

DISCUSSION PAPER SERIES

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Labor Supply over Time**

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ABSTRACT

The Evolution of the Wage Elasticity of Labor Supply over Time*

The uncompensated wage elasticity of labor supply is a fundamental parameter in economics. Despite its central role, very few papers have studied directly how it has changed over time. We examine the evolution of the uncompensated labor supply elasticity using cross-sectional methods over the last four decades. We find robust evidence that the elasticities weakly increased between 2000 and 2020, which represents a striking reversal from the sizeable declines for single and married women between 1979 and 2000. We additionally find that these changes arose almost entirely on the extensive margin. We then conduct a series of counterfactual simulations to identify which factors are most responsible for these trends.

JEL Classification: D10, J22

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1 Introduction

The wage elasticity of labor supply is a central parameter in economics. It captures how a change in the net wage, perhaps induced by a change in taxes, retirement credits, or productivity, affects labor supply, as measured by the number of workers or work hours. With such a parameter in hand, and especially with knowledge of how it varies with observable characteristics, one can readily forecast how labor supply will respond to policy changes that primarily affect wages. Moreover, the magnitude of the wage elasticity has implications for numerous questions, such as optimal taxation, the causes of business cycles, and the role of human capital formation.

Despite the importance of the wage elasticity of labor supply, there exists limited evidence about how this parameter has changed over time. Several papers have studied changes in women's elasticities, documenting a strong decline for both married (Kumar and Liang, 2016; Blau and Kahn, 2007; Heim, 2007;) and single (Bishop et al., 2009) women. Most of these papers do not include data beyond the early 2000s, and one paper in particular finds that the declining trend slowed at the turn of the century, suggesting that newer estimates might tell a different story (Kumar and Liang, 2016). A recent meta-analysis also finds declining elasticities for women in both Europe and the US (Bargain and Peichl, 2016), but the authors conjecture that changes in how researchers have estimated labor elasticities may account for some of this trend. There is little direct analysis of the trends in labor supply elasticities for men outside of meta-analyses and cross-paper comparisons, which are also subject to concerns regarding changing empirical methodologies over time.

In this paper, we use a unified econometric approach to examine how the uncompensated wage elasticity of labor supply has changed over the last four decades. First, we provide a theoretical discussion on why elasticities might evolve over time and a review of the existing literature on labor supply elasticity trends. We then describe a static discrete choice model and estimation strategy that exploits variation in wages due to variation in marginal tax rates across households and income ranges. At the same time, we examine the importance of our modeling decisions, particularly those that might have varying effects over time, and test the robustness of our estimated trends to these

decisions. In doing so, we contribute to the methodological literature that assesses the sensitivity of labor supply research to its modeling assumptions. See Loeffler et al. (2018) for an excellent recent example.

We have three primary findings. First, there is robust evidence that labor supply elasticities were either increasing or flat for all demographic groups (men and women, single and married) since 2000. For both single and married women, this is a dramatic reversal from the steep declines during the 1980s and 1990s. Second, these changes in elasticities for women arose almost entirely on the extensive margin. Third, using the structure of our model, we conduct a series of counterfactual simulations to identify which factors are most responsible for these changing trends for women. These simulations suggest that increasing educational levels contributed to the decline for women from 1979-2000, as did the expansion of the EITC for single women with dependents. We also find consistent evidence that fixed costs of working put upward pressure on elasticities for women since 2000. Finally, our results suggest that the substantial changes in the wage structure over the last four decades affected the elasticities very little.

2 Background and literature review

Numerous integrative surveys have summarized the vast literature on labor supply elasticities; see Blundell and MaCurdy (1999) and Keane (2011) for two examples. In this section, we briefly lay out the basic issues related to our research question, heavily relying on the exposition in Keane (2011).

2.1 The key elasticities

In a static model, two key wage elasticities arise. The first is the Marshallian (or uncompensated) elasticity e_M , which measures how hours worked h change with a change in wage w :

$$e_M = \frac{w}{h} \frac{\partial h}{\partial w}. \quad (1)$$

The second is the Hicksian (or compensated) elasticity e_H , which measures how hours change with a change in wage, holding utility u constant:

$$e_H = \frac{w}{h} \frac{\partial h}{\partial w} \Big|_u. \quad (2)$$

Under the assumption that leisure is a normal good, the Hicksian elasticity is greater than the Marshallian elasticity.

In a life-cycle model, these two elasticities measure the effect of a permanent (or parametric) change in wages – the Marshallian elasticity when the permanent wage change is uncompensated and the Hicksian elasticity when the permanent wage change is compensated. In addition, the life-cycle model introduces the Frisch (or intertemporal) elasticity, which measures how labor supply responds to known wage changes between two periods. Based on the standard assumption of diminishing marginal utility, the Frisch elasticity is greater than the other two.

Which elasticity is relevant depends on the particular policy being considered. The effect of a newly imposed tax to fund a public good might be best approximated with the Marshallian elasticity, whereas the imposition of a tax to fund a universal income transfer might be best approximated by the Hicksian elasticity. The evaluation of a change in tax rate with age, such as that associated with the Social Security retirement earnings test, might be best approximated with the Frisch elasticity.

Regardless of which elasticity is targeted, the econometrician's assumptions and empirical specifications may significantly affect their estimates of labor supply elasticities. Key issues include the simultaneity of wages and hours, the treatment of taxes, measurement error in wages and non-labor income, the treatment of missing wages for non-workers, the possibility of non-separabilities between consumption and leisure and over time, the choice of control set, the treatment of potentially endogenous variables, and the sources of dynamics such as human capital accumulation. Blundell and MaCurdy (1999) and Keane (2011) include detailed discussions of these and other econometric issues. The literature is large and complex, and given this complexity,

empirical studies often must make compromises at various points in their analysis.

2.2 Why might elasticities vary over time?

Within the canonical model of labor supply where jobs are only indexed by the wage and workers can freely choose their hours, various extant hypotheses can explain why labor supply elasticities might change. Secular changes in wages or non-labor income, including changes in government programs that provide income to non-workers, could affect the Marshallian elasticity (Bishop et al., 2009; Heim, 2007). Changes in the composition of the population (e.g., changes in the distribution of age, marriage rates, or the number of children) can also affect the distribution of preferences for consumption and leisure.

Additional explanations for evolving labor supply elasticities arise outside of the canonical model. Certain hours-wage bundles may be restricted by the demand side of the labor market, and these restrictions can loosen or tighten over time. Similarly, time-varying fixed costs of work (e.g., commuting) may make certain hours-wage bundles particularly unappealing. The composition of non-pecuniary job attributes can also change over time, affecting individuals' willingness to work at all or work long hours (Blau and Kahn, 2007; Atrostic, 1982).

2.3 Evidence on trends in labor supply elasticities

Several papers have examined changes in the labor supply elasticities of women, and the title of one notable example succinctly summarizes the literature: “The Incredible Shrinking Elasticities: Married Female Labor Supply, 1978-2002” (Heim, 2007). Based on March Current Population Survey (CPS) data from 1979 through 2003, Heim finds that the wage elasticity declined by about 60 percent from an initial base of 0.36.¹ Blau and Kahn (2007) examine changes for married women using March CPS data from 1980 through 2000, finding that the wage elasticity dropped by just over 50 percent from an initial base of about 0.80. Both papers find that the extensive margin elasticity changed more than the conditional hours elasticity, and neither finds that the downward

¹Unless otherwise specified, we report Marshallian elasticities when referencing results from previous studies.

trend diminished in the later years of their samples. Kumar and Liang (2016) also examine the labor supply elasticities of married women, but they use the 1980 through 2006 Panel Study of Income Dynamics (PSID).² They find large declines in elasticities, largely driven by the extensive margin, but they provide some evidence that the declines level off during the final years of their sample period.

Moving from married women to single women, Bishop et al. (2009) estimate changes in the wage elasticity for single women using the March CPS from 1979 through 2003. With a continuous choice model and imputed wages for all workers, they conclude that the wage elasticity of labor supply declined by about 80 percent from an initial base of about 0.20. Unlike the literature for married women, they find that elasticities fell more at the intensive margin than the extensive margin. There is little evidence that the downward trend diminished towards the end of their sample period.

Several systematic literature reviews also provide evidence about how the wage elasticity has changed over time. Keane (2011) provides a list of estimates from eight different studies that exhibit little change from 1980 to 2001 in the wage elasticity for men. Based on an exhaustive list of studies from both the United States and Europe, Bargain and Peichl (2016) do not find evidence of a systematic trend in wage elasticities for men, but they do observe a downward trend in elasticities for married and single women. Importantly, Bargain and Peichl (2016) demonstrate that researchers are increasingly using discrete choice estimation methods to estimate wage elasticities, and the downward trends in female elasticities are somewhat flatter when using estimates from these discrete choice studies as opposed to estimates from continuous choice studies.

3 Empirical methods

Many of the recent papers that estimate the wage elasticity of labor supply use the discrete choice framework pioneered by van Soest (1995). This approach is particularly well suited to examining

²Although the authors provide some estimates that exploit the panel nature of their data, we focus on the estimates obtained from pooled models that are similar to those estimated by Heim (2007) and Blau and Kahn (2007).

our question. First, it directly incorporates non-participation into the labor supply decision, allowing us to easily study the extensive and intensive margins in a common framework. Second, it allows us to incorporate fixed costs of working and nonconvexities in the wage-hours locus. Third, after estimating structural parameters, we can directly examine counterfactual scenarios.

We opt for a static model instead of a dynamic life-cycle model. Static models continue to play a prominent role in assessing the responsiveness of hours to wages; Bargain and Peichl (2016) list numerous examples of recent papers that estimate a static model, and two prominent papers that provide a synthesis of our understanding of Hicksian elasticities rely on estimates from static models (Keane, 2011; Chetty et al., 2011). In addition, static discrete choice models are significantly less computationally intensive than are dynamic discrete choice models, and computation time is an important consideration because we estimate separate sets of parameters for each year and demographic group. With that said, important questions remain regarding identification in these models. Our approach will be to follow the typical methods from the recent literature, with a focus on applying consistent methods over time so that we can focus on trends.

3.1 A static discrete choice model of labor supply

For notational simplicity, we first describe our discrete choice model for single (non-married) individuals. Suppose an individual i chooses hours of work per week h_{ij} from a set of J different alternatives. For singles, $h_{ij} \in \{0, 10, 20, 30, 40, 50, 60\}$, so $J = 7$. We assume that the individual earns a constant pre-tax hourly wage w_i regardless of their hours choice. Each choice of weekly work hours delivers a different level of weekly consumption c_{ij} and leisure l_{ij} . Consumption is equal to the sum of household labor income ($w_i \times h_{ij}$) and non-labor income y_i , after taxes and government assistance. The tax and government assistance function varies with income and individual characteristics x_i . Leisure is equal to the total time endowment per week less weekly work hours.³

³We assume that individuals have 112 total hours per week to devote to work or leisure with the remaining 56 hours spent on sleep and personal care.

Individuals have preferences over consumption and leisure, which are fully determined by their choice of hours of work, wage rate, non-labor income, and individual characteristics. Preferences also vary directly with some individual characteristics (e.g., age). The utility of individual i choosing hours of work j is given by

$$v_{ij}(w_i, y_i, x_i) = u_{ij}(w_i, y_i, x_i) + \varepsilon_{ij}, \quad (3)$$

where v_{ij} is total utility, u_{ij} is the non-random component of utility, and ε_{ij} captures idiosyncratic choice-specific preference heterogeneity that is unobserved to the econometrician but known by the individual.

We follow van Soest (1995) and adopt the translog function for u_{ij} .⁴

$$u_{ij} = \beta^c \ln c_{ij} + \beta^{cc} (\ln c_{ij})^2 + \beta_i^l \ln l_{ij} + \beta^{ll} (\ln l_{ij})^2 + \beta^{cl} \ln c_{ij} \ln l_{ij} + f_i(h_{ij}). \quad (4)$$

We allow the parameter β_i^l to vary with individual characteristics (a quadratic in the logarithm of age and number of dependents). The term $f_i(h_{ij})$ allows for fixed utility decrements of working non-zero hours and working between 10 and 30 hours per week; these utility decrements might arise due to the fixed costs of working, or they might capture employers' choices to not offer these hours packages (van Soest, 1995).⁵ We allow fixed costs to vary with number of dependents and whether the household has a dependent under 5 years old, allowing them to capture factors such as average childcare costs. We do not impose any parameter restrictions that would force the utility function to be quasi-concave. Instead, we check *ex post* that the marginal utility of consumption is positive and decreasing over the relevant range of choices for most observations.

⁴As documented by Löffler et al. (2018), the translog function is a common choice in the labor supply literature. Other popular specifications include a Box-Cox function or a quadratic function. In their sensitivity testing, Löffler et al. find that the choice of utility function among these three had little effect on estimated elasticities.

⁵Researchers often find that models without fixed costs or other restrictions on the probability of choosing a part-time job poorly fit the observed working patterns of their data (e.g., van Soest (1995), Euwals and van Soest (1999), Dagsvik et al. (2011)). Alternatives to fixed utility decrements include adding a fixed cost to consumption (Euwals and van Soest, 1999), separate modeling of the probability of receiving part-time job offers (Dagsvik and Strøm, 2006), and more flexible modeling of preferences (L. Flood et al., 2004). We explore the sensitivity of our results to this specification in Section 5.2.

For married households, we amend the basic specification to include a quadratic function of the logarithm of leisure for both spouses, as well as an interaction between the logarithms of leisure of each. Each spouse has their own fixed utility decrements of working non-zero hours and working between 10 and 30 hours, and there is an added fixed cost when both spouses are working. The choice set for married couples is all combinations of the seven hours choices for each spouse, delivering 49 different hours choices for the couple.

As is common in the literature, we specify that ε_{ij} has an extreme value type I distribution and is independent of any other variables in the model. Based on this distributional assumption, the probability of individual i choosing choice j , denoted p_{ij} , is given by the closed-form expression:

$$p_{ij}(w_i, y_i, x_i) \equiv \Pr(v_{ij}(w_i, y_i, x_i) \geq v_{ik}(w_i, y_i, x_i), \forall k \neq j) = \frac{\exp(u_{ij}(w_i, y_i, x_i))}{\sum_{k=1}^J \exp(u_{ik}(w_i, y_i, x_i))}. \quad (5)$$

This expression is the familiar conditional logit form for choice probabilities.

Our baseline specification does not include a random utility term, departing from many previous studies that include this term in order to relax the independence of irrelevant alternatives (IIA) assumption. We find that our empirical results are strikingly insensitive to the inclusion of random utility terms, as we describe in more detail in Section 5.2.

3.2 Predicting wages and estimating simulated likelihood function

Non-workers do not have an observable wage, so their wage must be predicted before their conditional choice probabilities can be calculated. The standard approach in the literature is to use a Heckman selection model to predict wages for non-working women (Heckman, 1979). To avoid relying on non-linearities in the functional form for identification, the Heckman model requires an instrument that affects the probability of working but not the expected wage conditional on working. The number of dependents, indicators for dependent age ranges, spousal income, and non-labor income are plausible choices for instruments (van Soest, 1995, Euwals and van Soest, 1999, Bargain et al., 2014, Apps et al., 2016, Kumar and Liang, 2016), and they lead to reasonable

and robust wage model parameters for women; however, they perform poorly as instruments for men.⁶ As a result, we use a Heckman selection model to predict wages for women, but estimate a linear model without the selection variables via ordinary least squares to predict wages for men. See Appendix Section A for more details on the wage equations.

Wages are often predicted for workers in addition to non-workers (Löffler et al., 2018). This may mitigate bias due to measurement error in hourly wages and more accurately reflects a world in which households choose their hours worked based on expected wages instead of a realized wage draw. Furthermore, imputing wages for workers and non-workers alike allows for closer comparisons to the continuous-choice literature where everyone’s wages are instrumented with non-labor income and number of dependents (Heim, 2007, Kumar and Liang, 2016) or imputed with group-level averages (Blau and Kahn, 2007). Our baseline model uses predicted wages for both workers and non-workers, but we test the sensitivity of our results to this choice in Section 5.2.

Whether wages are predicted for only non-workers or for everyone, the prediction error introduces a bias in standard maximum likelihood estimation. To accommodate prediction error in our likelihood function, we follow the established practice of “integrating it out” using maximum simulated likelihood (MSL). In practice, this amounts to pre-specifying the distribution of the prediction error, taking draws from this assumed distribution, and averaging the likelihood function over the draws.

The simulated likelihood contribution for a single individual is:

$$L_{iR} = \sum_{r=1}^R p_{ij}(w_{ir}, y_i, x_i)^{1[j=j^*]}, \quad w_{ir} \sim_{iid} F_{w_i} \quad (6)$$

where p_{ij} is the conditional choice probability given in equation 5, j^* is the observed work hours choice, F_{w_i} is the distribution of wages for individual i , w_{ir} is a particular wage draw from the distribution of F_{w_i} , and R is the total number of draws. We use 50 draws from a Halton sequence

⁶Heckman wage estimates for men are extremely sensitive to small changes in the sample or model specification (e.g., a quadratic in non-labor income versus the log of non-labor income), and the selection parameter often switches from a small positive value to a large negative value. This is not the case when estimating wage parameters for women.

for simulating wages. See van Soest (1995) for a detailed description of this procedure.⁷

3.3 Estimating the elasticities

With parameter estimates in hand, we can compute elasticities. Specifically, we use the parameter estimates and equation 5 to predict the probability that each individual i chooses each choice j . We then calculate the expected hours worked for each individual as the probability-weighted average of the hours choices. Next, we vary the wage for each individual and recalculate the predicted probabilities of each choice and expected hours worked. The percent change in expected hours worked is the numerator for the estimated elasticity, and the percent change in wages is the denominator. We report the mean estimated elasticities across individuals and derive standard errors using a parametric bootstrap with 100 draws from the joint distribution of utility parameters.

For the Marshallian own-wage elasticity, our estimated elasticity for each individual is given by:

$$e_M = \frac{\sum_j h_j * (p_j(w^1) - p_j(w^0))}{\sum_j h_j * p_j(w^0)} * \frac{1}{\Delta w} = \frac{\sum_j h_j * (p_j(w^1) - p_j(w^0))}{\Delta w * \bar{h}(w^0)} \quad (7)$$

where w^0 is the individual's original wage, w^1 is a counterfactual wage chosen to be Δw percent higher than w^0 , and $\bar{h}(w^k)$ is the estimated hours worked when an individual is faced with wage w^k , i.e., $\bar{h}(w^k) = \sum_j h_j * p_j(w^k)$. The quantities are evaluated for individual i with a non-labor income of y_i and characteristics x_i , which we suppress to simplify notation. For all of our reported wage elasticities, we choose counterfactual wages that are one percent higher than the individual's original wage, but our findings are not sensitive to this choice.

To provide further information about the underlying source of hours changes, we decompose the Marshallian elasticity into extensive (e_M^{EXT}) and intensive (e_M^{INT}) components:

$$e_M^{EXT} = \frac{[(1 - p_0(w^1)) - (1 - p_0(w^0))] * \sum_{j \neq 0} h_j * q_j(w^0)}{\Delta w * \bar{h}(w^0)} \quad (8)$$

⁷Halton sequences are deterministic sequences that cover domains of integration more evenly than do independent pseudo-random draws. Train (2009) argues that simulations using Halton draws exhibit greater accuracy than those using pseudo-random draws, particularly in the context of logit choice models. Our findings are insensitive to using 100 draws versus 50.

and

$$e_M^{INT} = \frac{[(1 - p_0(w^1))] * \sum_{j \neq 0} h_j * (q_j(w^1) - q_j(w^0))}{\Delta w * \bar{h}(w^0)}, \quad (9)$$

where $q_j(w^k) = p_j(w^k)/(1 - p_0(w^k))$. This decomposition ensures that the underlying components sum to the Marshallian elasticity ($e_M = e_M^{EXT} + e_M^{INT}$), with e_M^{EXT} capturing the change in the probability of not working and e_M^{INT} capturing the change in expected hours conditional on working.

4 Data

Our primary data source is the 1979 through 2020 Annual Social and Economic March Supplement of the Current Population Survey (S. Flood et al., 2020). These surveys provide total earnings and hours worked for the previous year, as well as demographic information like number of dependents and state of residence. For the remainder of the paper, “year” refers to survey year in the CPS unless otherwise specified (e.g., the 2020 survey involves earnings and hours worked in 2019).

We restrict our sample to heads of households and their spouses in single-family households as defined by the Census Bureau.⁸ Single adults must be between 26 and 55 years old, and couples must have one spouse between 26 to 55 years old and the other spouse between 22 and 59 years old. We exclude individuals who are enrolled in school, disabled, self-employed, members of the armed forces, earn farm or business income, work unpaid in a family business, report real wages less than \$6.45 per hour (90% of the lowest federal minimum wage during the time frame) or more than \$75 per hour (≈ 99.5 th percentile of wages for those working at least 500 hours last year), or report non-labor income less than \$0 or greater than \$50,000 (≈ 99.5 th percentile).⁹ We also exclude individuals whose earnings in any category (e.g., wage, dividend, rental income) exceed the minimum topcoded value, in real dollars, over our time frame.¹⁰ We do not exclude individuals

⁸Single-family households do not necessarily exclude multi-generational households where grandchildren or parents reside with the head of household. Approximately 6% of single-family households contain a parent, sibling, grandchild, or other non-sibling relative to the head of household.

⁹All values are converted to 2019 dollars (survey year 2020) using the Consumer Price Index Research Series (CPI-U-RS).

¹⁰The topcoding thresholds used in the CPS vary significantly over time, and subsetting the sample on individuals

with imputed survey responses, but we test the robustness of our results to doing so in Section 5.2. If either spouse meets our exclusion criteria, we exclude the entire household. For married couples, if the age-year sample includes more than 5,000 households, we take a random sample of 5,000 households to reduce the computational burden of estimating our model.

To measure labor supply, we use usual hours worked per week from the prior year and discretize hours into seven choices by rounding to the nearest ten: 0, 10, 20, 30, 40, 50, and 60 hours per week. We compute the hourly wage from wage and salary income in the prior year divided by the usual work hours per week multiplied by weeks worked in the prior year. Non-labor income is the sum of dividend income, interest income, rental income and other property income, alimony, child support, and other non-property income. Appendix Section A contains complete details of the sample construction, basic descriptive statistics, and parameters from the wage estimation.

We supplement the CPS with two additional data sources. The first is NBER's TAXSIM, which allows us to calculate after-tax income by state and year utilizing micro-level information on earnings, state of residence, and household structure (Feenberg and Coutts, 1993). The second is the Urban Institute's TRIM3, which allows us to calculate the social program benefits for which a household qualifies (e.g., AFDC and SNAP) based on their household earnings, state of residence, and household structure. Data from TRIM3 are available from survey years 1994 to 2019, so we will restrict our initial analysis to this time frame; however, we will also present results for the longer 1979-2020 panel without a benefit simulator.¹¹ See Appendix Section C for further details on how we use TAXSIM and TRIM3 to predict taxes and social program benefits.

As an initial look at the data, Figure 1 shows the labor force participation rate, average annual hours worked conditional on working, average wage conditional on working, and average non-labor income from 1979 through 2020 for four demographic groups: single and married men and women. The well-documented changes are readily apparent. Labor force participation, measured

with earnings below the topcoded threshold of their particular year makes the samples less comparable over time. See Appendix Section B for the topcode thresholds over time and the minimum threshold in each earnings category which we subset our sample on.

¹¹While TRIM3 benefit simulations are available for 2001, they do not include observations from the SCHIP expansion, and the individual identifiers which are normally used to merge the TRIM3 data to the ASEC data do not match. Thus, we set the benefit simulator to zero in 2001.

as the share of survey respondents who participated in the labor market in the prior week, decreased very slightly for men but increased significantly for single and married women in the 1980s and 1990s. Among the employed, annual hours worked, measured as the product of usual hours worked per week in the prior year and weeks worked in the prior year, and wages, measured as pre-tax wage and salary income in the prior year divided by annual hours worked, increased for all four demographic groups despite a brief decline in the late 2000s. Non-labor income is sensitive to broader business cycles and does not have a clear upward or downward trend over time.

For a more detailed look at labor force behavior, Table 1 shows the distribution of hours worked for select years across our primary sample period. The modal choice of each demographic group is 40 hours per week, and for every group except for married women, more than 60 percent choose 40 hours in most years. Married women are also the most likely demographic group to not work, with 20 to 35 percent reporting 0 hours. Men, both single and married, are more likely to work 50 or more hours per week than work 30 or fewer hours. Married women are consistently more likely to work 30 or fewer hours than 50 or more hours. In every group, few individuals work 10, 20, or 30 hours, which is consistent with fixed costs to working being an important feature of the labor supply decision.

5 Results

We first present our baseline results for own-wage elasticities in Section 5.1, followed by a series of robustness checks in Section 5.2. Section 5.3 provides evidence regarding the sources of the changes over time based on counterfactual simulations.

5.1 Baseline results

To summarize, our baseline model uses a translog utility function with observed heterogeneity in preferences for leisure and fixed costs of working non-zero and part-time hours. We predict wages for all observations using a Heckman model for women and OLS for men. We present

results for a short panel (1994 through 2019) that includes social program benefits and a long panel (1979 through 2020) that excludes social program benefits. Utility parameter estimates from our maximum simulated likelihood estimation are presented for both the short and long panel models in Appendix Section D.

Before calculating elasticities, we assess whether our parameter estimates yield positive marginal utilities of consumption over the relevant range of choices. We find that for both the short- and long-panel baseline models, every observation across the sample period has a positive marginal utility of consumption at 10 hours of work and above.¹² In addition, we also compare the goodness of fit between actual hours worked and predicted hours worked according to the parameter estimates of the baseline model. Figure 2 presents the percent of observations at each hours choice (averaged across years) and the average probability of each hours choice calculated with the model's parameter estimates (also averaged across years). Overall, the model fits the distribution of hours worked quite well.¹³

We first present elasticities from our baseline model with the short panel to provide our best estimate of how the elasticities have varied from 2000 onward. Figure 3 plots the mean own-wage elasticity for each demographic group from 1994 through 2019 – the solid line denotes the mean own-wage elasticity, and the dashed lines denote the associated 95% confidence intervals. The same estimates are reported for select years in Table 2. For all four demographic groups, we additionally show the average annual change from 2000 to 2019; our choice for focusing on 2000 will become clearer below.

Single men have the lowest mean elasticity of the four groups, with levels generally between 0.10 and 0.26. The elasticities are higher for married men (typically between 0.25 and 0.40), followed by single women (typically between 0.80 and 1.20) and then married women (typically

¹²Many observations have negative marginal utility of consumption at 0 hours (an average of 80% of single men per year, 58% of single women, and 10% of married couples in the long panel), but very few unmarried observations report 0 hours of work per week, and the consumption level required for a positive marginal utility occurs between 0 and 10 hours for every observation. Thus, when comparing consumption levels at the zero-hour choice value and positive-hour choice values, all observations prefer the greater consumption value.

¹³Because our focus is on changes over time, we also compare the goodness of fit of our baseline model across time for the long panel model based on a chi-squared statistic (see Appendix Figure A4). Overall, the goodness of fit statistics are fairly constant over time, although they fluctuate more for married couples.

between 1 and 1.25).

For all four demographic groups, the slope of the elasticities since 2000 is positive, although barely so for single men (slope=0.0007). The only group for which the slope is positive enough to lead to a noticeable difference over the two decades is single women (slope=0.0058). Given the strong decline in elasticities reported in previous papers for women, these positive trends represent a substantial departure.

To estimate the trends for a longer period of time, we necessarily must remove the benefit simulator from our baseline model. Removing the benefit simulator also makes our specifications more comparable to the existing literature (e.g., Heim, 2007, Blau and Kahn, 2007), which does not always incorporate the role of social program benefits. Mean own-wage elasticities and their standard errors for the long panel are presented in Figure 4, along with the point estimates from the short panel. Estimates for the long panel for select years are reported in Table 3.

Turning to the results, the short and long panel point estimates are very similar for the years they overlap. The only demographic group for which there is any noticeable deviation is single women, with the short panel estimates generally smaller than the long panel estimates. The long panel estimates indicate increasing elasticities since 2000 for three of the demographic groups; the slope for single men is now negative (slope=-0.0005), but this is not substantively different from the small positive slope in the short panel.

In contrast, all four demographic groups exhibit declining elasticities between 1979 and 2000 based on the results from the long panel. These declines are appreciable, both in absolute terms and when compared to their absence between 2000 and 2020. Specifically, when comparing the slopes in Figure 4 to the period- and demographic-specific means, the average annual decline between 1979 and 2000 is -2.7% for single men, -3.4% for single women, -1.7% for married men, and -3.7% for married women. These findings are consistent with the prior literature, especially for single and married women.¹⁴ The findings that the elasticities also declined for men between 1979

¹⁴Our mean estimated elasticities are larger than those in most previous studies, although they are within the range of the estimates reported in Bargain and Peichl (2016). In Figure A5, we provide evidence that the large means are driven by a small number of observations with very large elasticities and that our key conclusions regarding trends are also apparent in the medians. Some of the difference in the medians versus means may also be due to the fact

and 2000 and that the declines stopped or reversed themselves for all groups after 2000 are new.

Using the formulas in Section 3.3, we decompose the mean own-wage elasticity into its extensive and intensive margins, presenting the results in Figure 5. For single and married men, the small declines in the total own-wage elasticities reflect declines at the intensive margin. In contrast, the total elasticities for single and married women are primarily driven by the extensive margin. As with men, the intensive margin elasticity for women has declined steadily since the 1980s, but the largest absolute declines in the first two decades, and subsequent increases in the latter two decades, are at the extensive margin. This pattern is consistent with the timing of changes in labor force participation documented in Figure 1: as wages increased between 1979 and 2020, the labor force participation rate increased markedly for single women and married women between 1979 and 2000, but then was largely flat thereafter.

Finally, to further examine the intertemporal patterns in elasticities within demographic groups, Figure 6 presents the trends in own-wage elasticities for men and women with and without dependents. Neither single nor married men's elasticities are systematically related to the presence of dependents, and the trends are practically identical. In contrast, for single women, the large declines in elasticities from 1979 to 2000 are almost exclusively driven by women with dependents. Post-2000, the trends are similar for single women with and without dependents. The trends are also similar for married women with and without dependents, both before 2000 and thereafter. We return to the potential mechanisms driving these patterns below.

5.2 Robustness to alternative specifications

Our documented trends are robust to a variety of specification changes relative to the baseline model. This section describes how we tested those specifications – regarding whether we include a random utility parameter, include observations with imputed data, predict wages for both workers

that we do not make use of parameter-based sample restrictions (such as dropping observations with non-positive marginal utilities of consumption). We also find evidence, provided below and in Appendix Figure A9, that the choice of whether to use predicted wages for all respondents or for only non-workers influences the magnitudes of the mean estimates, but not the trends.

and non-workers, and include multiple levels of fixed costs of work – and their effects on the estimated elasticities. We discuss the results in this section and present the underlying figures in Appendix Section E.

As noted above, our baseline model departs from the bulk of the discrete choice literature in that we do not include random slopes (Löeffler et al., 2018). For our first robustness check, we include random slopes to relax the IIA assumption. Specifically, we add a normally distributed error term to the utility parameter on consumption, constant across choices but variable between households. We find that the estimated variance on the random coefficient is near zero for most demographic groups in most years, and as shown in Appendix Figure A6, our estimated mean own-wage elasticity estimates are virtually identical to those in our baseline model, with single men as the lone exception. This finding is not unexpected, as researchers typically estimate variances that are statistically indistinguishable from zero (van Soest, 1995, Callan and van Soest, 1996, van Soest et al., 2002, Dagsvik and Strøm, 2006, Brewer et al., 2006, Haan, 2006, Löeffler et al., 2018). However, the standard errors on the estimated variances are relatively large, making the standard errors on the elasticity estimates large as well. Given that it is computationally costly to include random slopes and the persistent finding that they matter little (including for the results presented here), we choose to exclude random slopes from our baseline model.

Our second robustness test involves dropping observations with imputed data in the CPS. Appendix Section E contains details on how we identify observations with imputed data, and in Appendix Figure A7 we show how imputation rates vary over time. One might worry that the steady increase in imputation rates, which escalated over the last decade, could be the source of the increases in estimated own-wage elasticities between 2000 and 2020. Appendix Figure A8 shows that this is not the case. Mean own-wage elasticities for single men and women are nearly identical between the samples with and without imputed observations in most years, and while the sample without imputed data leads to smaller elasticity estimates for married men and women, the patterns over time are unchanged.

Appendix Figure A9 presents mean own-wage elasticities when wages are predicted for non-

workers only, as opposed to the entire sample as in our baseline model. In their analysis, Loeffler et al. (2018) observe that estimated elasticities can double when predicting wages for everyone as opposed to only non-workers; we observe a similar result. For all four demographic groups, the mean wage elasticities are significantly larger when predicting wages for everyone, but the consistency of the trends over time varies by demographic group. The intertemporal patterns are similar for single and married women regardless of which observations have predicted wages - in the sense that there are declines between 1979 and 2000 followed by small increases between 2000 and 2020 - although the pre-2000 decline for married women is smaller in percentage terms when predicting wages for non-workers only. Elasticities for single and married men show a steady upward trend throughout the four decades when predicting wages for non-workers only, which contrasts with the large declines from 1979 to 2000 when predicting wages for everyone.

For our final robustness check, we change the specification of fixed costs. There has been significant debate in the literature on the proper way to incorporate fixed costs of work (see van Soest (1995), van Soest et al. (2002), and Dagsvik and Strøm (2006) for three unique approaches), and each method has its own advantages and drawbacks. Given the number of times we estimate our model on different samples, we opted to consider one approach, a fixed utility decrement, and we test the sensitivity of our results to including only a fixed cost of non-zero hours of work, only a fixed cost of part-time work, and no fixed cost at all. Since the primary purpose of including fixed costs is improving the fit of the model to the data, we first look to the fit of each specification. Appendix Figure A10 presents chi-squared statistics associated with the null that the data and predicted hours worked are equal over time, separately by demographic group and model specification. For all groups, the baseline model and model with only a part-time fixed cost of work fit the data equally well, with chi-squared statistics close to zero in all years. The model with only a non-zero fixed cost of work fits the data worse than the baseline model, and the model without any fixed costs has the worst fit of all.

Appendix Figure A11 presents the estimated mean own-wage elasticities for each demographic group over time based on the four fixed cost specifications. Given their similar goodness of fit, it is

not surprising that the baseline model and the model with only a part-time fixed cost lead to similar estimated elasticities. More surprising is how similar the elasticities are for the baseline model and other fixed cost models. With the exception of some very large elasticity estimates in the 1980s, the mean elasticity estimates across all four models are nearly identical for single men and married women. Elasticities for married men and single women follow similar trends over time regardless of the model, though there are differences in levels – models without any fixed cost and with a part-time fixed cost only are larger than the baseline model for married men, and models with a fixed cost for non-zero hours and without any fixed cost are smaller than the baseline model for single women.

5.3 Counterfactual simulations

To shed light on why the mean own-wage elasticity significantly declined between 1979 and 2000 but increased or remained relatively flat thereafter, we use our structural model to conduct a series of counterfactual simulations. Specifically, we partition the model into four mutually exclusive and exhaustive components – the wage distribution parameters, the tax parameters, covariates other than wages (state of residence, demographic factors, education, and non-labor income; hereafter collectively labeled “other input variables”), and the utility parameters – and then study the importance of each piece.

Each of these four pieces changed in potentially important ways over the last four decades. Single and married women experienced large wage increases on average between 1979 and 2000 (see Figure 1), along with increases in the wage returns to education (see Appendix Table A4 in Appendix A). We study taxes separately because of the broad-based decline in the marginal tax rate (see Appendix Figure A3) and the well-documented expansions of the EITC, which create negative marginal tax rates at low income levels, especially for single women with dependents. Appendix Tables A1 and A2 document changes over time in the other input variables among those in the labor force, such as the increase in average age, decrease in number of dependents, and increase in educational attainment. Finally, we examine the effect of holding utility parameters constant over

time. Given the large changes in extensive-margin elasticities for women that we found above, we expect changes in the fixed costs of work to be particularly important.¹⁵

To explore the role of each of these factors, we construct a series of counterfactual simulations that hold one piece fixed at its 1980 value for the entire sample period, while allowing the other pieces to vary; we then use the model to calculate how expected hours change with a simulated change in pre-tax wages to obtain a counterfactual own-wage elasticity estimate.¹⁶ The difference between the counterfactual elasticities and our estimated elasticities yields a measure of the role of changes over time in that piece on the change in elasticities.¹⁷

In Figure 7, we report the slopes of the linear time trend in mean own-wage elasticity (labeled “Total”) from 1979 to 2000 and from 2000 to 2020 for single and married men and women. Given the substantively different trends shown above, we separately report elasticities for women with and without dependents; these slopes correspond to the series shown in Figures 4 and 6. We also present the amount of those slopes that can be attributed to each of our four factors – wage parameters (labeled “Wage”), tax parameters (labeled “Tax”), other input variables (labeled “OthX”), and utility parameters (labeled “Util”) – based on our counterfactual analysis. The same results are presented in tabular form in Appendix Table A13.

For both single and married men, there is little change in the elasticities to explain: the “Total” bars are close to zero both pre- and post-2000, and the counterfactual simulations suggest

¹⁵Appendix Tables A10, A11, and A12 show the utility function parameters over time for different demographic groups. These parameters should not be compared over time directly, as they are identified up to an unobserved scale parameter that may vary over time (Train, 2009); however, percentage changes in parameters can be compared relative to one another if they come from estimations with shared scale parameters. For example, the fixed cost of working a part-time job for a single women without dependents decreased (in absolute value) by 4.5% from 1980 to 1990 while the fixed cost for a single women with a dependent under age 5 increased (in absolute value) by 36%.

¹⁶We construct the counterfactual simulations that hold wages, taxes, or utility parameters fixed by applying to every year of data the wage, tax, or utility parameters estimated for 1980. The counterfactual simulations for holding the “other input variables” fixed entail constructing annual samples that have the 1980 distribution of those variables using multinomial logit (for state of residence), ordered logit (for age conditional on state of residence), and a nearest-neighbor algorithm (for spouse age, education, number of dependents, indicators for dependent age ranges, and non-labor income conditional on state of residence and age). See Appendix Section E for more details about the construction of the counterfactuals.

¹⁷Such counterfactual comparisons need not lead to estimates for each factor that add to the total change, and the role of a factor can vary depending on the base period. In Appendix Figure A12, we show results in which we hold all inputs/parameters fixed in 1980, but then allow the indicated input/parameters to vary, i.e., we use 1980 as the base period rather than the current year as the base period. We find that the results are insensitive to the choice of base period.

that changes in the utility parameters are sufficient to account for what little trends there are. In Appendix Figure A13, we decompose the role of changing utility parameters into changing consumption and leisure parameters and changing fixed costs of work parameters. These estimates suggest that the change in utility parameters stems mainly from changes in the marginal rate of substitution between consumption and leisure, with changes in the fixed costs of work playing a smaller role.

For single women without dependents, again there is relatively little change in the elasticities. The simulations suggest that changes in utility parameters and other input variables largely account for those changes. The change in the utility parameters was largely attributable to changes in the marginal rate of substitution between consumption and leisure (again see Appendix Figure A13) and the change in other input variables was driven by changing educational attainment (see Appendix Figure A14).¹⁸

The largest declines in elasticities from 1979-2000 occurred among single women with dependents and married women (both with and without dependents), but our counterfactual simulations suggest that the underlying sources differ. For single women with dependents, the 1979-2000 decline was driven by changes in the other input variables and the tax structure. More granular counterfactuals suggest that changing educational attainment was the most relevant of the other input variables (see Appendix Figure A14) and that the expansions of the EITC explain nearly all the tax structure component (see Appendix Figure A15). After 2000, changes in the tax structure put further downward pressure on wage elasticities, but changes in utility parameters offset this downward pressure. The change in utility parameters was largely attributable to changes in the fixed cost of work as opposed to changes in the marginal rate of substitution between consumption and leisure (see Appendix Figure A13).

¹⁸To hold only one of the input variables constant at a time, we adopt an approach similar to that described by Rothe (2012) and assign variables according to their 1980 distribution and individuals' year-sex-marital status-specific percentile rank. Specifically, we calculate year-sex-marital status-specific percentile ranks, rounded to the nearest 0.001, and assign each year-sex-marital status-percentile cell the maximum value from the corresponding 1980-sex-marital status distribution. For discrete variables, we split ties in the percentile rank randomly. This method preserves both the 1980 distribution of each variable and the year-specific correlations between the imputed and non-imputed variables.

For married women with and without dependents, changes in utility parameters account for most of the pre-2000 decline in elasticities, followed by the other input variables and then taxes. For the 1979-2000 decline for both groups, changes in the marginal rate of substitution between consumption and leisure played an important role for the declining importance in utility, and changes in educational attainment largely accounted for the changes of other input variables (see Appendix Figures [A13](#) and [A14](#)). For all groups of women – single and married, with and without dependents – fixed costs of work put upward pressure on elasticities starting in 2000.

We close our counterfactual analysis by highlighting a persistent null result. Across all six demographic groups that we analyze, we find that the pronounced and well-documented changes in the wage structure in recent decades (e.g., Katz and Autor, [1999](#), Acemoglu and Autor, [2011](#), Hunt and Nunn, [2022](#), Binder and Bound, [2019](#)) have had relatively smaller effects on the evolution of wage elasticities. One explanation is that the changes in the wage structure led to both higher and lower wages for substantial shares of the labor market, so any resulting changes in elasticities partially offset. Moreover, overall shifts in the distribution of wages partly reflect changes in educational attainment, labor force demographics, etc., and our counterfactual nets those effects out.

6 Conclusion and discussion

Several significant and well-documented changes in the labor market have taken place in the last four decades, including the increasing labor force participation of married women, increasing wage inequality, increasing returns to education, aging workforce, and changing tax and transfer structure. In this paper, we examine trends in labor supply elasticities and their relationship to these broader labor market changes, primarily focusing on four demographic groups: single and married men and single and married women. Our results suggest that own-wage elasticities have either increased or remained relatively constant since 2000 for all four groups. For single and married women, this finding is a remarkable reversal of the “incredible shrinking elasticities” found for the

1980s and 1990s in previous studies. For both groups of women, the extensive margin accounts for nearly all of the pre-2000 declines and the cessation of those declines after 2000.

We find that our estimated trends are robust to some common alternative modeling assumptions used in the literature, including computationally demanding procedures like the use of random-slope logits. This finding is significant because researchers who make simplifications along these dimensions can choose to increase complexity in other dimensions, such as in the richness of the choice set or other non-convexities in the budget set. We also find that several alternative modeling assumptions can appreciably affect the level of elasticities (such as whether to predict wages for all individuals or for non-workers only, the treatment of imputations, and the specification for fixed costs), as Loeffler et al. (2018) found. This finding demonstrates the importance of our strategy of applying a common set of assumptions to all years of the data to better isolate the trends in elasticities.

We then perform a series of counterfactual simulations to better understand the evolution of the estimated elasticities over the past four decades. For both single and married women, a relatively large fraction of the declining elasticity from 1979 to 2000 was attributable to increases in educational attainment. Increasing educational attainment continued to put downward pressure on elasticities for married women after 2000, but these effects were offset by changes in utility parameters. Notably, we find that the dramatic changes in the wage structure in the past four decades explain little of the intertemporal patterns in wage elasticities, either before or after 2000.

Our simulations suggest that the expansions of the EITC, which created negative marginal tax rates for low-income workers with dependents, put downward pressure over time on the elasticities of single women with dependents. A large and influential literature finds that the EITC has had large effects on the extensive margin, but only modest effects on the intensive margin (see Hotz (2003) and Nichols and Rothstein (2015) for useful reviews). Likewise, we find that the sharp decline in the elasticities of single women with dependents between 1979 and 2000 was mostly driven by the extensive margin. Furthermore, consistent with evidence that the 1993 expansion in particular had the largest impact on the labor market (Meyer and Rosenbaum, 2001 and Nichols

and Rothstein, 2015), we find the effect of the EITC on the elasticities of single women with dependents post-2000 was less than a third of the pre-2000 effect.

In contrast to the large implied role of EITC for single women with dependents, we find little evidence for a role of the EITC (and for taxes more generally) for single women without dependents, either before or after 2000. Taken together, the simulations imply that the variation in the generosity of the EITC - both over time and across groups - played a significant role in explaining analogous variation in labor supply elasticities.

Finally, our simulations show that the well-documented changes in the wage structure from 1980 to 2020 have had relatively little effect on wage elasticities. In contrast, fixed costs to working have put upward pressure on elasticities for women since 2000. Such a finding is consistent with the continued rise of childcare costs (Laughlin, 2013), but the effects of such trends would be better studied directly than through our model's composite specification of fixed costs.

References

- Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In D. Card & O. Ashenfelter (Eds.). Elsevier. [https://doi.org/10.1016/S0169-7218\(11\)02410-5](https://doi.org/10.1016/S0169-7218(11)02410-5)
- Apps, P., Kabátek, J., Rees, R., & van Soest, A. (2016). Labor supply heterogeneity and demand for child care of mothers with young children. *Empirical Economics*, 51, 1641–1677. <https://doi.org/10.1007/s00181-015-1046-4>
- Atrostic, B. K. (1982). The demand for leisure and nonpecuniary job characteristics. *The American Economic Review*, 72(3), 428–440. www.jstor.org/stable/1831542
- Bargain, O., Orsini, K., & Peichl, A. (2014). Comparing labor supply elasticities in Europe and the United States: New results. *Journal of Human Resources*, 49(3), 723–838. <https://doi.org/10.3368/jhr.49.3.723>
- Bargain, O., & Peichl, A. (2016). Own-wage labor supply elasticities: Variation across time and estimation methods. *IZA Journal of Labor Economics*, 5(10), 1–31. <https://doi.org/10.1186/s40172-016-0050-z>
- Binder, A. J., & Bound, J. (2019). The declining labor market prospects of less-educated men. *Journal of Economic Perspectives*, 33(2), 163–90. <https://doi.org/10.1257/jep.33.2.163>
- Bishop, K., Heim, B., & Mihaly, K. (2009). Single women’s labor supply elasticities: Trends and policy implications. *ILR Review*, 63(1), 146–168. <https://doi.org/10.1177/001979390906300108>
- Blau, F. D., & Kahn, L. M. (2007). Changes in the labor supply behavior of married women: 1980–2000. *Journal of Labor Economics*, 25(3), 393–438. <https://doi.org/10.1086/513416>
- Blundell, R., & MaCurdy, T. (1999). Labor supply: A review of alternative approaches. In O. C. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (pp. 1559–1695). Elsevier. [https://doi.org/10.1016/S1573-4463\(99\)03008-4](https://doi.org/10.1016/S1573-4463(99)03008-4)
- Bollinger, C. R., Hirsch, B. T., Hokayem, C. M., & Ziliak, J. P. (2019). Trouble in the tails? what we know about earnings nonresponse 30 years after Lillard, Smith, and Welch. *Journal of Labor Economics*, 127(5), 2143–2185. <https://doi.org/10.1086/701807>

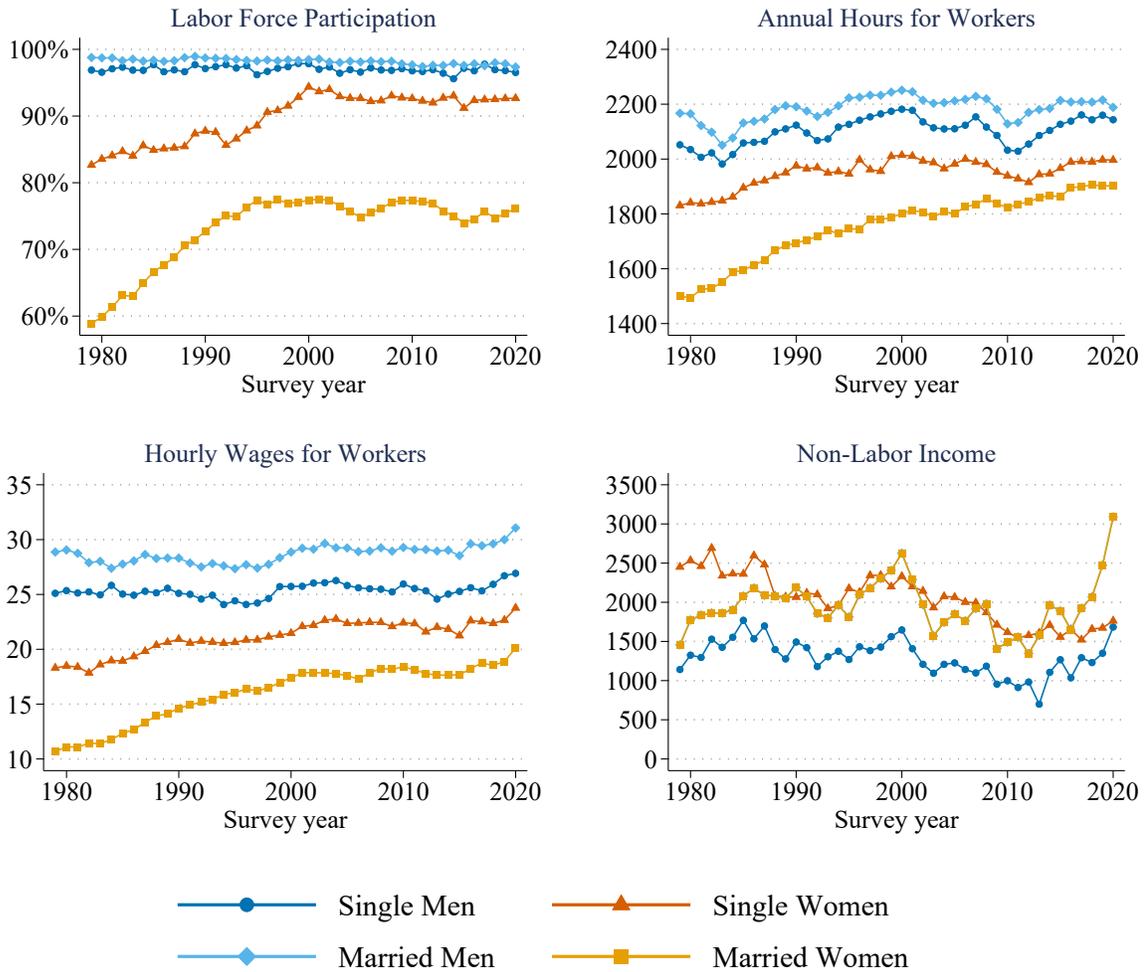
- Brewer, M., Duncan, A., Shephard, A., & Suárez, M. J. (2006). Did working families' tax credit work? The impact of in-work support on labour supply in Great Britain. *Labour Economics*, 13(6), 699–720. <https://doi.org/10.1016/j.labeco.2005.11.002>
- Callan, T., & van Soest, A. (1996). *Family labor supply and taxes in Ireland* (Working Paper No. 78). Economic and Social Research Institute. <https://www.esri.ie/system/files?file=media/file-uploads/2015-07/WP078.pdf>
- Chetty, R., Guren, A., Manoli, D., & Weber, A. (2011). Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins. *The American Economic Review*, 101(3), 471–475. <https://doi.org/10.1257/aer.101.3.471>
- Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica*, 39(5), 829–844. <https://doi.org/10.2307/1909582>
- Dagsvik, J. K., Jia, Z., Orsini, K., & Camp, G. V. (2011). Subsidies on low-skilled workers' social security contributions: The case of Belgium. *Empirical Economics*, 40, 779–806. <https://doi.org/10.1007/s00181-010-0367-6>
- Dagsvik, J. K., & Strøm, S. (2006). Sectoral labour supply, choice restrictions and functional form. *Journal of Applied Econometrics*, 21(6), 803–826. <https://doi.org/10.1002/jae.866>
- Euwals, R., & van Soest, A. (1999). Desired and actual labour supply of unmarried men and women in the Netherlands. *Labour Economics*, 6(1), 95–118. [https://doi.org/10.1016/S0927-5371\(98\)00018-9](https://doi.org/10.1016/S0927-5371(98)00018-9)
- Feenberg, D., & Coutts, E. (1993). An introduction to the TAXSIM model. *Journal of Policy Analysis and Management*, 12(1), 189–194. <https://doi.org/10.2307/3325474>
- Flood, L., Hansen, J., & Wahlberg, R. (2004). Household labor supply and welfare participation in Sweden. *Journal of Human Resources*, 39(4), 1008–1032. <https://doi.org/10.3368/jhr.XXXIX.4.1008>

- Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. (2020). Integrated Public Use Microdata Series, Current Population Survey: Version 8.0 [dataset]. <https://doi.org/10.18128/D030.V8.0>
- Haan, P. (2006). Much ado about nothing: conditional logit vs. random coefficient models for estimating labour supply elasticities. *Applied Economics Letters*, 13(4), 251–256. <https://doi.org/10.1080/13504850500396348>
- Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, 47(1), 153–161. <https://doi.org/10.2307/1912352>
- Heim, B. T. (2007). The incredible shrinking elasticities: Married female labor supply, 1978-2002. *Journal of Human Resources*, 42(4), 881–918. <https://doi.org/10.3368/jhr.XLII.4.881>
- Hotz, V. J. (2003). The Earned Income Tax Credit. In *Means-tested transfer programs in the United States* (pp. 141–198). National Bureau of Economic Research, Inc.
- Hunt, J., & Nunn, R. (2022). Has U.S. employment really polarized? a critical reappraisal. *Labour Economics*, 75, 102–117. <https://doi.org/j.labeco.2022.102117>
- Jaeger, D. A. (1997). Reconciling the old and new Census Bureau education questions: Recommendations for researchers. *Journal of Business and Economic Statistics*, 15(3), 300–309. <https://doi.org/10.1080/07350015.1997.10524708>
- Katz, L. F., & Autor, D. H. (1999). Changes in the wage structure and earnings inequality. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics*, vol. 3a (pp. 1463–1555).
- Keane, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature*, 49(4), 961–1075. <https://doi.org/10.1257/jel.49.4.961>
- Kumar, A., & Liang, C.-Y. (2016). Declining female labor supply elasticities in the United States and implications for tax policy: Evidence from panel data. *National Tax Journal*, 69(3), 481–516. <https://doi.org/10.17310/ntj.2016.3.01>
- Laughlin, L. (2013). *Who's minding the kids? Child care arrangements: Spring 2011* (Current Population Reports P70-135). U.S. Census Bureau. [census.gov/library/publications/2013/demo/p70-135.pdf](https://www.census.gov/library/publications/2013/demo/p70-135.pdf)

- Löffler, M., Peichl, A., & Siegloch, S. (2018). *The sensitivity of structural labor supply estimations to modeling assumptions* (IZA Discussion Papers No. 11425). IZA Institute of Labor Economics. <http://ftp.iza.org/dp11425.pdf>
- Meyer, B. D., & Rosenbaum, D. T. (2001). Welfare, the Earned Income Tax Credit, and the labor supply of single mothers. *The Quarterly Journal of Economics*, 116(3), 1063–1114. <https://doi.org/10.1162/00335530152466313>
- Nichols, A., & Rothstein, J. (2015). *The Earned Income Tax Credit (EITC)* (Working Paper No. 21211). National Bureau of Economic Research. <https://doi.org/10.3386/w21211>
- Rothe, C. (2012). Partial distribution policy effects. *Econometrica*, 80(5), 2269–2301. <https://doi.org/10.3982/ECTA9671>
- TAXSIM. <https://taxsim.nber.org>
- Train, K. (2009). *Discrete choice models with simulation* (2nd ed.). Cambridge University Press.
- TRIM3 project website [Downloaded on January 25, 2023]. <https://trim3urban.org>
- van Soest, A. (1995). Structural models of family labor supply: A discrete choice approach. *Journal of Human Resources*, 30(1), 63–88. <https://doi.org/10.2307/146191>
- van Soest, A., Das, M., & Gong, X. (2002). A structural labour supply model with flexible preferences. *Journal of Econometrics*, 107(1-2), 345–374. [https://doi.org/10.1016/S0304-4076\(01\)00128-2](https://doi.org/10.1016/S0304-4076(01)00128-2)
- Zedlewski, S., & Giannarelli, L. (2015). *TRIM: A tool for social policy analysis* (Research Report). Urban Institute. <https://www.urban.org/sites/default/files/publication/82921/2000878-TRIM-A-Tool-for-Social-Policy-Analysis.pdf>

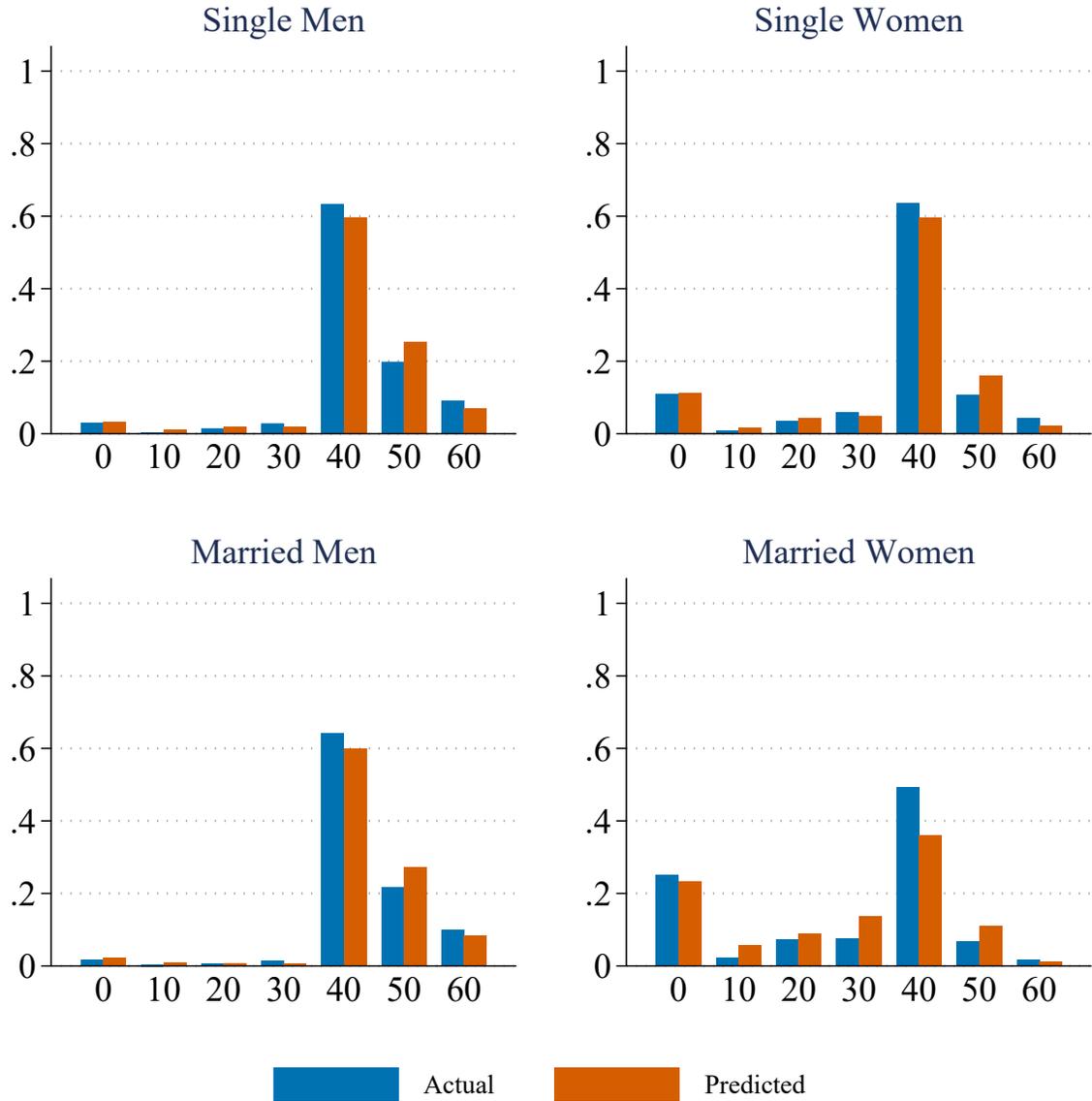
7 Tables and Figures

Figure 1: Labor Force Trends by Demographic Group



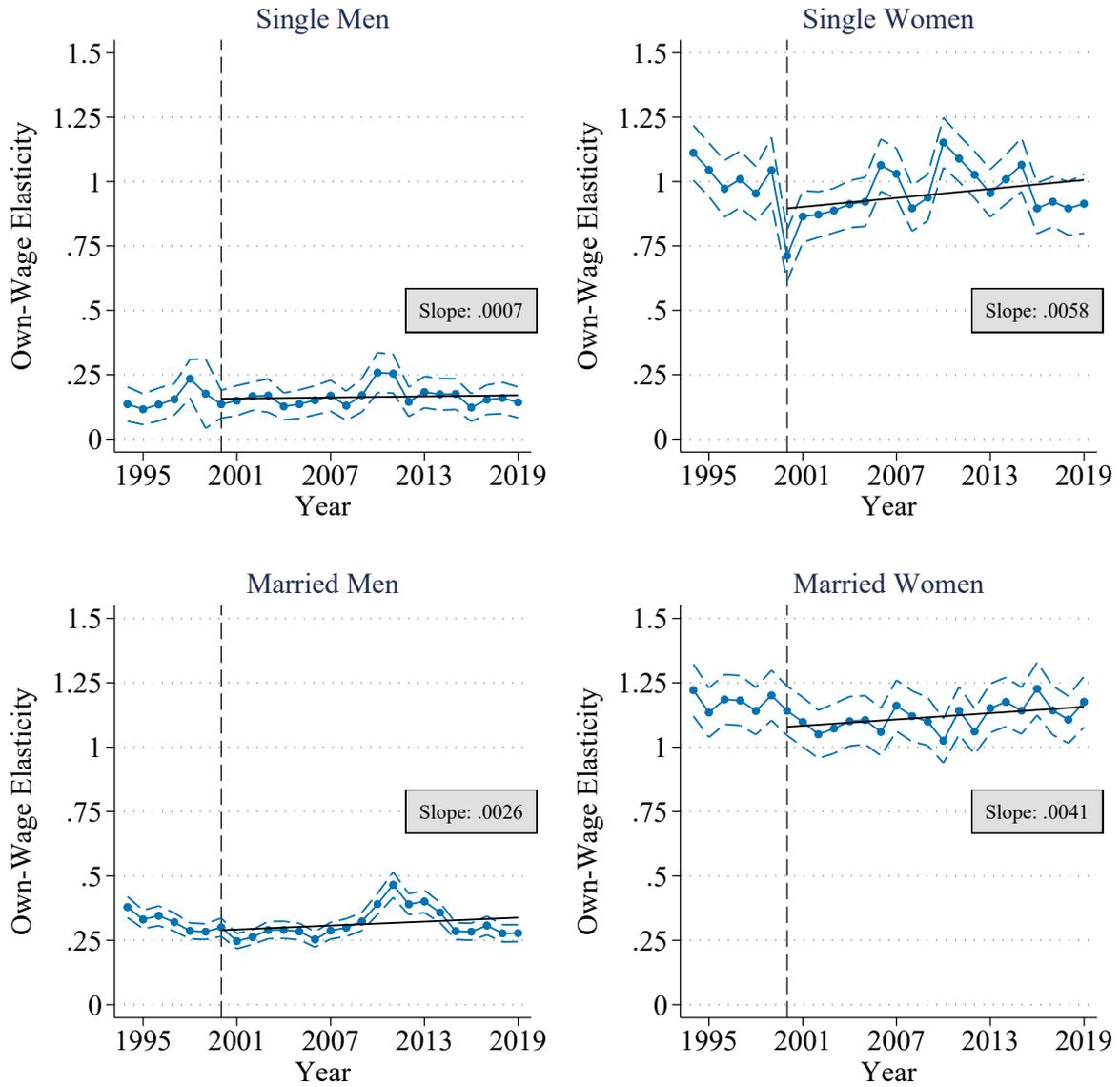
Notes: This figure presents trends in labor force participation, annual hours worked, hourly wages, and non-labor income separately by sex and marital status. Labor force participation is the share of respondents who reported participating in the labor market in the prior week. Annual hours worked are the product of usual hours worked per week in the prior year and weeks worked in the prior year. Hourly wages are the quotient of pre-tax wage and salary income in the prior year and annual hours worked. Non-labor income is all non-wage or salary income in the household and is identical between married men and women. Hourly wages and non-labor income are in 2019 dollars. Observations are weighted by their ASEC person-level survey weight. Source: 1979-2020 CPS-ASEC.

Figure 2: Goodness of Fit for the Long-Panel Baseline Model



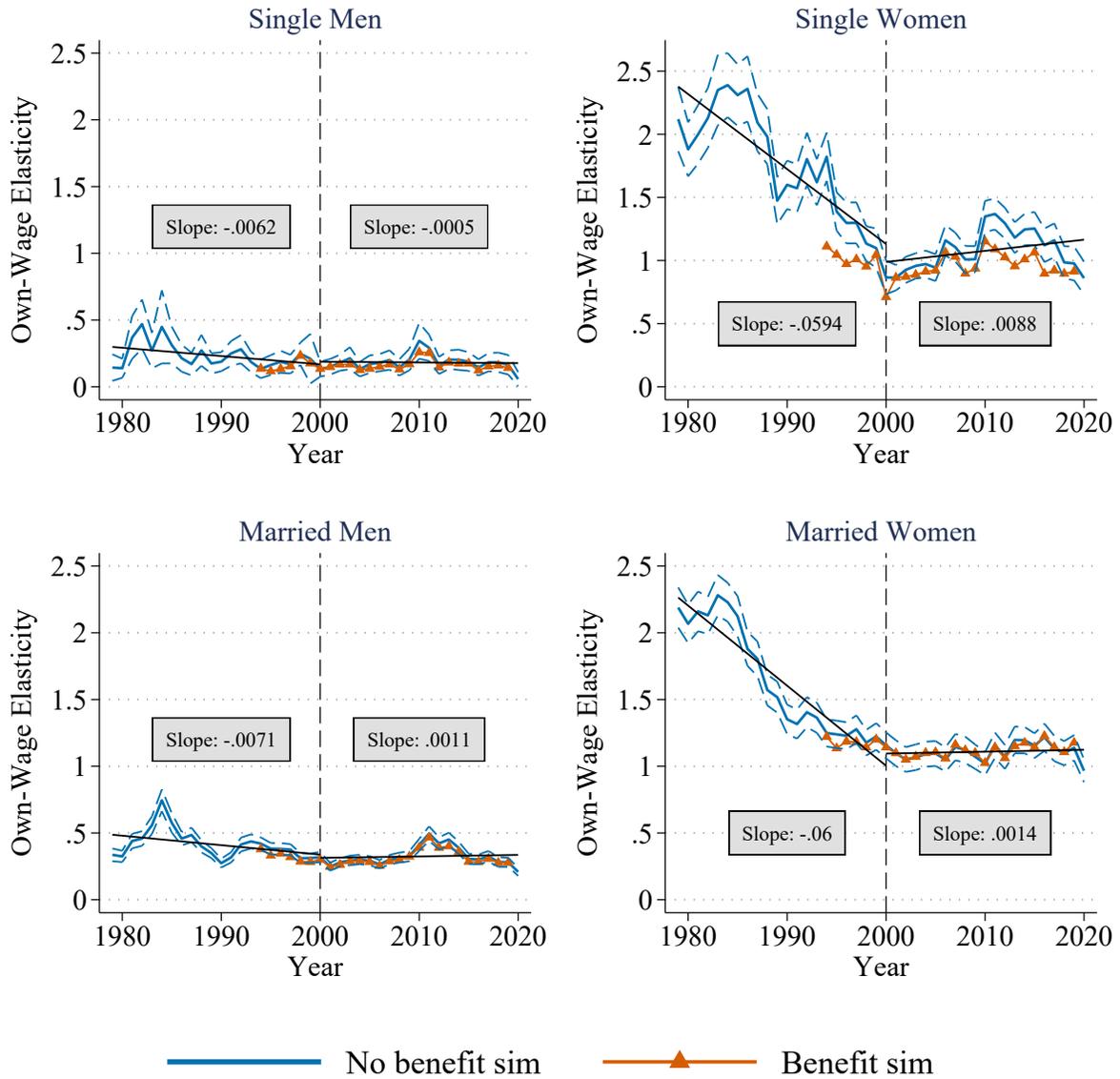
Notes: This figure presents the average hours worked per week for each demographic group from 1979 to 2020 and the average probability of each hour choice according to the parameter estimates of our baseline model without the benefit simulator. For married households, probabilities are summed over the spouse's hours. Source of actual hours: 1979-2020 CPS-ASEC.

Figure 3: Mean Own-Wage Elasticities for the Short-Panel Model



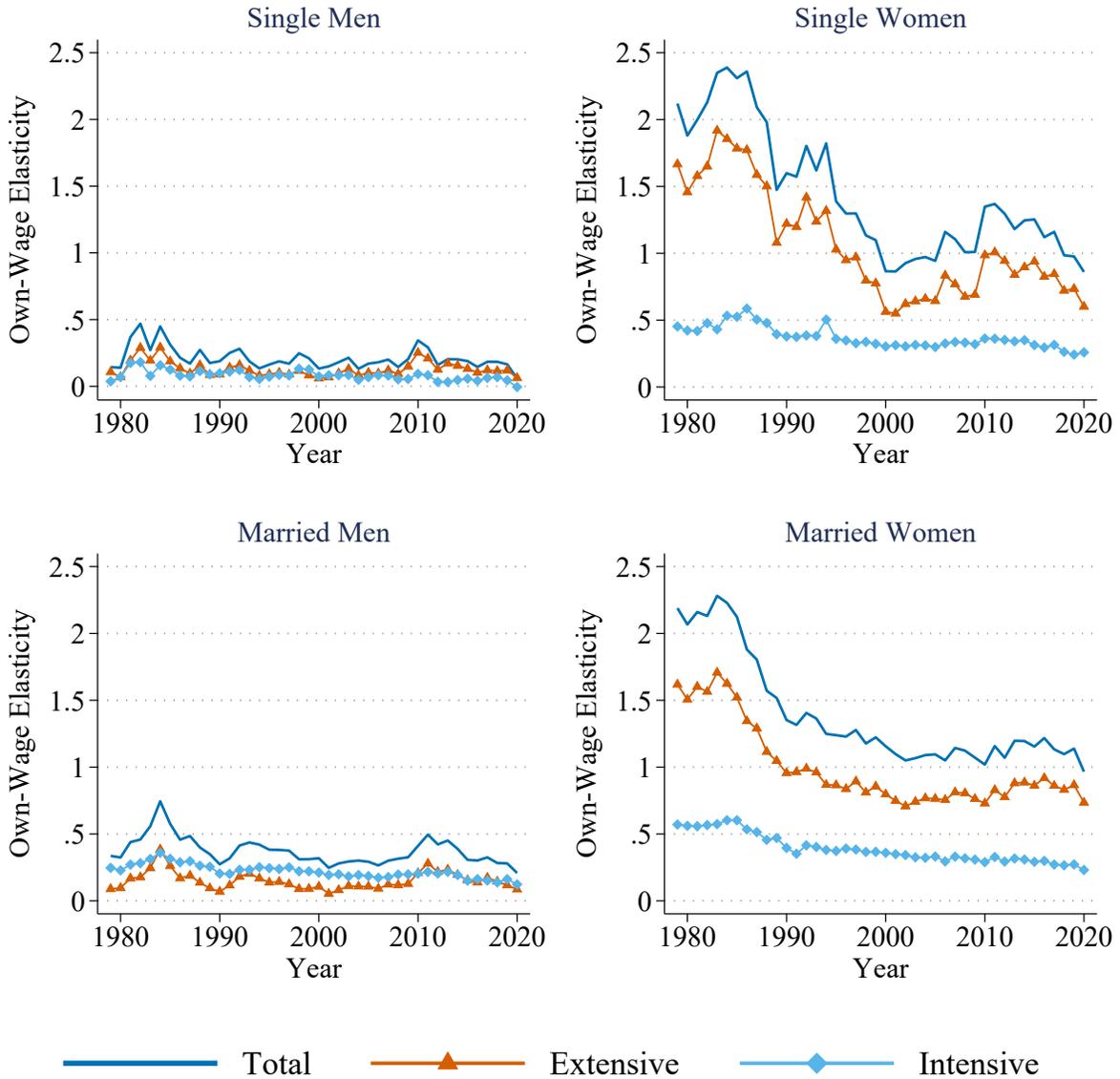
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines. A linear trend line from 2000 to 2019 is also presented, along with the annual slope of the trend.

Figure 4: Mean Own-Wage Elasticities for the Short- and Long-Panel Models



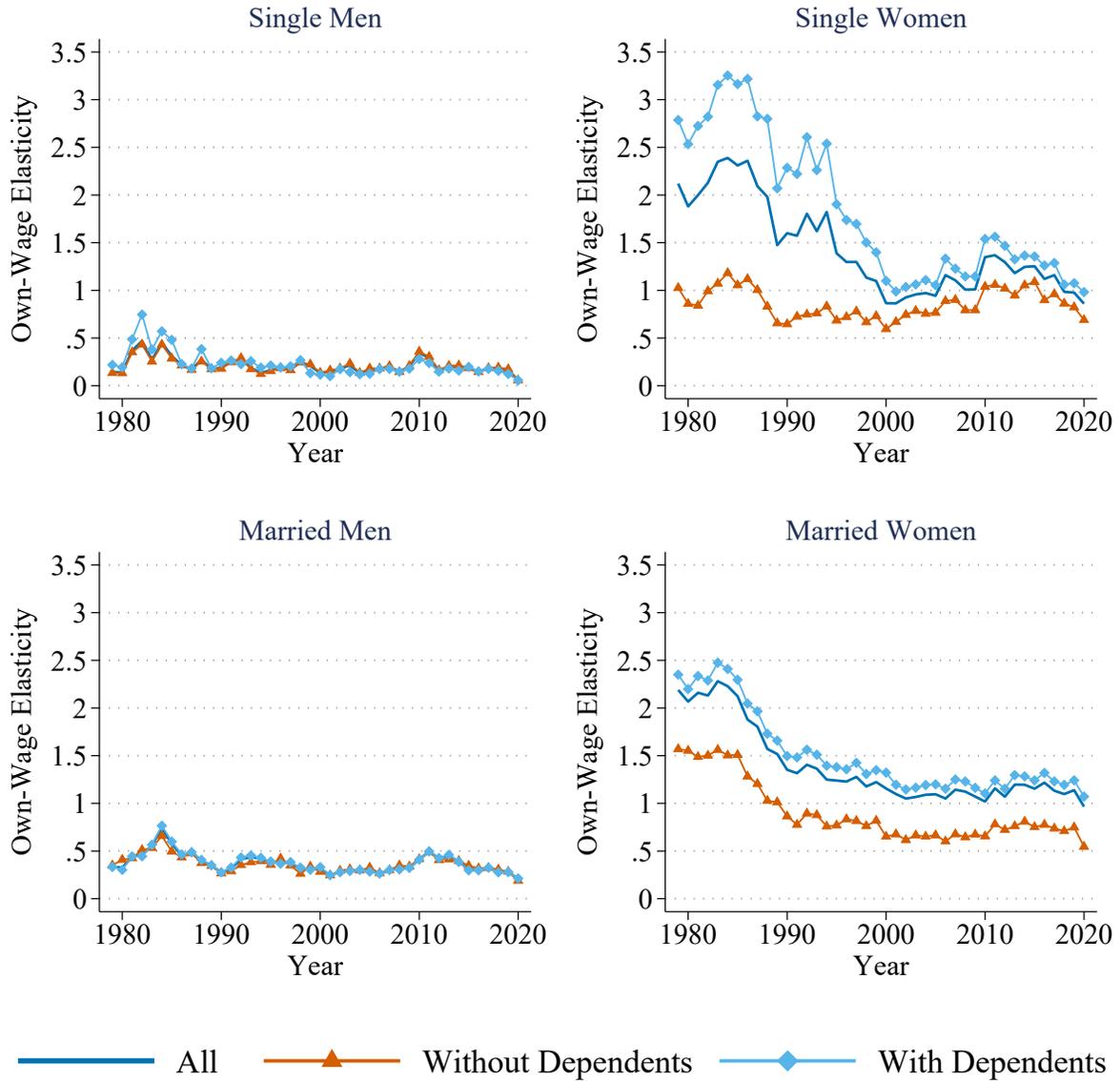
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status without the benefit simulator. Confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines. Linear trend lines from 1979 to 2000 and 2000 to 2020 are also presented. Elasticity estimates from the model with a benefit simulator are presented for reference and denoted with orange triangles.

Figure 5: Mean Own-Wage Elasticities Decomposed by Extensive and Intensive Margins



Notes: This figure presents the estimated trends in mean total, extensive margin, and intensive margin own-wage elasticities separately by sex and marital status. We decompose the total own-wage elasticity into the extensive margin elasticity and intensive margin elasticity according to the formulas in Section 3.3. Estimates are based on our baseline model without the benefit simulator.

Figure 6: Mean Own-Wage Elasticities by Number of Dependents



Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status without the benefit simulator. Estimates based on the entire sample are denoted by a solid blue line. Estimates based on a sample of individuals without dependents are denoted by the orange line with triangle markers. Estimates based on a sample of individuals with dependents are denoted by the light blue line with diamond markers.

Figure 7: Counterfactuals



Notes: This figure presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “Total” is based on the elasticities from the long-panel baseline model, allowing all of the model inputs and parameters to change each year. The other bars are based on just allowing one set of factors to change: “Wage” corresponds to the wage model parameters, “Tax” corresponds to the tax function parameters, “OthX” corresponds to all other explanatory variables (demographics, education, non-labor income), and “Util” corresponds to the utility model parameters. See the text for further details.

Table 1: Distribution of Work Hours

	1980	1990	2000	2010	2020
<i>Panel A: Single Men</i>					
10 hours	0.56	0.39	0.32	0.24	0.28
20 hours	2.01	1.16	1.32	2.04	1.10
30 hours	2.25	2.36	1.85	4.23	3.40
40 hours	66.45	61.96	59.58	62.87	65.59
50 hours	19.77	22.88	25.03	16.48	18.68
60 hours	7.60	9.28	10.42	7.87	7.74
Observations	2,443	2,784	2,723	3,926	2,574
<i>Panel B: Single Women</i>					
0 hours	14.07	12.39	4.49	9.30	6.35
10 hours	1.15	0.66	0.51	0.91	0.70
20 hours	3.10	3.04	3.09	3.77	3.59
30 hours	5.22	4.27	5.67	6.52	5.92
40 hours	65.66	62.62	65.58	64.17	67.57
50 hours	8.18	12.89	14.20	10.76	11.75
60 hours	2.62	4.12	6.46	4.58	4.13
Observations	4,663	4,706	4,000	6,198	3,840
<i>Panel C: Married Men</i>					
0 hours	0.64	0.84	1.02	3.91	1.81
10 hours	0.10	0.09	0.07	0.12	0.06
20 hours	0.40	0.65	0.47	1.03	0.60
30 hours	0.81	1.32	0.94	2.66	1.18
40 hours	68.44	63.33	60.85	64.10	68.93
50 hours	20.78	24.13	24.58	19.03	18.87
60 hours	8.83	9.64	12.06	9.15	8.54
<i>Panel D: Married Women</i>					
0 hours	34.86	24.22	20.21	22.70	22.60
10 hours	3.30	2.46	2.24	1.93	1.28
20 hours	8.96	7.90	7.03	6.06	4.76
30 hours	6.24	7.39	7.48	7.52	5.87
40 hours	42.58	49.97	51.83	52.18	55.52
50 hours	3.46	6.52	9.09	7.49	8.03
60 hours	0.60	1.53	2.12	2.12	1.94
Observations	15,859	12,328	10,345	15,446	9,055

Notes: This table contains the distribution of weekly work hours by year and demographic group. Observations are weighted by their ASEC person-level survey weight. Source: 1979-2020 CPS-ASEC.

Table 2: Baseline Model Elasticities for the Short Panel, 1994-2019

	1995	2000	2005	2010	2015
<i>Panel A: Single Men</i>					
Own-wage	0.116 (0.030)	0.136 (0.028)	0.136 (0.028)	0.258 (0.040)	0.175 (0.031)
Extensive margin	0.067 (0.014)	0.056 (0.013)	0.083 (0.014)	0.174 (0.025)	0.111 (0.017)
Intensive margin	0.049 (0.019)	0.080 (0.018)	0.053 (0.017)	0.084 (0.017)	0.064 (0.016)
Observations	2,801	2,723	3,726	3,926	3,413
<i>Panel B: Single Women</i>					
Own-wage	1.045 (0.053)	0.712 (0.051)	0.921 (0.049)	1.151 (0.050)	1.065 (0.053)
Extensive margin	0.643 (0.036)	0.388 (0.034)	0.561 (0.034)	0.777 (0.039)	0.743 (0.042)
Intensive margin	0.403 (0.023)	0.324 (0.022)	0.360 (0.019)	0.374 (0.015)	0.322 (0.016)
Observations	4,505	4,000	6,409	6,198	5,223
<i>Panel C: Married men</i>					
Own-wage	0.331 (0.018)	0.301 (0.018)	0.284 (0.016)	0.391 (0.021)	0.286 (0.017)
Extensive margin	0.101 (0.012)	0.091 (0.013)	0.102 (0.011)	0.191 (0.016)	0.135 (0.013)
Intensive margin	0.230 (0.012)	0.210 (0.011)	0.183 (0.010)	0.200 (0.012)	0.151 (0.009)
<i>Panel D: Married Women</i>					
Own-wage	1.135 (0.049)	1.141 (0.049)	1.105 (0.048)	1.025 (0.044)	1.142 (0.046)
Extensive margin	0.789 (0.037)	0.784 (0.037)	0.769 (0.036)	0.729 (0.033)	0.849 (0.036)
Intensive margin	0.345 (0.017)	0.357 (0.017)	0.336 (0.017)	0.296 (0.016)	0.293 (0.015)
Observations	5,000	5,000	5,000	5,000	5,000

Notes: This table contains the estimated elasticities for single and married men and women in a subset of years using a benefit simulator. Elasticity derivations are provided in Section 3. Standard errors are calculated using a parametric bootstrap with 100 draws from the joint distribution of utility parameters.

Table 3: Baseline Model Elasticities for the Long Panel, 1979-2020

	1980	1990	2000	2010	2020
<i>Panel A: Single Men</i>					
Own-wage	0.139 (0.036)	0.188 (0.036)	0.133 (0.029)	0.344 (0.068)	0.058 (0.027)
Extensive margin	0.070 (0.017)	0.090 (0.018)	0.059 (0.014)	0.252 (0.046)	0.063 (0.015)
Intensive margin	0.069 (0.025)	0.098 (0.022)	0.074 (0.019)	0.093 (0.026)	-0.005 (0.015)
Observations	2,443	2,784	2,723	3,926	2,574
<i>Panel B: Single Women</i>					
Own-wage	1.881 (0.109)	1.600 (0.098)	0.866 (0.068)	1.349 (0.063)	0.861 (0.067)
Extensive margin	1.458 (0.082)	1.221 (0.075)	0.563 (0.051)	0.986 (0.051)	0.602 (0.049)
Intensive margin	0.423 (0.035)	0.379 (0.031)	0.303 (0.023)	0.363 (0.018)	0.259 (0.023)
Observations	4,663	4,706	4,000	6,198	3,840
<i>Panel C: Married men</i>					
Own-wage	0.324 (0.022)	0.274 (0.017)	0.319 (0.020)	0.411 (0.023)	0.209 (0.015)
Extensive margin	0.097 (0.015)	0.069 (0.012)	0.107 (0.015)	0.208 (0.017)	0.086 (0.011)
Intensive margin	0.228 (0.014)	0.204 (0.011)	0.212 (0.011)	0.204 (0.012)	0.123 (0.009)
<i>Panel D: Married Women</i>					
Own-wage	2.067 (0.073)	1.352 (0.056)	1.156 (0.050)	1.019 (0.044)	0.966 (0.044)
Extensive margin	1.506 (0.057)	0.957 (0.042)	0.797 (0.037)	0.730 (0.033)	0.735 (0.035)
Intensive margin	0.561 (0.024)	0.396 (0.019)	0.359 (0.017)	0.290 (0.015)	0.231 (0.013)
Observations	5,000	5,000	5,000	5,000	5,000

Notes: This table contains the estimated elasticities for single and married men and women in a subset of years without using a benefit simulator. Elasticity derivations are provided in Section 3. Standard errors are calculated using a parametric bootstrap with 100 draws from the joint distribution of utility parameters.

Appendix

A Construction of variables from March CPS

As described in the main text, we use data from the 1979 through 2020 Annual Social and Economic March Supplement of the Current Population Survey (CPS). In this section, we describe how we construct our variables from the CPS. Tables [A1](#) and [A2](#) present the basic descriptive statistics for all four demographic groups, Tables [A3](#) and [A4](#) present the results from the Heckman selection wage models for men and women, and Tables [A5](#) and [A6](#) present the results from the OLS wage models for men and women.

Household construction We restrict our sample to single-family households, which are households that the Census Bureau defines as having only one sub-family. Within these households, we match spouses using the *sploc* variable from IPUMS. We identify dependents as any child, stepchild, grandchild, other relative under the age of 18, or sibling under the age of 18 that resides in the household. We topcode the number of dependents at nine.

Educational attainment We use the method proposed in Jaeger ([1997](#)) to map different education levels into five categories: did not complete high school, completed high school, attended some college, earned a college degree, earned an advanced degree.

Hours worked We use usual hours worked per week from the prior year as our continuous hours variable. We then discretize hours as follows: less than five hours, 0 hours; between five and 14 hours, 10 hours; between 15 and 24 hours, 20 hours; between 25 and 34 hours, 30 hours; between 35 and 44 hours, 40 hours; between 45 and 54 hours, 50 hours; greater than or equal to 55 hours, 60 hours.

Non-labor income We calculate non-labor income as the sum of dividend income, interest income, rental income and other property income, alimony, child support, and other non-property

income. For years 1988 and later, dividend income and rental income are separately recorded in the CPS. Prior to 1988, they are recorded together in one category. For the purpose of using TAXSIM, if the combined category is positive, we assume that 16.5% of the combined category is dividend income and 83.5% is rental income. If the combined category is negative, we assume 100% of the combined category is property income. This split approximates the relative ratio of dividend income to rental income from 1988 and later. We assume that non-labor income is shared for the entire household.

Hourly wage We calculate hourly wages as pre-tax wage and salary income for the prior year divided by the product of usual hours worked per week in the prior year and weeks worked for pay in the prior year. We code hourly wage as “missing” if usual hours worked or weeks worked are zero or if wage and salary income is missing. Throughout our analysis, we use imputed wages for these non-workers (and often for the workers, too). We impute wages using two approaches: the standard Heckman selection model to account for selection into employment and OLS. First, we divide the sample into men and women and use +/- 1 year rolling bins for improved power (e.g., the wage model for 2000 includes 1999 and 2001). Then for each sex and year sample, we jointly estimate a wage model where log wage, in 2019 dollars, is a function of a quadratic in age, educational attainment, marital status, number of dependents, and region of residence as defined by the Census Bureau (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf). For the Heckman model, the selection equation uses the same variables as the wage model with indicators for dependents’ ages and a quadratic of spouse labor income plus non-labor income as the excluded instruments.

Real wages and income We use the Consumer Price Index Research Series Using Current Methods (CPI-U-RS) to convert all after-tax wages and non-labor income to 2019 dollars (survey year 2020).

Table A1: Descriptive Statistics, Single Men and Women

	1980	1990	2000	2010	2020
<i>Panel A: Men</i>					
Non-zero hours	0.99	0.98	0.99	0.94	0.97
Hours if > 0	42.39	43.26	43.81	42.21	42.60
Hourly wage	25.35	25.10	25.73	25.95	26.93
Non-labor income	1,325	1,493	1,647	998	1,684
Age	37.12	37.31	39.31	40.62	39.88
Dependents	0.22	0.20	0.21	0.21	0.23
1[Dep. Age 0-2]	0.01	0.01	0.01	0.01	0.01
1[Dep. Age 3-5]	0.01	0.02	0.02	0.02	0.02
1[Dep. Age 6-12]	0.04	0.04	0.05	0.05	0.06
High school completed	0.30	0.36	0.33	0.33	0.30
Some college	0.22	0.21	0.29	0.28	0.28
Bachelor's degree	0.19	0.22	0.22	0.23	0.26
Advanced degree	0.10	0.09	0.09	0.09	0.11
Observations	2,443	2,784	2,723	3,926	2,574
<i>Panel B: Women</i>					
Non-zero hours	0.86	0.88	0.96	0.91	0.94
Hours if > 0	39.12	40.35	40.94	39.73	39.94
Hourly wage	18.48	20.92	21.47	22.42	23.77
Non-labor income	2,534	2,066	2,331	1,616	1,763
Age	38.28	38.39	40.12	40.43	40.14
Dependents	1.34	1.06	0.97	1.03	0.99
1[Dep. Age 0-2]	0.08	0.08	0.05	0.07	0.06
1[Dep. Age 3-5]	0.11	0.11	0.09	0.10	0.10
1[Dep. Age 6-12]	0.32	0.27	0.26	0.26	0.26
High school completed	0.40	0.39	0.31	0.28	0.24
Some college	0.18	0.23	0.32	0.34	0.30
Bachelor's degree	0.12	0.17	0.19	0.21	0.25
Advanced degree	0.05	0.08	0.09	0.10	0.15
Observations	4,663	4,706	4,000	6,198	3,840

Notes: This table contains descriptive statistics for select years of our analytic sample. Panel A presents statistics for single men and Panel B presents statistics for single women. Years correspond to the survey year in the CPS. Hourly wages and non-labor income are in 2019 dollars. Observations are weighted by their ASEC person-level survey weight. Source: 1979-2020 CPS-ASEC.

Table A2: Descriptive Statistics, Married Men and Women

	1980	1990	2000	2010	2020
<i>Panel A: Men</i>					
Non-zero hours	0.99	0.99	0.99	0.96	0.98
Hours if > 0	43.39	43.68	44.43	43.14	43.07
Hourly wage	29.06	28.31	28.86	29.28	31.06
Non-labor income	1,773	2,187	2,626	1,491	3,091
Age	39.68	39.31	40.76	41.84	42.07
Dependents	1.73	1.53	1.51	1.53	1.54
1[Dep. Age 0-2]	0.19	0.19	0.18	0.18	0.18
1[Dep. Age 3-5]	0.20	0.21	0.20	0.20	0.20
1[Dep. Age 6-12]	0.40	0.37	0.38	0.36	0.37
High school completed	0.37	0.39	0.33	0.32	0.28
Some college	0.17	0.21	0.27	0.27	0.25
Bachelor's degree	0.16	0.18	0.21	0.22	0.26
Advanced degree	0.07	0.09	0.10	0.11	0.14
Observations	15,859	12,328	10,345	15,446	9,055
<i>Panel B: Women</i>					
Non-zero hours	0.66	0.76	0.80	0.78	0.78
Hours if > 0	43.39	43.68	44.43	43.14	43.07
Hourly wage	11.09	14.63	17.40	18.40	20.12
Non-labor income	1,773	2,187	2,626	1,491	3,091
Age	37.06	37.05	38.73	39.86	40.16
Dependents	1.73	1.53	1.51	1.53	1.54
1[Dep. Age 0-2]	0.19	0.19	0.18	0.18	0.18
1[Dep. Age 3-5]	0.20	0.21	0.20	0.20	0.20
1[Dep. Age 6-12]	0.40	0.37	0.38	0.36	0.37
High school completed	0.49	0.46	0.34	0.27	0.22
Some college	0.16	0.21	0.29	0.29	0.25
Bachelor's degree	0.12	0.17	0.21	0.25	0.29
Advanced degree	0.03	0.05	0.08	0.12	0.18
Observations	15,859	12,328	10,345	15,446	9,055

Notes: This table contains descriptive statistics for select years of our analytic sample. Panel A presents statistics for married men and Panel B presents statistics for married women. Years correspond to the survey year in the CPS. Hourly wages and non-labor income are in 2019 dollars. Observations are weighted by their ASEC person-level survey weight. Source: 1979-2020 CPS-ASEC.

Table A3: Heckman Selection Wage Model, Men

Selection equation	1980	1990	2000	2010	2020
Age	-0.018 (0.019)	-0.009 (0.021)	0.039 (0.020)	0.004 (0.012)	0.008 (0.022)
Age ² /100	0.011 (0.022)	0.003 (0.025)	-0.055 (0.024)	-0.015 (0.015)	-0.014 (0.025)
H.S. completed	0.049 (0.042)	0.482 (0.043)	0.284 (0.051)	0.246 (0.033)	0.182 (0.079)
Some college	0.125 (0.054)	0.619 (0.054)	0.467 (0.056)	0.410 (0.036)	0.169 (0.086)
Bachelor's degree	0.179 (0.060)	0.748 (0.064)	0.500 (0.063)	0.615 (0.040)	0.163 (0.104)
Advanced degree	0.231 (0.077)	0.718 (0.081)	0.552 (0.079)	0.742 (0.051)	-0.053 (0.112)
Married	0.342 (0.058)	0.369 (0.057)	0.282 (0.059)	0.294 (0.036)	0.195 (0.058)
Dependents	-0.038 (0.016)	-0.006 (0.021)	0.025 (0.023)	0.021 (0.013)	0.008 (0.019)
1[Dep. Age 0-2]	-0.067 (0.054)	-0.161 (0.055)	-0.156 (0.054)	-0.021 (0.034)	-0.118 (0.049)
1[Dep. Age 3-5]	-0.117 (0.045)	-0.073 (0.052)	-0.087 (0.050)	-0.103 (0.030)	-0.076 (0.045)
1[Dep. Age 6-12]	-0.086 (0.043)	-0.010 (0.052)	-0.038 (0.049)	-0.086 (0.028)	-0.086 (0.041)
East South Central	0.219 (0.079)	0.253 (0.096)	-0.057 (0.092)	0.201 (0.059)	0.192 (0.094)
Middle Atlantic	-0.179 (0.051)	0.076 (0.055)	-0.224 (0.066)	0.063 (0.043)	-0.070 (0.071)
Mountain	0.333 (0.072)	0.231 (0.074)	-0.143 (0.070)	0.106 (0.041)	0.101 (0.066)
New England	0.124 (0.069)	0.133 (0.072)	-0.131 (0.076)	0.078 (0.042)	-0.019 (0.077)
Pacific	0.204 (0.058)	0.032 (0.060)	-0.246 (0.065)	0.010 (0.037)	-0.073 (0.062)
South Atlantic	0.190 (0.059)	0.287 (0.060)	-0.166 (0.065)	0.000 (0.035)	0.005 (0.063)
West North Central	0.237 (0.073)	0.275 (0.083)	-0.069 (0.076)	0.237 (0.042)	0.022 (0.075)
West South Central	0.526 (0.095)	0.175 (0.071)	-0.066 (0.077)	0.150 (0.044)	0.172 (0.072)
Other income (in \$1000s)	-0.063 (0.020)	0.057 (0.017)	0.009 (0.016)	0.002 (0.010)	-0.042 (0.012)
Other income ² (in millions)	0.003 (0.003)	-0.006 (0.001)	-0.004 (0.001)	-0.003 (0.001)	0.003 (0.001)
Constant	2.187 (0.404)	1.323 (0.420)	0.991 (0.417)	1.004 (0.259)	1.559 (0.484)

Heckman Selection Wage Model, Men (continued)

Wage equation	1980	1990	2000	2010	2020
Age	0.059 (0.002)	0.051 (0.002)	0.049 (0.002)	0.048 (0.002)	0.043 (0.004)
Age ² /100	-0.060 (0.002)	-0.049 (0.003)	-0.050 (0.003)	-0.049 (0.003)	-0.044 (0.004)
H.S. completed	0.239 (0.005)	0.266 (0.007)	0.308 (0.008)	0.274 (0.008)	0.272 (0.012)
Some college	0.303 (0.006)	0.372 (0.007)	0.442 (0.008)	0.433 (0.008)	0.425 (0.012)
Bachelor's degree	0.416 (0.006)	0.540 (0.008)	0.646 (0.008)	0.659 (0.008)	0.648 (0.012)
Advanced degree	0.446 (0.008)	0.590 (0.009)	0.735 (0.009)	0.778 (0.009)	0.787 (0.013)
Married	0.125 (0.006)	0.119 (0.006)	0.122 (0.006)	0.124 (0.006)	0.107 (0.008)
Dependents	0.003 (0.002)	0.000 (0.002)	0.006 (0.002)	0.004 (0.002)	0.007 (0.003)
East South Central	-0.170 (0.009)	-0.155 (0.011)	-0.134 (0.010)	-0.056 (0.010)	-0.099 (0.014)
Middle Atlantic	-0.038 (0.006)	0.022 (0.007)	-0.020 (0.008)	0.065 (0.008)	0.027 (0.013)
Mountain	-0.115 (0.007)	-0.135 (0.008)	-0.113 (0.008)	0.004 (0.008)	-0.032 (0.011)
New England	-0.160 (0.008)	0.014 (0.008)	-0.046 (0.008)	0.057 (0.008)	0.045 (0.014)
Pacific	-0.024 (0.007)	-0.002 (0.008)	-0.047 (0.008)	0.048 (0.007)	0.046 (0.011)
South Atlantic	-0.146 (0.007)	-0.105 (0.007)	-0.084 (0.007)	-0.008 (0.007)	-0.054 (0.011)
West North Central	-0.133 (0.008)	-0.166 (0.009)	-0.129 (0.008)	-0.045 (0.007)	-0.036 (0.012)
West South Central	-0.172 (0.008)	-0.168 (0.009)	-0.146 (0.008)	-0.047 (0.008)	-0.061 (0.012)
Constant	1.519 (0.042)	1.489 (0.047)	1.482 (0.050)	1.447 (0.047)	1.641 (0.073)
Selection term: λ	-0.385 (0.005)	-0.002 (0.017)	0.066 (0.013)	0.087 (0.011)	-0.421 (0.010)
Observations	52,701	44,369	47,486	57,693	25,822

Notes: This table contains parameter estimates from the Heckman selection wage model described in Appendix Section A. The outcome variable is logged hourly wage in 2019 dollars. Robust standard errors in parentheses.

Table A4: Heckman Selection Wage Model, Women

Selection equation	1980	1990	2000	2010	2020
Age	0.050 (0.007)	0.076 (0.008)	0.073 (0.009)	0.040 (0.007)	0.047 (0.011)
Age ² /100	-0.086 (0.008)	-0.110 (0.010)	-0.096 (0.011)	-0.046 (0.009)	-0.052 (0.014)
H.S. completed	0.496 (0.015)	0.659 (0.020)	0.585 (0.023)	0.564 (0.022)	0.545 (0.036)
Some college	0.705 (0.020)	0.996 (0.024)	0.917 (0.025)	0.924 (0.022)	0.923 (0.037)
Bachelor's degree	0.936 (0.023)	1.227 (0.027)	1.053 (0.028)	1.050 (0.025)	1.144 (0.039)
Advanced degree	1.300 (0.047)	1.518 (0.045)	1.266 (0.039)	1.266 (0.030)	1.445 (0.044)
Married	-0.172 (0.027)	-0.016 (0.032)	-0.393 (0.035)	-0.300 (0.026)	-0.361 (0.044)
Dependents	-0.079 (0.006)	-0.122 (0.008)	-0.081 (0.008)	-0.096 (0.007)	-0.118 (0.010)
1[Dep. Age 0-2]	-0.596 (0.021)	-0.522 (0.020)	-0.480 (0.020)	-0.402 (0.017)	-0.347 (0.026)
1[Dep. Age 3-5]	-0.446 (0.019)	-0.404 (0.018)	-0.398 (0.018)	-0.300 (0.015)	-0.265 (0.023)
1[Dep. Age 6-12]	-0.221 (0.016)	-0.172 (0.018)	-0.171 (0.018)	-0.115 (0.015)	-0.088 (0.022)
East South Central	0.017 (0.028)	-0.014 (0.035)	-0.071 (0.036)	-0.014 (0.033)	-0.198 (0.044)
Middle Atlantic	-0.176 (0.021)	-0.124 (0.023)	-0.214 (0.027)	-0.067 (0.026)	-0.167 (0.043)
Mountain	0.029 (0.023)	0.072 (0.029)	-0.137 (0.027)	-0.080 (0.025)	-0.133 (0.038)
New England	0.062 (0.025)	0.165 (0.030)	0.072 (0.032)	0.148 (0.027)	0.079 (0.049)
Pacific	0.073 (0.022)	-0.012 (0.026)	-0.168 (0.027)	-0.074 (0.024)	-0.208 (0.037)
South Atlantic	0.044 (0.021)	0.099 (0.024)	-0.088 (0.026)	-0.035 (0.022)	-0.153 (0.036)
West North Central	0.152 (0.025)	0.207 (0.031)	0.254 (0.032)	0.279 (0.026)	0.203 (0.044)
West South Central	0.055 (0.024)	-0.061 (0.028)	-0.167 (0.029)	-0.100 (0.025)	-0.193 (0.038)
Other income (in \$1000s)	-0.062 (0.007)	-0.042 (0.008)	-0.025 (0.008)	-0.019 (0.006)	-0.046 (0.011)
Other income ² (in millions)	-0.001 (0.000)	-0.003 (0.001)	-0.002 (0.000)	-0.002 (0.000)	-0.001 (0.001)
Constant	0.554 (0.139)	-0.378 (0.165)	0.336 (0.176)	0.339 (0.150)	0.384 (0.233)

Heckman Selection Wage Model, Women (continued)

Wage equation	1980	1990	2000	2010	2020
Age	0.045 (0.002)	0.058 (0.003)	0.055 (0.003)	0.047 (0.002)	0.044 (0.004)
Age ² /100	-0.055 (0.003)	-0.069 (0.003)	-0.062 (0.003)	-0.050 (0.003)	-0.047 (0.005)
H.S. completed	0.212 (0.007)	0.267 (0.008)	0.300 (0.009)	0.330 (0.009)	0.294 (0.016)
Some college	0.338 (0.009)	0.456 (0.009)	0.488 (0.009)	0.534 (0.009)	0.488 (0.016)
Bachelor's degree	0.514 (0.010)	0.673 (0.010)	0.743 (0.010)	0.811 (0.010)	0.783 (0.016)
Advanced degree	0.701 (0.014)	0.826 (0.012)	0.946 (0.011)	1.031 (0.010)	1.001 (0.017)
Married	-0.106 (0.006)	-0.050 (0.005)	-0.021 (0.005)	-0.008 (0.005)	-0.006 (0.007)
Dependents	-0.059 (0.003)	-0.066 (0.002)	-0.053 (0.002)	-0.039 (0.002)	-0.038 (0.003)
East South Central	-0.112 (0.010)	-0.120 (0.011)	-0.120 (0.011)	-0.074 (0.011)	-0.122 (0.014)
Middle Atlantic	-0.009 (0.008)	0.073 (0.008)	0.005 (0.009)	0.066 (0.009)	0.048 (0.014)
Mountain	-0.054 (0.008)	-0.078 (0.009)	-0.104 (0.009)	-0.017 (0.009)	-0.039 (0.012)
New England	-0.038 (0.009)	0.097 (0.009)	0.015 (0.009)	0.074 (0.009)	0.074 (0.015)
Pacific	0.052 (0.008)	0.072 (0.009)	0.000 (0.009)	0.072 (0.008)	0.065 (0.012)
South Atlantic	-0.042 (0.008)	-0.021 (0.007)	-0.047 (0.008)	0.022 (0.007)	-0.023 (0.012)
West North Central	-0.055 (0.009)	-0.083 (0.009)	-0.074 (0.009)	-0.017 (0.008)	0.003 (0.013)
West South Central	-0.084 (0.009)	-0.085 (0.009)	-0.129 (0.009)	-0.053 (0.009)	-0.053 (0.013)
Constant	1.798 (0.046)	1.371 (0.051)	1.371 (0.051)	1.340 (0.048)	1.450 (0.075)
Selection term: λ	0.260 (0.019)	0.239 (0.012)	0.266 (0.011)	0.277 (0.009)	0.272 (0.012)
Observations	58,894	49,867	52,773	64,727	28,624

Notes: This table contains parameter estimates from the Heckman selection wage model described in Appendix Section A. The outcome variable is logged hourly wage in 2019 dollars. Robust standard errors in parentheses.

Table A5: OLS Wage Model, Men

Wage equation	1980	1990	2000	2010	2020
Age	0.060 (0.002)	0.051 (0.002)	0.049 (0.002)	0.048 (0.002)	0.045 (0.003)
Age ² /100	-0.061 (0.002)	-0.049 (0.003)	-0.050 (0.003)	-0.049 (0.003)	-0.046 (0.004)
H.S. completed	0.249 (0.005)	0.266 (0.007)	0.306 (0.008)	0.270 (0.008)	0.287 (0.011)
Some college	0.314 (0.006)	0.373 (0.007)	0.439 (0.008)	0.427 (0.008)	0.446 (0.012)
Bachelor's degree	0.429 (0.006)	0.540 (0.007)	0.644 (0.008)	0.651 (0.008)	0.674 (0.012)
Advanced degree	0.459 (0.008)	0.590 (0.009)	0.732 (0.009)	0.769 (0.009)	0.809 (0.013)
Married	0.138 (0.006)	0.119 (0.006)	0.121 (0.006)	0.121 (0.005)	0.119 (0.008)
Dependents	0.002 (0.002)	0.000 (0.002)	0.006 (0.002)	0.004 (0.002)	0.006 (0.003)
East South Central	-0.169 (0.009)	-0.155 (0.011)	-0.134 (0.010)	-0.059 (0.010)	-0.101 (0.014)
Middle Atlantic	-0.046 (0.006)	0.022 (0.007)	-0.019 (0.008)	0.064 (0.008)	0.018 (0.013)
Mountain	-0.114 (0.007)	-0.135 (0.008)	-0.113 (0.008)	0.002 (0.008)	-0.031 (0.011)
New England	-0.159 (0.007)	0.015 (0.008)	-0.045 (0.008)	0.056 (0.008)	0.043 (0.013)
Pacific	-0.024 (0.007)	-0.002 (0.008)	-0.046 (0.008)	0.048 (0.007)	0.036 (0.011)
South Atlantic	-0.146 (0.007)	-0.105 (0.007)	-0.083 (0.007)	-0.007 (0.007)	-0.062 (0.011)
West North Central	-0.132 (0.007)	-0.166 (0.009)	-0.129 (0.008)	-0.048 (0.007)	-0.039 (0.012)
West South Central	-0.166 (0.008)	-0.168 (0.009)	-0.146 (0.008)	-0.049 (0.008)	-0.060 (0.012)
Constant	1.455 (0.041)	1.489 (0.047)	1.490 (0.050)	1.463 (0.047)	1.542 (0.070)
Observations	52,251	43,824	46,938	55,643	25,276

Notes: This table contains parameter estimates from the OLS regression described in Appendix Section A. The outcome variable is logged hourly wage in 2019 dollars. Robust standard errors in parentheses.

Table A6: OLS Wage Model, Women

Wage equation	1980	1990	2000	2010	2020
Age	0.033 (0.002)	0.048 (0.002)	0.045 (0.002)	0.039 (0.002)	0.037 (0.004)
Age ² /100	-0.039 (0.003)	-0.055 (0.003)	-0.050 (0.003)	-0.042 (0.003)	-0.039 (0.004)
H.S. completed	0.160 (0.005)	0.201 (0.007)	0.241 (0.008)	0.261 (0.008)	0.229 (0.015)
Some college	0.270 (0.007)	0.369 (0.008)	0.407 (0.008)	0.436 (0.008)	0.388 (0.014)
Bachelor's degree	0.431 (0.007)	0.577 (0.008)	0.660 (0.009)	0.711 (0.008)	0.674 (0.015)
Advanced degree	0.600 (0.011)	0.719 (0.010)	0.851 (0.010)	0.916 (0.009)	0.871 (0.015)
Married	-0.046 (0.004)	-0.022 (0.005)	0.027 (0.005)	0.037 (0.004)	0.050 (0.006)
Dependents	-0.035 (0.002)	-0.043 (0.002)	-0.035 (0.002)	-0.020 (0.002)	-0.018 (0.003)
East South Central	-0.125 (0.009)	-0.128 (0.011)	-0.120 (0.010)	-0.076 (0.010)	-0.109 (0.014)
Middle Atlantic	0.009 (0.008)	0.087 (0.008)	0.025 (0.008)	0.076 (0.009)	0.066 (0.014)
Mountain	-0.061 (0.008)	-0.090 (0.009)	-0.095 (0.008)	-0.007 (0.008)	-0.029 (0.012)
New England	-0.057 (0.008)	0.083 (0.009)	0.009 (0.009)	0.063 (0.008)	0.067 (0.014)
Pacific	0.046 (0.008)	0.076 (0.008)	0.017 (0.008)	0.085 (0.008)	0.087 (0.012)
South Atlantic	-0.053 (0.007)	-0.034 (0.007)	-0.041 (0.008)	0.027 (0.007)	-0.009 (0.011)
West North Central	-0.079 (0.008)	-0.107 (0.009)	-0.097 (0.008)	-0.042 (0.008)	-0.017 (0.012)
West South Central	-0.097 (0.008)	-0.085 (0.009)	-0.119 (0.009)	-0.043 (0.008)	-0.036 (0.012)
Constant	2.037 (0.041)	1.646 (0.047)	1.600 (0.048)	1.572 (0.046)	1.662 (0.072)
Observations	40,977	39,451	44,128	52,864	23,200

Notes: This table contains parameter estimates from the OLS regression described in Appendix Section A. The outcome variable is logged hourly wage in 2019 dollars. Robust standard errors in parentheses.

B Topcoding

The topcoding thresholds, and how topcoded values are treated, changes over our sample period. Until 1995, income variables were topcoded by the maximum value allowed in the survey. From 1996 to 2010, income variables were given a “replacement value threshold”, and any value that exceeded the threshold was given the mean value of similar individuals. As of 2011, income variables are given a “swap value threshold”, and any value that exceeds the threshold is swapped with another individual’s value within a pre-specified interval around the initial value. Across all years, even within topcoding regimes, the threshold values change, and some variables move in and out of having a threshold value altogether. For more information, see https://cps.ipums.org/cps/topcodes_tables.shtml.

Appendix Figure A1 presents the topcode values for different income variables over time. While the threshold for the primary labor income variable, INCLONGJ, increases in nominal terms over time, almost all the non-labor other income variable thresholds decrease significantly in 1999 when they are added to the income swap regime. Furthermore, the nominal threshold is constant, or increases only slightly, for most the non-labor income variables through 2010. Thus, the minimum threshold in real dollars is often the threshold value in effect during 2009. The list of minimum threshold values, in 2019 dollars, are shown below.

Variable	Threshold	Year
INCLONGJ	\$171,135	1995
OINCWAGE	\$36,188	2002
INCINT	\$26,382	2014
INCDIVID	\$17,855	2009
INCRENT	\$36,188	2002
INCALIM	\$53,565	2009
INCCHILD	\$17,855	2009
INCASIST	\$32,978	2014
INCOTHER	\$29,758	2009

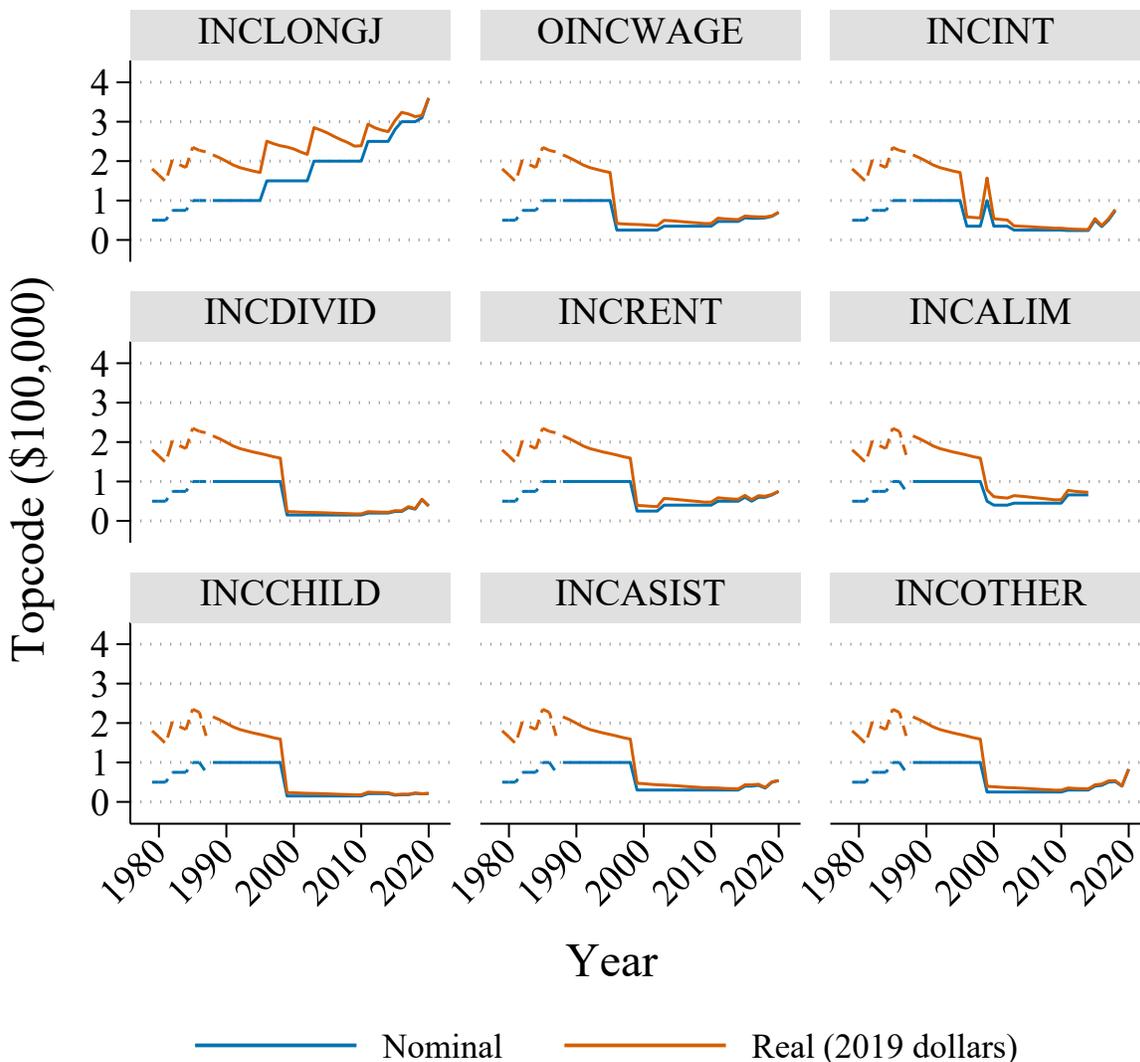
Most of these variables are subsumed in other variables prior to 1988. To extend our thresholds to these earlier years, we use the minimum threshold of INCLONGJ for INCWAGE, the sum of minimum thresholds of INCDIVID and INCRENT for INCDRT, and the sum of minimum

thresholds of INCALIM, INCCHILD, INCASIST, and INCOTHER for INCALOTH.

Appendix Figure A2 presents the share of individuals that exceed our minimum threshold values and the actual threshold values over time, aggregated by labor income and non-labor income variables. Before calculating these shares, we limit the sample to our population of interest: adults in single-family households aged between 26 and 55 (or, if married, one spouse is aged between 26 to 55, and the other spouse is aged between 22 and 59) who are not enrolled in school, disabled, self-employed, members of the armed forces, earn farm or business income, or work unpaid in a family business.

As expected, our imposed topcode affects a larger share of individuals than the actual threshold, with the exception of a small share of individuals in 1980 and 1981. This is due to the threshold for INCWAGE falling below the minimum threshold for INCLONGJ in these two years. Overall, our sample restriction removes fewer than 3.4% of individuals, though the rate increases over time. It reaches a maximum value in 2020 with 7.3% of individuals excluded due to exceeding the minimum threshold for at least one of the income variables.

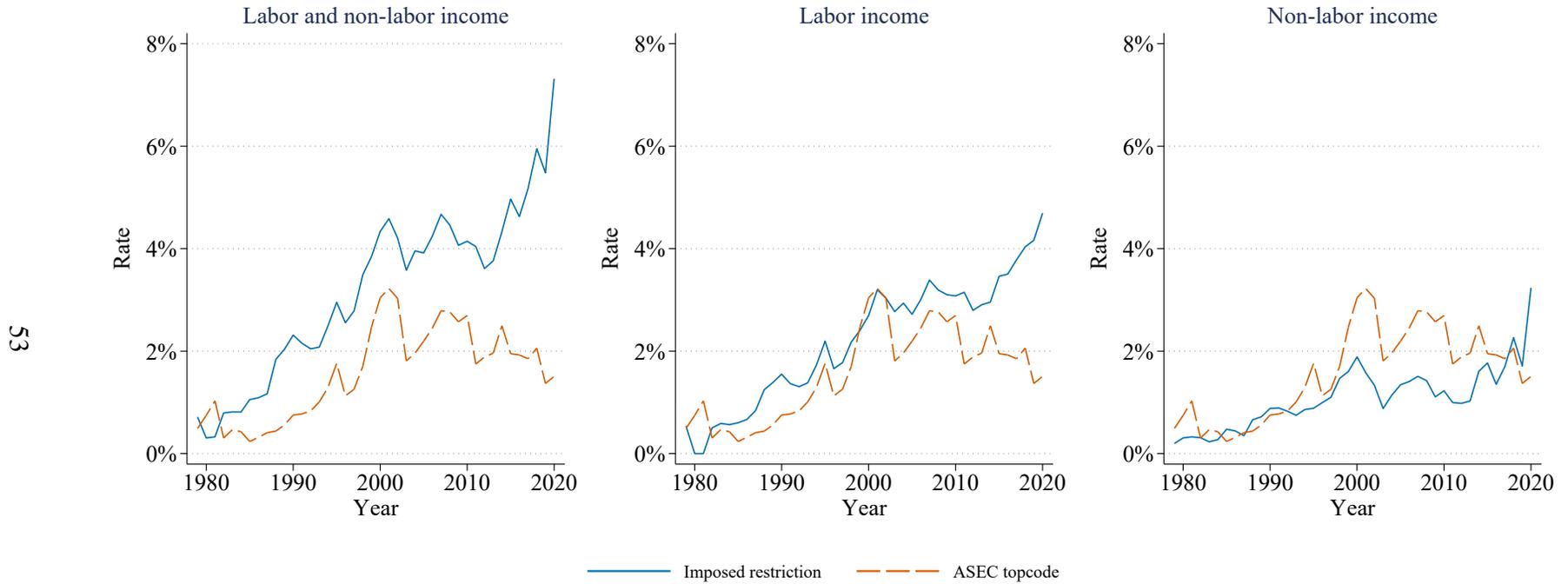
Figure A1: Topcode Thresholds (1979-2020)



Graphs by income variable

Notes: Each graph plots the change in topcode threshold over time for nine different income variables. Dashed lines represent topcode thresholds adopted from other variables: INCLONJ and OINCWAGE were combined in INCWAGE until 1988, INCDIVID and INCRENT were combined in INCDRT until 1988, and INCALIM, INCCHILD, INCASIST, and INCOTHER were combined in INCALOTH until 1988. INCALIM was subsumed in INCOTHER beginning in 2015. INCINT no longer had a topcode threshold beginning in 2019. Source: 1979-2020 CPS-ASEC.

Figure A2: Share of Individuals that Exceed Minimum Threshold



Notes: Each graph plots the share of observations that exceed our minimum threshold value and actual threshold value over time. The first graph plots the share of observations that exceed the threshold value for any income variable. The second graph plots the share of observations that exceed the threshold values for labor income. The third graph plots the share of observations that exceed the threshold values for non-labor income variables.

C Using TAXSIM and TRIM3 to Predict After-tax Wages and Social Assistance benefits

To fully exploit variation in the tax system, we would like to calculate after-tax income for each hours choice a household could make (seven for single men and women, 49 for married couples). Given we are using simulation methods that rely on 50 wage draws for each household, this entails calculating post-tax income 350 times for each single man and woman and 2,450 times for each married couple in our sample. This amounts to calculating after-tax income upwards of 138 billion times for our baseline model alone.

To make this computationally feasible with TAXSIM, we rely on a strategy similar to that described by Loeffler et al. (2018), estimating a flexible parametric tax function and then using the tax function to predict after-tax wages. To ensure sufficient coverage for our flexible function, we create 12 income draws for each observation from across their year and marital status-specific income distribution. More specifically, we calculate the 10th, 20th, ..., 80th, 90th, 99th, and 99.9th percentile of the wage income distribution for each year and marital status, and then we take random draws between the 0 and 10th percentile, 10th and 20th percentile, ... , 90th and 99th percentile, and 99th and 99.9th percentiles. We add a final draw where both labor and non-labor income are set to 0. Next, we use NBER's TAXSIM version 27 to calculate after-tax income at each of these 12 income draws, and then we estimate after-tax income as a linear spline of before-tax income, with kink points at the 10th, 20th, ... , 90th, and 99th percentiles of before-tax income. The parameters of the spline vary by year, marital status, state of residence, and number of dependents (0, 1, 2, or 3+).

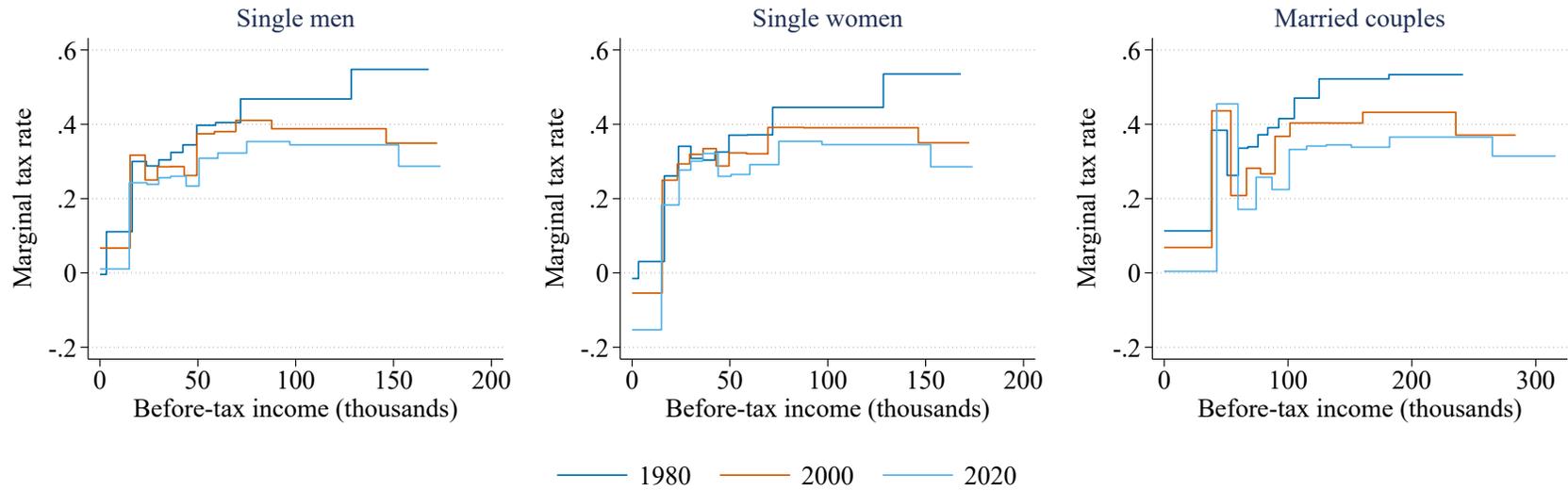
Unsurprisingly, the spline fits the simulated data very well; the r-squared is over 99.5% in every year cross marital status regression. To test its fit on real data, we apply TAXSIM to the actual observed earnings of each household in our sample and compare the calculated taxes with the predicted taxes from the spline. In absolute value, the median error in 2019 dollars (predicted taxes minus calculated taxes) is \$243 and the mean error is \$573. 90% of observations have an error of less than \$1,484. For comparison, the average taxes are \$15,958.

We use the Urban Institute's TRIM3 and a flexible regression to predict government assistance. TRIM3 provides information on eligibility and receipt of government assistance (i.e., SNAP/Food Stamps and TANF/ADFC) for each household in our sample. TRIM3 requires users to input assumptions and/or interpretations about economic behavior and the rules governing federal programs. Therefore, the conclusions presented in this paper are attributable only to the authors and not any researcher at the Urban Institute. For more information on TRIM3, see Zedlewski and Giannarelli (2015).

We model government assistance according to Cragg's hurdle model (Cragg, 1971), where the probability of receiving and accepting non-zero government assistance is a function of state of residence, number of dependents (0, 1, 2, or 3+), an indicator for non-zero asset income, an indicator for home ownership, indicators for having dependents between 0 and 2 years of age, 3 and 5 years of age, and 6 and 12 years of age, and a linear spline of income with kink points at the 5th, 10th, ... , 30th, and 35th percentiles of the income distribution. Conditional on non-zero government assistance, the dollar amount accepted is a linear function of state of residence, number of dependents, and a linear spline of income interacted with number of dependents.

The hurdle model does not fit the data as well as the tax model fits the tax data, but it still captures the key features of the data. For households that do not receive any government assistance, the model predicts an average probability of non-zero assistance of 5.4%. For households that do receive government assistance, the model predicts an average probability of non-zero assistance of 58.5%. In absolute value, the median error (predicted assistance received minus actual assistance received) is \$25 and the mean error is \$452 (2019 dollars). 90% of observations have an error of less than \$1,340. For reference, the average government assistance received (unconditional on being non-zero) is \$490.

Figure A3: Marginal Tax Rates Over Time



Notes: This figure presents the estimated marginal tax rates in our spline of the TAXSIM model for 1980, 2000, and 2020. As our spline varies by state of residence and number of dependents, the marginal tax rates are averages weighted by the number of households per state of residence and number of dependents. The knot points are adjusted for inflation and presented in 2019 dollars.

D Utility function parameter estimates

This section includes utility function parameter estimates for select years and goodness of fit estimates. The utility function parameter estimates are for the short panel, which includes simulated benefits, and the long panel, which does not.

Table A7: Baseline Model Parameter Estimates for the Short Panel, Single Men

	1995	2000	2005	2010	2015
Log(Consumption)	-6.90 (6.75)	9.46 (7.07)	-9.29 (5.86)	2.16 (6.03)	-4.03 (6.61)
Log(Leisure)	53.20 (49.80)	158.09 (55.82)	62.48 (43.89)	106.45 (42.59)	81.11 (45.06)
× Log(Age)	-1.78 (24.03)	-39.92 (26.37)	-23.86 (20.73)	5.49 (19.41)	-6.41 (21.25)
× Log(Age) ²	0.62 (3.30)	5.98 (3.62)	3.61 (2.85)	-0.41 (2.66)	1.02 (2.91)
× Dependents	0.05 (0.24)	-0.13 (0.27)	-0.53 (0.19)	-0.47 (0.23)	-0.84 (0.23)
Log(Consumption) ²	0.58 (0.16)	0.39 (0.16)	0.69 (0.13)	0.55 (0.14)	0.61 (0.15)
Log(Leisure) ²	-4.93 (2.20)	-5.79 (2.38)	-1.18 (1.96)	-10.22 (2.08)	-5.78 (2.08)
Log(C) × Log(L)	-0.40 (1.05)	-3.11 (1.12)	-0.21 (0.93)	-2.22 (0.95)	-1.06 (0.99)
Hours > 0	2.10 (0.46)	2.83 (0.50)	2.87 (0.41)	1.02 (0.35)	2.03 (0.38)
× Dependents	0.35 (0.22)	0.50 (0.38)	0.22 (0.23)	-0.05 (0.18)	-0.32 (0.19)
× 1[Dep. Age 0-5]	-1.57 (0.53)	-0.16 (1.21)	-0.53 (0.70)	-0.48 (0.43)	-0.82 (0.45)
Hours ∈ {10, 20, 30}	-3.52 (0.16)	-4.11 (0.19)	-4.12 (0.15)	-3.29 (0.12)	-3.80 (0.15)
Observations	2,801	2,723	3,726	3,926	3,413

Notes: This table contains parameter estimates for our baseline model with a benefit simulator for single men in a subset of years. The specific utility function is described in Section 3.1.

Table A8: Baseline Model Parameter Estimates for the Short Panel, Single Women

	1995	2000	2005	2010	2015
Log(Consumption)	50.58 (8.38)	84.69 (10.16)	70.53 (7.49)	109.47 (8.17)	105.70 (9.27)
Log(Leisure)	583.41 (75.95)	566.53 (81.30)	544.19 (66.64)	858.41 (72.63)	709.43 (73.98)
× Log(Age)	-35.42 (34.12)	14.13 (36.80)	10.00 (30.78)	-41.01 (31.71)	32.44 (32.86)
× Log(Age) ²	5.05 (4.70)	-1.38 (5.06)	-1.07 (4.23)	5.87 (4.36)	-4.17 (4.51)
× Dependents	-0.34 (0.22)	0.07 (0.22)	-0.15 (0.19)	0.63 (0.21)	0.57 (0.21)
Log(Consumption) ²	1.69 (0.15)	1.07 (0.17)	1.56 (0.15)	1.13 (0.14)	0.85 (0.16)
Log(Leisure) ²	-38.35 (3.33)	-41.40 (3.76)	-38.41 (2.88)	-55.81 (3.12)	-56.71 (3.36)
Log(C) × Log(L)	-15.79 (1.66)	-20.66 (1.98)	-19.39 (1.50)	-26.13 (1.56)	-24.34 (1.66)
Hours > 0	1.05 (0.30)	1.33 (0.38)	1.21 (0.30)	0.44 (0.31)	-0.29 (0.33)
× Dependents	-0.17 (0.09)	-0.01 (0.12)	-0.07 (0.10)	-0.29 (0.11)	-0.31 (0.11)
× 1[Dep. Age 0-5]	-0.72 (0.20)	-0.94 (0.28)	-0.91 (0.23)	-1.02 (0.23)	-0.84 (0.24)
Hours ∈ {10, 20, 30}	-2.89 (0.10)	-3.24 (0.12)	-3.42 (0.10)	-3.47 (0.10)	-3.25 (0.11)
Observations	4,505	4,000	6,409	6,198	5,223

Notes: This table contains parameter estimates for our baseline model with a benefit simulator for single women in a subset of years. The specific utility function is described in Section 3.1.

Table A9: Baseline Model Parameter Estimates for the Short Panel, Married

	1995	2000	2005	2010	2015
Log(Consumption)	50.73 (12.37)	55.64 (11.71)	28.52 (9.34)	14.15 (10.06)	-17.48 (9.37)
Log(Leisure _m)	135.39 (51.57)	255.27 (56.32)	239.28 (50.29)	154.88 (49.30)	15.31 (45.73)
× Log(Age _m)	26.84 (24.84)	-37.40 (25.54)	-41.04 (24.26)	13.69 (23.69)	-5.68 (22.37)
× Log(Age _m) ²	-2.55 (3.39)	5.91 (3.49)	6.14 (3.31)	-1.70 (3.22)	1.18 (3.04)
× Dependents	-0.30 (0.15)	-0.09 (0.15)	-0.43 (0.15)	-0.48 (0.14)	-0.40 (0.13)
Log(Leisure _f)	299.25 (38.69)	335.83 (40.55)	199.57 (38.18)	181.53 (37.68)	201.53 (36.90)
× Log(Age _f)	0.36 (19.32)	-8.55 (20.10)	44.09 (19.43)	20.64 (18.78)	6.66 (18.72)
× Log(Age _f) ²	0.39 (2.68)	1.33 (2.78)	-6.15 (2.69)	-2.86 (2.59)	-1.00 (2.57)
× Dependents	1.56 (0.15)	1.40 (0.16)	1.20 (0.15)	0.74 (0.15)	0.85 (0.15)
Log(Consumption) ²	1.87 (0.28)	2.21 (0.26)	2.29 (0.22)	2.38 (0.22)	2.76 (0.23)
Log(Leisure _m) ²	-9.75 (1.87)	-8.00 (1.96)	-9.57 (1.60)	-12.49 (1.54)	-1.70 (1.34)
Log(Leisure _f) ²	-26.68 (1.05)	-27.68 (1.10)	-24.84 (1.04)	-22.80 (1.00)	-23.96 (0.99)
Log(C) × Log(L _m)	-9.92 (1.22)	-11.37 (1.28)	-7.90 (0.99)	-7.90 (1.04)	-2.40 (0.87)
Log(C) × Log(L _f)	-6.58 (0.80)	-7.55 (0.82)	-5.83 (0.74)	-3.31 (0.72)	-3.45 (0.65)

Baseline Model Parameter Estimates for the Short Panel, Married (cont.)

	1995	2000	2005	2010	2015
Log(L _m) × Log(L _f)	3.67 (1.79)	4.88 (1.80)	4.63 (1.66)	7.73 (1.63)	11.82 (1.46)
Hours _m > 0	4.77 (0.80)	5.92 (1.19)	4.01 (1.33)	2.47 (0.85)	2.61 (0.86)
× Dependents	0.51 (0.24)	-0.63 (0.32)	0.18 (0.43)	-0.60 (0.23)	0.08 (0.25)
× 1[Dep. Age 0-5]	0.65 (0.53)	2.92 (0.97)	0.48 (0.86)	1.72 (0.55)	-0.05 (0.54)
Hours _m ∈ {10, 20, 30}	-5.11 (0.19)	-5.89 (0.21)	-4.89 (0.17)	-4.10 (0.14)	-5.18 (0.18)
Hours _f > 0	-0.94 (0.80)	-1.09 (1.17)	-1.10 (1.32)	-0.86 (0.84)	-3.14 (0.85)
× Dependents	0.59 (0.27)	-0.48 (0.35)	0.44 (0.44)	-0.45 (0.24)	0.17 (0.27)
× 1[Dep. Age 0-5]	0.60 (0.60)	2.77 (1.03)	-0.13 (0.90)	0.65 (0.58)	-0.81 (0.60)
Hours _f ∈ {10, 20, 30}	-2.19 (0.07)	-2.19 (0.07)	-2.21 (0.07)	-2.28 (0.08)	-2.20 (0.08)
Hours _m > 0 & Hours _f > 0	-0.04 (0.78)	0.42 (1.16)	0.50 (1.31)	0.36 (0.82)	2.25 (0.82)
× Dependents	-0.24 (0.27)	0.65 (0.35)	-0.25 (0.44)	0.59 (0.24)	-0.07 (0.27)
× 1[Dep. Age 0-5]	-1.68 (0.60)	-3.82 (1.03)	-0.91 (0.90)	-1.45 (0.58)	0.02 (0.60)
Observations	5,000	5,000	5,000	5,000	5,000

Notes: This table contains parameter estimates for our baseline model with a benefit simulator for married men and women in a subset of years. The specific utility function is described in Section 3.1.

Table A10: Baseline Model Parameter Estimates for the Long Panel, Single Men

	1980	1990	2000	2010	2020
Log(Consumption)	-14.22 (9.21)	0.61 (8.00)	1.95 (7.45)	-11.61 (7.13)	-28.76 (7.15)
Log(Leisure)	41.41 (58.38)	100.13 (55.72)	132.27 (56.09)	37.59 (47.04)	18.18 (50.85)
× Log(Age)	-37.46 (28.56)	-20.06 (27.07)	-40.30 (26.26)	6.72 (20.99)	-14.01 (23.90)
× Log(Age) ²	5.61 (3.94)	3.26 (3.73)	6.02 (3.61)	-0.56 (2.87)	1.84 (3.27)
× Dependents	-0.21 (0.28)	-0.36 (0.28)	-0.04 (0.27)	-0.45 (0.23)	0.06 (0.26)
Log(Consumption) ²	1.23 (0.24)	0.81 (0.20)	0.58 (0.18)	1.06 (0.21)	0.84 (0.16)
Log(Leisure) ²	5.43 (2.87)	-3.43 (2.65)	-3.67 (2.47)	-3.50 (2.59)	-1.97 (2.33)
Log(C) × Log(L)	-0.79 (1.52)	-2.64 (1.27)	-2.23 (1.16)	-0.98 (1.17)	3.26 (1.09)
Hours > 0	3.93 (0.59)	3.02 (0.52)	3.34 (0.54)	1.80 (0.41)	2.08 (0.52)
× Dependents	-0.54 (0.27)	-0.72 (0.25)	-0.08 (0.36)	-0.71 (0.24)	-0.26 (0.21)
× 1[Dep. Age 0-5]	-1.15 (1.15)	-0.86 (0.82)	-0.50 (1.24)	-0.28 (0.52)	1.59 (1.09)
Hours ∈ {10, 20, 30}	-4.26 (0.19)	-3.79 (0.17)	-4.11 (0.19)	-3.36 (0.12)	-3.79 (0.17)
Observations	2,443	2,784	2,723	3,926	2,574

Notes: This table contains parameter estimates for our baseline model without a benefit simulator for single men in a subset of years. The specific utility function is described in Section 3.1.

Table A11: Baseline Model Parameter Estimates for the Long Panel, Single Women

	1980	1990	2000	2010	2020
Log(Consumption)	45.65 (8.93)	29.74 (9.50)	64.90 (11.34)	80.94 (8.83)	45.46 (10.91)
Log(Leisure)	475.62 (68.45)	323.69 (70.28)	487.45 (81.66)	671.45 (72.61)	424.82 (79.91)
× Log(Age)	-44.35 (31.68)	1.70 (32.16)	-2.30 (35.54)	-37.15 (30.83)	-5.48 (34.13)
× Log(Age) ²	6.12 (4.36)	-0.18 (4.43)	0.61 (4.88)	5.21 (4.23)	0.96 (4.67)
× Dependents	0.87 (0.17)	1.23 (0.20)	1.54 (0.22)	1.50 (0.20)	0.96 (0.22)
Log(Consumption) ²	1.77 (0.13)	1.80 (0.16)	1.32 (0.16)	1.33 (0.12)	1.26 (0.16)
Log(Leisure) ²	-24.28 (2.78)	-20.42 (3.45)	-32.18 (4.09)	-41.10 (3.34)	-29.11 (4.17)
Log(C) × Log(L)	-15.14 (1.72)	-11.94 (1.74)	-17.66 (2.14)	-21.14 (1.66)	-13.52 (1.98)
Hours > 0	3.71 (0.33)	3.76 (0.35)	3.25 (0.39)	2.63 (0.30)	3.33 (0.41)
× Dependents	-0.43 (0.09)	-0.66 (0.12)	-0.60 (0.13)	-0.82 (0.11)	-0.83 (0.13)
× 1[Dep. Age 0-5]	-1.86 (0.29)	-2.45 (0.31)	-1.49 (0.34)	-1.24 (0.28)	-1.46 (0.32)
Hours ∈ {10, 20, 30}	-3.56 (0.11)	-3.40 (0.11)	-3.25 (0.12)	-3.25 (0.09)	-3.33 (0.12)
Observations	4,663	4,706	4,000	6,198	3,840

Notes: This table contains parameter estimates for our baseline model without a benefit simulator for single women in a subset of years. The specific utility function is described in Section 3.1.

Table A12: Baseline Model Parameter Estimates for the Long Panel, Married

	1980	1990	2000	2010	2020
Log(Consumption)	112.36 (17.04)	75.55 (12.60)	74.07 (10.86)	42.92 (9.21)	6.10 (7.66)
Log(Leisure _m)	102.22 (61.42)	208.74 (57.70)	307.18 (58.62)	213.81 (51.12)	-57.31 (47.38)
× Log(Age _m)	90.23 (28.56)	30.17 (27.42)	-39.32 (26.18)	14.25 (24.09)	34.94 (24.41)
× Log(Age _m) ²	-11.42 (3.89)	-3.08 (3.75)	6.20 (3.58)	-1.77 (3.27)	-4.66 (3.30)
× Dependents	0.03 (0.15)	-0.19 (0.16)	-0.03 (0.15)	-0.37 (0.14)	-0.38 (0.13)
Log(Leisure _f)	422.41 (41.28)	336.40 (38.79)	357.38 (41.01)	215.25 (37.33)	230.73 (36.91)
× Log(Age _f)	3.31 (19.27)	7.22 (19.21)	-8.75 (20.25)	16.95 (18.56)	19.81 (18.84)
× Log(Age _f) ²	0.11 (2.68)	-0.56 (2.67)	1.36 (2.80)	-2.35 (2.56)	-2.73 (2.58)
× Dependents	1.14 (0.15)	1.46 (0.16)	1.42 (0.16)	0.83 (0.14)	1.09 (0.15)
Log(Consumption) ²	2.70 (0.27)	2.00 (0.23)	1.94 (0.20)	1.80 (0.17)	2.00 (0.16)
Log(Leisure _m) ²	-7.13 (2.90)	-14.54 (2.38)	-10.23 (2.10)	-15.01 (1.72)	-0.53 (1.43)
Log(Leisure _f) ²	-30.44 (1.21)	-28.70 (1.13)	-28.16 (1.13)	-23.22 (1.01)	-26.89 (1.07)
Log(C) × Log(L _m)	-17.99 (2.21)	-13.08 (1.55)	-13.39 (1.36)	-10.50 (1.15)	-2.43 (0.91)
Log(C) × Log(L _f)	-14.45 (1.15)	-9.21 (0.88)	-8.43 (0.83)	-4.55 (0.71)	-5.50 (0.61)

Baseline Model Parameter Estimates for the Long Panel, Married (cont.)

	1980	1990	2000	2010	2020
Log(L _m) × Log(L _f)	3.25 (1.96)	3.84 (1.94)	3.19 (1.84)	5.40 (1.68)	10.28 (1.48)
Hours _m > 0	6.97 (1.50)	6.52 (1.54)	6.71 (1.29)	3.80 (1.00)	5.98 (1.23)
× Dependents	1.68 (0.51)	-0.51 (0.31)	-1.38 (0.32)	-1.21 (0.20)	-0.63 (0.30)
× 1[Dep. Age 0-5]	0.59 (1.18)	-0.20 (1.07)	3.36 (1.09)	2.33 (0.62)	-0.66 (0.88)
Hours _m ∈ {10, 20, 30}	-6.72 (0.25)	-5.05 (0.18)	-5.82 (0.21)	-4.03 (0.14)	-5.69 (0.20)
Hours _f > 0	-1.72 (1.50)	0.81 (1.54)	-0.21 (1.28)	0.54 (0.98)	-1.01 (1.23)
× Dependents	2.31 (0.53)	-0.22 (0.36)	-1.22 (0.35)	-1.02 (0.21)	-0.31 (0.32)
× 1[Dep. Age 0-5]	-1.52 (1.33)	-1.69 (1.19)	3.23 (1.14)	1.27 (0.65)	-1.16 (0.92)
Hours _f ∈ {10, 20, 30}	-2.63 (0.08)	-2.43 (0.08)	-2.20 (0.07)	-2.30 (0.08)	-2.51 (0.08)
Hours _m > 0 & Hours _f > 0	1.42 (1.49)	-1.38 (1.53)	-0.43 (1.26)	-0.99 (0.97)	0.14 (1.21)
× Dependents	-2.11 (0.53)	0.47 (0.36)	1.38 (0.35)	1.14 (0.21)	0.41 (0.32)
× 1[Dep. Age 0-5]	0.18 (1.33)	0.58 (1.19)	-4.30 (1.15)	-2.09 (0.66)	0.39 (0.92)
Observations	5,000	5,000	5,000	5,000	5,000

Notes: This table contains parameter estimates for our baseline model without a benefit simulator for married men and women in a subset of years. The specific utility function is described in Section 3.1.

E Additional results

In this subsection, we first provide additional details regarding our robustness analysis and counterfactual simulations. We then present the additional empirical results discussed in the main text.

Random slopes Our baseline model takes the typical conditional logit form. To add random slopes to the model, the simulated likelihood function is made conditional on the random utility error and integrated out in a similar manner as the predicted wage error term, using 50 draws from a Halton sequence.

Estimates from including or excluding imputed data In the March Supplement of the CPS, there are two levels of imputation: whole unit imputation and individual question imputation. In our baseline specification, we include observations regardless of their imputation status (either whole unit or individual question). Here, we test the robustness of our results to excluding these observations with imputed data.

To identify observations with imputed data, we use data flags provided by IPUMS:

UH_SUPREC_A1/A2, QINCWAGE, QINCLONG, QOINCWAGE, QWKSWORK and QUHR-SWORKLY.

UH_SUPREC_A1/A2, which are available from 1991 onward, identify observations with complete non-response to the March Supplement or insufficient response to merge with the basic survey. In either case, the entire observation is imputed. QINCWAGE, which is available until 1987, identifies observations with imputed wage and salary earnings. QINCLONG and QOINCWAGE, which are available from 1988 onward, identify observations with imputed earnings from their longest job held in the year and earnings from other work included in wage and salary earnings, respectively. QWKSWORK and QUHR-SWORKLY, which are also available from 1988 onward, identify observations with imputed weeks worked and hours usually worked per week in the prior year.

Appendix Figure [A7](#) shows the percent of observations with imputed data over time. The average imputation rate across years is 20.6%, but the rate is increasing over time and exceeds 37%

in 2020. Increasing non-response is a previously documented phenomenon, and existing research suggests it does not appear uniformly across the income distribution (Bollinger et al., 2019). To test whether our elasticity trends are driven by imputation rate trends, we re-estimate our baseline model without the imputed observations. Figure A8 presents the results.

Predicting wages for everyone Our baseline model predicts wages for everyone. This figure shows the results when only predicting wages for non-workers.

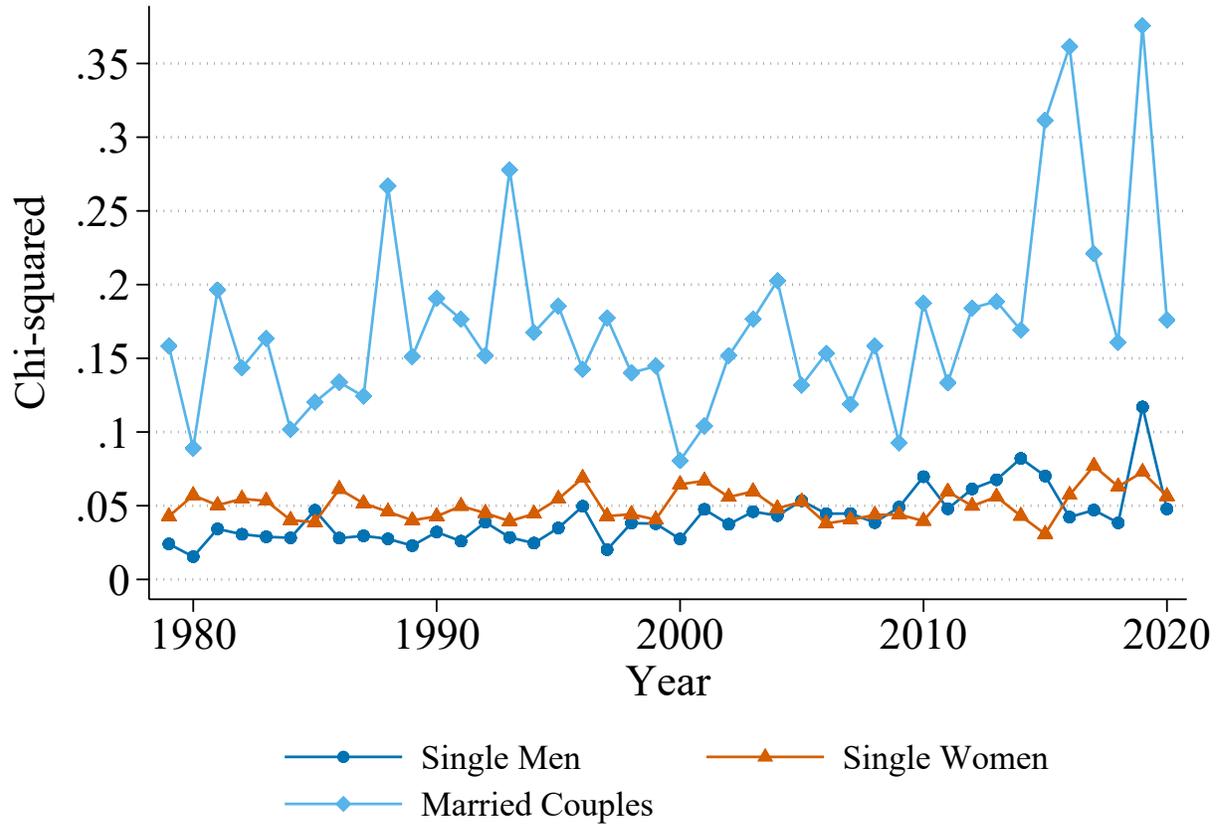
Fixed cost of work specifications Our baseline model allows for there to be a fixed utility change for working, and then again for working part time (10, 20, or 30 hours). This figure shows the results when eliminating these fixed costs.

Counterfactual simulation notes In our counterfactual simulations, it is straightforward to hold wages, taxes, and utility parameters constant in a particular year: we use just the parameter estimates that we estimated for a particular year. In contrast, the counterfactual simulations for holding the “other input variables” fixed is more difficult because it entails constructing a counterfactual joint distribution for these other variables. To do so, we construct annual samples that have the 1980 distribution of the variables used in estimation – state of residence; household head and spouse (if married) age and education; number of dependents; indicators for dependents aged less than 2, between 3 and 5, and between 6 and 12; and non-labor income – via multinomial logit (state of residence), ordered logit (age conditional on state of residence), and a nearest neighbor algorithm (conditional on state of residence and age).

For our additional simulations, we experiment with holding only one of the input variables constant at a time. To do so, we adopt a simplified approach to the one described by Rothe (2012) and assign factors according to their 1980 distribution and individuals’ year-sex-marital status-specific percentile rank. Specifically, we calculate year-sex-marital status specific percentile ranks, rounded to the nearest 0.001 and assign each year-sex-marital status-percentile cell the maximum value from the corresponding 1980-sex-marital status distribution. For discrete variables, we split

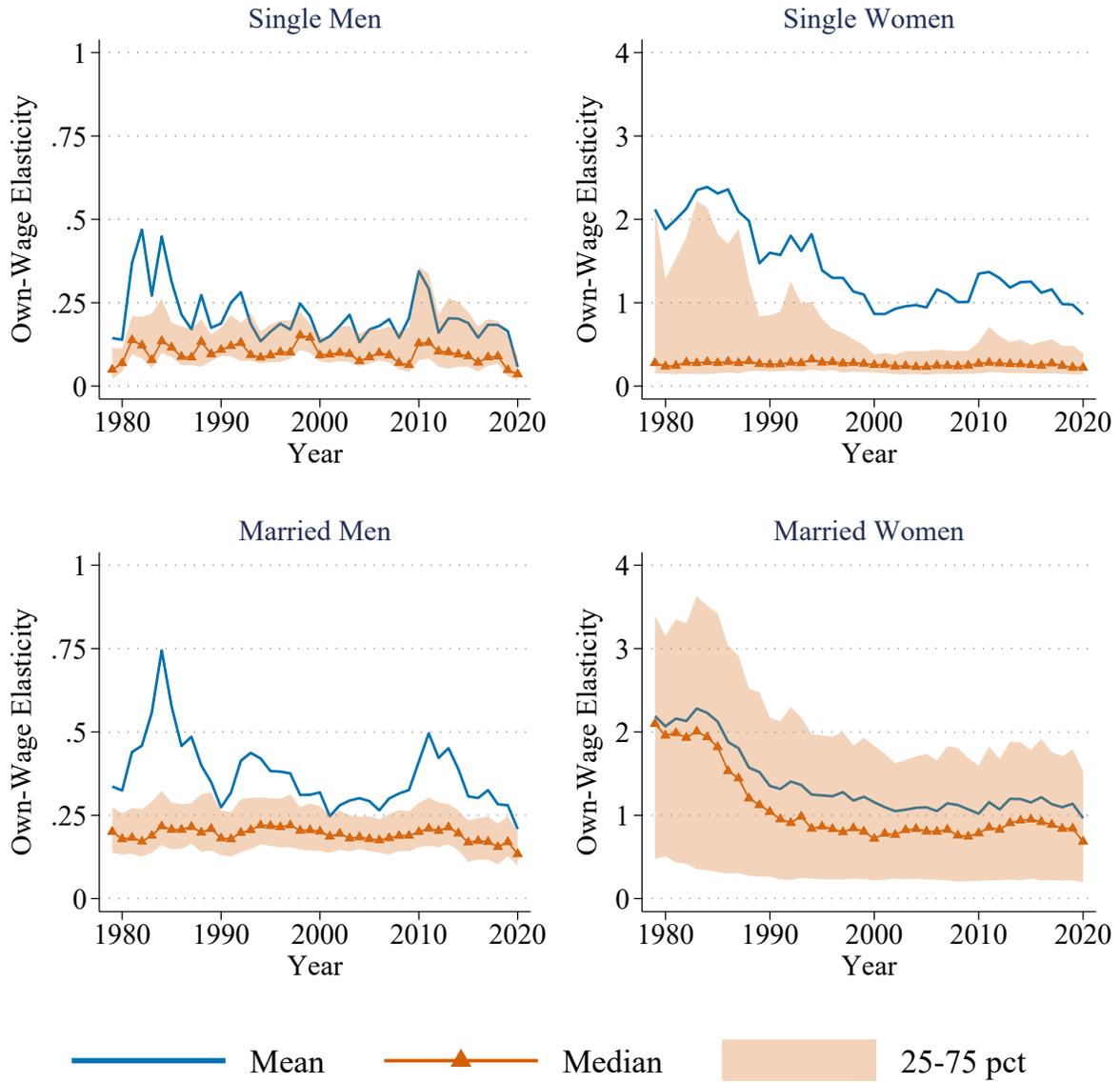
ties in the percentile rank randomly. This method preserves both the 1980 distribution of each variable and the year-specific correlations between the imputed and non-imputed variables.

Figure A4: Goodness of Fit over Time



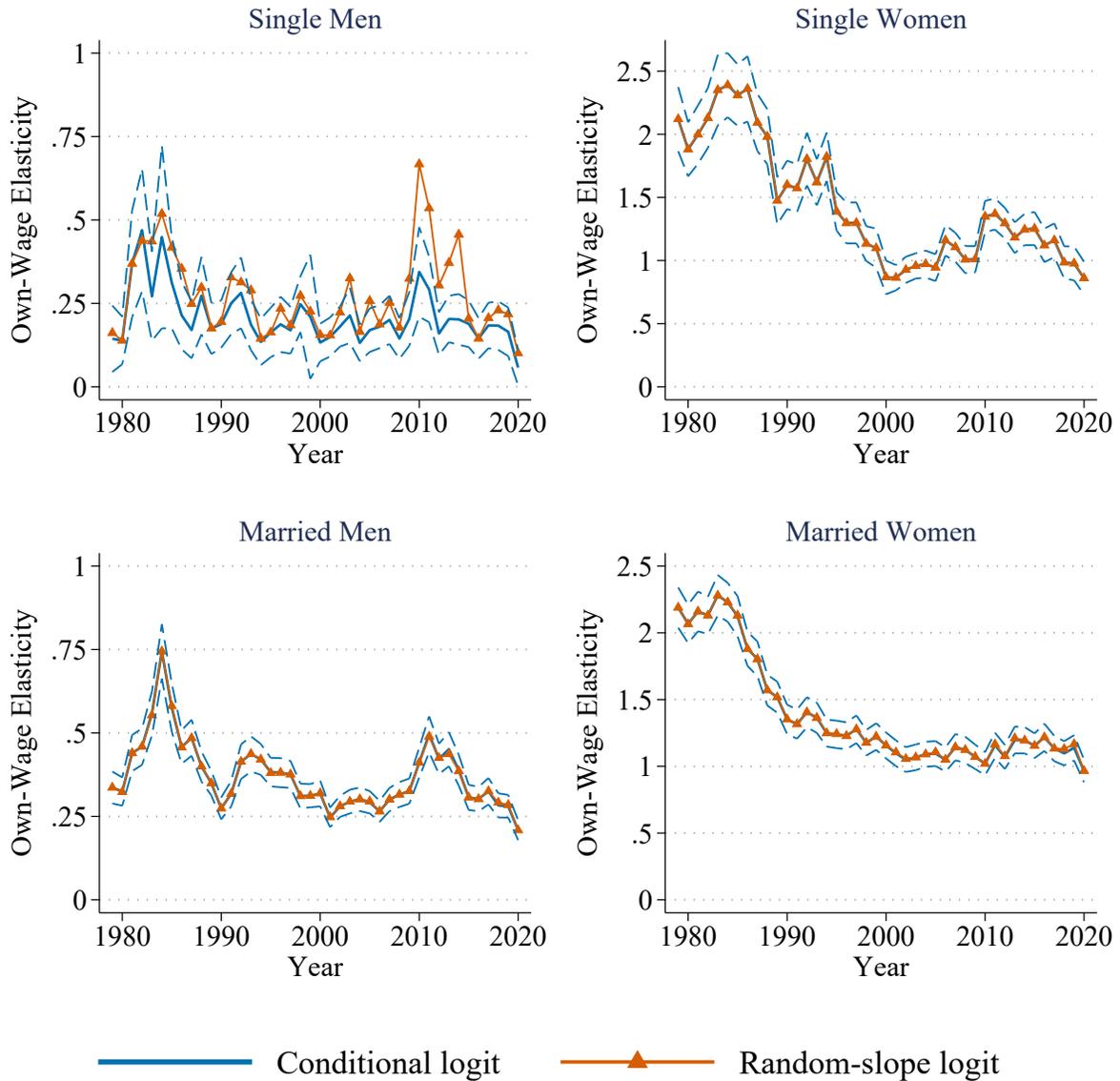
Notes: This figure presents the chi-squared statistics (squared errors divided by true probability summed across alternatives) for the fit between actual hours worked and predicted hours worked according to the parameter estimates of our baseline model without the benefit simulator.

Figure A5: Mean, Median, and Interquartile Range of Own-Wage Elasticities



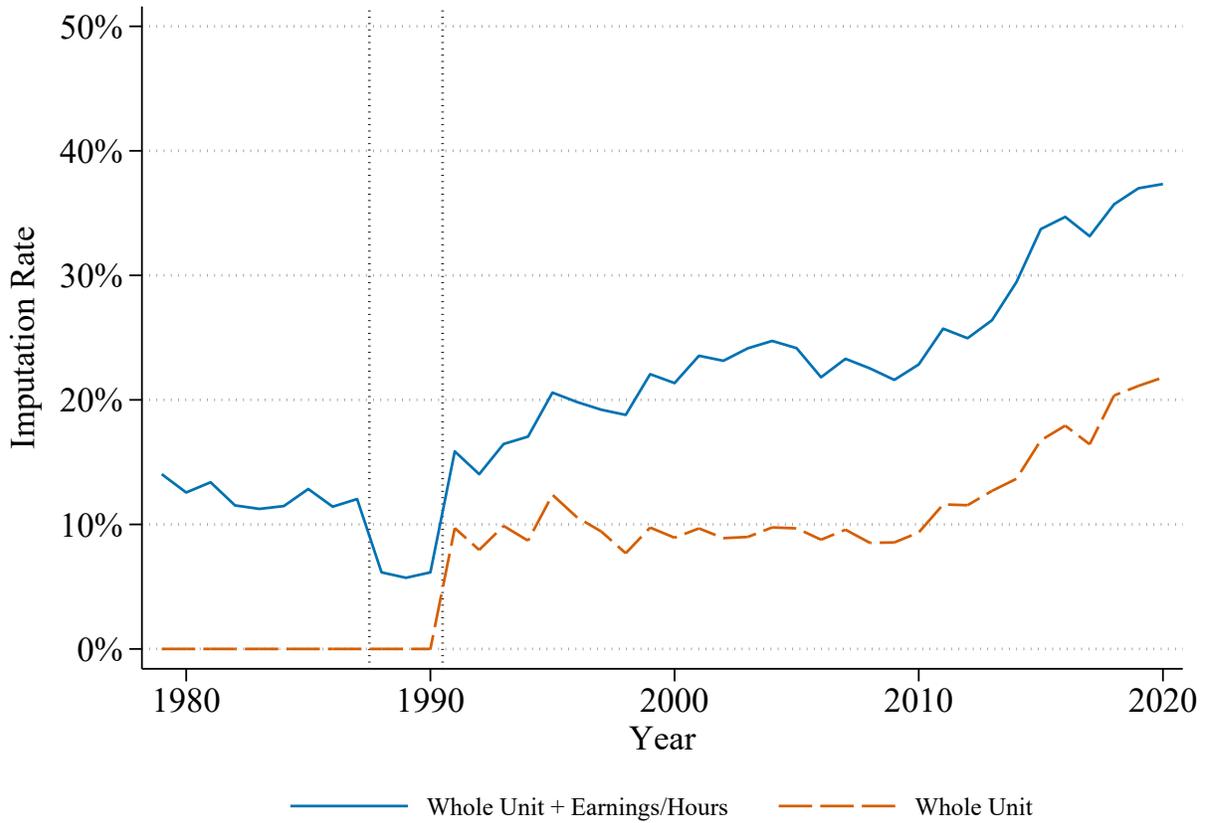
Notes: This figure presents estimated mean, median, and 25-75th percentile own-wage elasticities separately by sex and marital status using our baseline model without the benefit simulator.

Figure A6: Mean Own-Wage Elasticities, Random Slopes



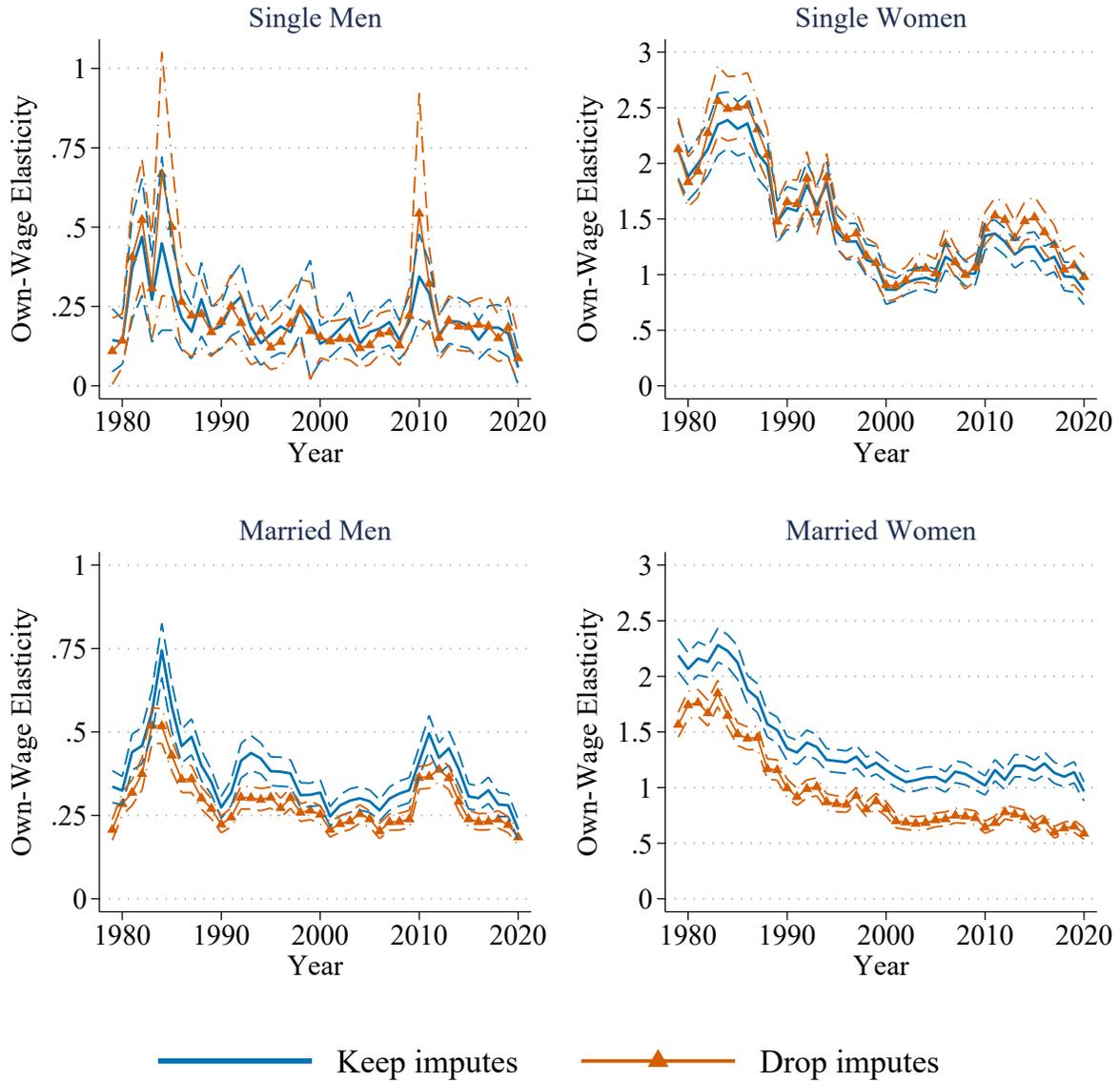
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model with random slopes (orange with triangle markers) is identical to the baseline model (solid blue line) except for the presence of a random coefficient on consumption. Confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines for the baseline model. Confidence intervals for the random slope model are orders of magnitude larger and not shown.

Figure A7: ASEC Imputation Rates (1979-2020)



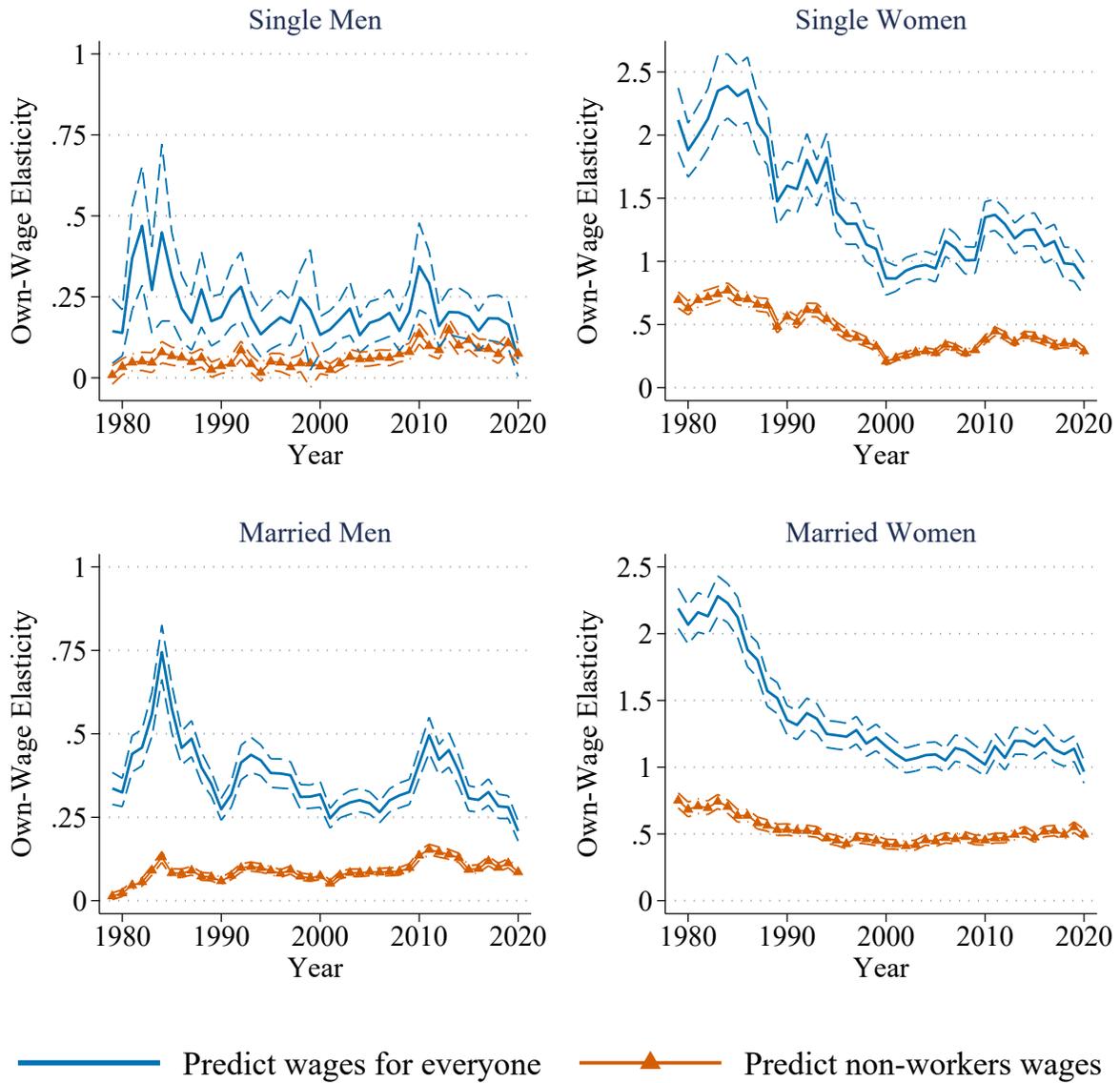
Notes: Whole unit imputation is based on UH_SUPREC_A1 (1991-2006) and UH_SUPREC_A2 (2007-2020). Earnings and hours imputation is based on the flags QINCWAGE (1979-1987), QINCLONG (1988-2020), QOINCWAGE (1988-2020), QWKSWORK (1988-2020), and QUHRWORKLY (1988-2020). Source: 1979-2020 CPS-ASEC.

Figure A8: Mean Own-Wage Elasticities, Baseline Estimates versus Estimates from Excluding Observations with Imputed Data



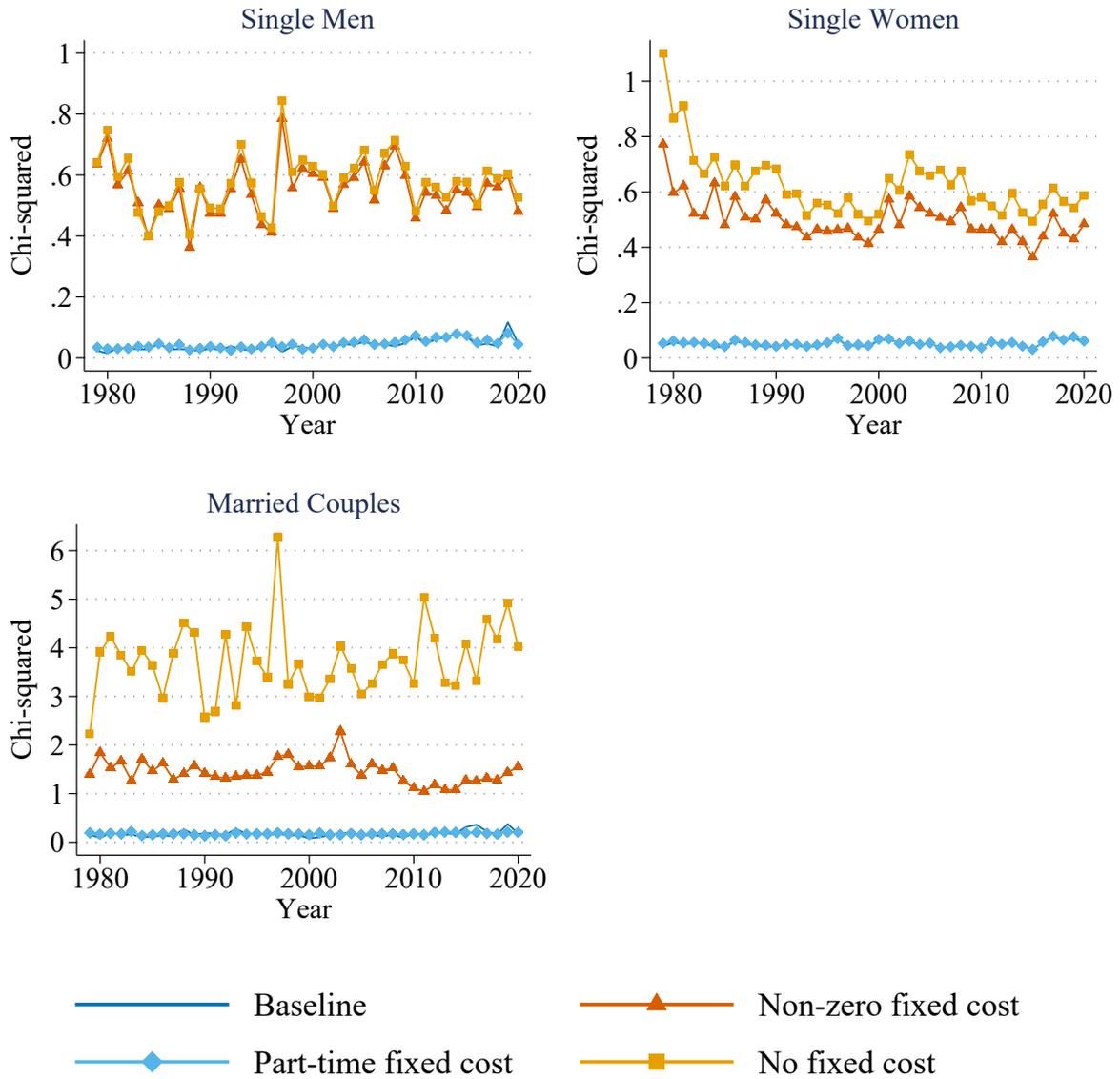
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model without imputed observations (orange with triangle markers) is identical to the baseline model (solid blue line) except for the change in sample. Confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines.

Figure A9: Mean Own-Wage Elasticities, Wages Predicted for Everyone or Non-workers Only



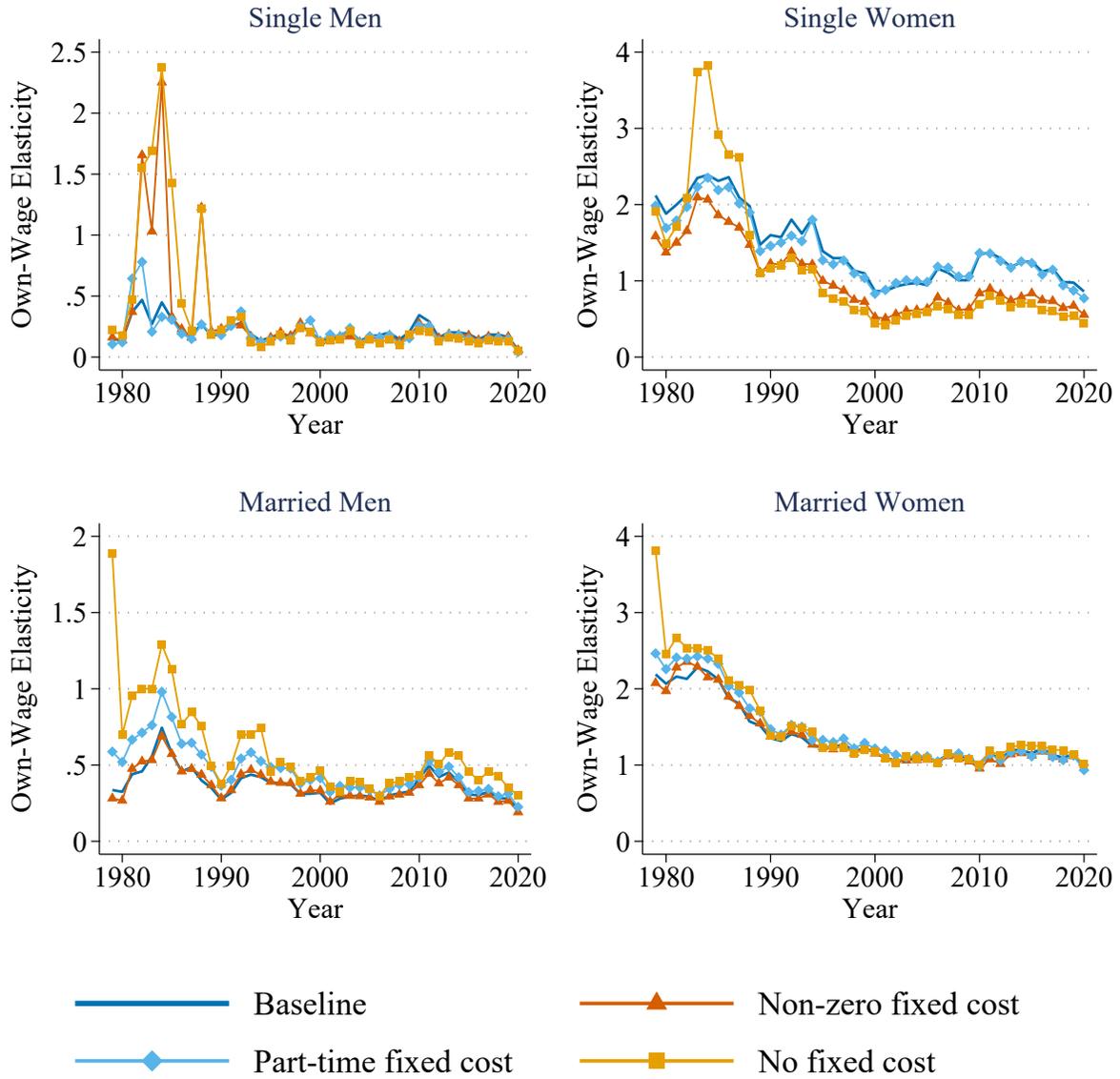
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model predicting wages for non-workers only (orange with triangle markers) is identical to the baseline model (solid blue line) except for the use of observed wages for workers. Confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines.

Figure A10: Goodness of Fit from Varying Fixed Costs of Work Specifications



Notes: This figure presents the chi-squared statistics (squared errors divided by true probability summed across alternatives) for the fit between actual hours worked and predicted hours worked according to varying models. The baseline model includes a fixed cost of working non-zero hours and a separate fixed cost of working part-time hours. The “non-zero fixed cost” model only includes a fixed cost of working non-zero hours. The “part-time fixed cost” only includes a fixed cost of working 10, 20, or 30 hours per week. The “no fixed cost” model drops both fixed costs.

Figure A11: Mean Own-Wage Elasticities, Baseline Estimates versus Estimates from Varying Fixed Costs of Work Specifications



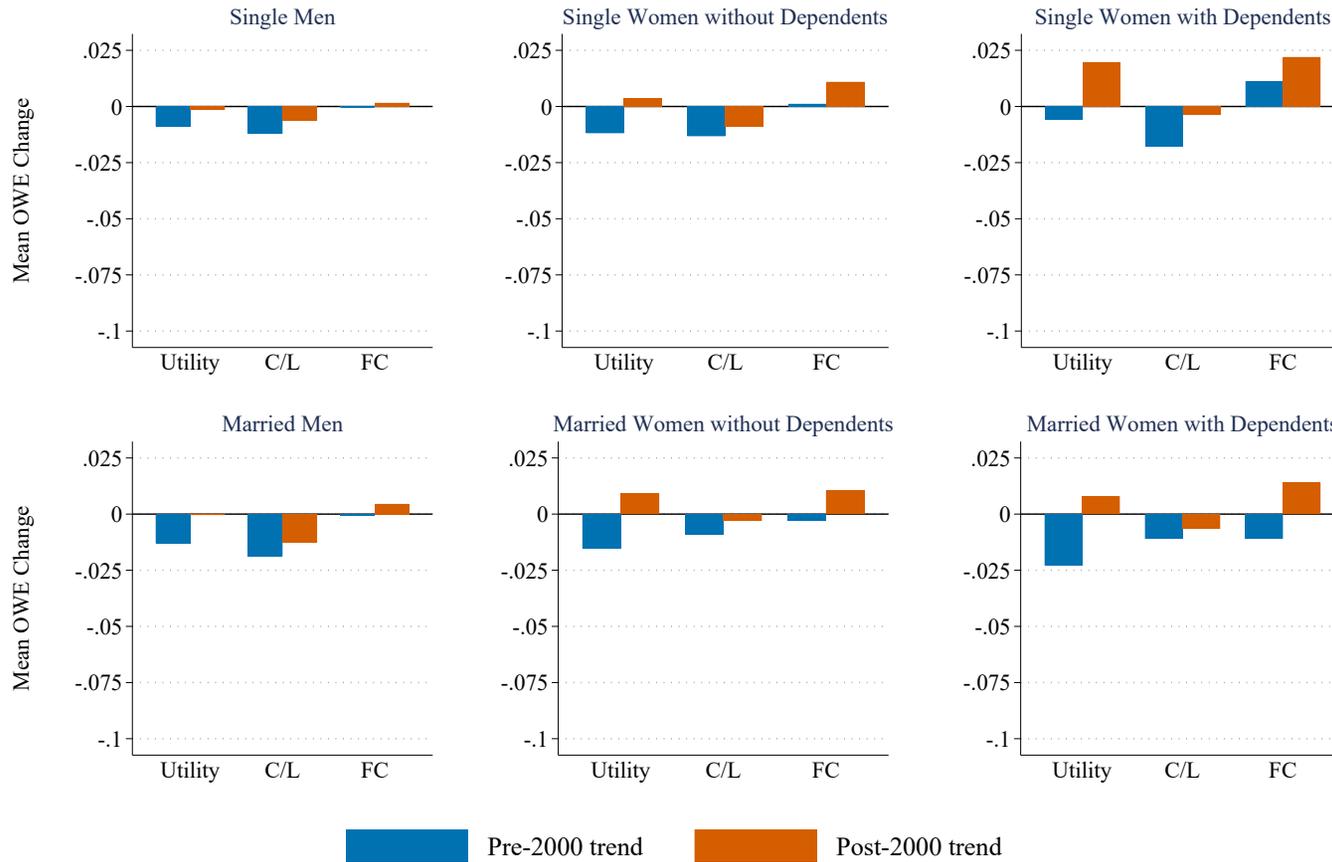
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. The baseline model includes a fixed cost of working non-zero hours and a separate fixed cost of working part-time hours. The “non-zero fixed cost” model only includes a fixed cost of working non-zero hours. The “part-time fixed cost” only includes a fixed cost of working 10, 20, or 30 hours per week. The “no fixed cost” model drops both fixed costs.

Figure A12: Alternative Counterfactuals



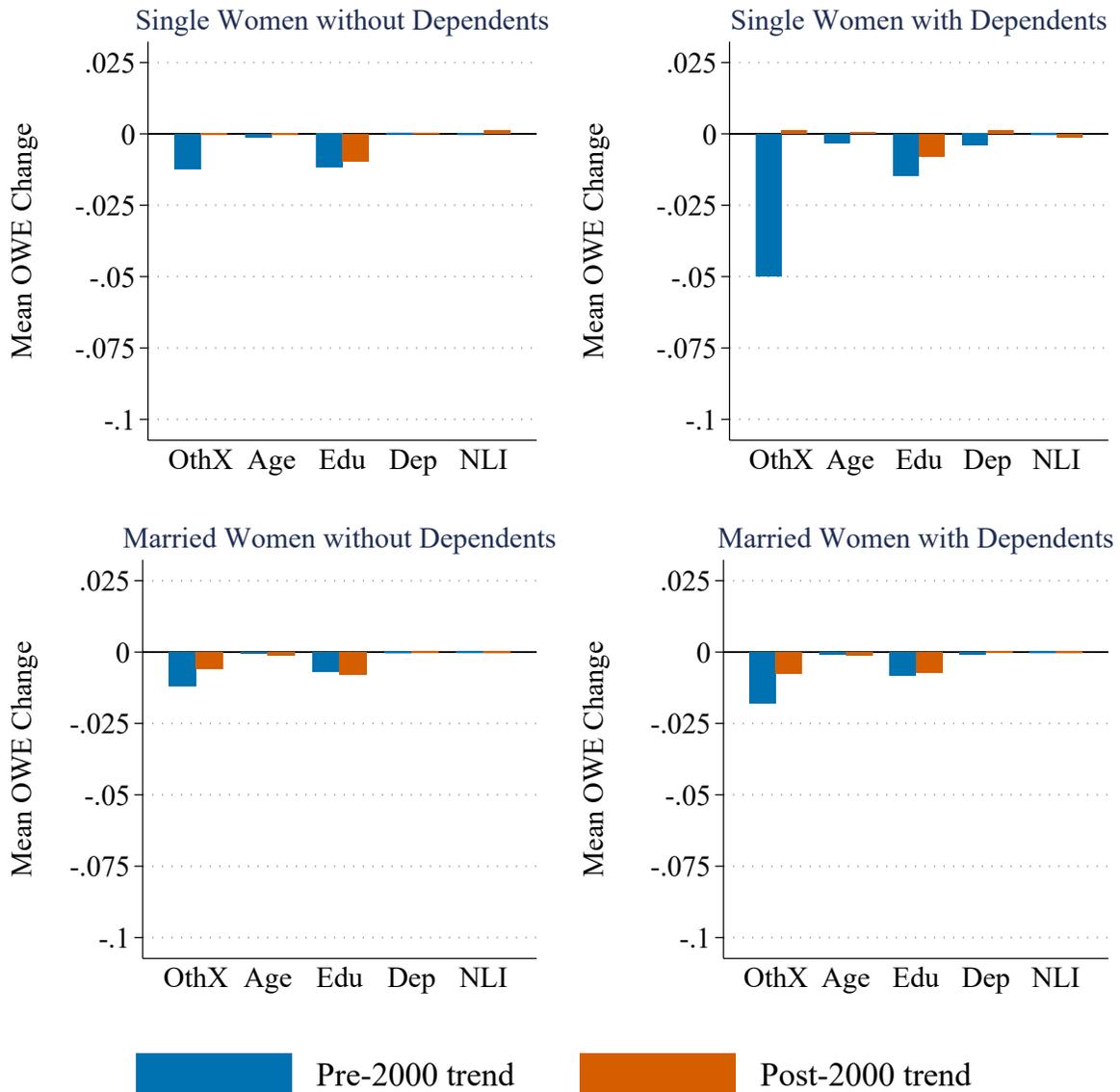
Notes: This figure presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “Total” is based on the elasticities from the long-panel baseline model, allowing all of the model inputs and parameters to change each year. The other bars are based on just allowing one set of factors to change: “Wage” corresponds to allowing the wage model parameters, “Tax” corresponds to the tax function parameters, “OthX” corresponds to all other explanatory variables (demographics, education, non-labor income), and “Util” corresponds to the utility model parameters. The counterfactuals in this figure are based on a “first-in” approach, where the listed inputs/parameters are allowed to vary by year and all other inputs/parameters are held at their 1980 level.

Figure A13: Utility Counterfactuals



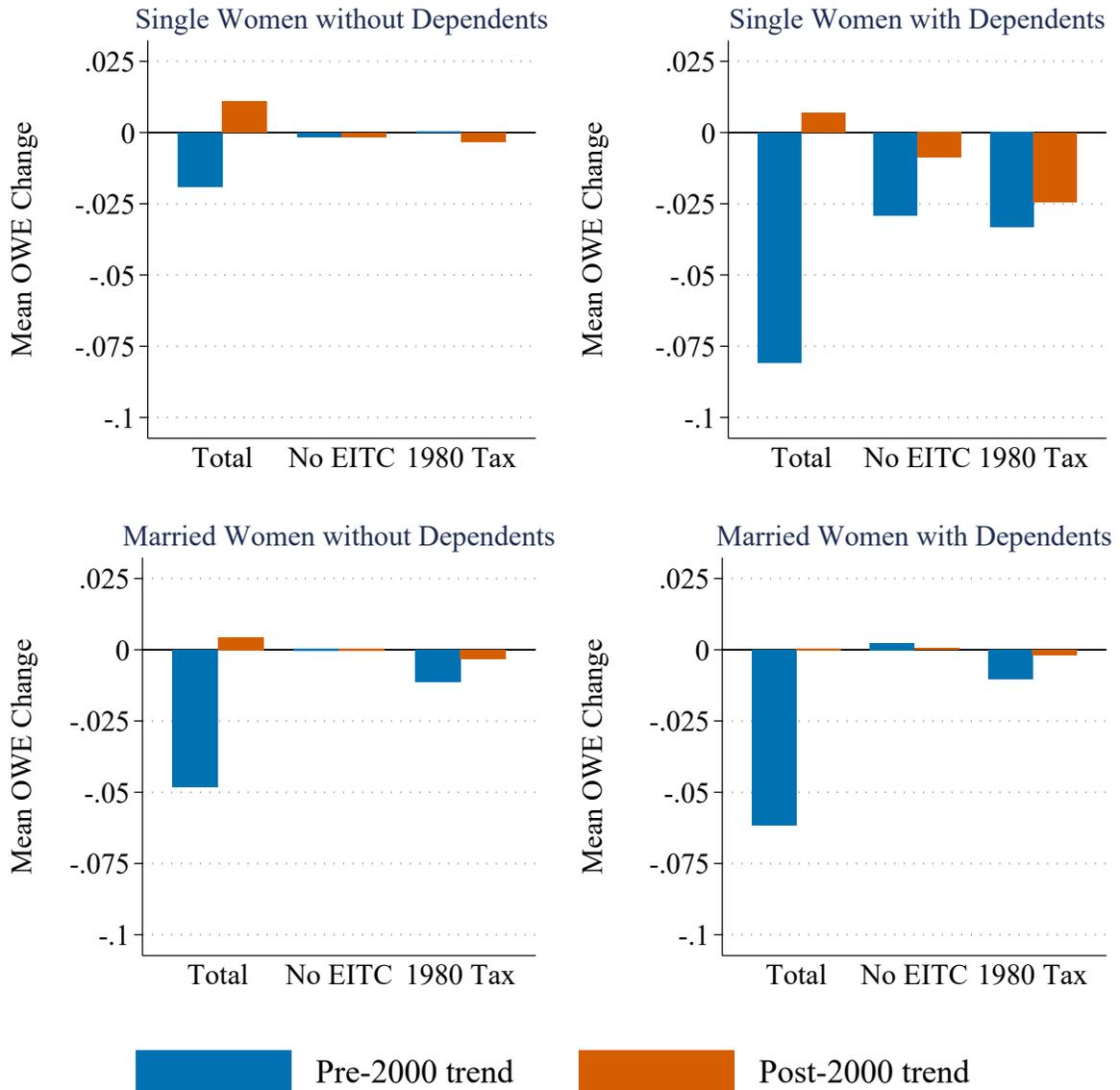
Notes: This figure presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “Utility” corresponds to the counterfactual holding all utility parameters constant at their 1980 values. “C/L” corresponds to the counterfactual holding only the consumption and leisure parameters constant at their 1980 values. “FC” corresponds to the counterfactual holding only the fixed cost parameters constant at their 1980 values.

Figure A14: Other Input Variables Counterfactuals



Notes: This figure presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “OthX” corresponds to the counterfactual imputing other input variables according to their 1980 distribution. “Age” corresponds to the counterfactual holding only the distribution of age constant. “Edu” corresponds to the counterfactual holding only the distribution of educational attainment constant. “Dep” corresponds to the counterfactual holding only the distribution of dependents and dependents’ ages constant. “NLI” corresponds to the counterfactual holding only the distribution of non-labor income constant.

Figure A15: EITC Counterfactuals



Notes: This figure presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “Total” is based on the the elasticities from the long-panel baseline model, allowing all of the model inputs and parameters to change each year. “No EITC” corresponds to the counterfactual setting the EITC to \$0 in every year. “1980 Tax” corresponds to the counterfactual holding the tax parameters constant at their 1980 values.

Table A13: Counterfactual Slopes

	Total	Wage	Tax	No EITC	OthX	Age	Edu	Dep	NLI	Util	C/L	FC
<i>Single Men</i>												
Pre-2000	-0.006	-0.007	-0.006	-0.006	-0.005	-0.006	-0.006	-0.006	-0.006	0.003	0.006	-0.006
Post-2000	-0.001	-0.001	0.000	-0.000	-0.001	-0.000	-0.000	-0.001	-0.001	0.001	0.006	-0.002
<i>Single Women without Dependents</i>												
Pre-2000	-0.019	-0.022	-0.019	-0.017	-0.007	-0.018	-0.007	-0.019	-0.019	-0.007	-0.006	-0.020
Post-2000	0.011	0.006	0.014	0.013	0.011	0.011	0.021	0.011	0.010	0.007	0.020	0.000
<i>Single Women with Dependents</i>												
Pre-2000	-0.081	-0.089	-0.047	-0.052	-0.031	-0.078	-0.066	-0.077	-0.081	-0.075	-0.063	-0.092
Post-2000	0.007	0.004	0.031	0.016	0.006	0.006	0.015	0.006	0.008	-0.013	0.011	-0.015
<i>Married Men</i>												
Pre-2000	-0.007	-0.009	-0.006	-0.006	-0.002	-0.007	-0.004	-0.007	-0.007	0.006	0.012	-0.006
Post-2000	0.001	-0.002	0.003	0.002	0.003	0.001	0.003	0.001	0.001	0.001	0.014	-0.003
<i>Married Women without Dependents</i>												
Pre-2000	-0.048	-0.043	-0.037	-0.048	-0.036	-0.048	-0.041	-0.048	-0.048	-0.033	-0.039	-0.045
Post-2000	0.004	0.004	0.008	0.004	0.010	0.005	0.012	0.004	0.004	-0.005	0.007	-0.006
<i>Married Women with Dependents</i>												
Pre-2000	-0.061	-0.054	-0.051	-0.064	-0.043	-0.061	-0.053	-0.061	-0.062	-0.039	-0.050	-0.051
Post-2000	0.000	0.002	0.002	-0.000	0.008	0.002	0.008	0.000	0.000	-0.007	0.007	-0.014

Notes: This table presents the average annual change in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. “Total” is based on the elasticities from the long-panel baseline model, allowing all of the model inputs and parameters to change each year. The other columns are based on just allowing one set of factors to change: “Wage” corresponds to the wage model parameters, “Tax” corresponds to the tax function parameters, “OthX” corresponds to all other explanatory variables (age, education, number of dependents, non-labor income), and “Util” corresponds to the utility model parameters (consumption / leisure and fixed costs). The difference between slopes reported in “Total” and an individual factor is the portion of the elasticity trend over time we attribute to that factor and corresponds to the data plotted in Figures 7, A13, A14, and A15.