	-1	-3	10	12	-2
Denmark	-23	-9	-14	4	3	1
Finland	-26	-18	-9	9	12	-4
France	-32	-17	-14	8	11	-3
Germany	-29	-12	-17	12	18	-6
Greece	-7	-9	2	2	3	-1
Ireland	-23	-12	-11	13	22	-9
Italy	-12	-11	-2	10	14	-4
Japan	-14	-7	-6	4	11	-6
Netherlands	-6	7	-13	18	19	0
New Zealand	-12	-13	1	14	15	-1
Norway	-12	0	-12	2	6	-4
Portugal	-18	-10	-8	7	6	2
Spain	-36	-25	-11	22	22	0
Sweden	-10	-12	3	10	6	4
Switzerland	-15	-6	-9	2	7	-5
United Kingdom	-13	-9	-5	8	9	-1
Average	-17	-10	-7	9	12	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Table A.6: Decomposition of hours gap, population 15-54

(log points relative to US)	Change 1990s-1970s Total	Extensive	Intensive	Change 2010s-1990s Total	Extensive	Intensive
Australia	-10	-9	-1	9	12	-3
Austria	-15	-12	-3	1	9	-7
Belgium	-21	-10	-11	15	12	3
Canada	-5	-2	-3	10	12	-2
Denmark	-26	-12	-14	3	1	1
Finland	-25	-16	-9	6	9	-4
France	-29	-15	-14	6	9	-3
Germany	-27	-9	-17	7	13	-6
Greece	-7	-9	2	3	4	-1
Ireland	-23	-12	-11	13	22	-9
Italy	-9	-8	-2	7	11	-4
Japan	-14	-8	-6	5	11	-6
Netherlands	-3	10	-13	15	16	0
New Zealand	-15	-15	1	10	11	-1
Norway	-13	0	-12	2	6	-4
Portugal	-17	-8	-8	9	8	2
Spain	-35	-23	-11	22	22	0
Sweden	-12	-15	3	9	5	4
Switzerland	-18	-9	-9	3	7	-5
United Kingdom	-15	-10	-5	7	8	-1
Average	-17	-10	-7	8	10	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Table A.7: Decomposition of hours gap, population 25-64

(log points relative to US)	Change 1990s-1970s			Change 2010s-1990s		
	Total	Extensive	Intensive	Total	Extensive	Intensive
Australia	-9	-8	-1	10	13	-3
Austria	-12	-9	-3	2	10	-7
Belgium	-21	-10	-11	18	15	3
Canada	-2	1	-3	8	10	-2
Denmark	-21	-7	-14	5	4	1
Finland	-26	-17	-9	6	10	-4
France	-28	-14	-14	5	8	-3
Germany	-26	-9	-17	13	19	-6
Greece	-9	-11	2	1	1	-1
Ireland	-19	-8	-11	10	19	-9
Italy	-10	-9	-2	8	12	-4
Japan	-12	-6	-6	1	7	-6
Netherlands	-7	6	-13	17	18	0
New Zealand	-12	-12	1	14	15	-1
Norway	-13	0	-12	1	5	-4
Portugal	-11	-3	-8	5	3	2
Spain	-30	-19	-11	19	19	0
Sweden	-6	-8	3	10	6	4
Switzerland	-15	-6	-9	1	6	-5
United Kingdom	-12	-8	-5	10	10	-1
Average	-15	-8	-7	8	11	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Table A.8: Decomposition of hours gap, total population

(log points relative to US)	Change 1990s-1970s			Change 2010s-1990s		
	Total	Extensive	Intensive	Total	Extensive	Intensive
Australia	-10	-9	-1	9	12	-3
Austria	-4	0	-3	1	8	-7
Belgium	-26	-15	-11	14	11	3
Canada	-4	-1	-3	8	10	-2
Denmark	-21	-7	-14	-1	-2	1
Finland	-31	-22	-9	3	6	-4
France	-29	-15	-14	1	4	-3
Germany	-28	-10	-17	7	13	-6
Greece	-9	-11	2	-6	-5	-1
Ireland	-21	-10	-11	15	24	-9
Italy	-14	-13	-2	0	4	-4
Japan	-13	-7	-6	-6	1	-6
Netherlands	-3	10	-13	13	14	0
New Zealand	1	0	1	16	17	-1
Norway	-16	-4	-12	8	12	-4
Portugal	-10	-2	-8	3	1	2
Spain	-34	-23	-11	20	20	0
Sweden	-17	-19	3	11	7	4
Switzerland	-21	-12	-9	-2	3	-5
United Kingdom	-17	-13	-5	9	9	-1
Average	-16	-9	-7	6	8	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Table A.9: Hours per person relative to the United States, men 15-64

(US hours per person = 100)	1970s	1990s	2010s
Australia	109	98	105
Austria	110	100	96
Belgium	89	74	82
Canada	98	92	99
Denmark	97	79	82
Finland	97	81	88
France	103	77	80
Germany	104	79	85
Greece	109	106	98
Ireland	118	92	94
Italy	97	88	89
Japan	116	110	111
Netherlands	89	79	88
New Zealand	117	97	108
Norway	94	82	82
Portugal	119	98	98
Spain	114	82	85
Sweden	91	85	96
Switzerland	122	105	103
United Kingdom	106	92	99
Average	105	90	93

Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.10: Decomposition of hours gap, men 15-64

(log points	Change 1990s-1970s			Change 2010s-1990s		
relative to US)	Total	Extensive	Intensive	Total	Extensive	Intensive
Australia	-11	-10	-1	7	10	-3
Austria	-10	-6	-3	-5	3	-7
Belgium	-19	-8	-11	10	7	3
Canada	-6	-3	-3	8	10	-2
Denmark	-20	-6	-14	3	2	1
Finland	-18	-9	-9	9	12	-4
France	-29	-15	-14	4	7	-3
Germany	-28	-10	-17	7	13	-6
Greece	-3	-5	2	-7	-7	-1
Ireland	-24	-14	-11	1	10	-9
Italy	-11	-9	-2	2	6	-4
Japan	-6	0	-6	1	8	-6
Netherlands	-13	0	-13	11	11	0
New Zealand	-20	-20	1	11	12	-1
Norway	-14	-1	-12	1	5	-4
Portugal	-20	-11	-8	1	-1	2
Spain	-34	-22	-11	4	4	0
Sweden	-7	-10	3	13	9	4
Switzerland	-15	-6	-9	-2	2	-5
United Kingdom	-14	-9	-5	7	8	-1
Average	-16	-9	-7	4	7	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Table A.11: Hours per person relative to the United States, women 15-64

(US hours per person = 100)	1970s	1990s	2010s
Australia	96	91	105
Austria	102	87	98
Belgium	73	61	82
Canada	92	94	106
Denmark	110	84	88
Finland	133	91	99
France	101	73	82
Germany	97	72	87
Greece	69	67	80
Ireland	75	69	93
Italy	61	57	74
Japan	116	92	101
Netherlands	58	67	89
New Zealand	88	93	109
Norway	96	87	91
Portugal	103	89	103
Spain	68	50	82
Sweden	114	100	107
Switzerland	111	97	105
United Kingdom	103	92	101
Average	93	81	94

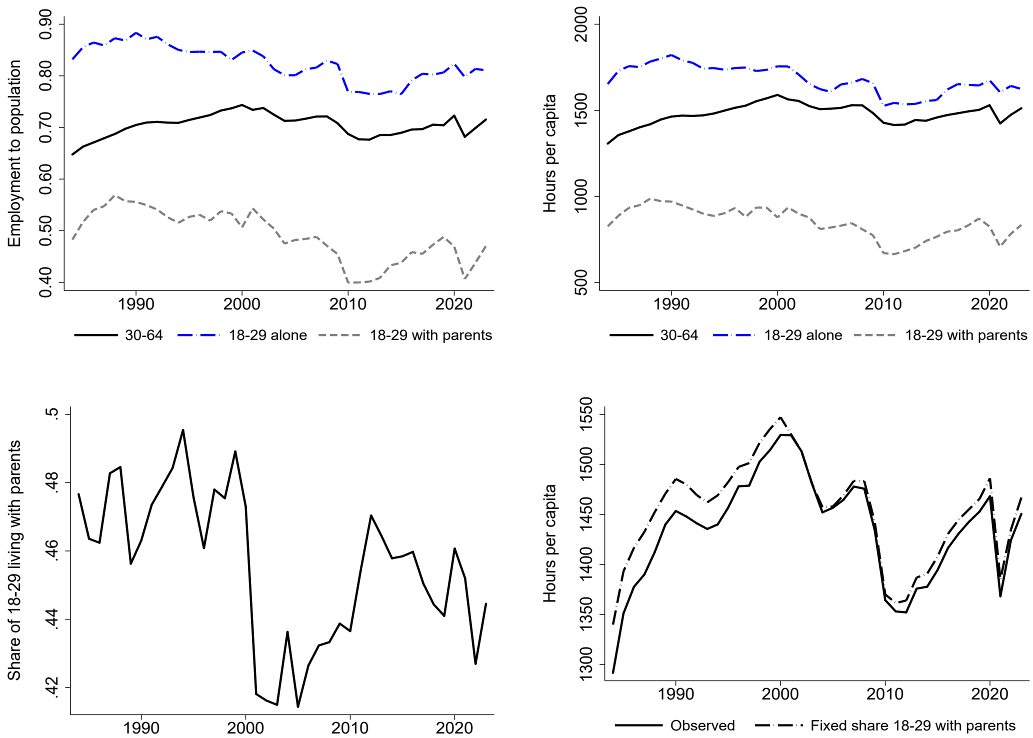
Notes: The table presents average hours per person from the OECD/PWT by decade relative to the United States. Hours per person in the United States are normalized to 100 in each column.

Table A.12: Decomposition of hours gap, women 15-64

(log points	Change 1990s-1970s			Change 2010s-1990s		
relative to US)	Total	Extensive	Intensive	Total	Extensive	Intensive
Australia	-6	-5	-1	15	18	-3
Austria	-16	-13	-3	12	20	-7
Belgium	-19	-8	-11	31	28	3
Canada	2	5	-3	13	14	-2
Denmark	-27	-13	-14	4	3	1
Finland	-38	-29	-9	8	12	-4
France	-33	-19	-14	13	16	-3
Germany	-31	-13	-17	20	26	-6
Greece	-2	-4	2	17	17	-1
Ireland	-8	3	-11	30	39	-9
Italy	-7	-5	-2	26	30	-4
Japan	-23	-17	-6	9	16	-6
Netherlands	15	28	-13	29	29	0
New Zealand	5	5	1	16	17	-1
Norway	-9	3	-12	4	8	-4
Portugal	-14	-6	-8	15	13	2
Spain	-31	-20	-11	51	51	0
Sweden	-13	-16	3	7	3	4
Switzerland	-14	-4	-9	8	13	-5
United Kingdom	-12	-7	-5	10	10	-1
Average	-14	-7	-7	17	19	-2

Notes: The table presents the decomposition of changes in hours per person for each country relative to the United States in equation (1).

Figure A.2: Adults living with parents in the United States



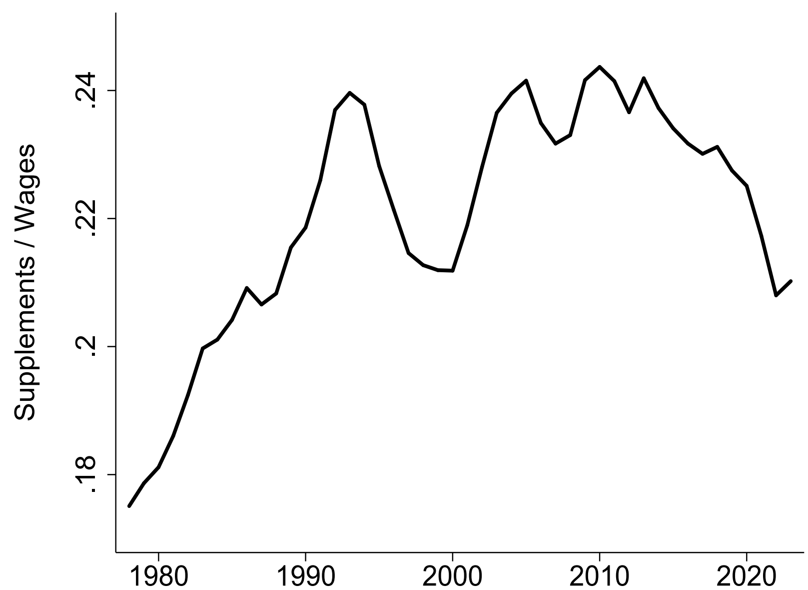
Notes: The figures present employment statistics of coresidence from the CPS. The last panel calculates the counterfactual evolution of hours worked holding the share of adults living with parents at its minimum value in the sample.

Table A.13: Back of the envelope calculations on effects of incarceration

	$p = 0.37$		$p = 0.50$		$p = 0.60$	
	1990s	2010s	1990s	2010s	1990s	2010s
e, never incarcerated	0.7	0.7	0.7	0.7	0.7	0.7
e, ever incarcerated	0.6	0.6	0.6	0.6	0.0	0.0
$100\times$ share, ever incarcerated	4.6	8.7	6.0	11.6	7.1	13.8
$100 \times \Delta e$, aggregate		-0.41		-0.56		-4.69

Notes: The table presents back of the envelope calculations on the effects of incarceration on hours worked. In the first two rows, e denotes employment. The third row denotes our estimate of the share of the working-age population that has ever been incarcerated. The fourth column calculates the aggregate decline in hours worked due to the rising share of those who have ever been incarcerated. p in the columns denotes the exit rate from incarceration.

Figure A.3: Supplements to Wages in the United States



Notes: The figure presents the ratio of supplements to compensation of labor. Data are from BEA NIPA Table 1.12, line 3 and line 6.

Table A.14: Variables included in non-labor income

Variable Name	Program
INCALOTH/INCSURV	survivor benefits
INCALOTH/INCCHILD	child support
INCALOTH/INCALIM	alimony
INCALOTH/INCASIST	assistance from friends or relatives
INCALOTH/INCOTHER	income from other sources
INCBUS,INCFARM	1/3 of business and farm income
SCF variables	imputed income from net liquid wealth
SCF variables	imputed income from retirement accounts and pensions
SCF variables	imputed income from net equity in investment homes
model adjustment	gap between resources and federal poverty level

Notes: The table presents the CPS and SCF variables that we include in our measurement of non-labor income.

Table A.15: CPS variables included in benefits

Model Name	Variable Name	Program
Welfare and UI	INCWELFR	welfare (TANF/AFDC), old age assistance
		aid to blind and disabled people,
		general/emergency assistance
	INCWKCOM/INCGOV	unemployment insurance
	INCUNEMP/INCGOV	workers' compensation
	INCDISAB/INCGOV	disability income
	INCVET/INCGOV	veterans' benefits
	INCEDUC/INCGOV	educational assistance
	INCSSI	supplemental security income
Other	STAMPVAL	food stamps (SNAP)
	SCHLLUNCH	school lunch subsidy
	HOUSSUB	housing subsidy
	HEATVAL	energy subsidy
Health	PMVCAID	Medicaid
	FFNGCARE	Medicare
Unaccounted		wn for $n \leq 800$

Notes: The table presents the CPS variables that we include in our measurement of benefits.

Table A.16: Summary statistics, U.S. CPS, Single Individuals

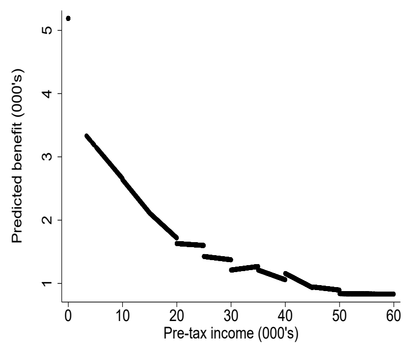
Employed	Mean	P01	P10	P50	P90	P99
n	2,057	840	1,360	2,080	2,600	3,640
w	29	6	11	24	50	103
wn	60,313	7,945	18,796	49,102	106,900	230,231
y	41,362	7,927	16,253	36,096	69,472	131,484
b	2,481	0	0	0	9,026	28,305
$(1-\tau_z)z$	5,845	-8,884	-1,694	3,392	14,617	46,053
Non-Employed	**Mean**	**P01**	**P10**	**P50**	**P90**	**P99**
b	16,078	0	0	13,523	33,798	69,172
$b_{\text{welfare,ui}}$	5,165	0	0	0	14,525	41,114
b_{health}	6,283	0	0	4,531	16,096	28,450
b_{labor}	2,654	0	0	0	7,617	37,551
b_{other}	1,975	0	0	0	6,863	13,375
$(1-\tau_z)z$	6,113	-6,769	-1,779	3,833	15,898	45,219
$b+(1-\tau_z)z$	22,091	-2,133	4,256	19,157	41,060	88,540

Notes: The table presents summary statistics of single individuals in the U.S. CPS data.

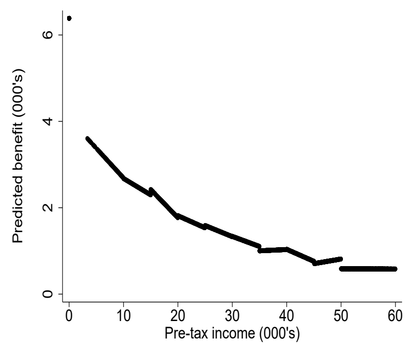
Table A.17: Summary statistics, U.S. CPS, Married Couples

Employed	Mean	P01	P10	P50	P90	P99
n_1	2,197	960	1,820	2,080	2,704	3,640
n_2	1,926	832	1,200	2,080	2,340	3,120
w_1	37	8	15	31	62	134
w_2	27	6	11	22	46	95
wn	134,505	31,506	59,900	115,227	219,668	472,552
y	90,303	26,843	46,070	80,371	141,165	273,419
b	2,067	0	0	0	6,992	26,543
$(1-\tau_z)z$	12,055	-9,171	-2,094	7,735	29,279	82,244
Head Employed	**Mean**	**P01**	**P10**	**P50**	**P90**	**P99**
n_1	2,212	920	1,720	2,080	2,860	3,861
w_1	41	7	14	33	70	198
y	63,451	11,148	24,615	53,430	107,763	301,040
b	6,415	0	0	976	18,492	49,080
$b_{\text{welfare,ui}}$	1,713	0	0	0	5,393	26,210
b_{health}	1,760	0	0	0	7,912	21,315
b_{labor}	2,540	0	0	0	8,262	32,901
$(1-\tau_z)z$	12,278	-21,097	-5,907	7,117	32,243	111,189
Spouse Employed	**Mean**	**P01**	**P10**	**P50**	**P90**	**P99**
n_2	1,941	832	1,200	2,080	2,340	3,120
w_2	27	5	10	21	47	105
y	41,251	7,891	15,231	34,255	72,176	148,763
b	14,561	0	0	9,350	34,964	89,289
$b_{\text{welfare,ui}}$	5,294	0	0	0	17,785	53,538
b_{health}	4,256	0	0	0	12,208	27,236
b_{labor}	4,583	0	0	0	12,485	63,613
$(1-\tau_z)z$	10,191	-31,922	-7,002	7,424	29,057	77,832
Non-Employed	**Mean**	**P01**	**P10**	**P50**	**P90**	**P99**
b	19,929	0	0	13,233	45,636	98,231
$b_{\text{welfare,ui}}$	6,170	0	0	0	20,061	56,175
b_{health}	7,872	0	0	5,711	20,406	35,764
b_{labor}	4,762	0	0	0	13,005	71,661
b_{other}	1,124	0	0	0	4,401	12,353
$(1-\tau_z)z$	26,703	-104,115	-18,721	14,104	102,691	188,049
$b+(1-\tau_z)z$	46,485	-79,456	-4,368	33,251	119,599	215,581

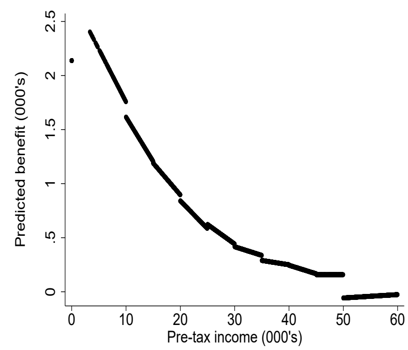
Notes: The table presents summary statistics of married couples in the U.S. CPS data.



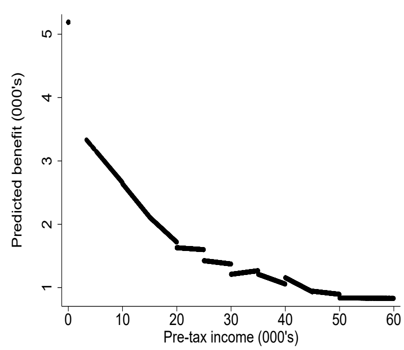
(a) Singles, Welfare and UI, $\beta_1 = 0.21$



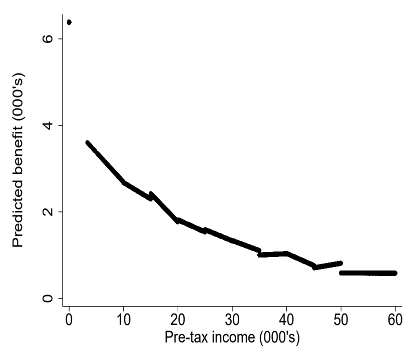
(b) Singles, Health, $\beta_1 = 0.33$



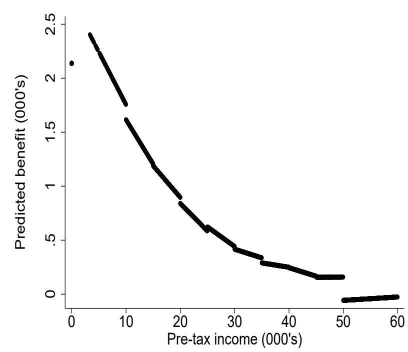
(c) Singles, Other, $\beta_1 = 0.09$



(d) Married, Welfare and UI, $\beta_1 = 0.08$



(e) Married, Health, $\beta_1 = 0.19$



(f) Married, Other, $\beta_1 = 0.03$

Figure A.4: Benefit Function by Subcategory

Notes: The figure shows estimates of the benefit function by subcategory of benefits.

Table A.18: Imputation of Sources of Heterogeneity

	Wage $\log \theta$			Disutility $\log \chi$			Benefit $\log \beta_0$	
	S	M,H	M,S	S	M,H	M,S	S	M
Female	-0.15			0.02			-0.03	
Age, Head	0.03	0.03	0.00	-0.04	0.04	-0.04	0.15	0.01
Age Squared, Head	-0.00	-0.00	-0.00	0.00	-0.00	0.00	-0.00	-0.00
Age, Spouse		0.01	0.04		-0.00	0.03		-0.01
Age Squared, Spouse		-0.00	-0.00		-0.00	-0.00		0.00
Mid State	0.03	0.02	0.02	-0.02	-0.01	0.02	0.00	0.06
High State	0.15	0.11	0.11	-0.06	-0.03	-0.00	0.05	0.24
Mid Education, Head	0.17	0.18	0.12	0.13	0.08	-0.06	0.20	-0.08
High Education, Head	0.50	0.50	0.23	0.10	0.17	-0.23	0.18	-0.16
Mid Education, Spouse		0.13	0.28		-0.02	0.19		-0.11
High Education, Spouse		0.22	0.69		-0.20	0.34		-0.17
Pr(participation)	-0.05	-0.67	-0.43	0.42	-0.06	-0.98	2.19	-1.23
Pr(participation), Squared	0.59	0.95	0.28	-0.35	-0.64	0.24	-0.91	1.07
R^2	0.25	0.25	0.27	0.03	0.04	0.02	0.07	0.08

Notes: The table presents the coefficients of the regressions used to impute the sources of heterogeneity. S denotes single individuals, M,H denotes married heads of couples, and M,S denotes married spouses of couples.

Table A.19: Dispersion of Sources of Heterogeneity

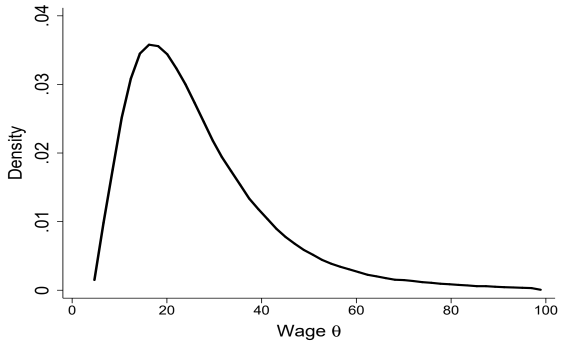
		Single Individuals		Married Individuals	
		Mean	Standard Deviation	Mean	Standard Deviation
All	z	6.3	7.7	13.0	19.4
	θ	28.7	26.0	31.9	28.7
	β_0	16.4	13.7	28.1	32.1
	χ	1.9	2.5	1.0	1.3
	κ	0.2	0.5	0.1	0.5
Employed	z	6.0	7.8	11.8	16.7
	θ	30.4	27.1	33.6	30.0
	β_0	15.3	10.6	28.6	32.7
	χ	2.0	2.5	1.0	1.2
	κ	0.1	0.4	-0.1	0.3
Non-employed	z	7.2	7.5	16.1	25.1
	θ	24.9	23.0	27.2	24.2
	β_0	19.0	18.9	26.8	30.5
	χ	1.9	2.5	1.0	1.3
	κ	0.6	0.3	0.7	0.4

Notes: The table presents the mean and standard deviation of the sources of heterogeneity. The values for z and β_0 are in thousands of dollars.

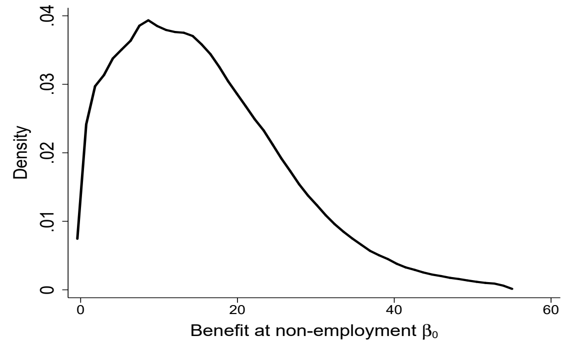
Table A.20: Correlation Matrix of Sources of Heterogeneity

		z	θ	β_0	χ	κ
Single Individuals	z	1.00				
	θ	0.44	1.00			
	β_0	0.01	0.09	1.00		
	χ	-0.11	-0.01	-0.11	1.00	
	κ	-0.02	0.05	-0.30	0.00	1.00
Married Individuals	z	1.00				
	θ	0.45	1.00			
	β_0	-0.05	0.00	1.00		
	χ	-0.08	0.05	-0.14	1.00	
	κ	-0.06	0.02	-0.18	0.07	1.00

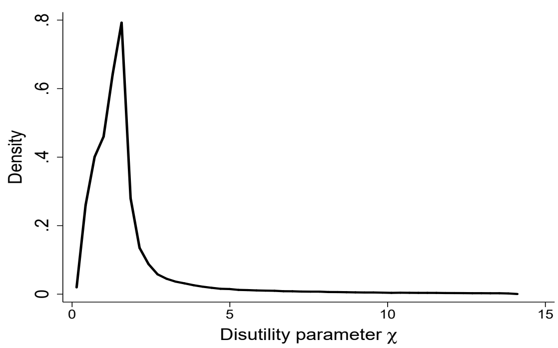
Notes: The table presents the correlation matrix of the sources of heterogeneity across all individuals.



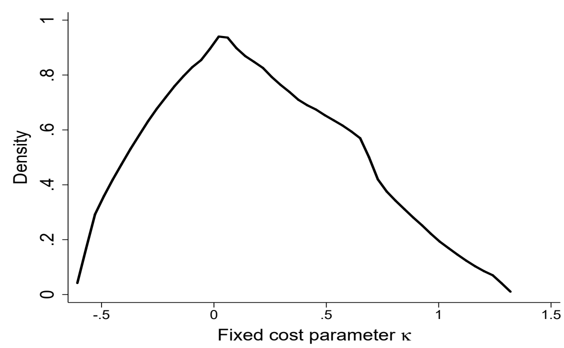
(a) Single



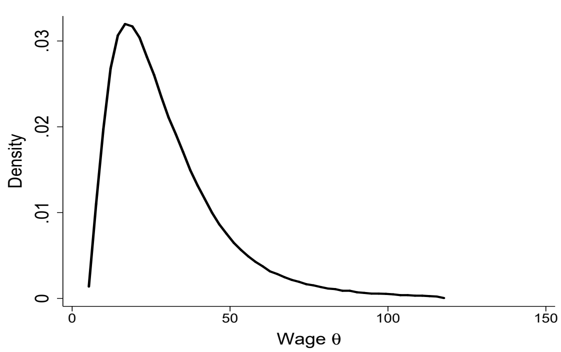
(b) Single



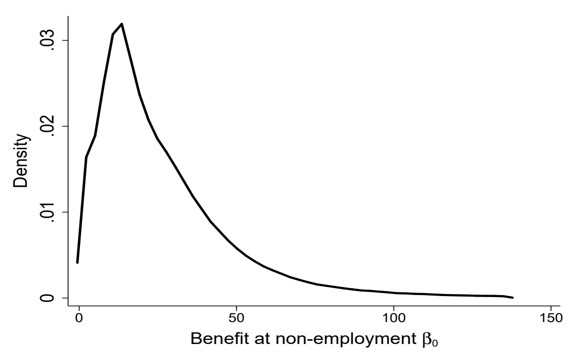
(c) Single



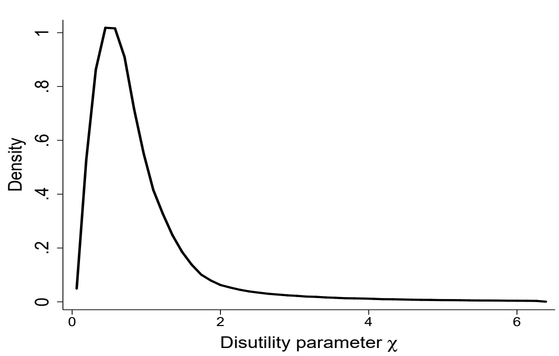
(d) Single



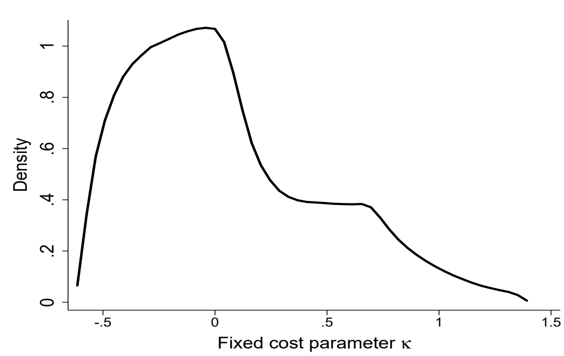
(e) Married



(f) Married



(g) Married



(h) Married

Figure A.5: Distributions of Sources of Heterogeneity

Notes: The figure shows the distributions of the sources of heterogeneity across all individuals.

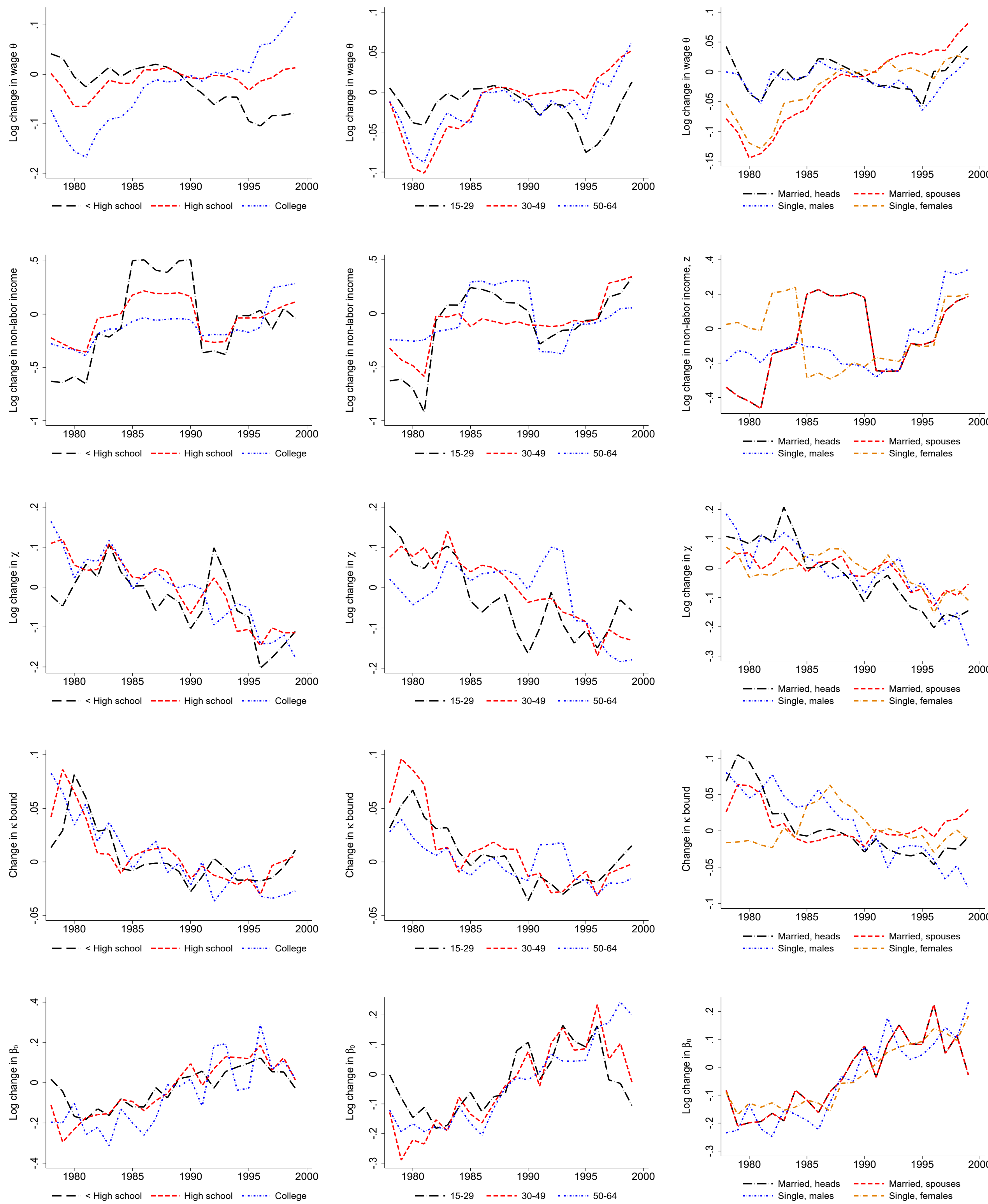


Figure A.6: Sources of Heterogeneity by Group, U.S. CPS, Boom

Notes: The figure presents the evolution of the means of the sources of heterogeneity by group, defined by education, age, and family status. The period is between 1978 and 1998.

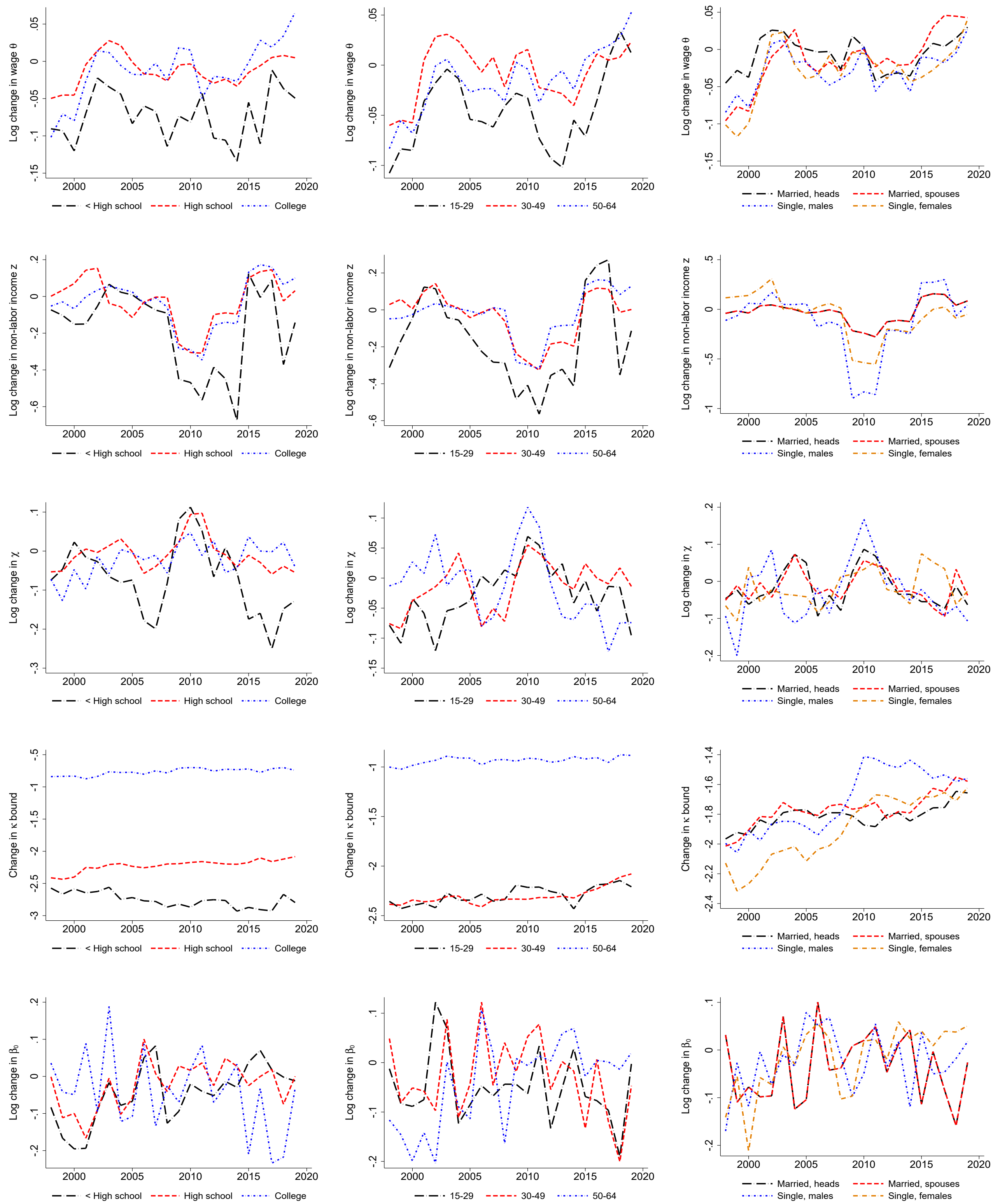


Figure A.7: Sources of Heterogeneity by Group, U.S. CPS, Bust

Notes: The figure presents the evolution of the means of the sources of heterogeneity by group, defined by education, age, and family status. The period is between 1998 and 2019.

Table A.21: Drivers of Hours Worked: U.S. CPS

	(p-points)		(log-points)	
Period: 1980-1990s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	5.2	9.9	10.0	11.7
Composition	3.0	5.1	3.2	7.1
Composition-Adjusted	2.2	4.8	6.8	4.6
Tax rate, τ_c	0.0	0.0	0.0	0.0
Tax rate, τ_z	0.0	0.0	0.0	0.0
Tax rate, τ_0	-0.1	-0.2	0.0	-0.3
Progressivity, τ_1	-0.1	0.0	0.0	0.4
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.2	-0.2	0.0	0.1
Benefit replacement, β_0/θ	-4.9	-11.4	1.0	-5.7
Health replacement, β_0/θ	-1.6	-3.7	0.3	-1.7
Other replacement, β_0/θ	-0.9	-1.6	0.2	-0.6
Welfare and UI replacement, β_0/θ	-1.4	-3.0	0.3	-1.4
Unaccounted replacement, β_0/θ	-0.5	-1.1	0.1	-0.4
Period: 2000-2010s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	-4.5	-6.8	9.2	13.0
Composition	-0.2	0.1	5.9	5.7
Composition-Adjusted	-4.3	-6.9	3.3	7.2
Tax rate, τ_c	0.0	0.0	0.0	0.0
Tax rate, τ_z	-0.1	-0.3	0.0	0.0
Tax rate, τ_0	0.1	0.2	0.0	0.5
Progressivity, τ_1	0.2	0.7	-0.1	0.5
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.2	0.6	-0.1	1.0
Benefit replacement, β_0/θ	-2.7	-4.3	0.1	-1.6
Health replacement, β_0/θ	-3.2	-6.3	0.5	-2.9
Other replacement, β_0/θ	-0.2	-0.4	0.0	-0.1
Welfare and UI replacement, β_0/θ	0.0	0.1	-0.1	0.1
Unaccounted replacement, β_0/θ	0.6	1.4	-0.2	0.7

Notes: The upper panel of the table presents results for the period between 1978 and 1998 and the lower panel presents results for the period between 1998 and 2019. Changes of variables are calculated as the difference between mean outcomes in the 1990s and mean outcomes between 1978 and 1982 in the first panel and differences between mean outcomes in the 2010s and mean outcomes between 1998 and 2002. The first row of each panel calculates the change of each variable in the raw data. The second row calculates the effects of composition and the third row calculates the compositionally-adjusted change in the data. The adjustment for composition holds fixed the share of each group in their respective average values, where groups are defined by the interaction of education, age, and family status. The other lines present the model-generated effects of keeping tax parameters and benefit programs fixed at their average values for each subperiod.

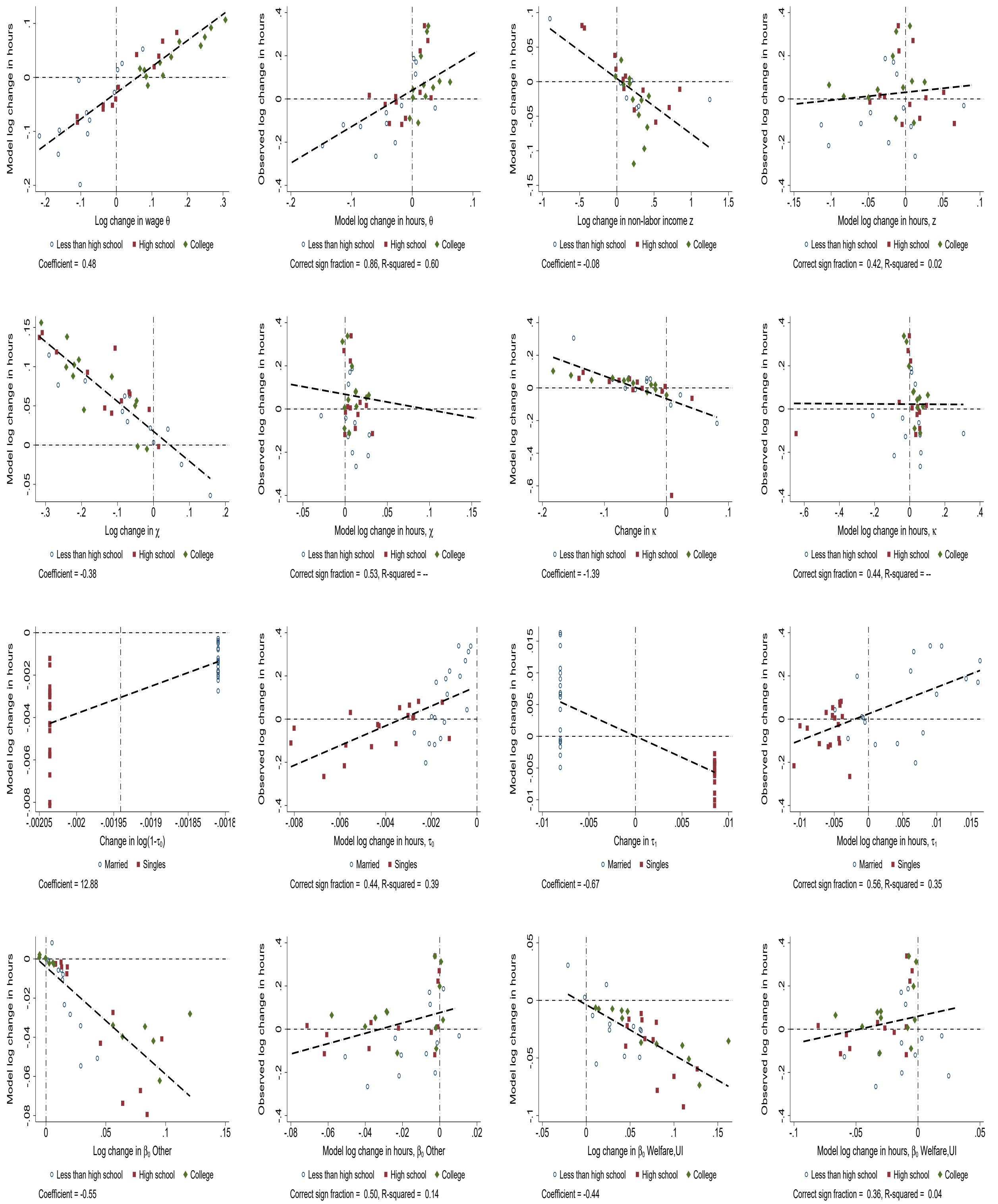


Figure A.8: U.S. Boom in Hours across Groups, 1978-1998

Notes: The figure shows the correlations across subgroups between changes in primitives, model-generated changes in total hours worked, and observed changes in total hours worked for the period between 1978 and 1998. Each dot represents a different group defined by the interaction of education, age, and family status, with the education groups being signified by circles, squares, and diamonds. A dashed line for the R-squared coefficient signifies that the relationship between model-generated changes in hours and observed changes in hours is negative.

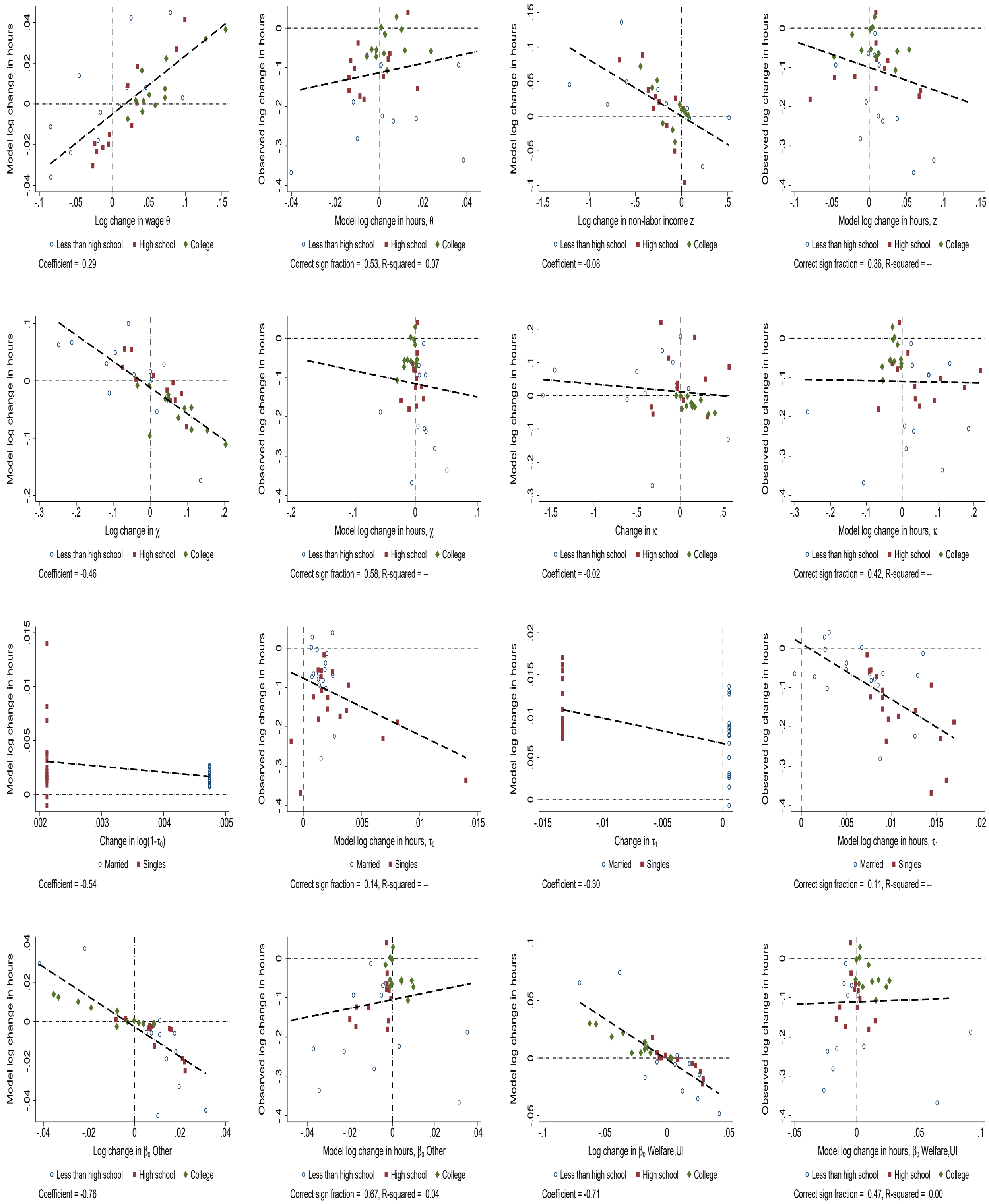


Figure A.9: U.S. Bust in Hours across Groups, 1998-2019

Notes: The figure shows the correlations across subgroups between changes in primitives, model-generated changes in total hours worked, and observed changes in total hours worked for the period between 1998 and 2019. Each dot represents a different group defined by the interaction of education, age, and family status, with the education groups being signified by circles, squares, and diamonds. A dashed line for the R-squared coefficient signifies that the relationship between model-generated changes in hours and observed changes in hours is negative.

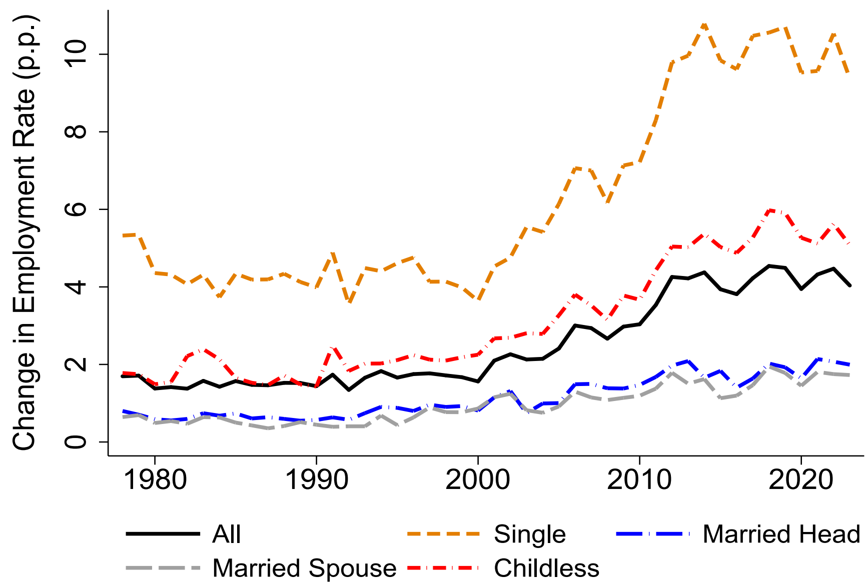


Figure A.10: Removing Health Benefits

Notes: The figure presents changes in the employment rate in percentage points by year for the aggregate population and by demographic group when we remove health benefits from total benefits, while keeping all other parameters and sources of heterogeneity constant.

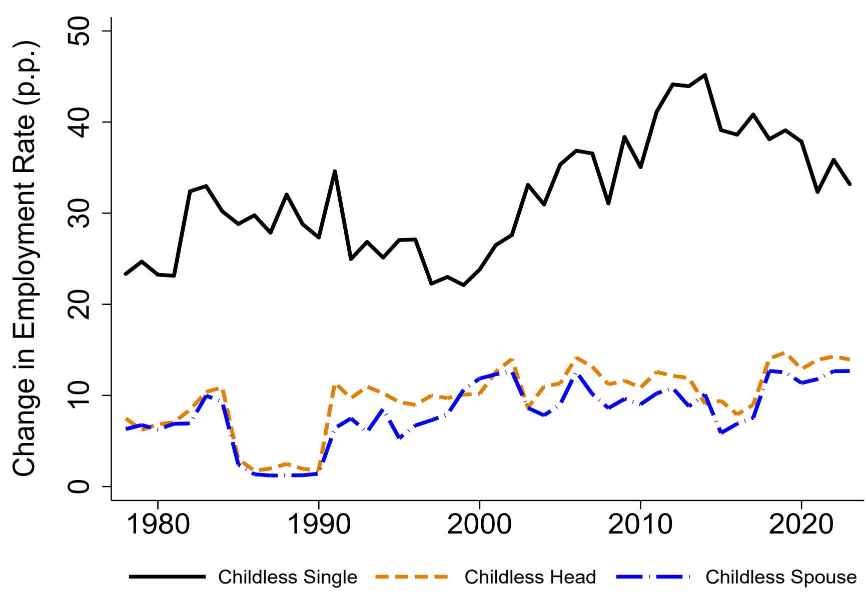


Figure A.11: Removing Health Benefits, Conditional on Positive Health Benefits

Notes: The figure presents changes in the employment rate in percentage points by year by demographic group when we remove health benefits from total benefits, conditional on receiving health benefits, while keeping all other parameters and sources of heterogeneity constant.

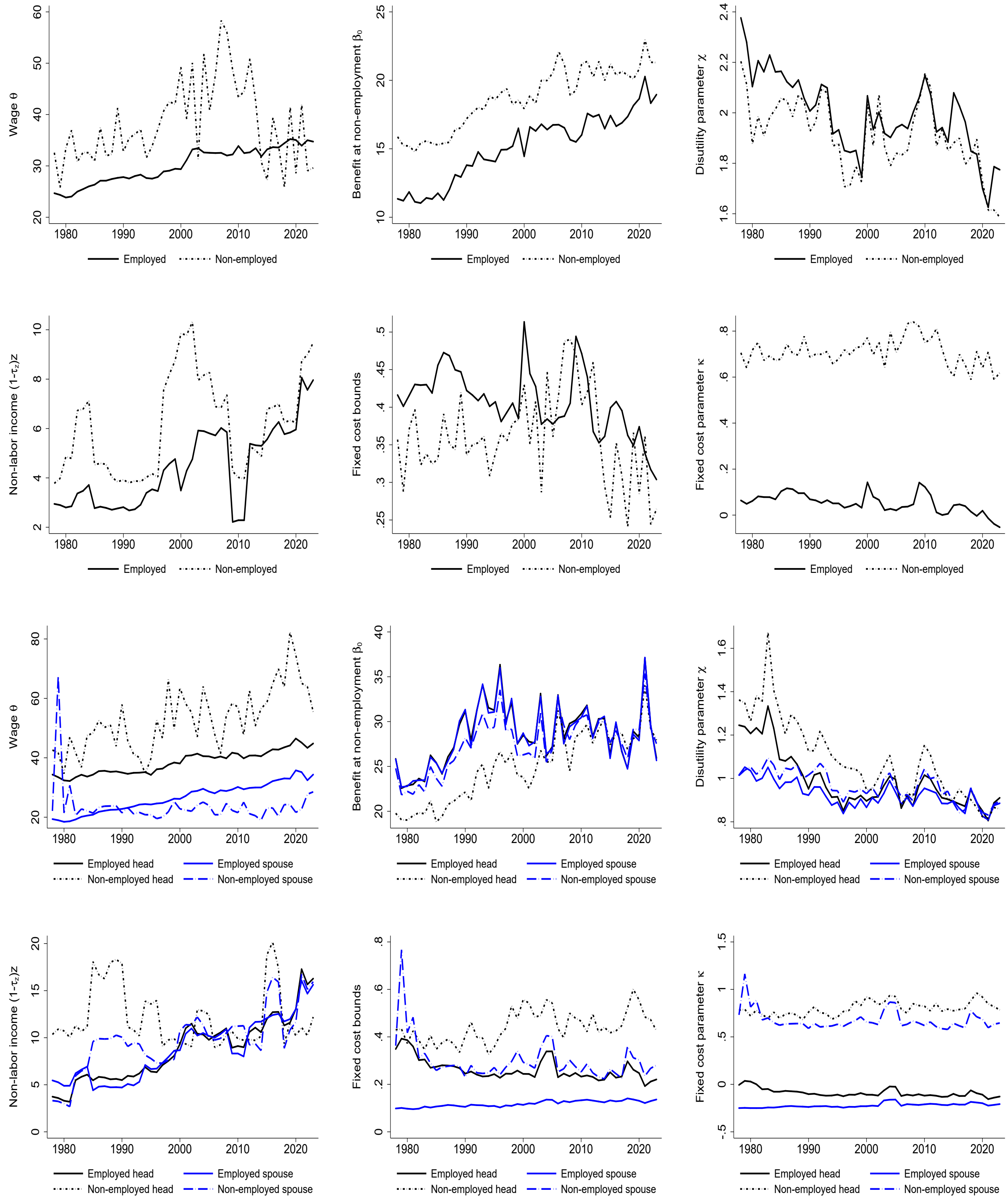
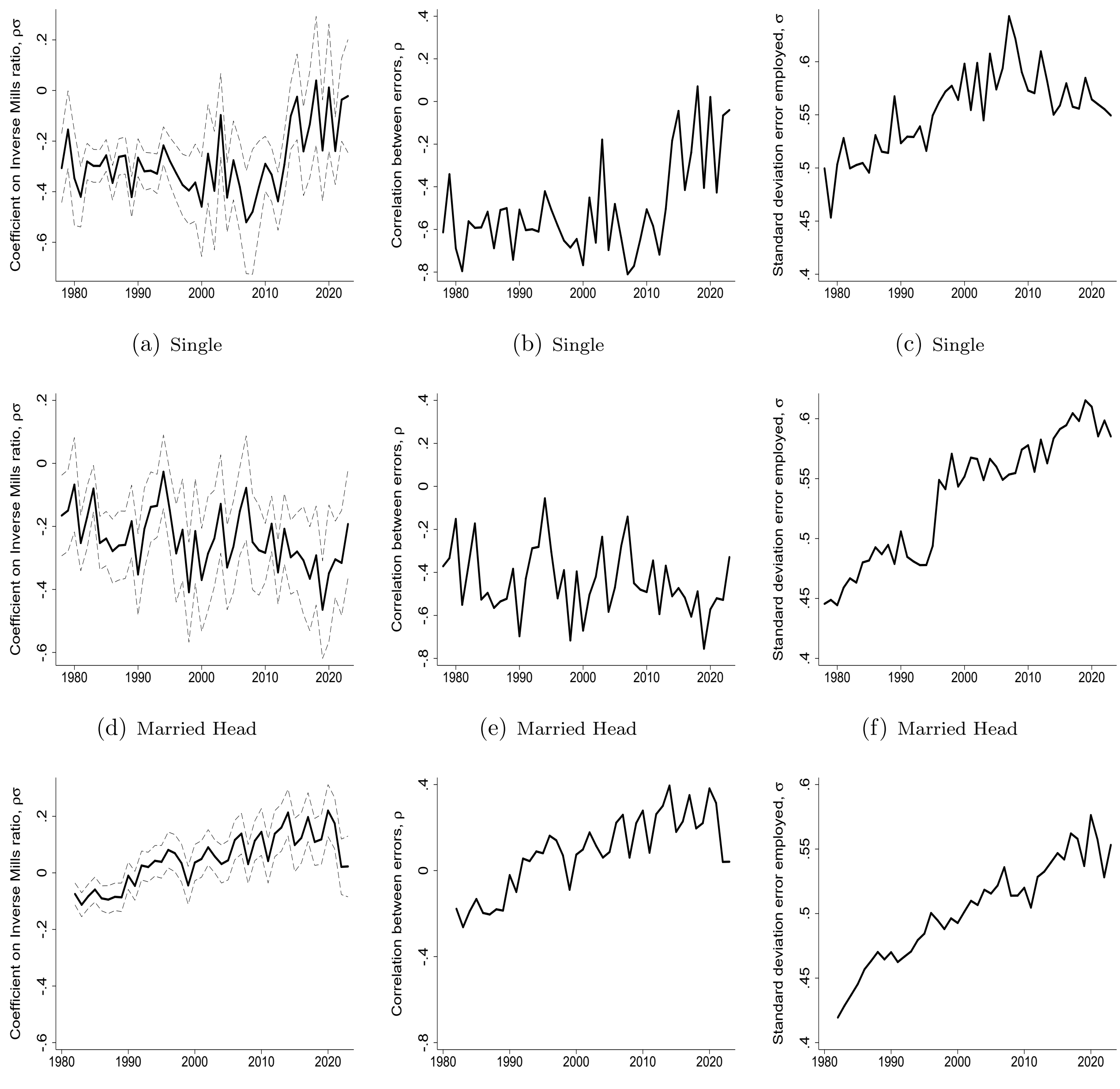


Figure A.12: Sources of Heterogeneity with Heckman Selection Model for Wages

Notes: The figure shows the evolution of the means of the sources of heterogeneity when we implement a Heckman selection model to impute the potential wages of the non-employed.



(a) Single (b) Single (c) Single

(d) Married Head (e) Married Head (f) Married Head

(g) Married Spouse (h) Married Spouse (i) Married Spouse

Figure A.13: Estimates from the Heckman Model

Notes: The figure shows our estimates of ρ, σ from the Heckman selection model we use to impute the potential wages of the non-employed. We exclude estimates for married spouses before 1982 to improve the visibility of the figure.

Table A.22: Drivers of Hours Worked: U.S. CPS, Heckman Model on Wages

	(p-points)	(log-points)		
Period: 1980-1990s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	5.2	9.9	10.0	2.6
Composition	3.0	5.1	3.2	6.1
Composition-Adjusted	2.2	4.8	6.8	-3.5
Wages, θ	-0.6	-1.6	1.6	-3.4
Non-labor income, z	-1.1	-2.4	0.0	0.2
Disutility of hours, χ	0.5	8.2	-0.2	0.1
Fixed cost, κ	1.6	2.4	2.1	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.7	-1.0	0.1	0.0
Health replacement, β_0/θ	-2.0	-4.6	0.3	-2.0
Period: 2000-2010s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	-4.5	-6.8	9.2	11.1
Composition	-0.2	0.1	5.9	6.3
Composition-Adjusted	-4.3	-6.9	3.3	4.8
Wages, θ	-0.3	-0.7	1.1	0.3
Non-labor income, z	0.7	1.7	1.1	0.0
Disutility of hours, χ	-0.1	-1.9	0.1	0.0
Fixed cost, κ	2.3	3.3	0.5	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.1	0.5	-0.1	1.0
Health replacement, β_0/θ	-3.4	-6.7	0.4	-2.9

Notes: The table shows the drivers of mean employment, hours worked, wages, and price of labor when we implement a Heckman selection model to impute the potential wages of the non-employed. This table is the analogous table to Table 5 in the main text.

Table A.23: Drivers of Hours Worked: U.S. CPS, Lower Wages of Non-Employed

	(p-points)		(log-points)	
Period: 1980-1990s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	5.2	9.9	10.0	11.8
Composition	3.0	5.1	3.2	7.3
Composition-Adjusted	2.2	4.8	6.8	4.5
Wages, θ	-0.4	-0.7	7.2	5.0
Non-labor income, z	-1.2	-2.6	0.1	0.1
Disutility of hours, χ	0.5	8.2	-0.2	0.2
Fixed cost, κ	1.3	1.8	0.0	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.2	-0.2	0.0	0.1
Health replacement, β_0/θ	-1.7	-3.8	0.3	-1.7
Period: 2000-2010s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	-4.5	-6.8	9.2	12.7
Composition	-0.2	0.1	5.9	5.7
Composition-Adjusted	-4.3	-6.9	3.3	6.9
Wages, θ	-0.1	0.0	3.1	2.6
Non-labor income, z	0.7	1.6	0.7	0.0
Disutility of hours, χ	-0.1	-1.8	0.1	0.0
Fixed cost, κ	1.9	2.8	0.3	0.1
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.2	0.6	-0.1	1.0
Health replacement, β_0/θ	-3.3	-6.5	0.6	-2.9

Notes: The table shows the drivers of mean employment, hours worked, wages, and price of labor when we lower the unobserved potential wages of the non-employed by 20 percent relative to the potential wages predicted in our baseline. This table is the analogous table to Table 5 in the main text.

Table A.24: Drivers of Hours Worked: U.S. CPS, Adjusted Value of Health Benefits

	(p-points)		(log-points)	
Period: 1980-1990s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	5.3	9.9	9.6	12.3
Composition	3.0	5.1	3.2	6.6
Composition-Adjusted	2.4	4.9	6.4	5.7
Wages, θ	-0.5	-0.8	7.3	5.0
Non-labor income, z	-1.8	-3.4	0.1	0.2
Disutility of hours, χ	0.2	6.4	-0.1	-0.1
Fixed cost, κ	0.9	1.3	0.1	0.0
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	-0.3	-0.5	0.0	0.1
Health replacement, β_0/θ	-1.3	-2.6	0.2	-0.8
Period: 2000-2010s	E-pop, e	Hours, en	Wages, w	Price labor, p
Data Change	-4.4	-6.7	9.0	14.4
Composition	-0.3	-0.1	5.9	5.5
Composition-Adjusted	-4.1	-6.6	3.1	9.0
Wages, θ	0.0	0.0	3.6	2.8
Non-labor income, z	1.1	2.3	1.0	-0.1
Disutility of hours, χ	-0.2	-3.7	0.1	0.1
Fixed cost, κ	-3.8	-4.5	-1.1	0.1
Tax system, $\tau_c, \tau_z, \tau_0, \tau_1$	0.2	0.7	-0.2	0.9
Health replacement, β_0/θ	-2.4	-4.5	0.2	-1.2

Notes: The table shows the drivers of mean employment, hours worked, wages, and price of labor when we adjust health benefits to equal 50 percent of their cost to the government. This table is the analogous table to Table 5 in the main text.

Table A.25: Coverage in LIS and LWS

Country	LIS	LWS
US	1978–2019	1995(3)2019
GER	1989–2019	2002(5)2017
CAN	1986–2019	2005, 2012, 2016, 2019
ESP	1993–2019 (except 2001–2003)	2002(3)2017
FRA	1996–2019	2009, 2014, 2017
UK	1978–2019	2009(2)2019
SWE	1992, 1995, 2013–2019	2002
ITA	1989(2)1995 1998(2)2016	2008(2)2016

Notes: The table shows the coverage in the LIS and LWS datasets. The notation $S(x)E$ denotes data exists every x years starting from year S and ending in year E.

Table A.26: Definition of Subperiods in the LIS/LWS Analyses

Dataset	Pre-2000 period		Post-2000 period	
	Period 1	Period 2	Period 1	Period 2
US	1978-1982	1990-1999	1998-2002	2010-2019
GER	1989-1992	1996-1999	1998-2002	2010-2019
CAN	1986-1989	1996-1999	1998-2002	2010-2019
ESP	1993-1995	1997-1999	1998-2002	2016-2019
FRA	1996-1997	1998-1999	2005-2007	2010-2019
UK	1978-1982	1990-1999	1998-2002	2017-2019
SWE	1992	1995	1995	2013-2019
ITA	1989-1991	1993-1998	2000-2004	2012-2016

Notes: The table presents the subperiods for each country in our LIS/LWS analyses.

Table A.27: Hours worked cutoffs for employment and taxation schemes across countries

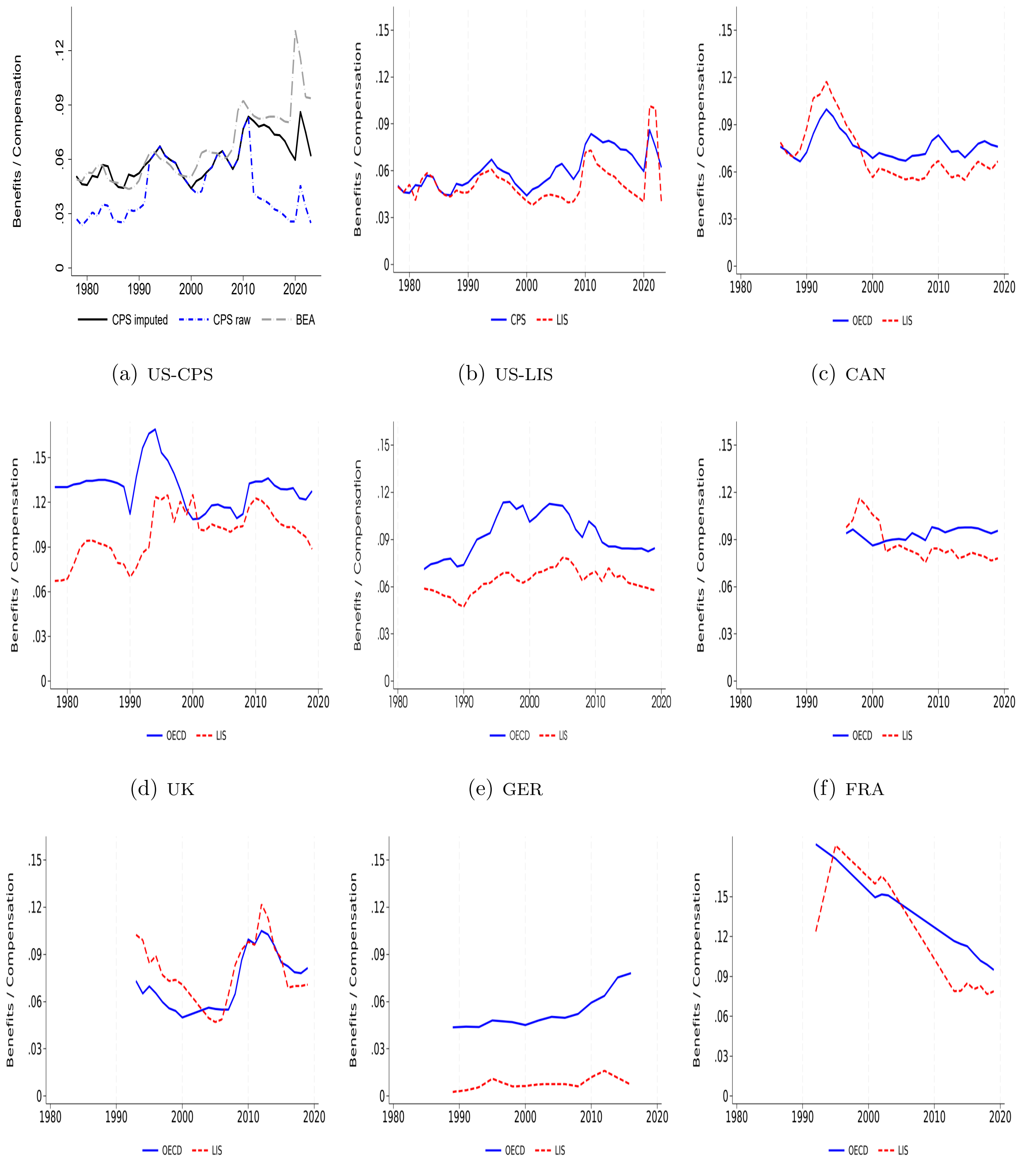
Country	Hours Cutoff	Employment Rate, OECD	Employment Rate, LIS	Taxation
US	800	71.8	63.7	Joint
GER	800	74.5	62.3	Income splitting
CAN	800	69.2	69.3	Individual
ESP	900	56.1	56.1	Joint
FRA	1,100	61.8	61.3	Joint
UK	800	71.5	65.0	Individual
SWE	800	77.2	74.1	Individual
ITA	950	55.0	54.6	Individual

Notes: The table presents annual hours worked cutoffs for employment, average employment rate in the aggregate OECD data between 1978 and 2019 and in our LIS sample, and taxation schemes across countries.

Table A.28: Parameter estimates: ϵ, γ, α, and β_1

Country	ϵ	γ	α	β_1 single	β_1 married
US CPS	0.51	1.07	0.68	1.23	0.54
US LIS	0.55	1.0	0.80	0.51	0.25
GER	0.45	0.88	8.70	0.74	0.19
CAN	0.52	1.08	0.32	0.30	0.19
ESP	0.52	0.98	1.49	0.96	0.45
FRA	0.43	1.21	0.10	0.59	0.32
UK	0.46	1.12	0.25	0.91	0.51
SWE	0.47	1.04	0.56	0.48	0.30
ITA	0.64	0.93	1.05	0.64	0.32

Notes: The table presents estimates of parameters ϵ, γ, α, and β_1 for each country in our sample.



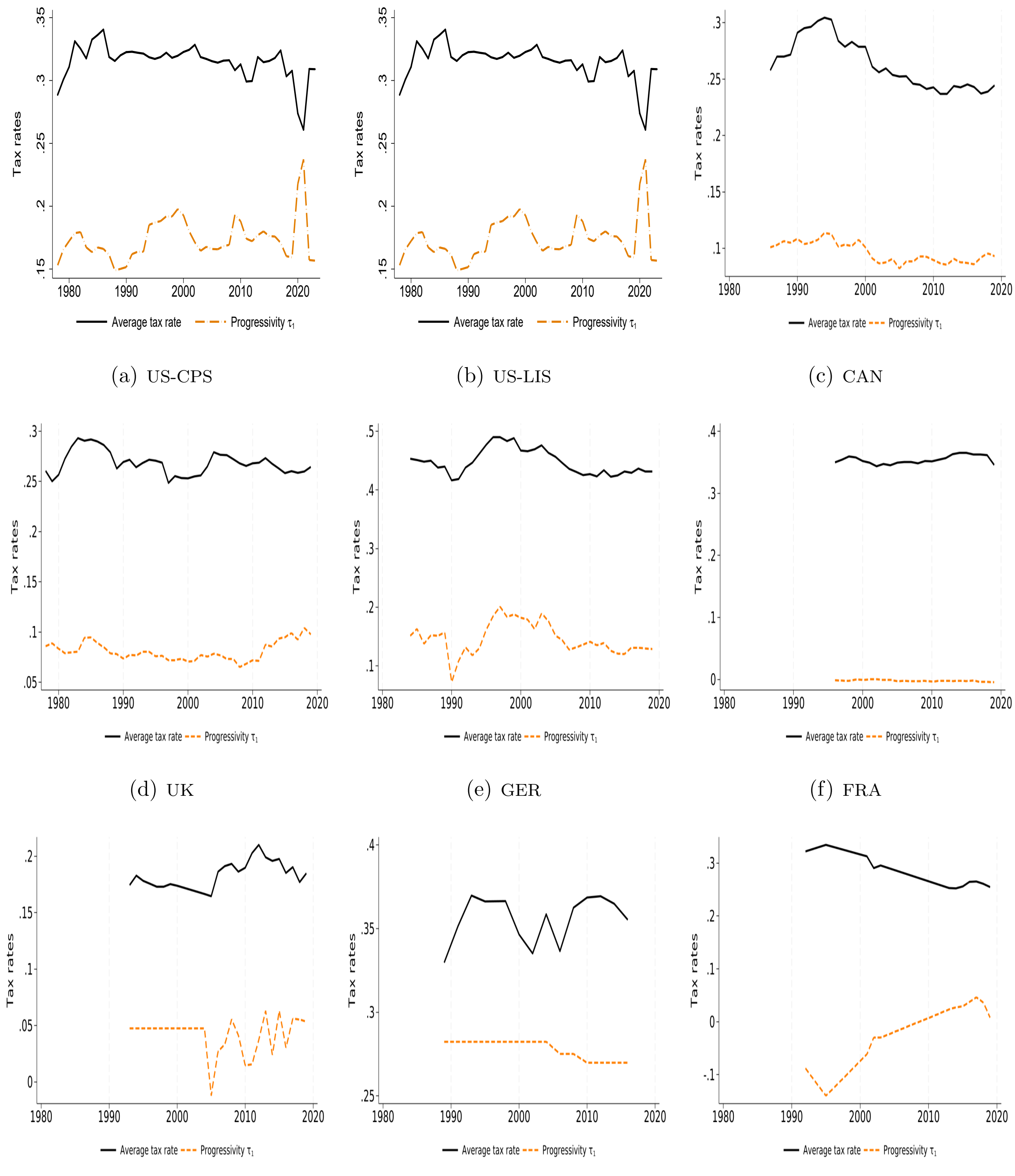
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.14: Benefits to Compensation Across Countries

Notes: The figure presents the ratio of benefits to compensation from labor in the OECD data and the LIS data. For the U.S. CPS data we repeat the comparison of the CPS data to the BEA data that we presented before in the first panel of Figure 6.



(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.15: Average Tax Rate and Progressivity Across Countries, Single Individuals

Notes: The figure presents the average tax rate and progressivity parameter τ_1 by country for single individuals.

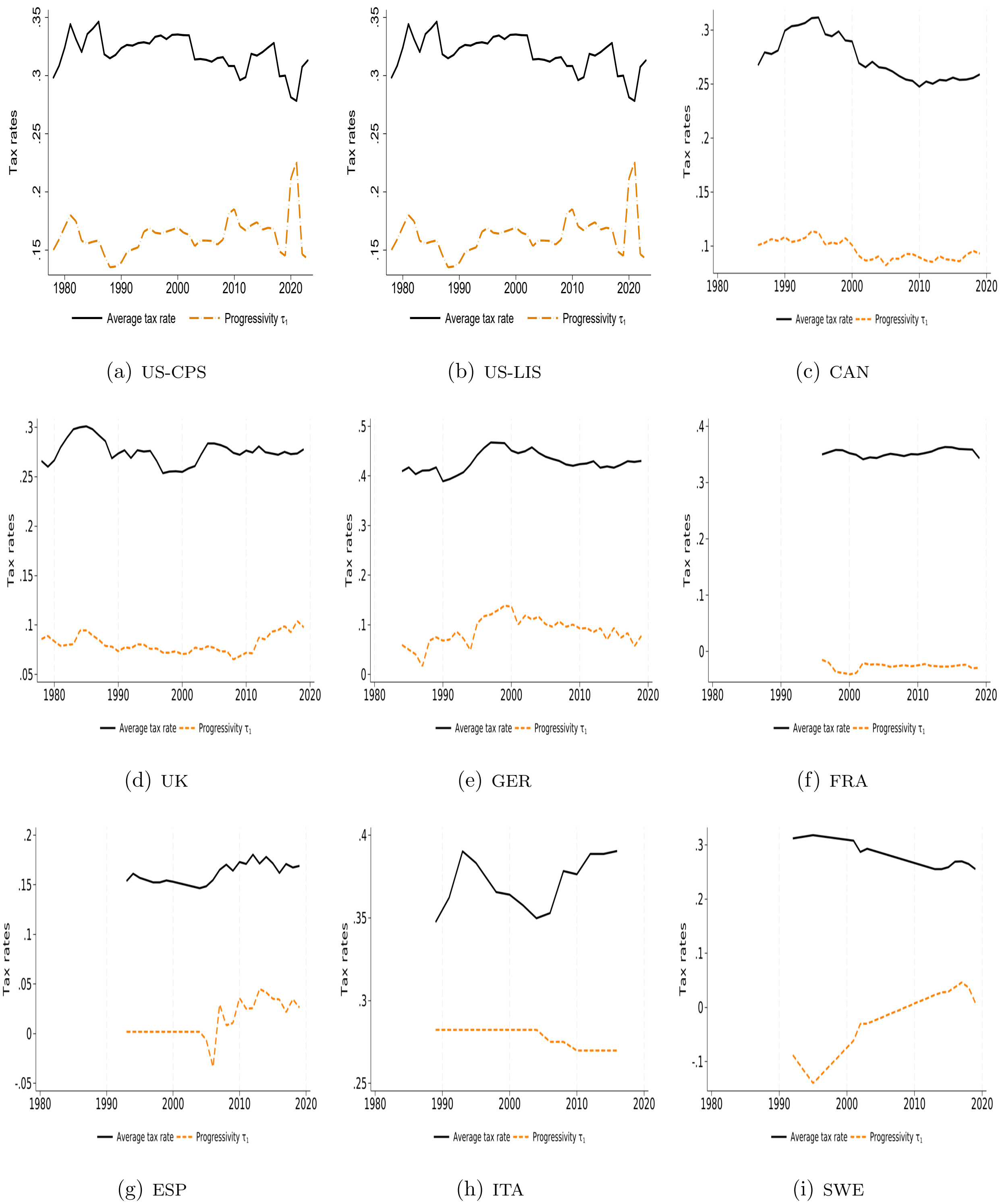
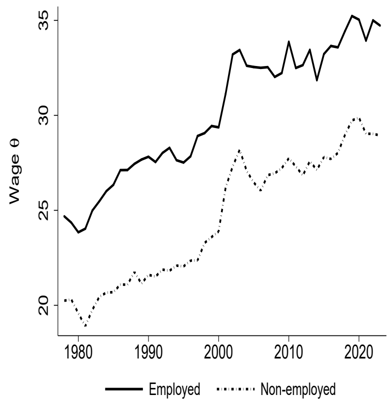


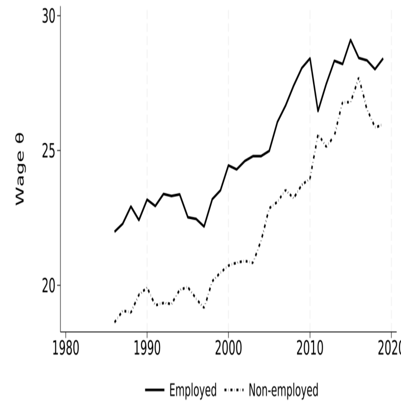
Figure A.16: Average Tax Rate and Progressivity Across Countries, Married Individuals

Notes: The figure presents the average tax rate and progressivity parameter τ_1 by country for married individuals.

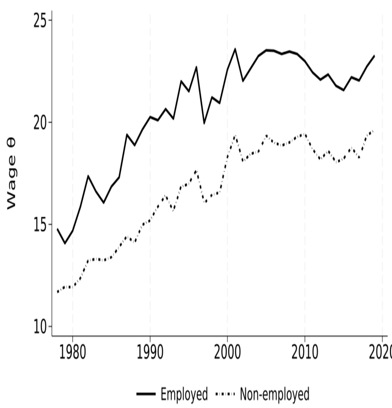


(a) US-CPS

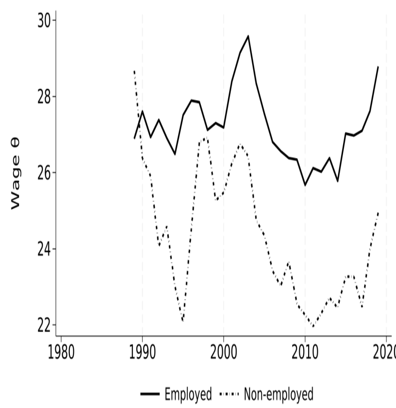
(b) US-LIS



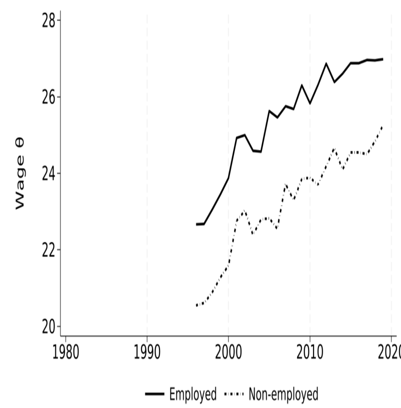
(c) CAN



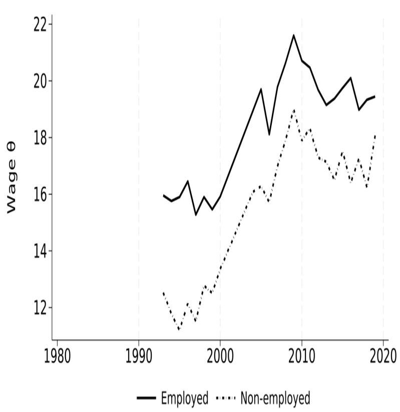
(d) UK



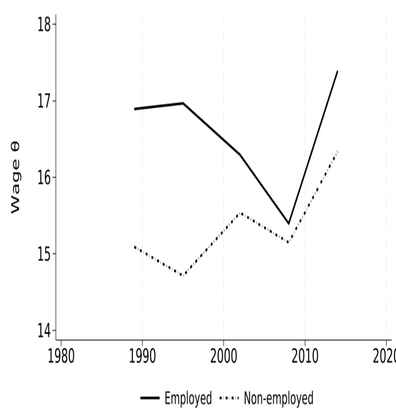
(e) GER



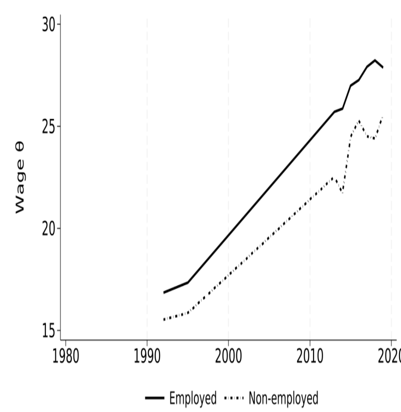
(f) FRA



(g) ESP



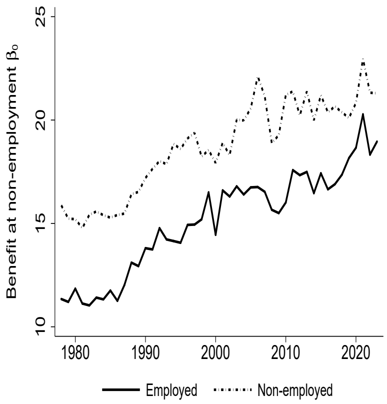
(h) ITA



(i) SWE

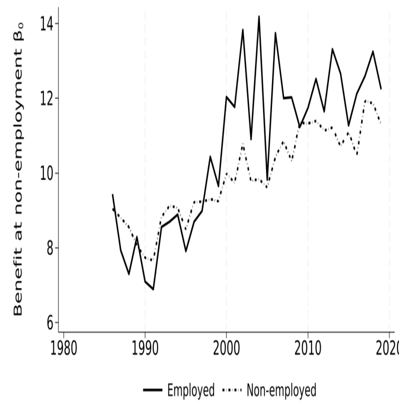
Figure A.17: Potential wages, singles

Notes: The figure presents the evolution of the mean potential wages by country for single individuals.



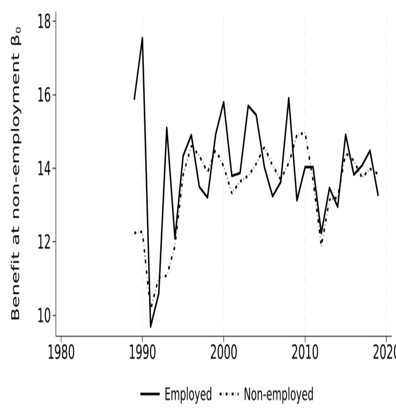
(a) US-CPS

(b) US-LIS

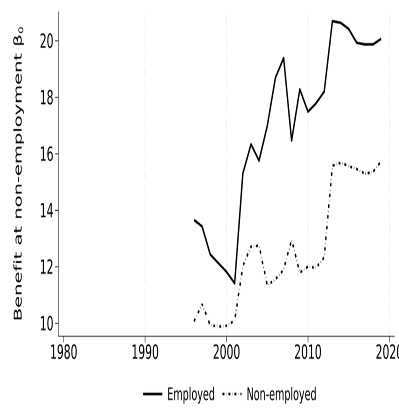


(c) CAN

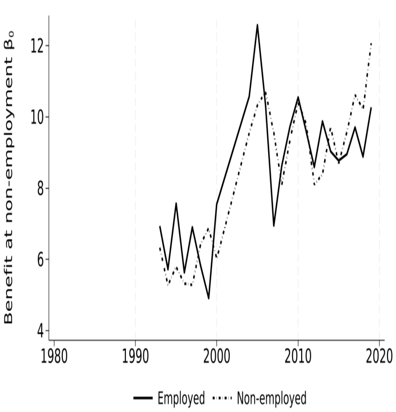
(d) UK



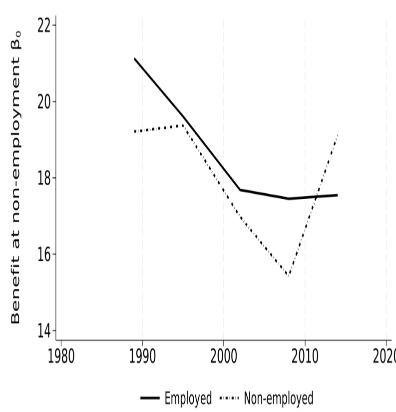
(e) GER



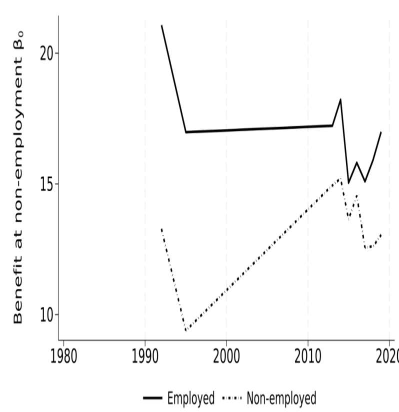
(f) FRA



(g) ESP



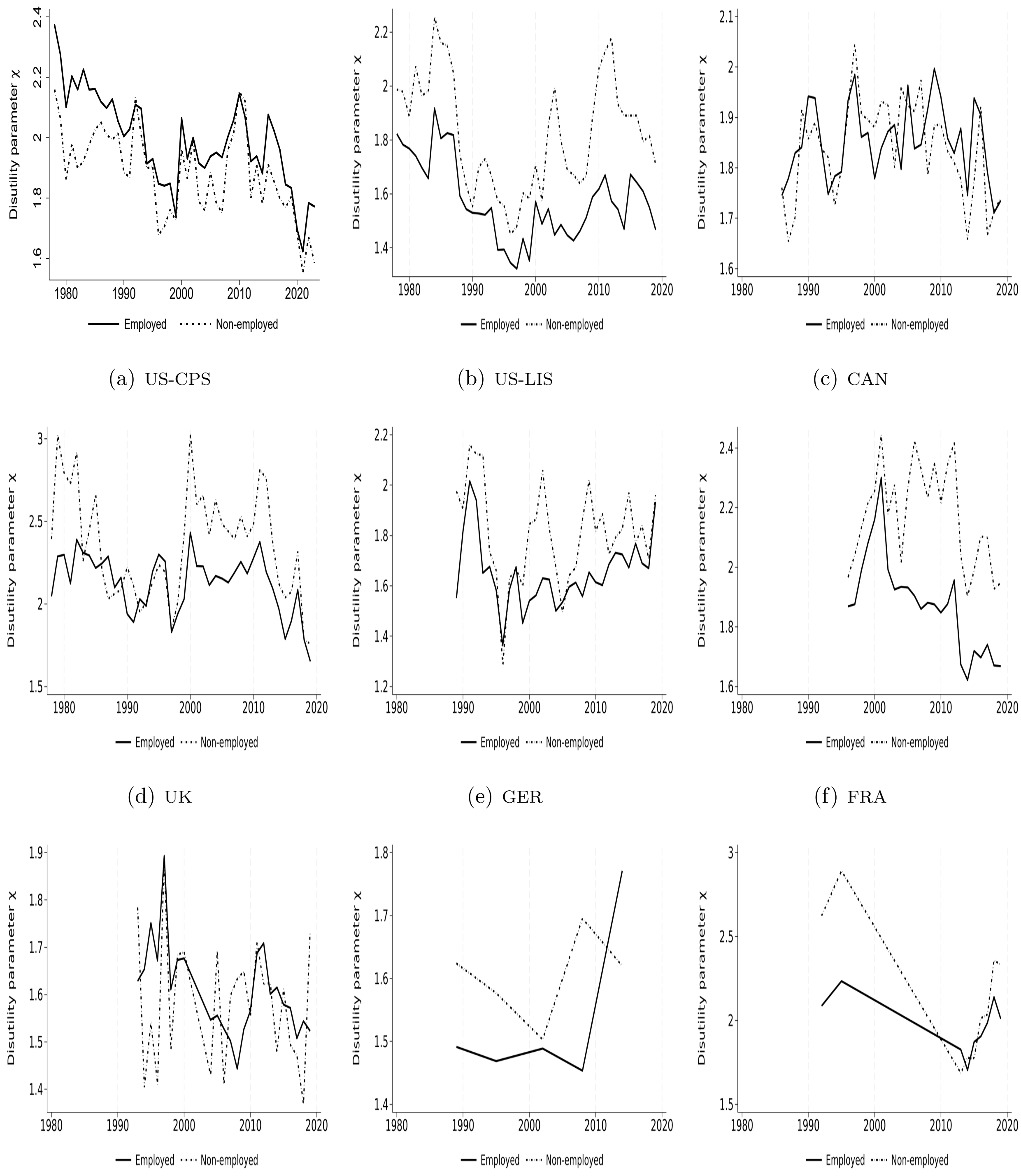
(h) ITA



(i) SWE

Figure A.18: Benefit upon non-employment, singles

Notes: The figure presents the evolution of the mean benefits upon non-employment by country for single individuals.



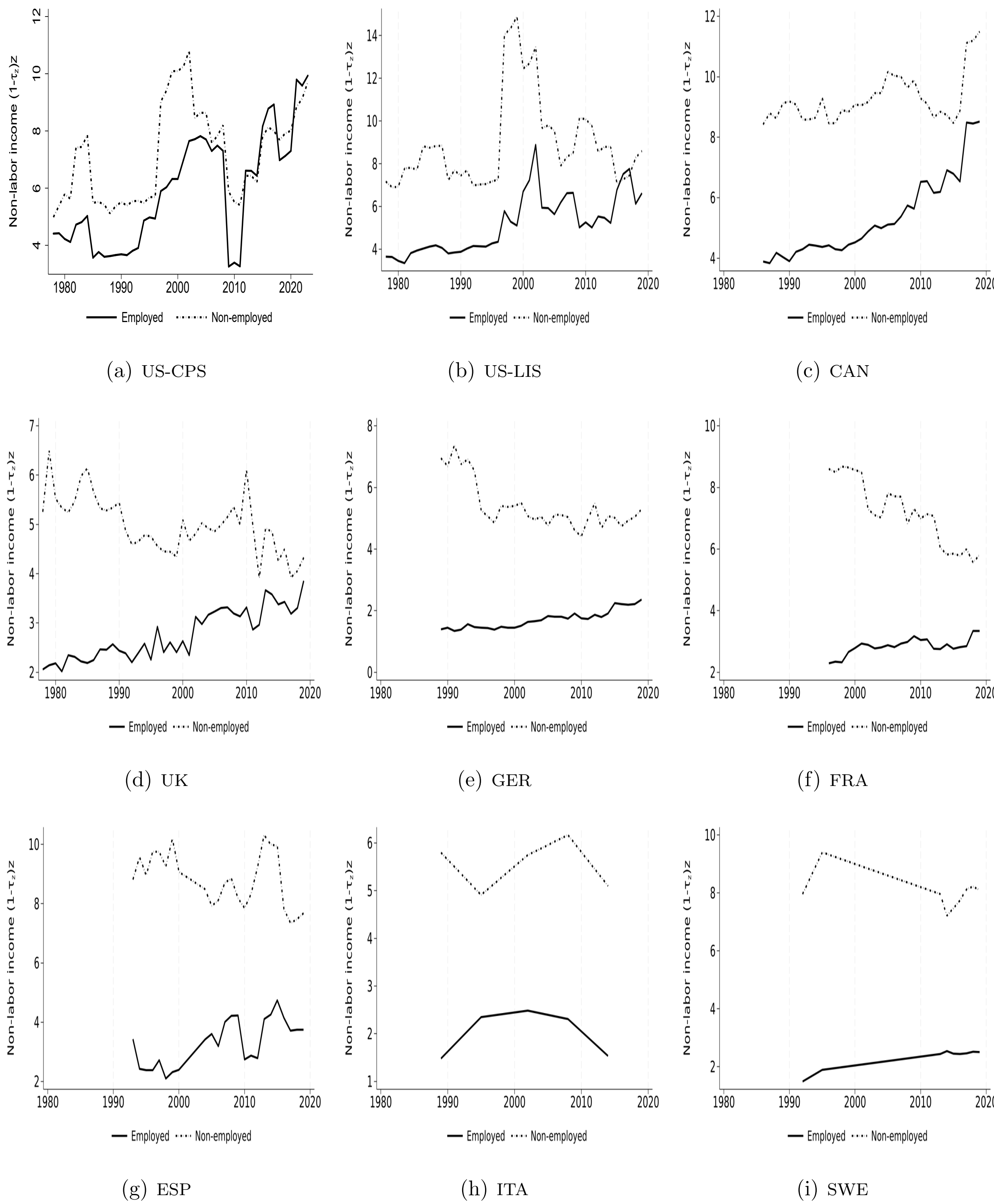
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.19: Disutility of work, singles

Notes: The figure presents the evolution of the mean disutility of work by country for single individuals.



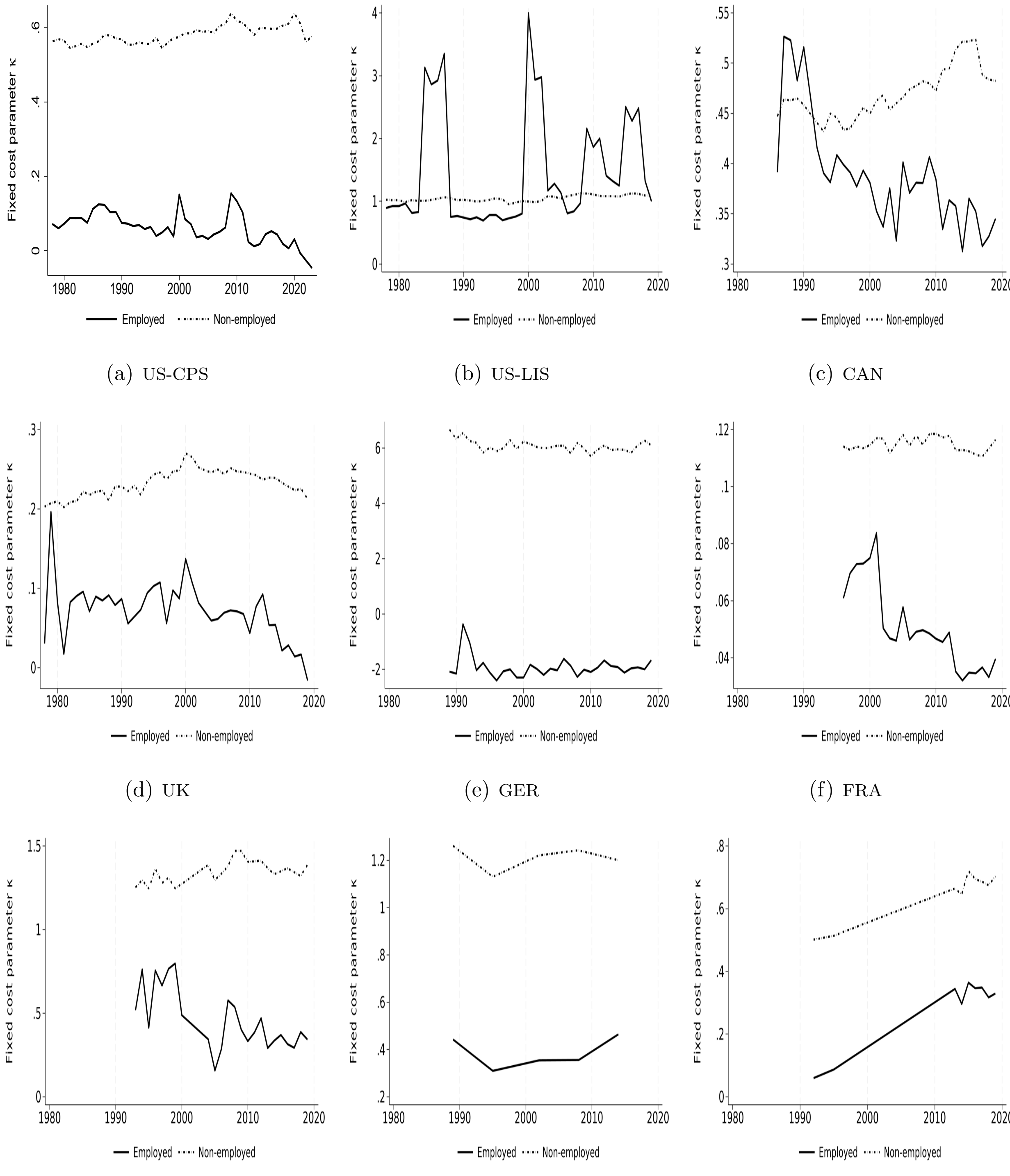
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.20: Non-labor income, singles

Notes: The figure presents the evolution of the mean non-labor income by country for single individuals.



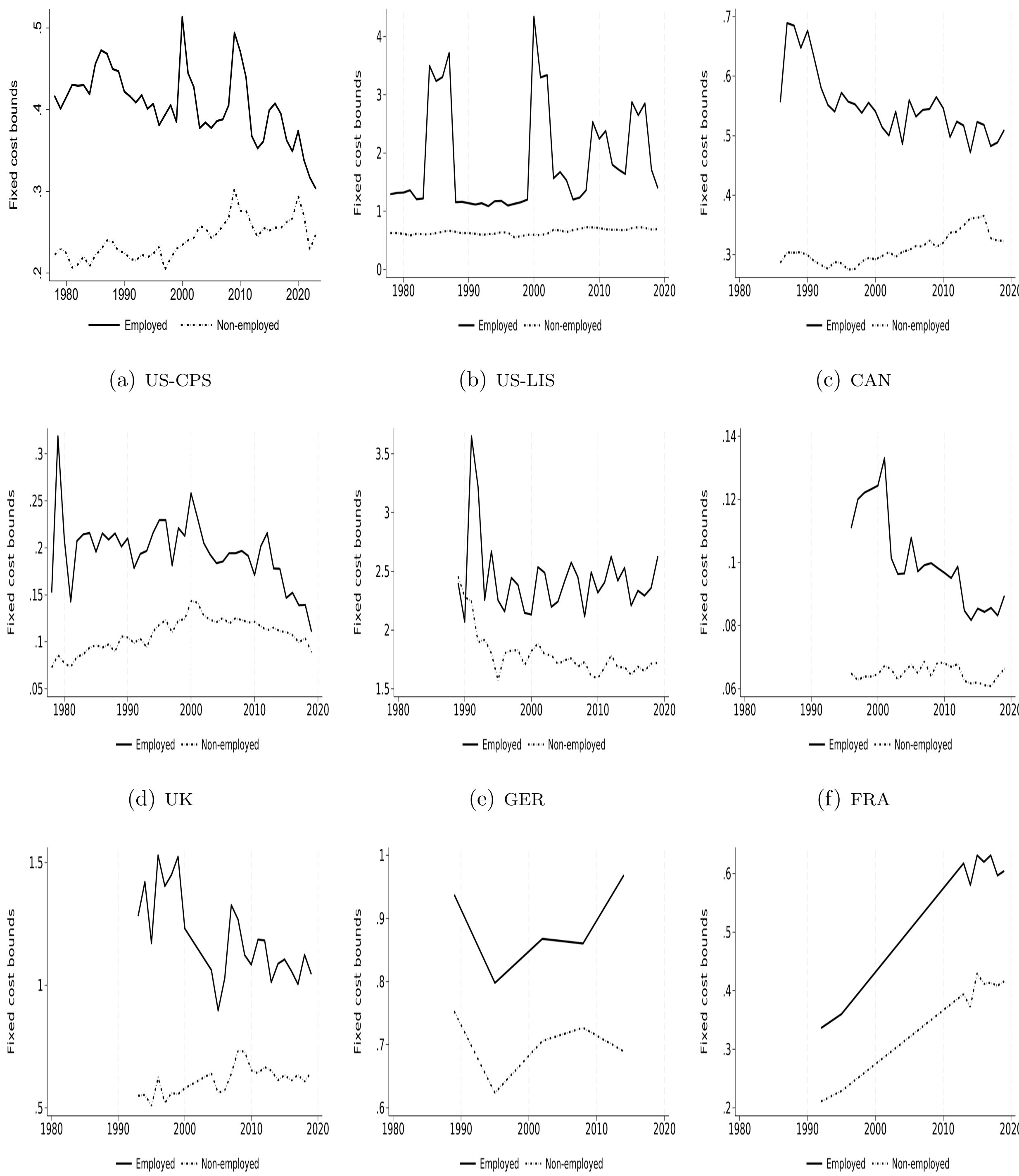
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.21: Fixed cost, singles

Notes: The figure presents the evolution of the mean fixed cost by country for single individuals.



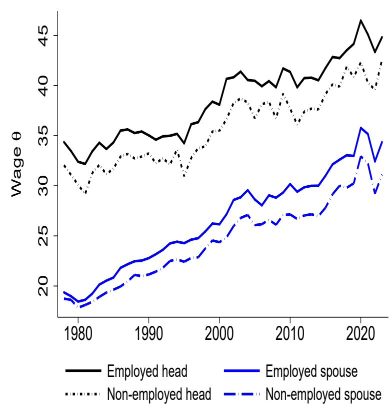
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

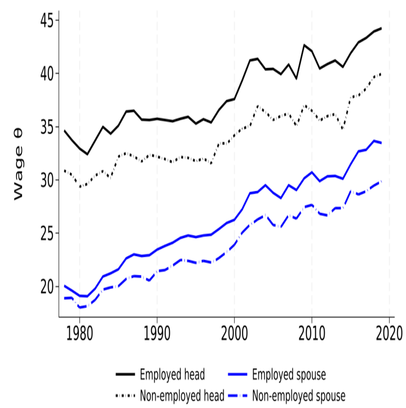
(g) ESP (h) ITA (i) SWE

Figure A.22: Fixed cost bounds, singles

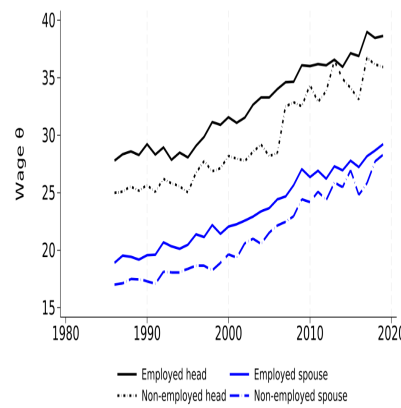
Notes: The figure presents the evolution of the mean fixed cost bounds by country for single individuals.



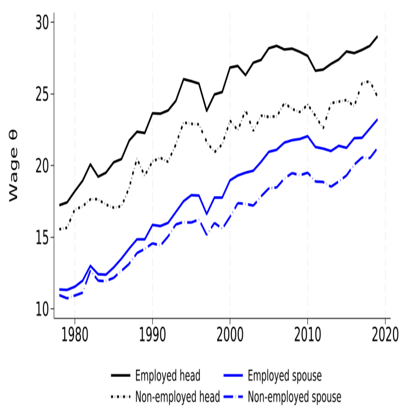
(a) US-CPS



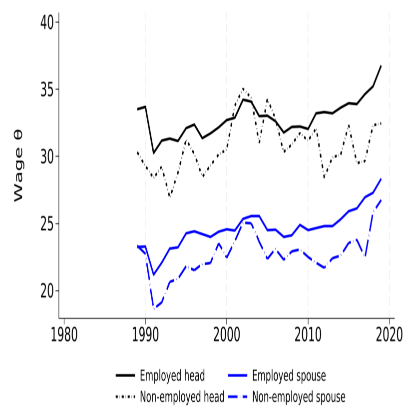
(b) US-LIS



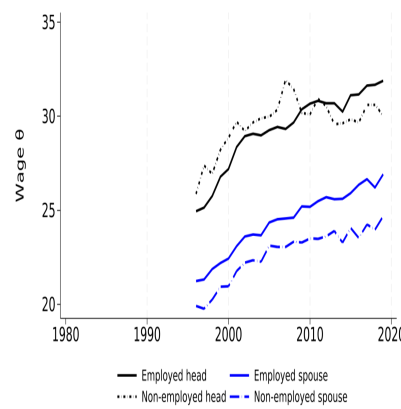
(c) CAN



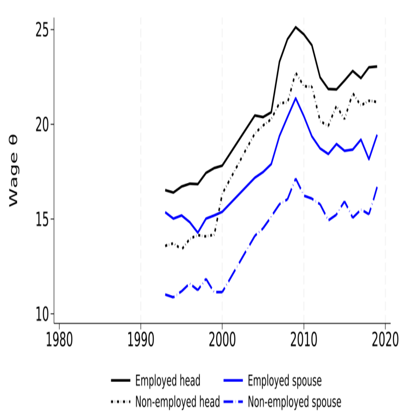
(d) UK



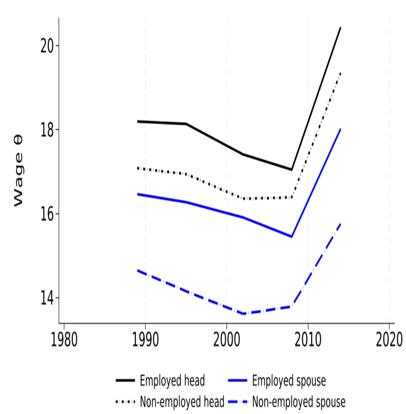
(e) GER



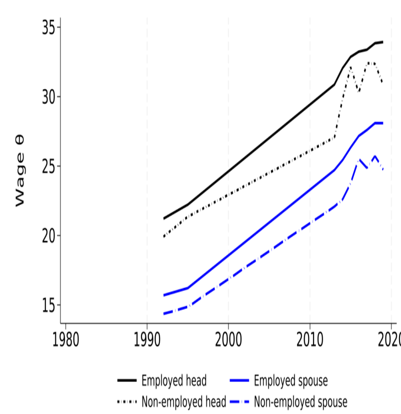
(f) FRA



(g) ESP



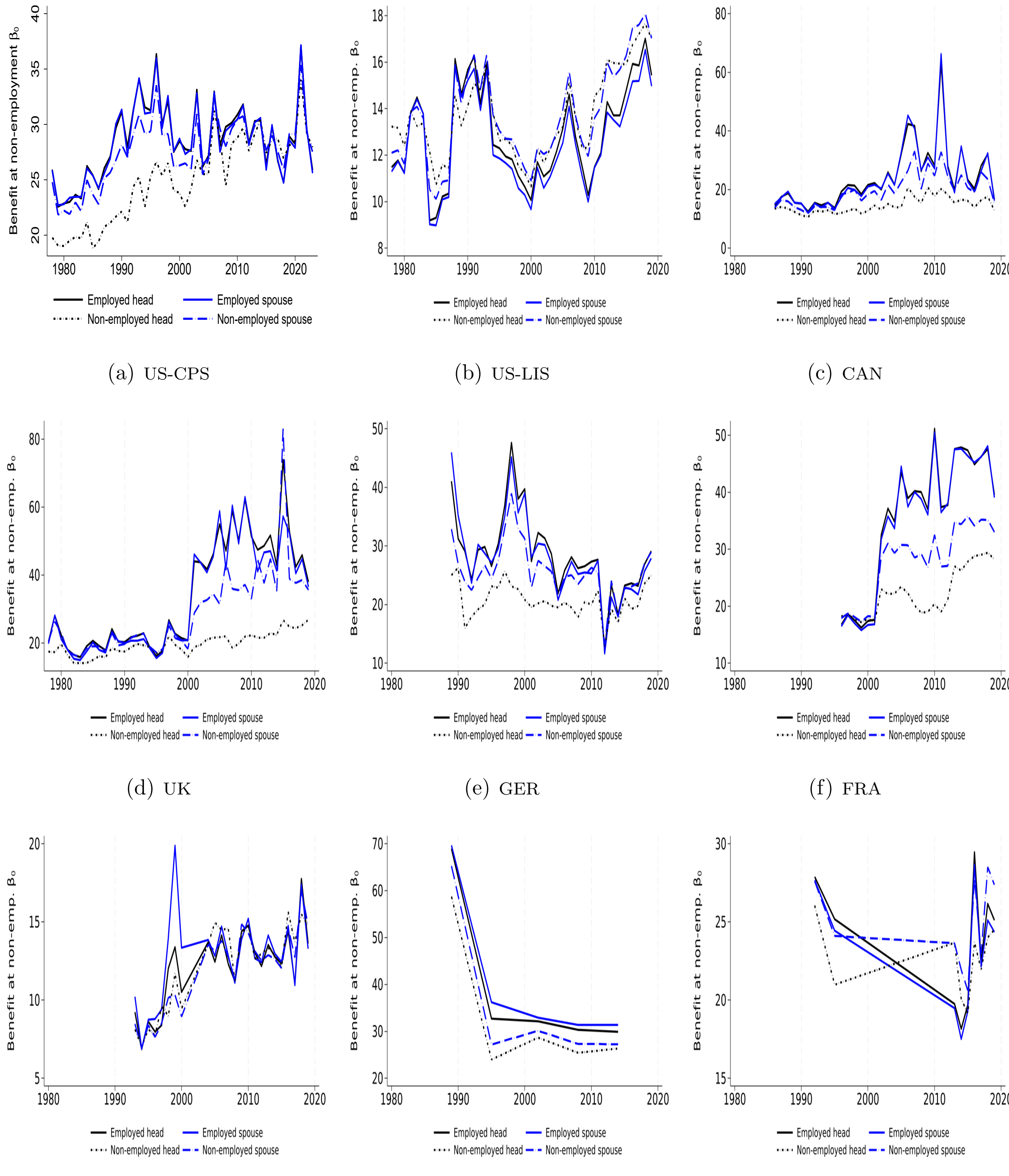
(h) ITA



(i) SWE

Figure A.23: Potential wages, married

Notes: The figure presents the evolution of the mean potential wages by country for married individuals.



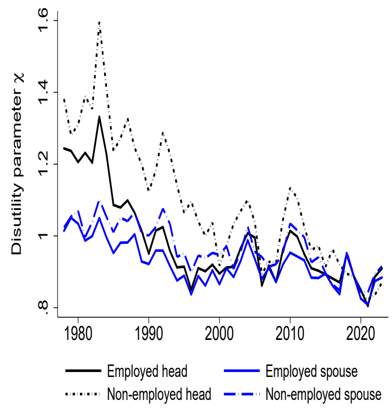
(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

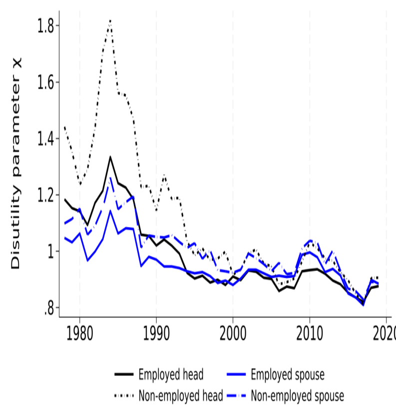
(g) ESP (h) ITA (i) SWE

Figure A.24: Benefit upon non-employment, married

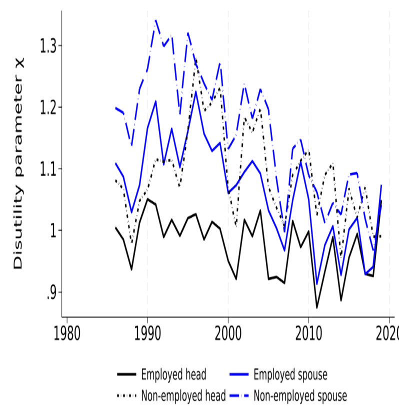
Notes: The figure presents the evolution of the mean benefit upon non-employment by country for married individuals.



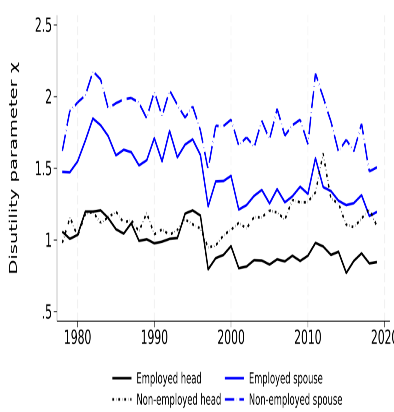
(a) US-CPS



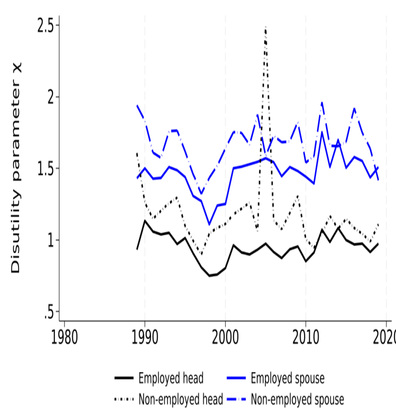
(b) US-LIS



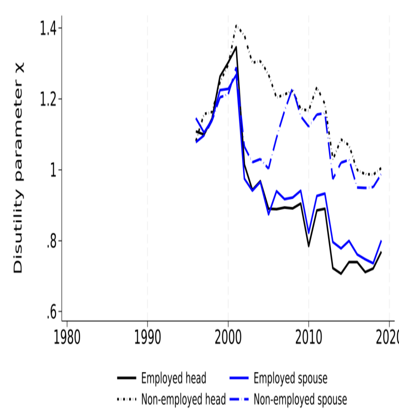
(c) CAN



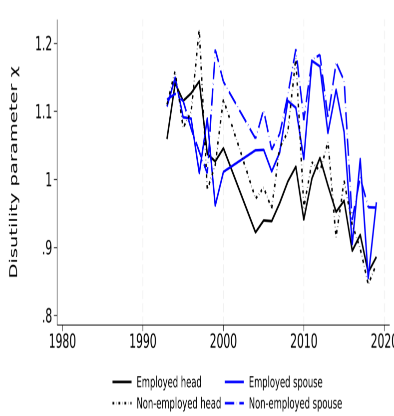
(d) UK



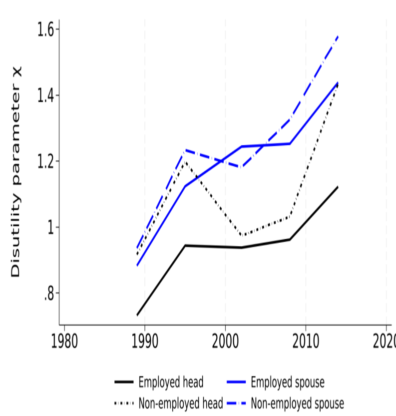
(e) GER



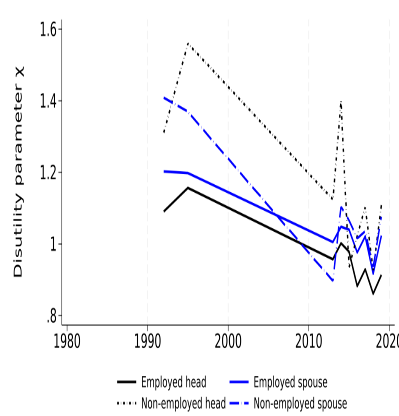
(f) FRA



(g) ESP



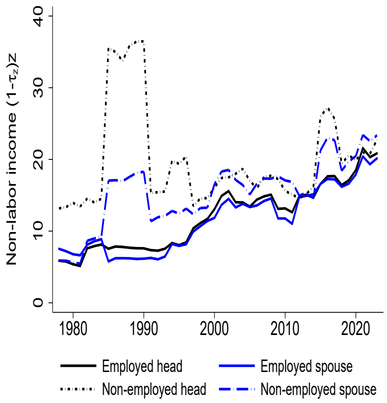
(h) ITA



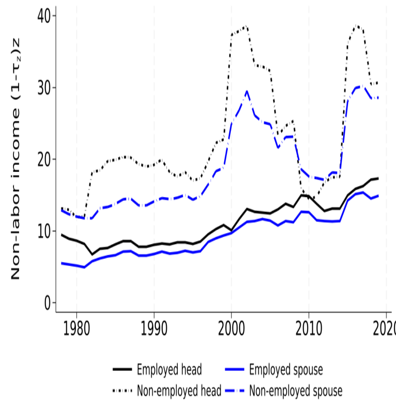
(i) SWE

Figure A.25: Disutility of work, married

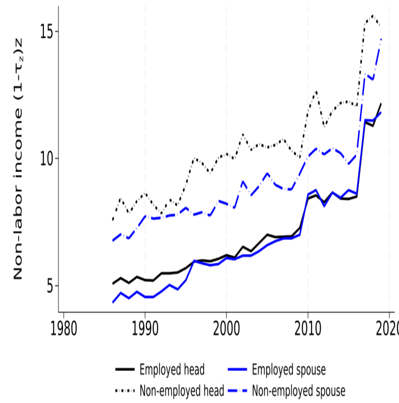
Notes: The figure presents the evolution of the mean disutility of work by country for married individuals.



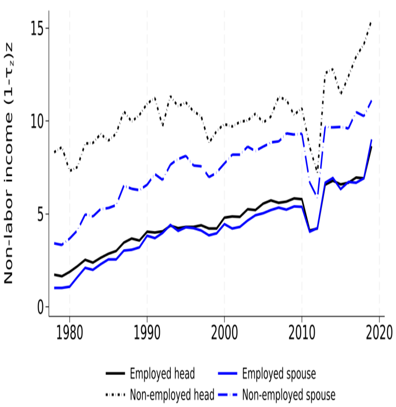
(a) US-CPS



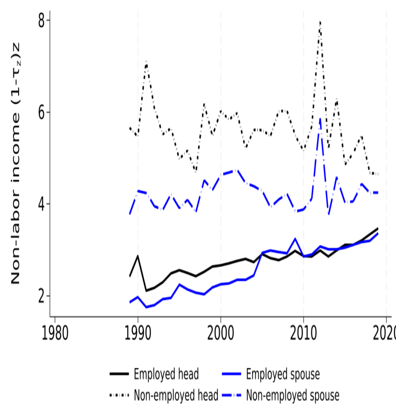
(b) US-LIS



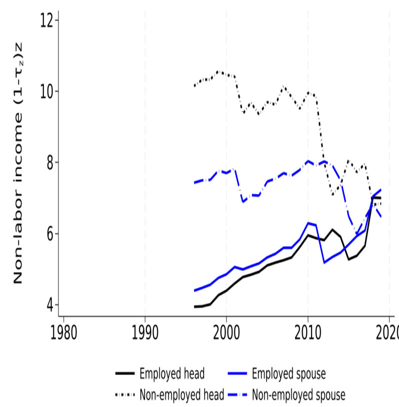
(c) CAN



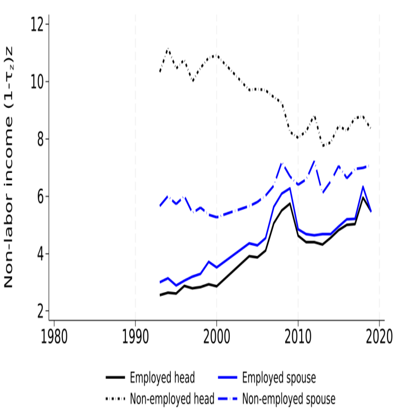
(d) UK



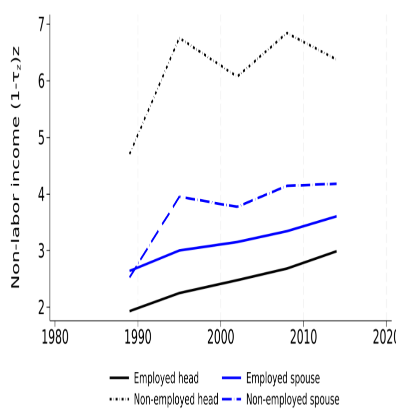
(e) GER



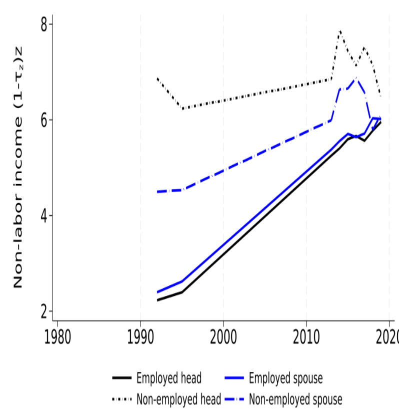
(f) FRA



(g) ESP



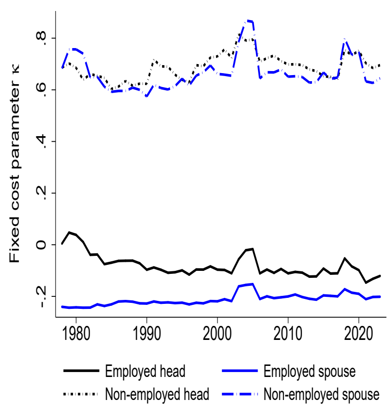
(h) ITA



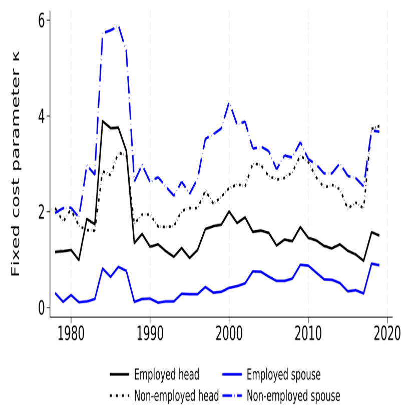
(i) SWE

Figure A.26: Non-labor income, married

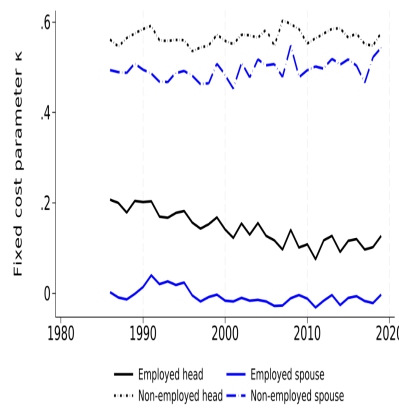
Notes: The figure presents the evolution of the mean non-labor income by country for married individuals.



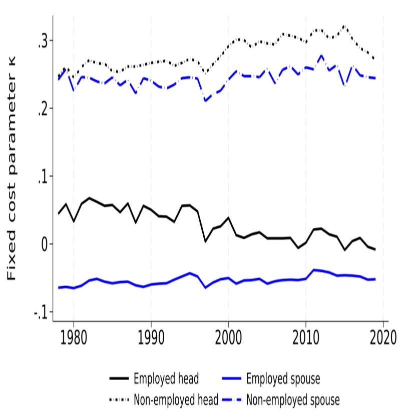
(a) US-CPS



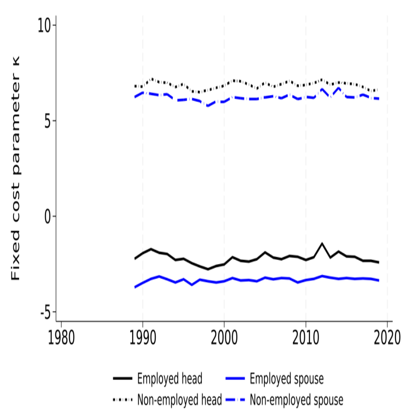
(b) US-LIS



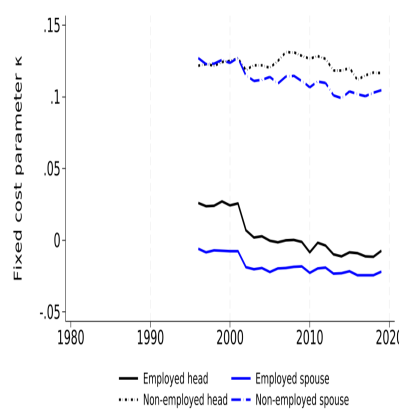
(c) CAN



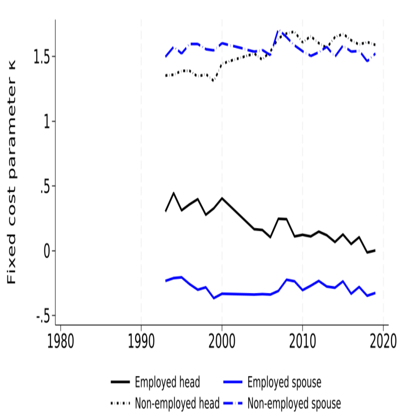
(d) UK



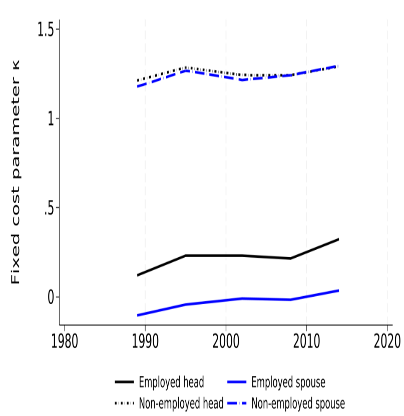
(e) GER



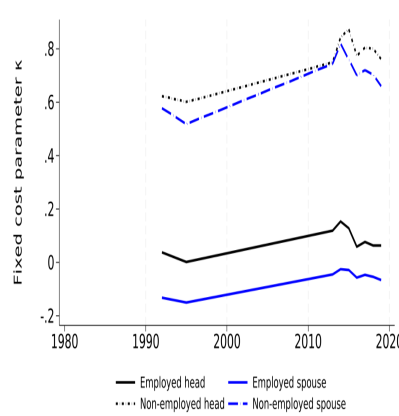
(f) FRA



(g) ESP



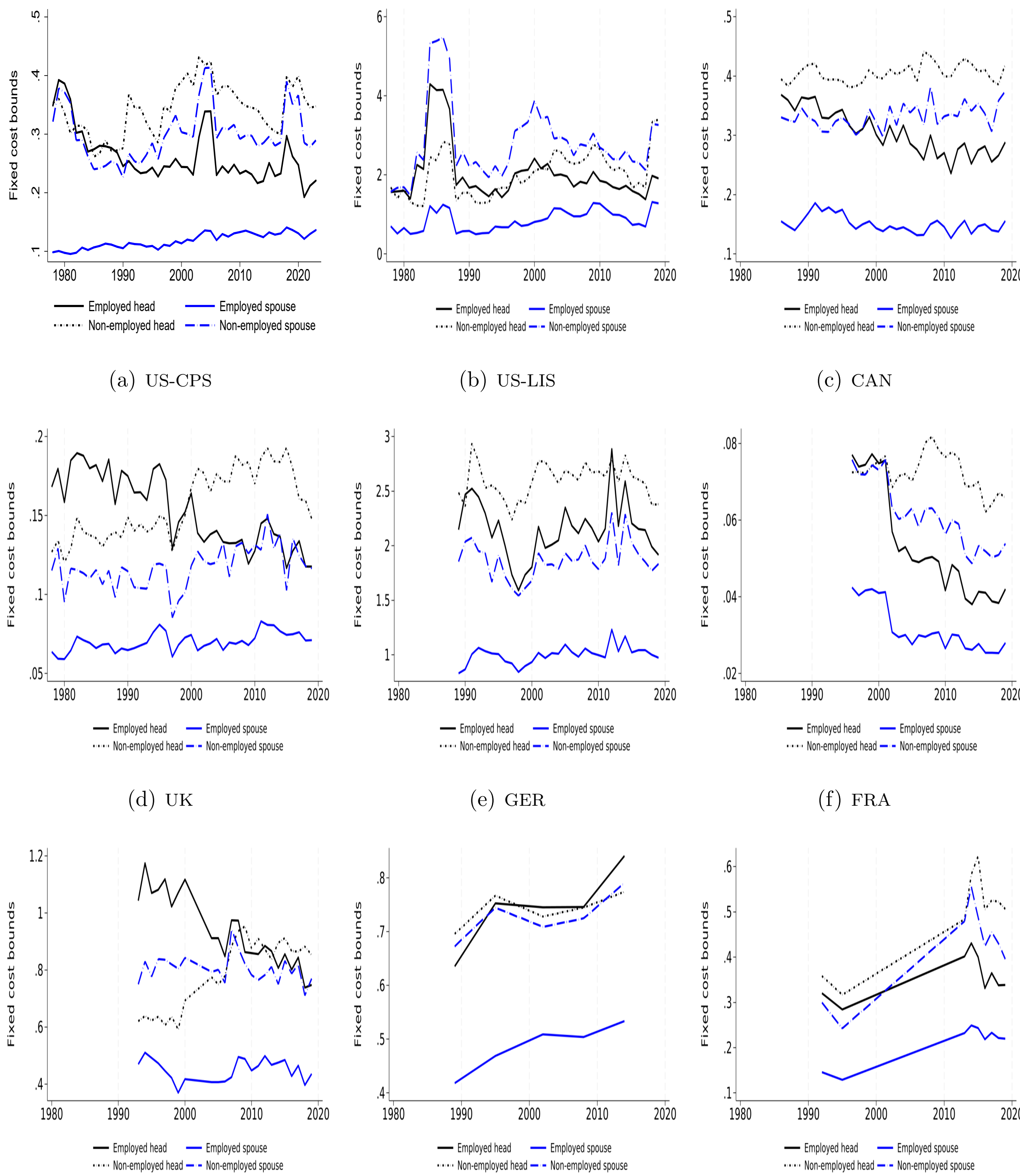
(h) ITA



(i) SWE

Figure A.27: Fixed cost, married

Notes: The figure presents the evolution of the mean fixed cost by country for married individuals.



(a) US-CPS (b) US-LIS (c) CAN

(d) UK (e) GER (f) FRA

(g) ESP (h) ITA (i) SWE

Figure A.28: Fixed cost bounds, married

Notes: The figure presents the evolution of the mean fixed cost bounds by country for married individuals.