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

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Abstract

The uncompensated wage elasticity of labor supply is a fundamental parameter in economics. Despite its central role, few papers have studied directly how it has changed over time. We examine the evolution of this elasticity over the last four decades. We find robust evidence that the elasticity weakly increased between 2000 and 2020, representing a striking reversal from the sizable declines for single and married women between 1979 and 2000. We additionally find that these changes mostly arose on the extensive margin. Using our model, we conduct a series of counterfactual simulations to identify the factors responsible for these trends.

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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 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 trends for men outside of meta-analyses and cross-paper comparisons, which are also subject to concerns regarding changing empirical methodologies over time. One notable exception is Bloemer (2023), who uses German Socioeconomic Panel data to study labor supply among men and women from 1998 to 2018.

In this paper, we examine how the uncompensated wage elasticity of labor supply has changed over the past four decades. First, we provide a theoretical discussion on why elasticities might evolve over time and a review of the existing literature on 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 estimated model parameters, we conduct a series of counterfactual simulations to identify the factors that are 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 had only modest effects on the elasticities.

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:

$$e_M = \frac{w}{h}\frac{\partial h}{\partial w}. \tag{1}$$

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

$$e_H = \frac{w}{h}\frac{\partial h}{\partial w}\bigg|_u. \tag{2}$$

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. To focus our analysis, this paper will exclusively consider the Marshallian 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 variables, 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 (Atrostic, 1982; Blau and Kahn, 2007).

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. 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 trend diminished in the later years of their samples. Kumar and Liang (2016) examine the labor supply elasticities of married women using the 1980 through 2006 Panel Study of Income Dynamics (PSID).[1] 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.

More recently, Bloemer (2023) estimates yearly elasticities for single and married men and women using the German Socioeconomic Panel from 1998 to 2018. Using a discrete choice model similar to the specifications we use below, Bloemer finds that wage elasticities increased for couples and both single men and women over this period. Elasticities increased the most for single men, from 0.04 to 0.15, followed by married women, from 0.20 to 0.25, and single women, from 0.14 to 0.17.

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

[1] Although 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).

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 a discrete choice framework pioneered by van Soest (1995). This approach is particularly well suited to examining 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 the 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. Typically, the identifying variation comes from differences in predicted wages, often estimated with instruments such as number of children and non-labor income, and differences in marginal tax rates across states and time. We do not attempt to defend the appropriateness of this variation nor improve upon it with novel instruments. Our goal is to follow the standard methods in the current literature to extend previously estimated trends for women for two additional decades and produce analogous results for men.

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.[2]

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

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

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}:[3]

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

[2]We 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.

[3]As documented by Loeffler 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, Loeffler et al. find that the choice of utility function among these three had little effect on estimated elasticities.

We allow the parameter β_i^l to vary with individual characteristics (a quadratic in the log of age and number of dependents).[4] 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 capture employers' choices to not offer these hours packages (van Soest, 1995).[5] We allow fixed costs to vary with the number of dependents and whether the household has a dependent under 5 years old, allowing them to capture factors such as average childcare costs.[6] 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.

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

[4] Our estimated elasticities are nearly identical if we allow the consumption parameter to vary with the same individual characteristics. We choose to incorporate observed heterogeneity in the utility of leisure because it is the more typical specification in the literature; see Loeffler et al. (2018).

[5] Researchers 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.

[6] Although several papers include childcare in a discrete choice model of labor supply, most assume that male labor supply is fixed or exogenous (e.g., Apps et al., 2016; Gong and Breunig, 2017). A notable exception is Thoresen and Vatto (2019), which jointly studies the childcare and family labor supply decisions in Norway. However, the Norwegian context is much simpler because a policy initiative made center-based care universally available for a fixed, low price.

probability of individual i choosing choice j, denoted p_{ij}, is given by the closed-form expression:

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

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 functions

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 the log of real wages for non-working individuals (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.[7] As a result, we use a Heckman selection model to predict the log of real 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 (Loeffler et al., 2018). This may mitigate bias due to measurement errors in reported earnings and hours, with the latter error

[7] Heckman 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.

typically leading to division bias. Using predicted wages for all observations also 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 log real 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:

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

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 for simulating wages. See van Soest (1995) for a detailed description of this procedure.[8]

[8]Halton 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.

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.[9]

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

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

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:

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

[9] We tested the robustness of our standard errors from our baseline model to using a nonparametric bootstrap with utility parameters and elasticities re-estimated on 100 samples drawn with replacement from the original sample. Neither method is consistently more or less precise for all four demographic groups, and in over 70% of years the standard errors from the parametric bootstrap are within 20% of the standard errors from the nonparametric bootstrap.

and

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

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.[10]

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.[11] 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 (≈99.5th 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 (≈99.5th percentile).[12] We also

[10]See Blundell et al. (2013) for a decomposition approach that aggregates over multiple types of workers.

[11]Single-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.

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

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.[13] We do not exclude 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.[14]

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 and key variable construction, such as hours worked and non-labor income, 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 nominal 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 nominal 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.[15] See Appendix Section C for

[13]The topcoding thresholds used in the CPS vary significantly over time, and subsetting the sample on individuals 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.

[14]We tested the effect of our sample size reduction on our baseline results, and our estimated elasticities from the larger sample are nearly identical to our estimated elasticities from the smaller sample.

[15]While 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

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 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. The significant gap in non-labor income between single women and single men is due to higher alimony and child support for single women than single men, and the narrowing of the gap in the 2010s is due to interest income growing for single men much faster than for single women.

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.

TRIM3 data to the ASEC data do not match. Thus, we set the benefit simulator to zero in 2001.

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. We present results concerning the distribution of elasticities in Section 5.3. Section 5.4 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 has a positive marginal utility of consumption at 10 hours of work and above.[16] 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.[17]

[16] Many 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.

[17] Because 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

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. We choose 2000 because it is near the end point of the prior research on labor elasticity trends and, as will be shown below, is approximately the point where the declines of the prior two decades stop.[18]

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 between 1 and 1.25). In practice, this implies that a married woman in 2000 earning the average wage and working the average number of hours who experiences a 1% increase in hourly wage ($21.75 to $21.97) is expected to increase her weekly hours by 1.14% (29.93 to 30.27).

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. Figure 4 presents mean own-wage elasticities and their standard errors for the long panel, along with the point estimates from the

A4). Overall, the goodness of fit statistics are fairly constant over time, although they fluctuate more for married couples.

[18] Estimates of a precise year where the trend changes differ by method and demographic group. For example, a supremum Wald test (Andrews, 1993) identifies 1998 as the structural break for single women, whereas a Bai-Perron test (Bai and Perron, 2002) identifies 2005 as the structural break.

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 substantial, both in absolute terms and when compared to the lack of visual evidence of further declines after 2000. Specifically, when comparing the slopes in Figure 4 to the period- and demographic-specific means, the 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.[19] The findings that the elasticities also declined for men between 1979 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

[19]Our 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 6, we provide evidence that the large means are partially 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 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. Similarly, Bloemer (2023) finds that magnitudes of elasticities are somewhat sensitive to specification, but that the upward trends are common across all specifications he considers.

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: wages increased throughout the 1979-2020 period, but labor force participation rates increased markedly for single women and married women only between 1979 and 2000, remaining roughly constant thereafter.

In Appendix Figure A5, we present cross-wage elasticities for married individuals. We find that they are small in magnitude, similar to previous studies (Bargain et al., 2014; Kumar and Liang, 2016; Devereux, 2004), and have a near-zero trend from 1979 to 2000. This is a departure from Kumar and Liang (2016), who estimate that married women experienced a decline in the absolute value of their cross-wage elasticity by 32-35% between 1979-1981 and 1989-1991; however, with yearly estimates we observe a large decline earlier in the decade that soon reverses. Our estimates and those of Kumar and Liang (2016) both imply small changes from 1990 to 2000. Looking beyond 2000, the trend in cross-wage elasticity for married men is marginally more negative than pre-2000 but still statistically indistinguishable from zero. For married women, there is a marked increase in cross-wage elasticity after 2000 – averaging +0.008 per year – resulting in a cross-wage elasticity that is 34% less negative in 2020 than in 2000.

To this point, we have interpreted our estimates as capturing changes over time in elasticities, but we cannot distinguish whether these represent changes over time itself or changes across cohorts. Hotchkiss (2022), for example, interprets the changes in estimated elasticities between Baby Boomers in the 1985 CPS, Gen X in the 2003 CPS, and Millennials in the 2019 CPS as capturing cohort effects. Hotchkiss speculates that differences across cohorts, such as Millennials' parents being disproportionately likely to both be in the labor force, may have induced systematic differences across cohorts in attitudes toward labor force participation.[20] We pursue strategies below to assess how changes over time are driven by observable characteristics at the cohort level, but we remain agnostic about whether changes that are unrelated to observables capture true time effects

[20] Similarly, Hotchkiss (2009) analyzes the decline in labor force participation rates in the 2000s, finding that it was largely driven by cross-cohort changes in the population share of demographic groups, rather than by changes in behavior within those groups.

or cohort effects.

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 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 (Loeffler 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; Loeffler 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 chose 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, which could reflect division bias when using actual reported wages, as described above in Section 3.2. 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 third 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. Our baseline specification allows for a fixed utility decrement that is allowed to vary with the number of dependents and whether the household has a dependent under 5 years old. As a robustness check, 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. Appendix Figure A10 presents chi-squared statistics associated with the null that actual and predicted hours worked are equal over time, separately by demographic group and model specification. For all groups, the baseline model and the 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 hours fixed cost of work fits the data worse than the baseline model. The model without 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. The baseline model and the model with only a part-time fixed cost lead to similar estimated elasticities, which is not surprising given their similar goodness of fit. 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 only a part-time fixed cost 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.

Finally, we consider the potential impact of our use of a discrete choice framework versus a continuous choice framework (e.g., Heim, 2007 and Kumar and Liang, 2016). We focus on married women and use a continuous estimation method following Heim (2007), who uses March CPS data as in our main specifications above. Appendix Figure A12 shows the resulting estimates of both extensive and intensive annual elasticities. Several notable patterns emerge. First, although the magnitudes of the estimates differ markedly from those in the bottom-right panel of Figure 4 above, the intertemporal patterns are similar, in the sense that the estimates decline sharply between 1979 and 2000 but stabilize afterward. Second, the estimates prior to 2000 are similar to those shown in panels A and C of Heim's Figure 2, both in terms of magnitude and trends. These patterns suggest that the striking reversal of the decline in married women's elasticities after 2000 is not merely an artifact of our use of discrete choice methods.

5.3 Distribution of baseline elasticity estimates

An advantage of our empirical strategy is that, because we estimate individual-level wage elasticities, we can analyze the full distribution of those elasticities rather than just the mean. In Figure 6 we show the mean, median, and various percentiles of the estimated elasticities by year. For all four demographic groups, the mean own-wage elasticity exceeds the median, and in the case of single women and married men, the mean is often closer to the 75th percentile than it is to the median. Furthermore, the difference between the 95th percentile and median greatly exceeds that of the difference between the median and 5th percentile for each group. The rightward skew of the distribution is pronounced for every group but married women.

To provide descriptive evidence about how the elasticities vary with observable characteristics, we fit a linear model that predicts the elasticities within each sex-marital status-year grouping based on a limited set of variables: pre-tax hourly wage (self and spouse), non-labor income, age (self and spouse), number and age of dependents, and state of residence. As a simple test to identify which of these variables have the most explanatory power for the variation in wage elasticities, we compare the explained sum of squares from a linear model of own-wage elasticities regressed on all the aforementioned variables to the partial sum of squares from a linear model excluding each variable individually. The results are in Table 4.

For every demographic group, predicted hourly wage has the highest or second-highest explanatory power (excluding the year). The number of dependents has the highest or second-highest explanatory power for single and married women. These findings motivate our next two figures.

Figure 7 presents how the mean own-wage elasticity changed over time for individuals in the lowest quartile of the distribution of predicted hourly wages versus those in the highest quartile. Individuals with the lowest wages have greater mean elasticities than those with the highest wages and significantly contribute to the skewness of the overall distribution. This is especially true for single women, where the mean elasticity of the low-wage group is 6.8 times that of the mean elasticity of the high-wage group, averaged over years. Despite their differences within each year, the low-wage and high-wage groups do not have markedly different trends when measured in percentage terms.

Figure 8 presents the trends in own-wage elasticities for men and women with and without dependents. For single men, most of the sample is childless (83%), so the overall elasticity closely matches that of the ”without dependents” group. Analogously, 79% of married men and women have children, so their overall elasticities are similar to the ”with dependents” groups. For single women, however, only 60% of the sample has a dependent, and those with a dependent have an own-wage elasticity three times that of those without a dependent at the beginning of the time series. The gap between these groups narrowed between 1979 and 2000, with an annual trend of -0.081 for those with dependents and -0.019 for those without dependents. After 2000, both trends are positive, with an annual change of +0.007 for those with dependents and +0.011 for those without. We explore the potential mechanisms of these trends, as well as those of the overall samples, in the following section.

5.4 Counterfactual simulations

To more formally shed light on *why* the mean own-wage elasticity significantly declined between 1979 and 2000 but weakly increased 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 – to study the importance of each.

Such simulations are particularly valuable because past studies that have focused on demographic characteristics were able to explain little of the pre-2000 decline in elasticities (e.g., Heim, 2007). Moreover, each of these four components changed in potentially important ways over the last four decades. Single and married women experienced large increases in average wages between 1979 and 2000 (see Figure 1), along with increases in 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 created 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 the 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, we expect changes in the fixed costs of work to be particularly important.[21]

To explore the role of each of these components, we construct a series of counterfactual simulations that hold one component fixed at its 1980 value for the entire sample period, while allowing the others to vary. For example, the "wage counterfactual" results compute the elasticities that would result if the wage function parameters (based on logged real wages) remained at their 1980 levels, but everything else – the distribution of age, education, non-labor income, the marginal tax rates, the utility parameters, etc. – continued to evolve over time. The difference between these counterfactual elasticities and our previously estimated elasticities yields a measure of how changes in the wage distribution affected those elasticities over time.[22]

Creating the wage, tax, and utility parameter counterfactuals are relatively straightforward, sequentially holding each fixed at their 1980 values. Because we are specifically interested in the effect of the EITC, we further refine the tax counterfactual into one where the EITC is set to zero but the marginal tax rates are allowed to vary as they did historically.[23] We also refine the utility

[21] Appendix 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 each other if they come from estimations with shared scale parameters. For example, the fixed cost of working a part-time job for single women without dependents decreased (in absolute value) by 4.5% from 1980 to 1990 while the fixed cost for single women with a dependent under age 5 increased (in absolute value) by 36%.

[22] Such counterfactual comparisons need not lead to estimates for each component that add to the total change, and the role of a component can vary depending on the base period. In Appendix Figure A13, 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.

[23] TAXSIM provides detailed output which allows us to set the federal and state EITC to zero while leaving other federal and state taxes at their actual levels. We then re-estimate our tax spline

parameter counterfactual by holding the consumption and leisure parameters fixed and allowing the fixed costs of work to vary over time (and alternatively holding the fixed costs of work fixed and allowing the consumption and leisure parameters to vary over time). This additional counterfactual allows us to disentangle the effect of changing marginal rates of substitution versus the effect of changing fixed costs.

For our counterfactual holding the other input variables fixed, we modify each year-sex-marital status sample to have 1980's joint distribution of state of residence, age, education, number and age of dependents, and non-labor income. To do so, we first use multinomial logits to assign state of residence in all years as it was distributed in 1980. Then, we assign age using ordered logits, conditioning on state of residence. Finally, we use a nearest-neighbor algorithm to select the remaining variables from a random observation in 1980 with the same sex, marital status, state of residence, and age. The resulting samples have the desired joint distribution of input variables – wages, taxes, expected hours worked, etc. – that can be used for counterfactual simulations.

As with the tax and utility parameters counterfactuals, we refine the counterfactual for other input variables to hone in on specific variables. Adopting a simplified version of the approach described by Rothe (2012), we assign variables to individuals according to 1980's distribution of the variable and each individual's year-sex-martial status-specific percentile rank for that variable. Specifically, we calculate year-sex-marital status-specific percentile ranks of the desired input variable, 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. The resulting counterfactual tells us the estimated change in elasticities if, for example, educational attainment was fixed at its 1980 distribution, but all other variables, including the correlation between educational attainment and those variables, evolved as they actually did.

Turning to the results for our broad counterfactual simulations, in Figure 9 we report the slopes

(see Appendix Section C) without the EITC and use the new parameters for our counterfactual.

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 8, respectively. 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 that changes in the utility parameters are sufficient to account for what little trends there are. In Appendix Figure A14, 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. However, these minor changes should not overshadow the fact that the main findings from our model estimation reflect the underlying descriptives from Figure 1: relatively little has changed for men over the last four decades.

For single women without dependents, the 1979-2000 decline is larger than that of men but smaller than that of the other three groups of women. 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 A14), and the change in other input variables was driven by changes in educational attainment (see Appendix Figure A15).

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 reasons differ across groups. 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 increasing educational attainment was the most relevant of the other input variables (see Appendix Figure A15) and that the expansions of the EITC explain nearly all the tax structure component (see Appendix Figure A16). Further supporting our finding that the EITC changes were important is our finding that much of the decline in elasticities was on the extensive margin, which is the margin where the EITC is intended to operate (see Figure 5). After 2000, changes in the tax structure put further downward pressure on wage elasticities, but changes in utility parameters, specifically in the fixed cost of work (see Appendix Figure A14), offset this downward pressure. The impact of increasing educational attainment waned in the post-2000 period.

For married women with and without dependents, changes in utility parameters are the largest factor in 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 in the changes in utility parameters, and changes in educational attainment largely accounted for the changes of other input variables (see Appendix Figures A14 and A15).

For all groups of women – single and married, with and without dependents – fixed costs of work put upward pressure on elasticities during the post-2000 period. With that said, the counterfactual simulations suggest that the role of fixed costs was most pronounced for women with children, consistent with existing evidence that childcare costs have increased (Laughlin, 2013).

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 small effects on the evolution of wage elasticities. One explanation for this finding is that overall shifts in the distribution of wages partly reflect changes in educational attainment, labor force demographics, etc., and our counterfactuals net out those effects. Another explanation for this finding is that the trends in elasticities across the wage distribution were somewhat similar (see Figure 7). With that said, it is still possible that 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.

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, an 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 (such as whether to predict wages for all individuals or for non-workers only, the treatment of imputations, and the specification for fixed costs) can appreciably affect the level of elasticities, 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 shed light on why elasticities changed over the past four decades. For both single and married women, increases in educational attainment drove a relatively large fraction of the declining elasticity from 1979 to 2000. Increasing educational attainment also continued to put downward pressure on elasticities for married women after 2000, but this was offset by changes in utility parameters.

Our simulations further 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 labor force participation, but only modest effects on the intensive margin of labor supply (e.g., 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 was three times larger before 2000 than afterward. 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.

Our counterfactual simulations additionally show that fixed costs to working have put upward pressure on elasticities for women since 2000. This finding is consistent with the continued rise of childcare costs (e.g., Laughlin, 2013), but the effects of such trends would be better studied directly than through our model's composite specification of fixed costs.

Finally, the well-documented changes in the wage structure from 1980 to 2020 have had relatively little effect on wage elasticities. This null finding is likely related to us accounting for changes in education separately from the wage structure, as well as to the similar trends in elasticities across the distribution of wages.

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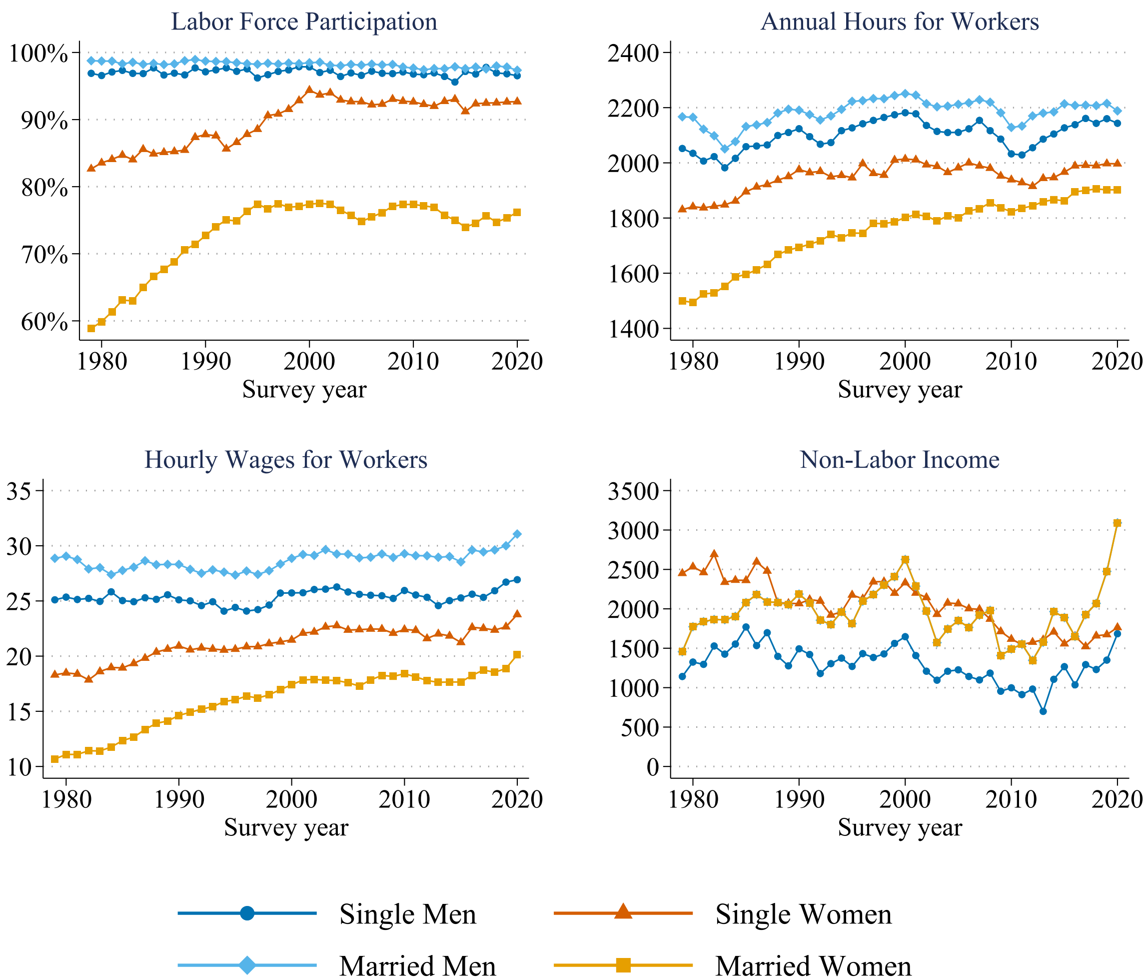
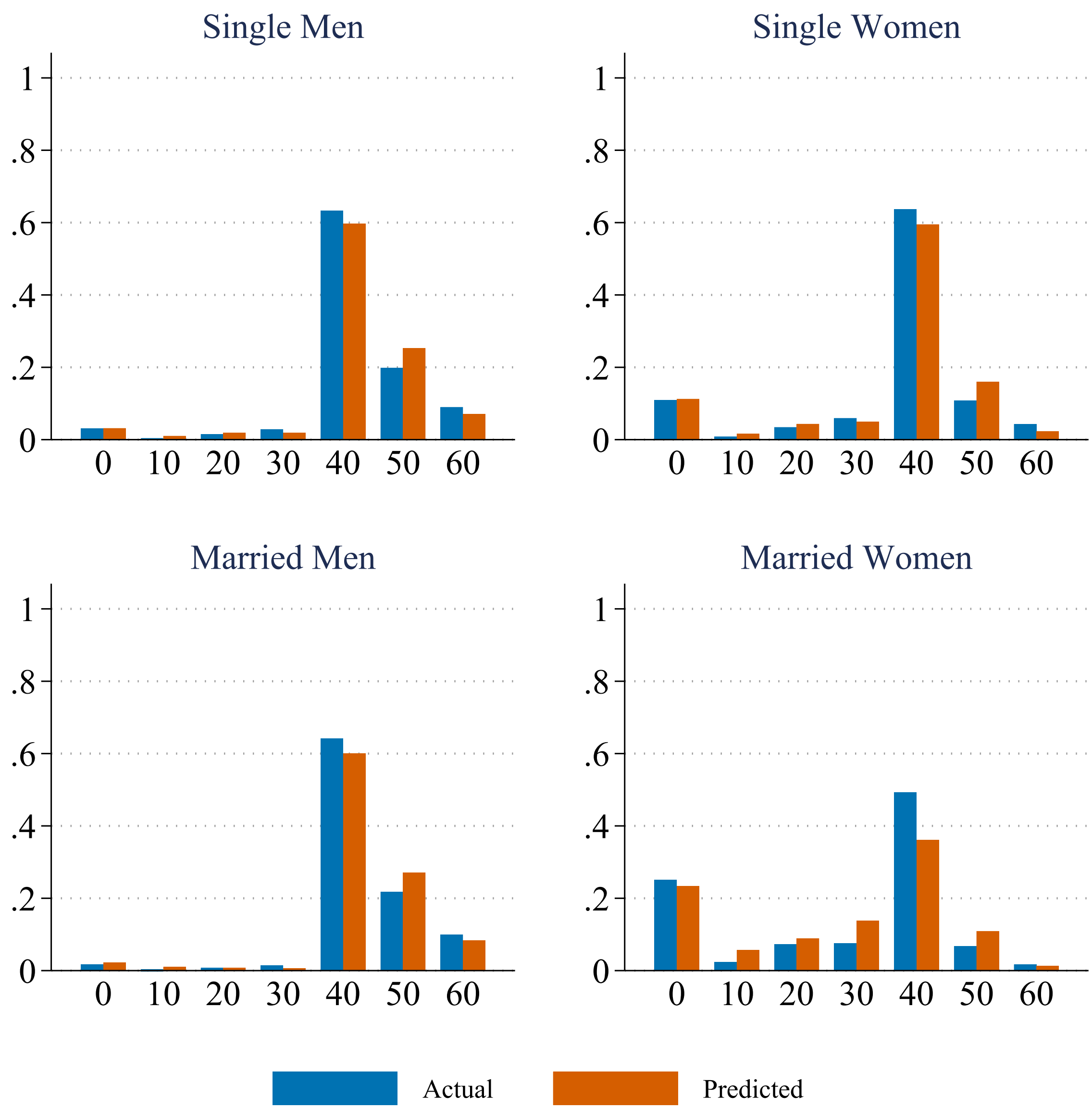
7 Tables and Figures

Figure 1: Labor Force Trends by Demographic Group



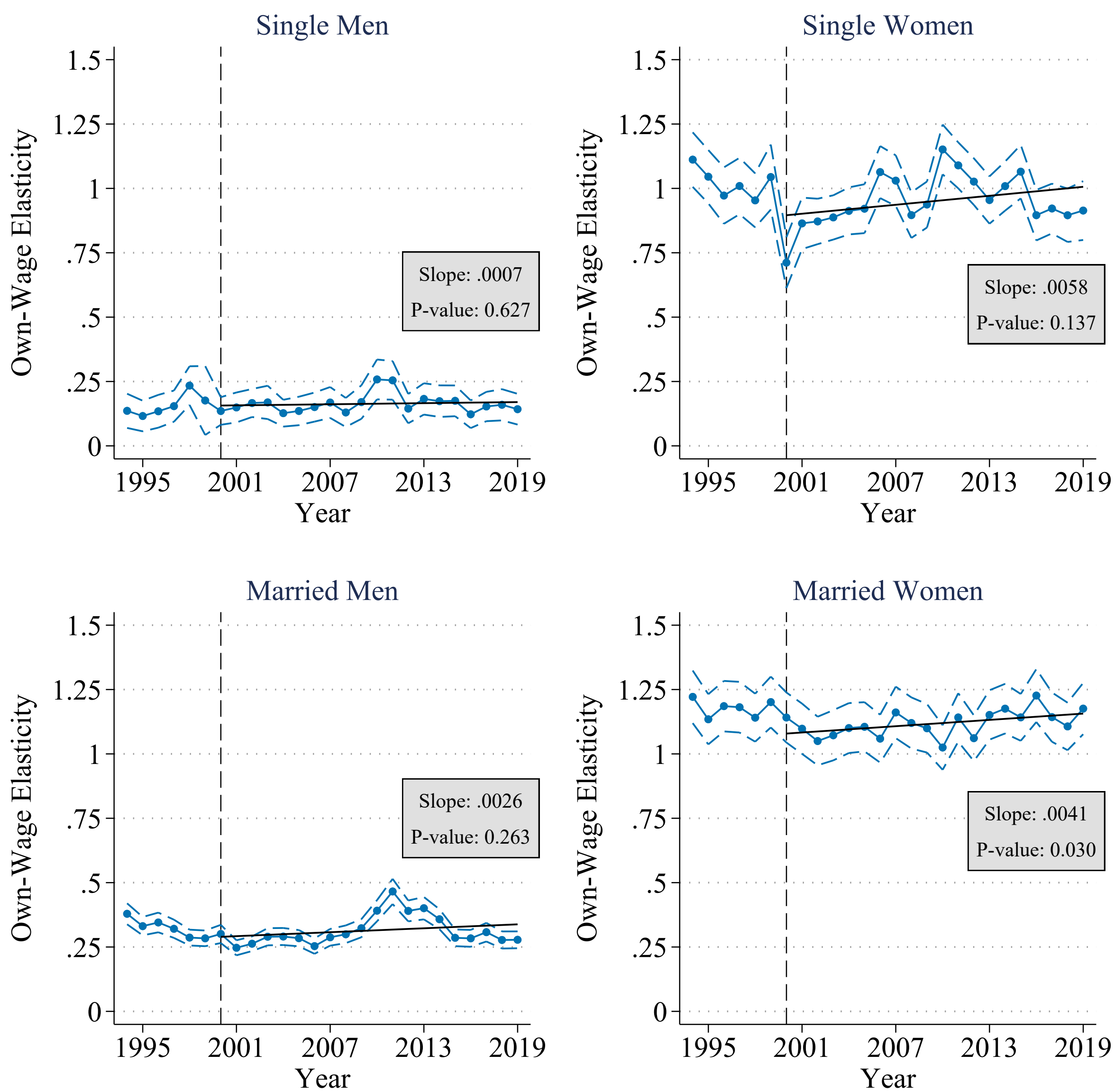
Notes: This figure presents trends in labor force participation, annual hours worked, hourly wages, and non-labor income separately by sex and marital status. Labor force participation is the share of respondents who reported participating in the labor market in the prior week. Annual hours worked are 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 (survey year) 2020 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



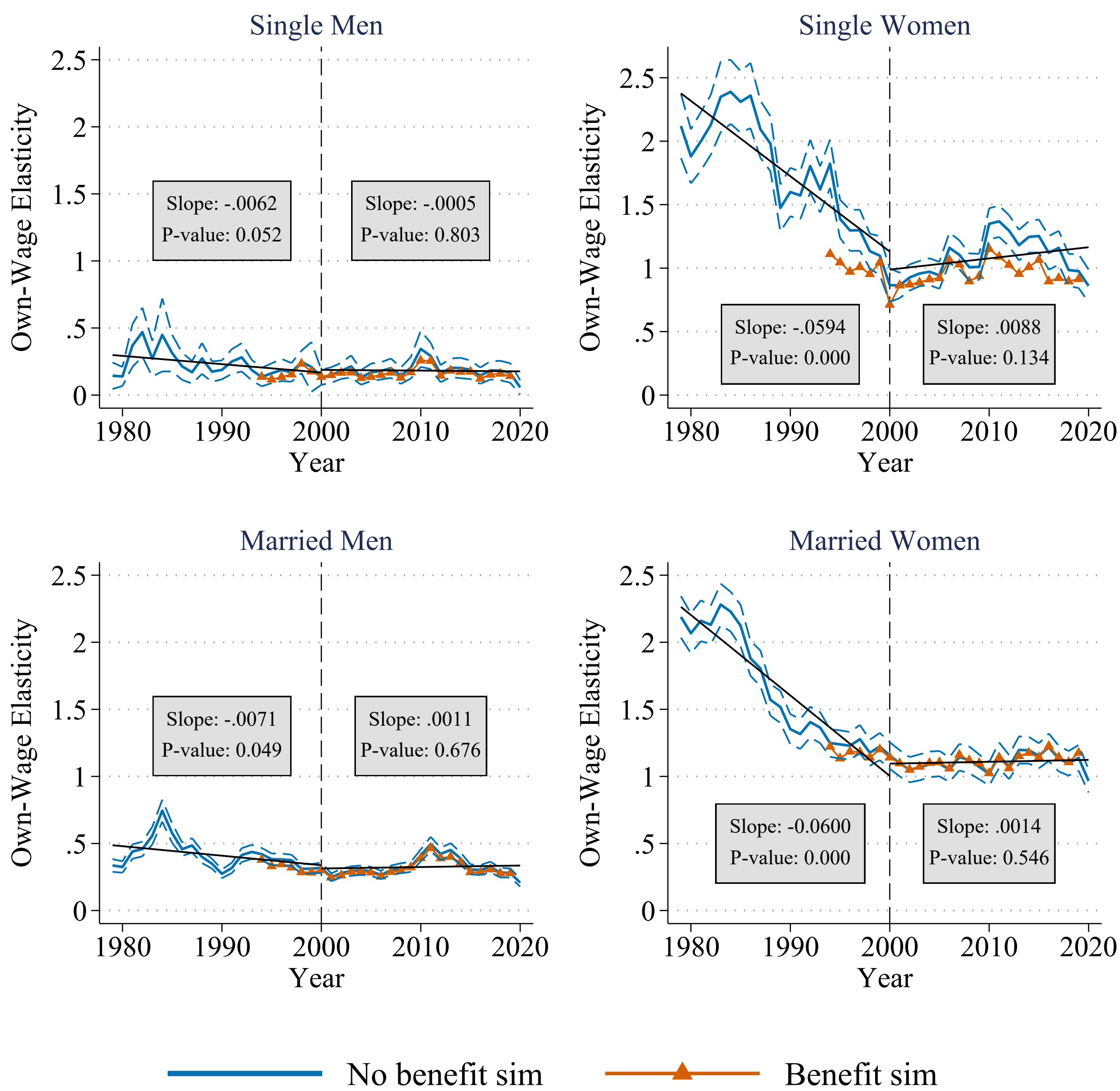
Notes: This figure presents the average hours worked per week for each demographic group from 1979 to 2020 and the average probability of each hour choice according to the parameter estimates of our baseline model without the benefit simulator. For married households, probabilities are summed over the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

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



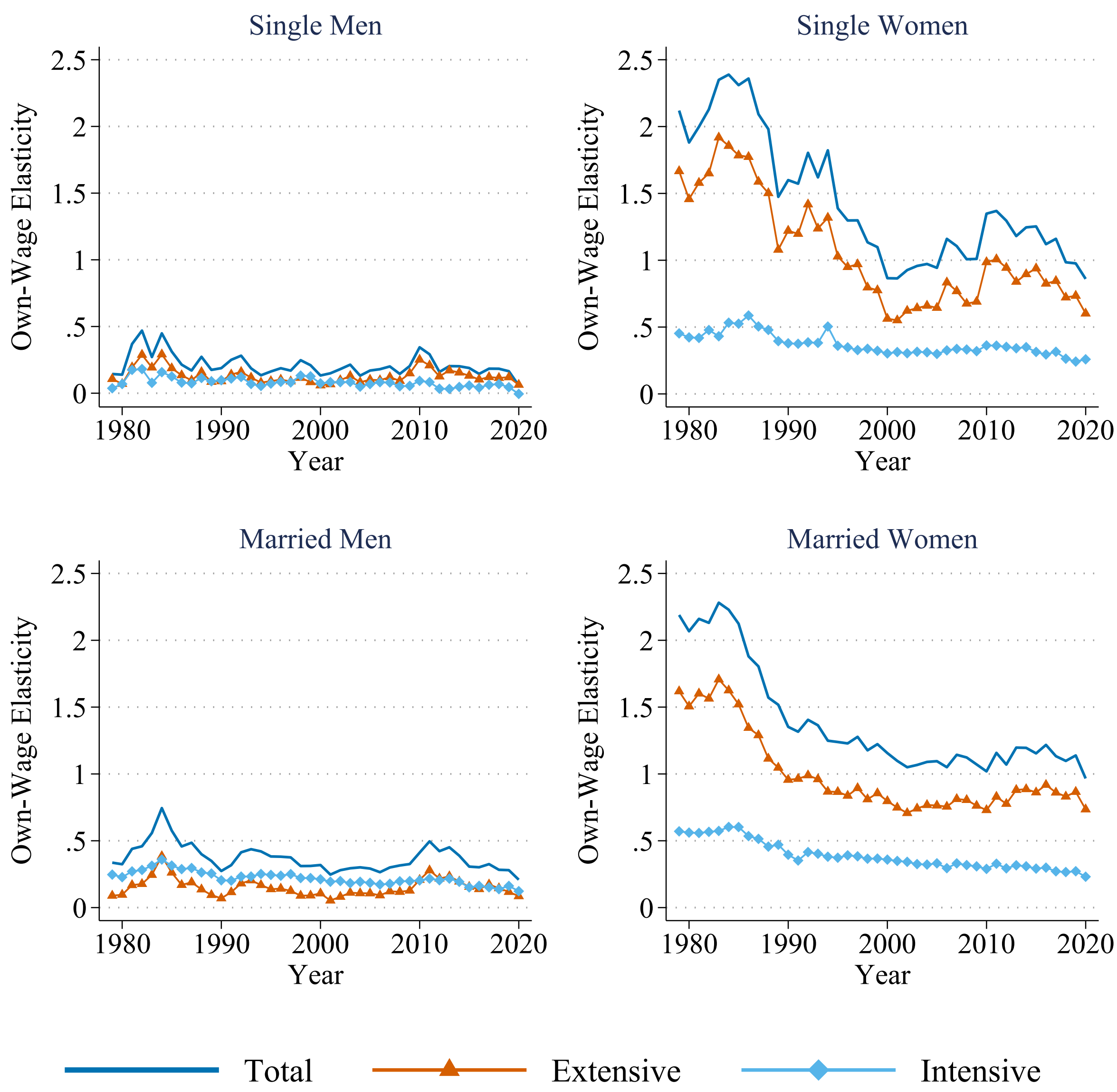
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines. A linear trend line from 2000 to 2019 is also presented, along with the annual slope of the trend and the p-value associated with the trend.

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



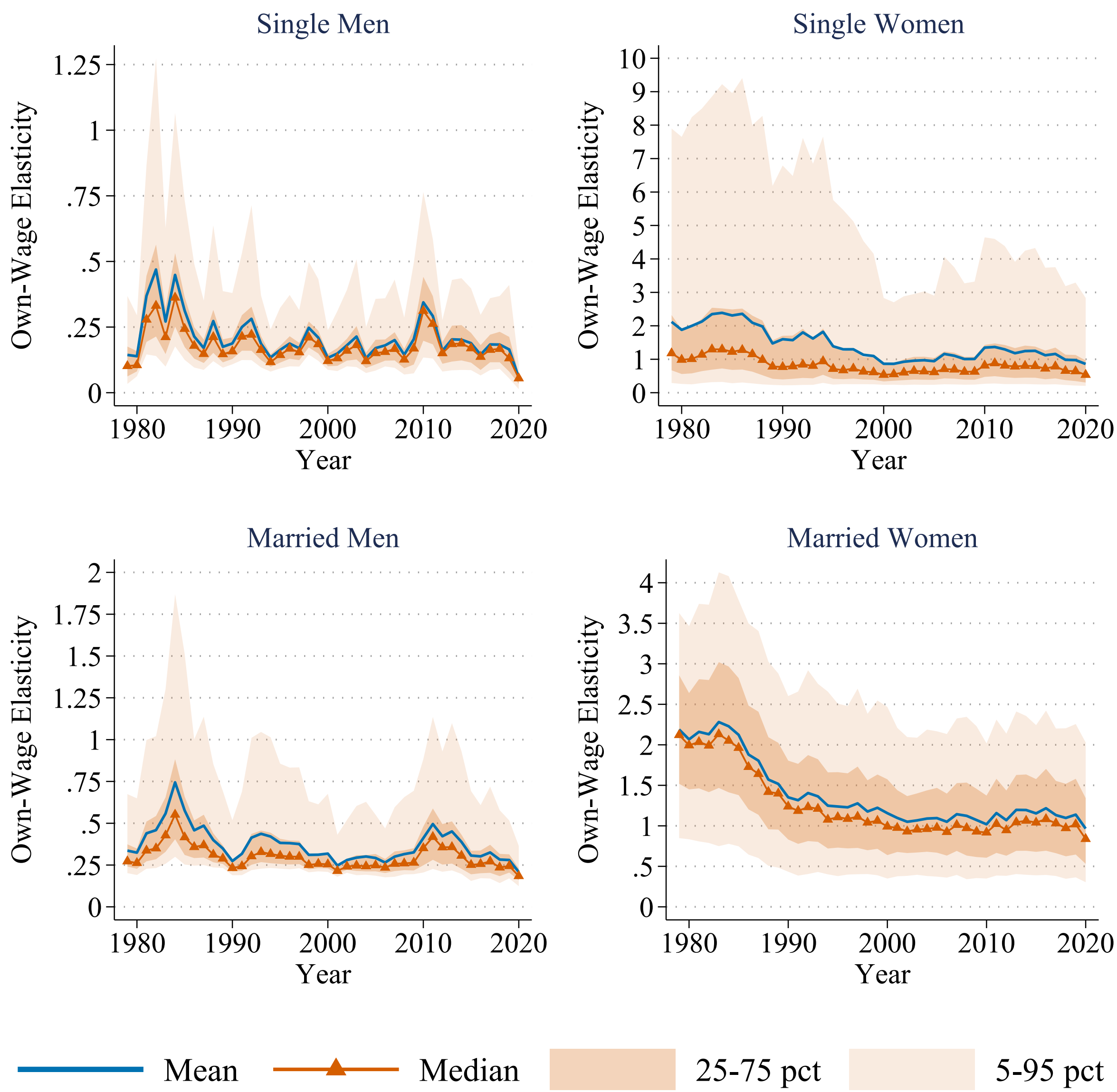
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status without the benefit simulator. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by dashed lines. Linear trend lines from 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



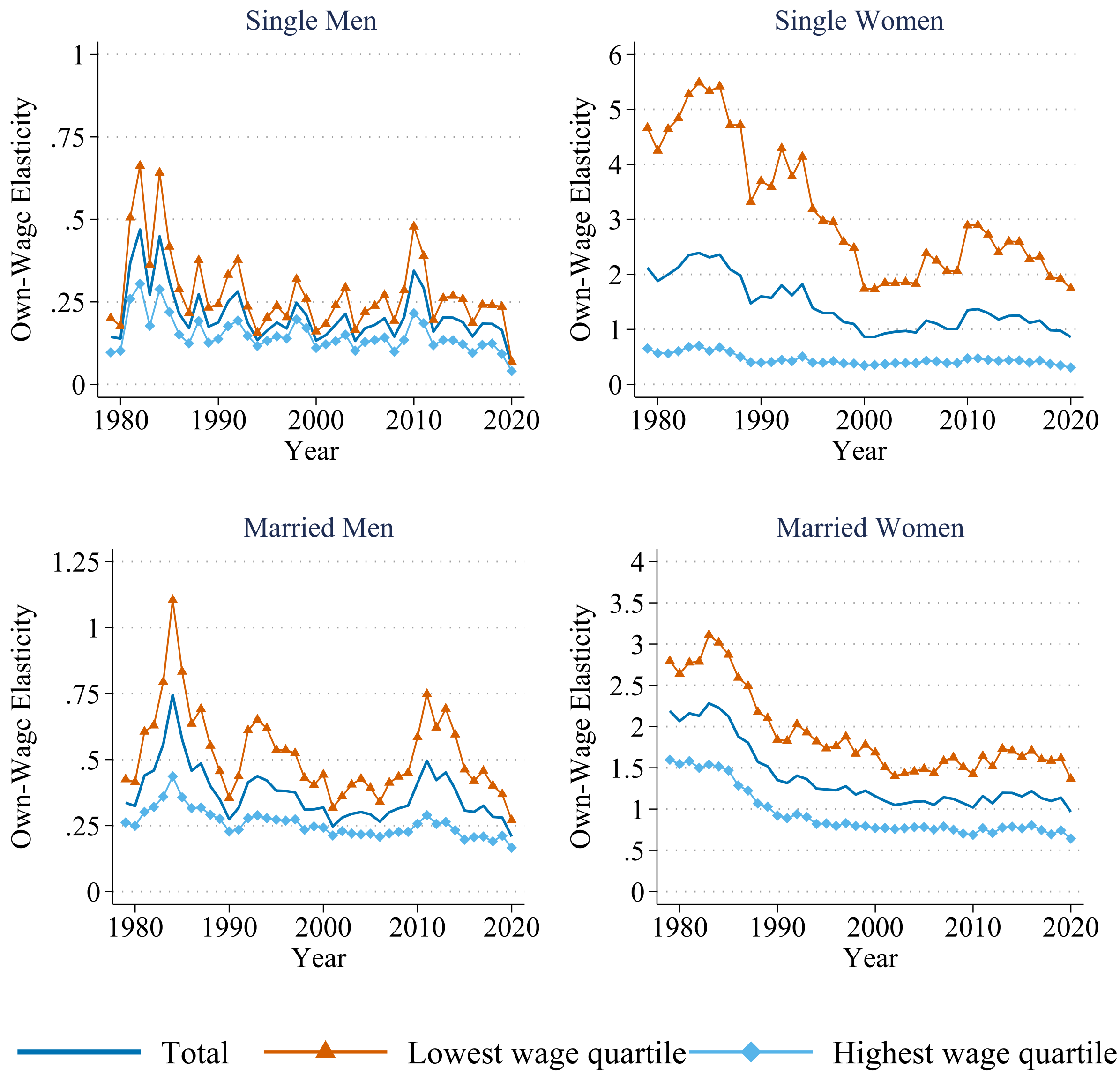
Notes: This figure presents the estimated trends in mean total, extensive margin, and intensive margin own-wage elasticities separately by sex and marital status. We decompose the total own-wage elasticity into the extensive margin elasticity and intensive margin elasticity according to the formulas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

Figure 6: Mean, Median, and Interquartile Range of Own-Wage Elasticities



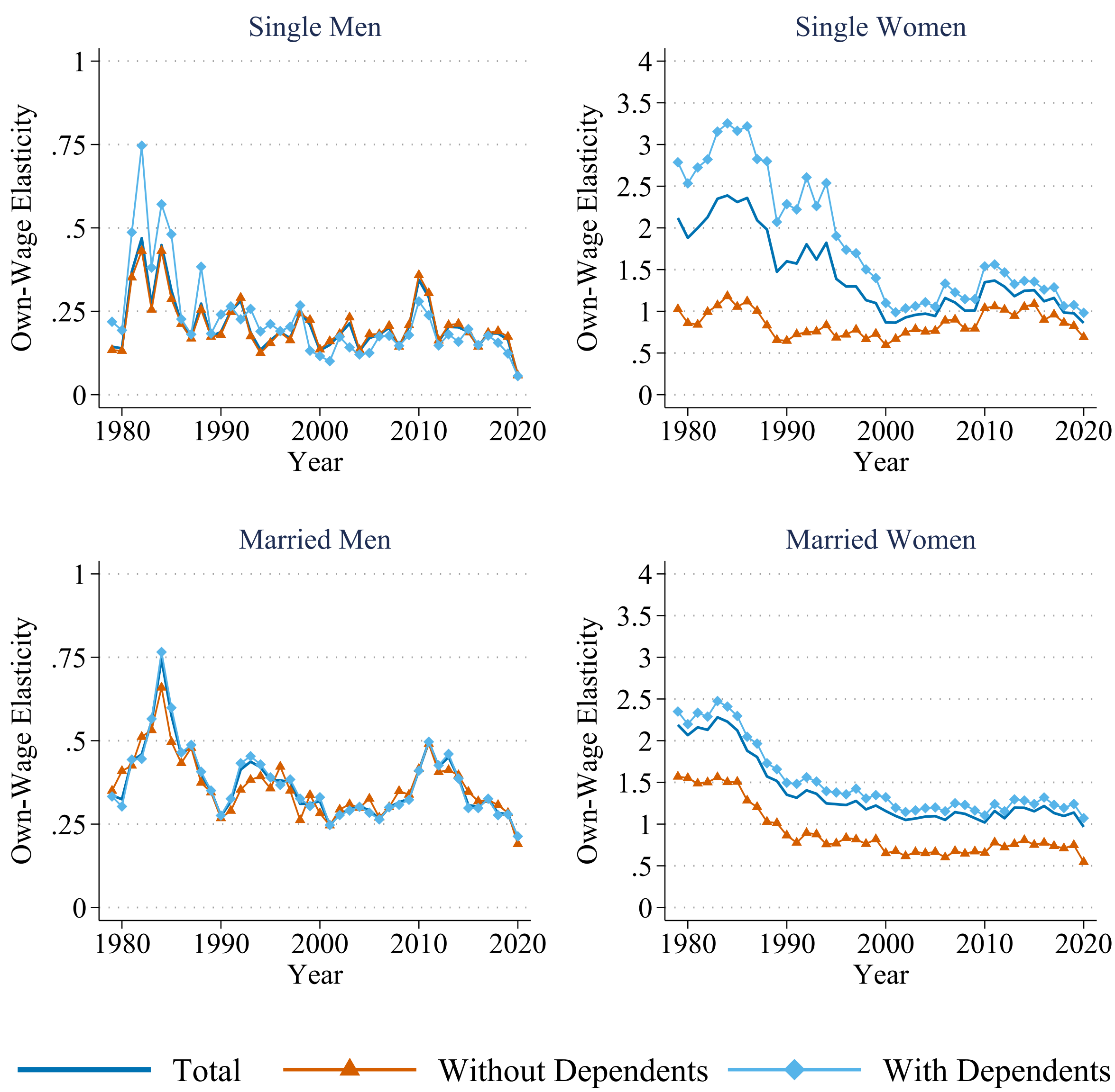
Notes: This figure presents estimated mean, median, 25-75th percentile, and 5th-95th percentiles of own-wage elasticities separately by sex and marital status using our baseline model without the benefit simulator.

Figure 7: Mean Own-Wage Elasticities by Wage Quartile



Notes: This figure presents estimated mean own-wage elasticities separately by wage quartile, sex, and marital status using our baseline model without the benefit simulator. Wage quartiles are calculated separately by sex, marital status, and year.

Figure 8: Mean Own-Wage Elasticities by Presence of Dependents



Notes: This figure presents estimated mean own-wage elasticities separately by presence of dependents, sex, and marital status using our baseline model without the benefit simulator.

Figure 9: Counterfactuals

Notes: This figure presents the linear time trend 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 fixing one set of factors to their 1980 values: “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. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by black lines.

Table 1: Distribution of Work Hours

	1980	1990	2000	2010	2020
	Panel A: Single Men				
0 hours	1.36	1.98	1.48	6.27	3.21
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
	Panel B: Single Women				
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
	Panel C: Married Men				
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
	Panel D: Married Women				
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**
		Panel A: Single Men			
Own-wage	0.116	0.136	0.136	0.258	0.175
	(0.030)	(0.027)	(0.028)	(0.039)	(0.030)
Extensive margin	0.067	0.056	0.083	0.174	0.111
	(0.015)	(0.013)	(0.014)	(0.026)	(0.018)
Intensive margin	0.049	0.080	0.053	0.084	0.064
	(0.019)	(0.018)	(0.017)	(0.017)	(0.016)
Observations	2,801	2,723	3,726	3,926	3,413
		Panel B: Single Women			
Own-wage	1.045	0.712	0.921	1.151	1.065
	(0.053)	(0.050)	(0.048)	(0.049)	(0.053)
Extensive margin	0.643	0.388	0.561	0.777	0.743
	(0.036)	(0.034)	(0.034)	(0.039)	(0.042)
Intensive margin	0.403	0.324	0.360	0.374	0.322
	(0.023)	(0.022)	(0.019)	(0.015)	(0.016)
Observations	4,505	4,000	6,409	6,198	5,223
		Panel C: Married men			
Own-wage	0.331	0.301	0.284	0.391	0.286
	(0.018)	(0.018)	(0.016)	(0.021)	(0.017)
Extensive margin	0.101	0.091	0.102	0.191	0.135
	(0.012)	(0.013)	(0.011)	(0.016)	(0.013)
Intensive margin	0.230	0.210	0.183	0.200	0.151
	(0.013)	(0.011)	(0.010)	(0.012)	(0.009)
		Panel D: Married Women			
Own-wage	1.135	1.141	1.105	1.025	1.142
	(0.050)	(0.050)	(0.049)	(0.044)	(0.046)
Extensive margin	0.789	0.784	0.769	0.729	0.849
	(0.037)	(0.037)	(0.036)	(0.033)	(0.036)
Intensive margin	0.345	0.357	0.336	0.296	0.293
	(0.017)	(0.018)	(0.018)	(0.016)	(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**
		Panel A: Single Men			
Own-wage	0.139	0.188	0.133	0.344	0.058
	(0.036)	(0.036)	(0.029)	(0.068)	(0.027)
Extensive margin	0.070	0.090	0.059	0.252	0.063
	(0.017)	(0.018)	(0.014)	(0.046)	(0.015)
Intensive margin	0.069	0.098	0.074	0.093	-0.005
	(0.025)	(0.022)	(0.019)	(0.026)	(0.015)
Observations	2,443	2,784	2,723	3,926	2,574
		Panel B: Single Women			
Own-wage	1.881	1.600	0.866	1.349	0.861
	(0.109)	(0.097)	(0.067)	(0.063)	(0.066)
Extensive margin	1.458	1.221	0.563	0.986	0.602
	(0.081)	(0.075)	(0.050)	(0.051)	(0.049)
Intensive margin	0.423	0.379	0.303	0.363	0.259
	(0.035)	(0.031)	(0.023)	(0.018)	(0.023)
Observations	4,663	4,706	4,000	6,198	3,840
		Panel C: Married men			
Own-wage	0.324	0.274	0.319	0.411	0.209
	(0.022)	(0.017)	(0.020)	(0.023)	(0.015)
Extensive margin	0.097	0.069	0.107	0.208	0.086
	(0.015)	(0.012)	(0.014)	(0.017)	(0.011)
Intensive margin	0.228	0.204	0.212	0.204	0.123
	(0.014)	(0.011)	(0.011)	(0.012)	(0.009)
		Panel D: Married Women			
Own-wage	2.067	1.352	1.156	1.019	0.966
	(0.076)	(0.057)	(0.050)	(0.044)	(0.044)
Extensive margin	1.506	0.957	0.797	0.730	0.735
	(0.058)	(0.043)	(0.038)	(0.034)	(0.035)
Intensive margin	0.561	0.396	0.359	0.290	0.231
	(0.024)	(0.020)	(0.018)	(0.015)	(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.

Table 4: ANOVA of Own-wage Elasticity from Baseline Model (Long Panel)

	Single Men	**Single Women**	**Married Men**	**Married Women**
Model sum of squares	44.6%	50.4%	34.7%	61.3%
Predicted wage	11.0	10.3	10.5	8.5
Spouse predicted wage	–	–	1.2	1.7
Non-labor income	7.8	0.6	0.0	0.1
Age	0.7	0.0	0.4	0.1
Number of dependents	1.0	10.5	1.4	6.0
Dependents aged 0 to 2	0.1	1.2	0.0	1.5
Dependents aged 3 to 5	0.2	1.6	0.0	3.0
State of residence	1.3	0.4	1.8	0.9
Year	24.6	3.6	12.9	17.2

Notes: This table presents the fraction of total sum of squares explained by a linear model of own-wage elasticity regressed on predicted hourly wage (real dollars), spouse predicted hourly wage (real dollars), non-labor income (real dollars), age, number of dependents, an indicator for dependents aged between 0 and 2 years, an indicator for dependents aged between 3 and 5 years, state of residence, and year. Individual variable fractions are based on comparing the full model sum of squares to a reduced model sum of squares with the selected variable removed.

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 2020 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 survey year 2020 dollars (actual year 2019).

Table A1: Descriptive Statistics, Single Men and Women

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

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Heckman Selection Wage Model, Men (continued)

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

Table A4: Heckman Selection Wage Model, Women

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

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Heckman Selection Wage Model, Women (continued)

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

Table A5: OLS Wage Model, Men

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

Table A6: OLS Wage Model, Women

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

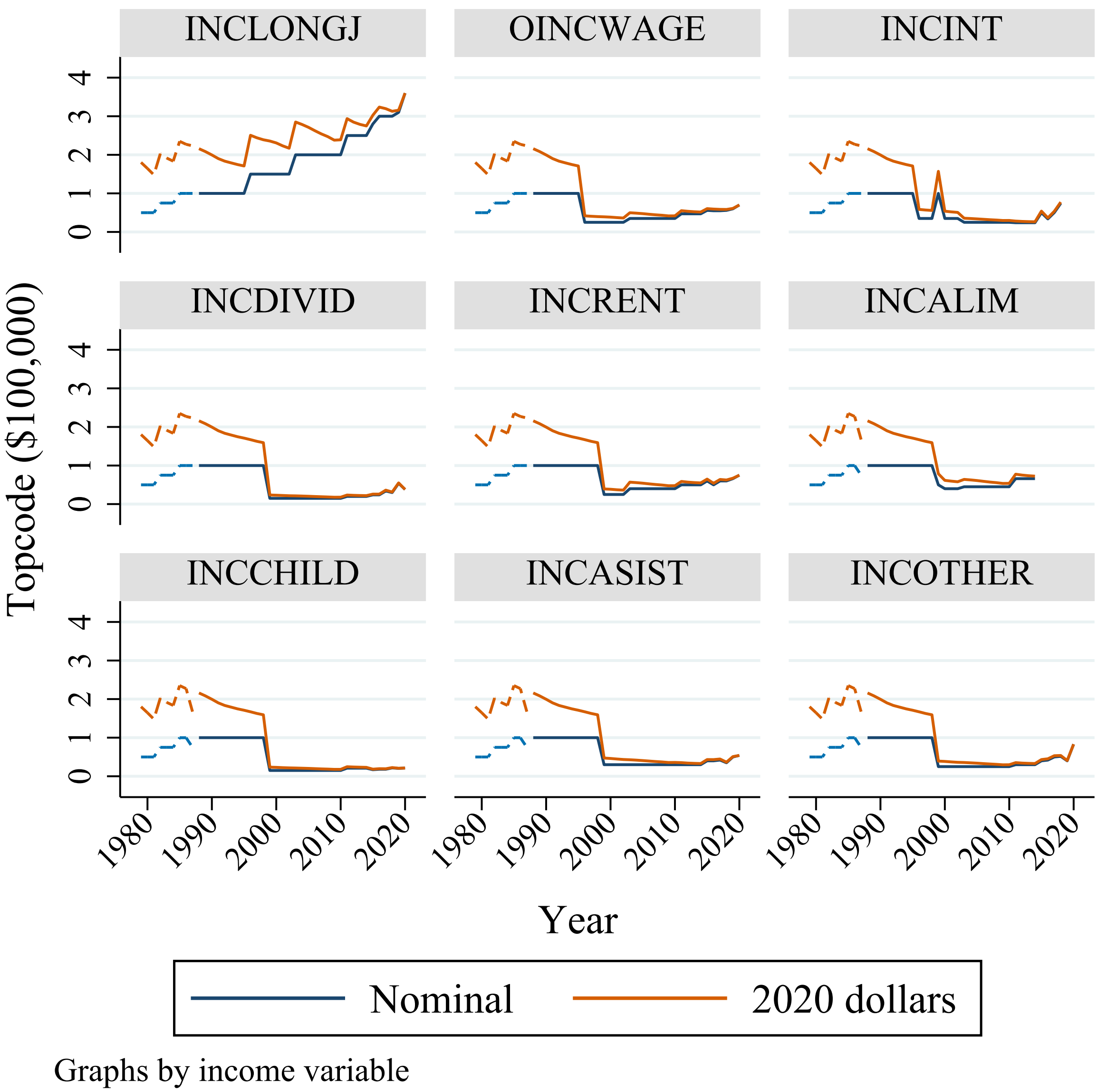
Variable	**Threshold**	**Year**
INCLONGJ	$171,135	1995
OINCWAGE	$36,188	2002
INCINT	$26,382	2014
INCDIVID	$17,855	2009
INCRENT	$36,188	2002
INCALIM	$53,565	2009
INCCHILD	$17,855	2009
INCASIST	$32,978	2014
INCOTHER	$29,758	2009

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.

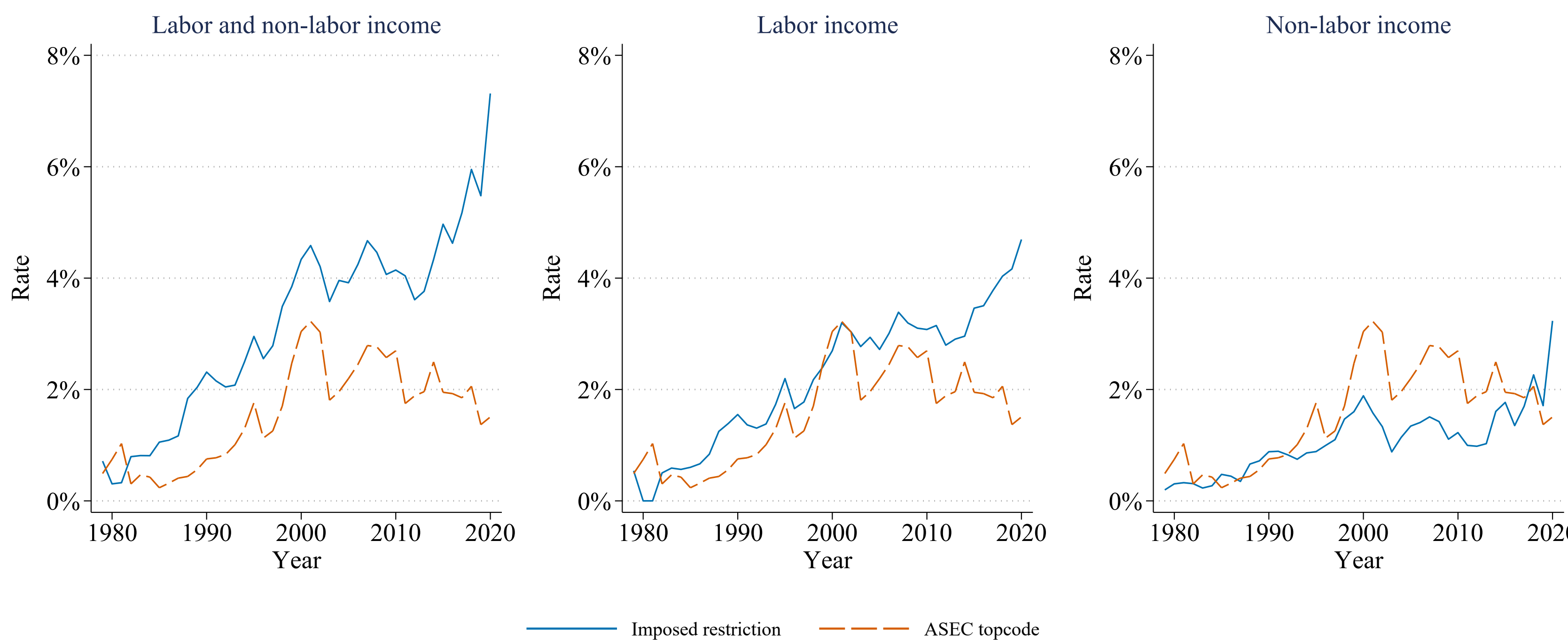
As expected, our imposed topcode affects a larger share of individuals than the actual threshold, with the exception of a small share of individuals in 1980 and 1981. This is due to the threshold for INCWAGE falling below the minimum threshold for INCLONGJ in these two years. Overall, our sample restriction 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)



Notes: Each graph plots the change in topcode threshold over time for nine different income variables in nominal and (survey year) 2020 dollars. 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 nominal 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, martial status, state of residence, and number of dependents (0, 1, 2, or 3+).

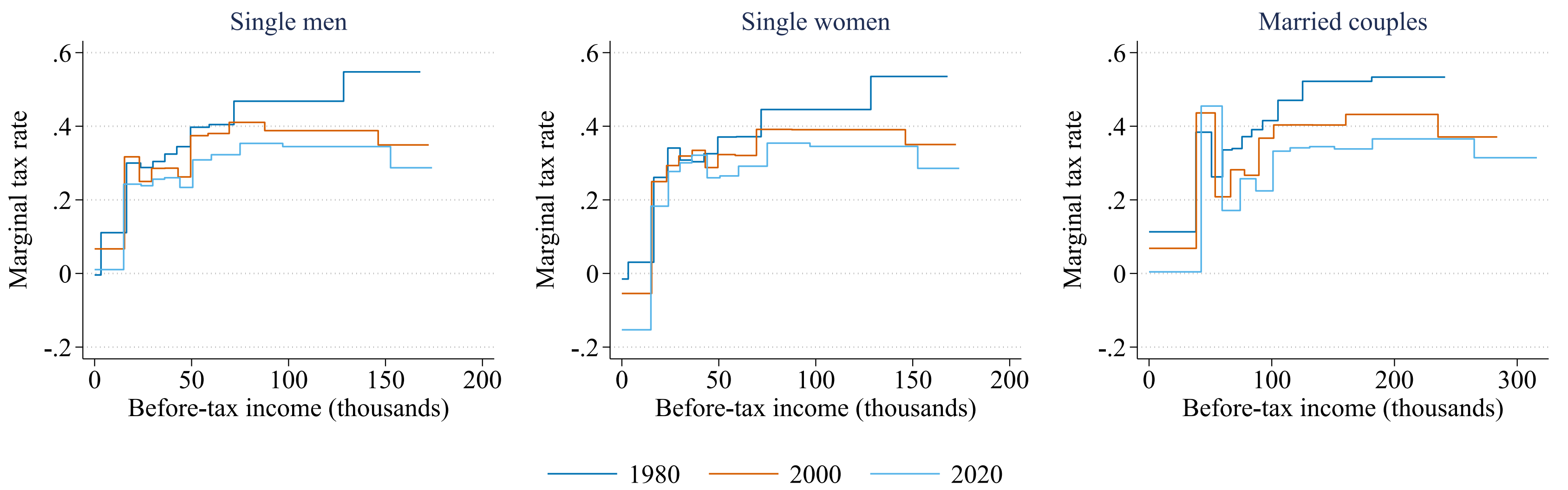
Unsurprisingly, the spline fits the simulated data very well; the r-squared is over 99.5% in every year cross marital status regression. To test its fit on real data, we apply TAXSIM to the actual observed earnings of each household in our sample and compare the calculated taxes with the predicted taxes from the spline. In absolute value, the median error in 2020 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 (2020 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 (survey year) 2020 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	9.46	-9.29	2.16	-4.03
	(6.75)	(7.07)	(5.86)	(6.03)	(6.61)
Log(Leisure)	53.20	158.09	62.48	106.45	81.11
	(49.80)	(55.82)	(43.89)	(42.59)	(45.06)
$\times$ Log(Age)	-1.78	-39.92	-23.86	5.49	-6.41
	(24.03)	(26.37)	(20.73)	(19.41)	(21.25)
$\times$ Log(Age)^2	0.62	5.98	3.61	-0.41	1.02
	(3.30)	(3.62)	(2.85)	(2.66)	(2.91)
$\times$ Dependents	0.05	-0.13	-0.53	-0.47	-0.84
	(0.24)	(0.27)	(0.19)	(0.23)	(0.23)
Log(Consumption)^2	0.58	0.39	0.69	0.55	0.61
	(0.16)	(0.16)	(0.13)	(0.14)	(0.15)
Log(Leisure)^2	-4.93	-5.79	-1.18	-10.22	-5.78
	(2.20)	(2.38)	(1.96)	(2.08)	(2.08)
Log(C) $\times$ Log(L)	-0.40	-3.11	-0.21	-2.22	-1.06
	(1.05)	(1.12)	(0.93)	(0.95)	(0.99)
Hours > 0	2.10	2.83	2.87	1.02	2.03
	(0.46)	(0.50)	(0.41)	(0.35)	(0.38)
$\times$ Dependents	0.35	0.50	0.22	-0.05	-0.32
	(0.22)	(0.38)	(0.23)	(0.18)	(0.19)
$\times$ 1[Dep. Age 0-5]	-1.57	-0.16	-0.53	-0.48	-0.82
	(0.53)	(1.21)	(0.70)	(0.43)	(0.45)
Hours $\in \{10, 20, 30\}$	-3.52	-4.11	-4.12	-3.29	-3.80
	(0.16)	(0.19)	(0.15)	(0.12)	(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	84.69	70.53	109.47	105.70
	(8.38)	(10.16)	(7.49)	(8.17)	(9.27)
Log(Leisure)	583.41	566.53	544.19	858.41	709.43
	(75.95)	(81.30)	(66.64)	(72.63)	(73.98)
$\times$ Log(Age)	-35.42	14.13	10.00	-41.01	32.44
	(34.12)	(36.80)	(30.78)	(31.71)	(32.86)
$\times$ Log(Age)^2	5.05	-1.38	-1.07	5.87	-4.17
	(4.70)	(5.06)	(4.23)	(4.36)	(4.51)
$\times$ Dependents	-0.34	0.07	-0.15	0.63	0.57
	(0.22)	(0.22)	(0.19)	(0.21)	(0.21)
Log(Consumption)^2	1.69	1.07	1.56	1.13	0.85
	(0.15)	(0.17)	(0.15)	(0.14)	(0.16)
Log(Leisure)^2	-38.35	-41.40	-38.41	-55.81	-56.71
	(3.33)	(3.76)	(2.88)	(3.12)	(3.36)
Log(C) $\times$ Log(L)	-15.79	-20.66	-19.39	-26.13	-24.34
	(1.66)	(1.98)	(1.50)	(1.56)	(1.66)
Hours > 0	1.05	1.33	1.21	0.44	-0.29
	(0.30)	(0.38)	(0.30)	(0.31)	(0.33)
$\times$ Dependents	-0.17	-0.01	-0.07	-0.29	-0.31
	(0.09)	(0.12)	(0.10)	(0.11)	(0.11)
$\times$ 1[Dep. Age 0-5]	-0.72	-0.94	-0.91	-1.02	-0.84
	(0.20)	(0.28)	(0.23)	(0.23)	(0.24)
Hours $\in \{10, 20, 30\}$	-2.89	-3.24	-3.42	-3.47	-3.25
	(0.10)	(0.12)	(0.10)	(0.10)	(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	55.64	28.52	14.15	-17.48
	(12.37)	(11.71)	(9.34)	(10.06)	(9.37)
Log(Leisure$_m$)	135.39	255.27	239.28	154.88	15.31
	(51.57)	(56.32)	(50.29)	(49.30)	(45.73)
$\times$ Log(Age$_m$)	26.84	-37.40	-41.04	13.69	-5.68
	(24.84)	(25.54)	(24.26)	(23.69)	(22.37)
$\times$ Log(Age$_m$)^2	-2.55	5.91	6.14	-1.70	1.18
	(3.39)	(3.49)	(3.31)	(3.22)	(3.04)
$\times$ Dependents	-0.30	-0.09	-0.43	-0.48	-0.40
	(0.15)	(0.15)	(0.15)	(0.14)	(0.13)
Log(Leisure$_f$)	299.25	335.83	199.57	181.53	201.53
	(38.69)	(40.55)	(38.18)	(37.68)	(36.90)
$\times$ Log(Age$_f$)	0.36	-8.55	44.09	20.64	6.66
	(19.32)	(20.10)	(19.43)	(18.78)	(18.72)
$\times$ Log(Age$_f$)^2	0.39	1.33	-6.15	-2.86	-1.00
	(2.68)	(2.78)	(2.69)	(2.59)	(2.57)
$\times$ Dependents	1.56	1.40	1.20	0.74	0.85
	(0.15)	(0.16)	(0.15)	(0.15)	(0.15)
Log(Consumption)^2	1.87	2.21	2.29	2.38	2.76
	(0.28)	(0.26)	(0.22)	(0.22)	(0.23)
Log(Leisure$_m$)^2	-9.75	-8.00	-9.57	-12.49	-1.70
	(1.87)	(1.96)	(1.60)	(1.54)	(1.34)
Log(Leisure$_f$)^2	-26.68	-27.68	-24.84	-22.80	-23.96
	(1.05)	(1.10)	(1.04)	(1.00)	(0.99)
Log(C) $\times$ Log(L$_m$)	-9.92	-11.37	-7.90	-7.90	-2.40
	(1.22)	(1.28)	(0.99)	(1.04)	(0.87)
Log(C) $\times$ Log(L$_f$)	-6.58	-7.55	-5.83	-3.31	-3.45
	(0.80)	(0.82)	(0.74)	(0.72)	(0.65)

Continued on next page.

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

	1995	**2000**	**2005**	**2010**	**2015**
$\text{Log}(\text{L}_m) \times \text{Log}(\text{L}_f)$	3.67	4.88	4.63	7.73	11.82
	(1.79)	(1.80)	(1.66)	(1.63)	(1.46)
$\text{Hours}_m > 0$	4.77	5.92	4.01	2.47	2.61
	(0.80)	(1.19)	(1.33)	(0.85)	(0.86)
$\times$ Dependents	0.51	-0.63	0.18	-0.60	0.08
	(0.24)	(0.32)	(0.43)	(0.23)	(0.25)
$\times$ 1[Dep. Age 0-5]	0.65	2.92	0.48	1.72	-0.05
	(0.53)	(0.97)	(0.86)	(0.55)	(0.54)
$\text{Hours}_m \in \{10, 20, 30\}$	-5.11	-5.89	-4.89	-4.10	-5.18
	(0.19)	(0.21)	(0.17)	(0.14)	(0.18)
$\text{Hours}_f > 0$	-0.94	-1.09	-1.10	-0.86	-3.14
	(0.80)	(1.17)	(1.32)	(0.84)	(0.85)
$\times$ Dependents	0.59	-0.48	0.44	-0.45	0.17
	(0.27)	(0.35)	(0.44)	(0.24)	(0.27)
$\times$ 1[Dep. Age 0-5]	0.60	2.77	-0.13	0.65	-0.81
	(0.60)	(1.03)	(0.90)	(0.58)	(0.60)
$\text{Hours}_f \in \{10, 20, 30\}$	-2.19	-2.19	-2.21	-2.28	-2.20
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
$\text{Hours}_m > 0$ & $\text{Hours}_f > 0$	-0.04	0.42	0.50	0.36	2.25
	(0.78)	(1.16)	(1.31)	(0.82)	(0.82)
$\times$ Dependents	-0.24	0.65	-0.25	0.59	-0.07
	(0.27)	(0.35)	(0.44)	(0.24)	(0.27)
$\times$ 1[Dep. Age 0-5]	-1.68	-3.82	-0.91	-1.45	0.02
	(0.60)	(1.03)	(0.90)	(0.58)	(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	0.61	1.95	-11.61	-28.76
	(9.21)	(8.00)	(7.45)	(7.13)	(7.15)
Log(Leisure)	41.41	100.13	132.27	37.59	18.18
	(58.38)	(55.72)	(56.09)	(47.04)	(50.85)
$\times$ Log(Age)	-37.46	-20.06	-40.30	6.72	-14.01
	(28.56)	(27.07)	(26.26)	(20.99)	(23.90)
$\times$ Log(Age)^2	5.61	3.26	6.02	-0.56	1.84
	(3.94)	(3.73)	(3.61)	(2.87)	(3.27)
$\times$ Dependents	-0.21	-0.36	-0.04	-0.45	0.06
	(0.28)	(0.28)	(0.27)	(0.23)	(0.26)
Log(Consumption)^2	1.23	0.81	0.58	1.06	0.84
	(0.24)	(0.20)	(0.18)	(0.21)	(0.16)
Log(Leisure)^2	5.43	-3.43	-3.67	-3.50	-1.97
	(2.87)	(2.65)	(2.47)	(2.59)	(2.33)
Log(C) $\times$ Log(L)	-0.79	-2.64	-2.23	-0.98	3.26
	(1.52)	(1.27)	(1.16)	(1.17)	(1.09)
Hours > 0	3.93	3.02	3.34	1.80	2.08
	(0.59)	(0.52)	(0.54)	(0.41)	(0.52)
$\times$ Dependents	-0.54	-0.72	-0.08	-0.71	-0.26
	(0.27)	(0.25)	(0.36)	(0.24)	(0.21)
$\times$ 1[Dep. Age 0-5]	-1.15	-0.86	-0.50	-0.28	1.59
	(1.15)	(0.82)	(1.24)	(0.52)	(1.09)
Hours $\in \{10, 20, 30\}$	-4.26	-3.79	-4.11	-3.36	-3.79
	(0.19)	(0.17)	(0.19)	(0.12)	(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	29.74	64.90	80.94	45.46
	(8.93)	(9.50)	(11.34)	(8.83)	(10.91)
Log(Leisure)	475.62	323.69	487.45	671.45	424.82
	(68.45)	(70.28)	(81.66)	(72.61)	(79.91)
$\times$ Log(Age)	-44.35	1.70	-2.30	-37.15	-5.48
	(31.68)	(32.16)	(35.54)	(30.83)	(34.13)
$\times$ Log(Age)^2	6.12	-0.18	0.61	5.21	0.96
	(4.36)	(4.43)	(4.88)	(4.23)	(4.67)
$\times$ Dependents	0.87	1.23	1.54	1.50	0.96
	(0.17)	(0.20)	(0.22)	(0.20)	(0.22)
Log(Consumption)^2	1.77	1.80	1.32	1.33	1.26
	(0.13)	(0.16)	(0.16)	(0.12)	(0.16)
Log(Leisure)^2	-24.28	-20.42	-32.18	-41.10	-29.11
	(2.78)	(3.45)	(4.09)	(3.34)	(4.17)
Log(C) $\times$ Log(L)	-15.14	-11.94	-17.66	-21.14	-13.52
	(1.72)	(1.74)	(2.14)	(1.66)	(1.98)
Hours > 0	3.71	3.76	3.25	2.63	3.33
	(0.33)	(0.35)	(0.39)	(0.30)	(0.41)
$\times$ Dependents	-0.43	-0.66	-0.60	-0.82	-0.83
	(0.09)	(0.12)	(0.13)	(0.11)	(0.13)
$\times$ 1[Dep. Age 0-5]	-1.86	-2.45	-1.49	-1.24	-1.46
	(0.29)	(0.31)	(0.34)	(0.28)	(0.32)
Hours $\in \{10, 20, 30\}$	-3.56	-3.40	-3.25	-3.25	-3.33
	(0.11)	(0.11)	(0.12)	(0.09)	(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	75.55	74.07	42.92	6.10
	(17.04)	(12.60)	(10.86)	(9.21)	(7.66)
Log(Leisure$_m$)	102.22	208.74	307.18	213.81	-57.31
	(61.42)	(57.70)	(58.62)	(51.12)	(47.38)
$\times$ Log(Age$_m$)	90.23	30.17	-39.32	14.25	34.94
	(28.56)	(27.42)	(26.18)	(24.09)	(24.41)
$\times$ Log(Age$_m$)^2	-11.42	-3.08	6.20	-1.77	-4.66
	(3.89)	(3.75)	(3.58)	(3.27)	(3.30)
$\times$ Dependents	0.03	-0.19	-0.03	-0.37	-0.38
	(0.15)	(0.16)	(0.15)	(0.14)	(0.13)
Log(Leisure$_f$)	422.41	336.40	357.38	215.25	230.73
	(41.28)	(38.79)	(41.01)	(37.33)	(36.91)
$\times$ Log(Age$_f$)	3.31	7.22	-8.75	16.95	19.81
	(19.27)	(19.21)	(20.25)	(18.56)	(18.84)
$\times$ Log(Age$_f$)^2	0.11	-0.56	1.36	-2.35	-2.73
	(2.68)	(2.67)	(2.80)	(2.56)	(2.58)
$\times$ Dependents	1.14	1.46	1.42	0.83	1.09
	(0.15)	(0.16)	(0.16)	(0.14)	(0.15)
Log(Consumption)^2	2.70	2.00	1.94	1.80	2.00
	(0.27)	(0.23)	(0.20)	(0.17)	(0.16)
Log(Leisure$_m$)^2	-7.13	-14.54	-10.23	-15.01	-0.53
	(2.90)	(2.38)	(2.10)	(1.72)	(1.43)
Log(Leisure$_f$)^2	-30.44	-28.70	-28.16	-23.22	-26.89
	(1.21)	(1.13)	(1.13)	(1.01)	(1.07)
Log(C) $\times$ Log(L$_m$)	-17.99	-13.08	-13.39	-10.50	-2.43
	(2.21)	(1.55)	(1.36)	(1.15)	(0.91)
Log(C) $\times$ Log(L$_f$)	-14.45	-9.21	-8.43	-4.55	-5.50
	(1.15)	(0.88)	(0.83)	(0.71)	(0.61)

Continued on next page.

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

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

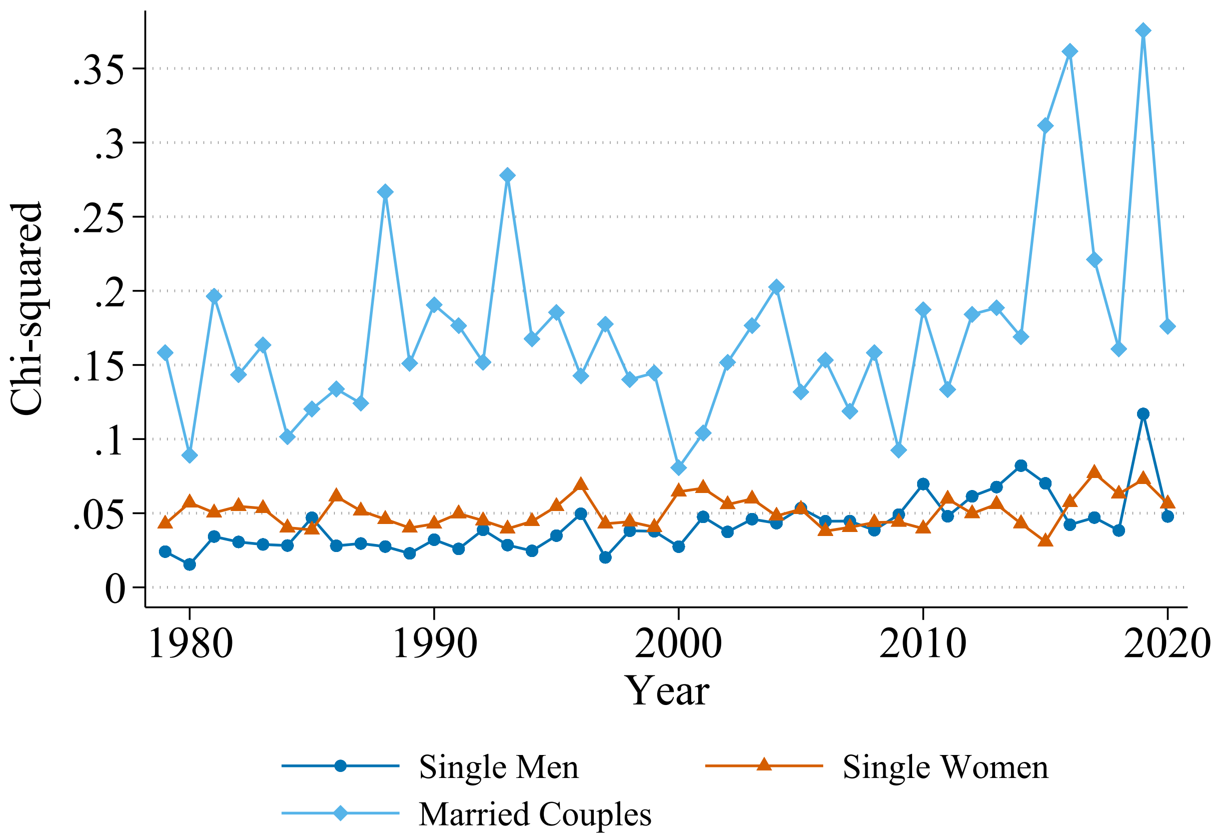
in 2020. Increasing non-response is a previously documented phenomenon, and existing research suggests it does not appear uniformly across the income distribution (Bollinger et al., 2019). To test whether our elasticity trends are driven by imputation rate trends, we re-estimate our baseline model without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

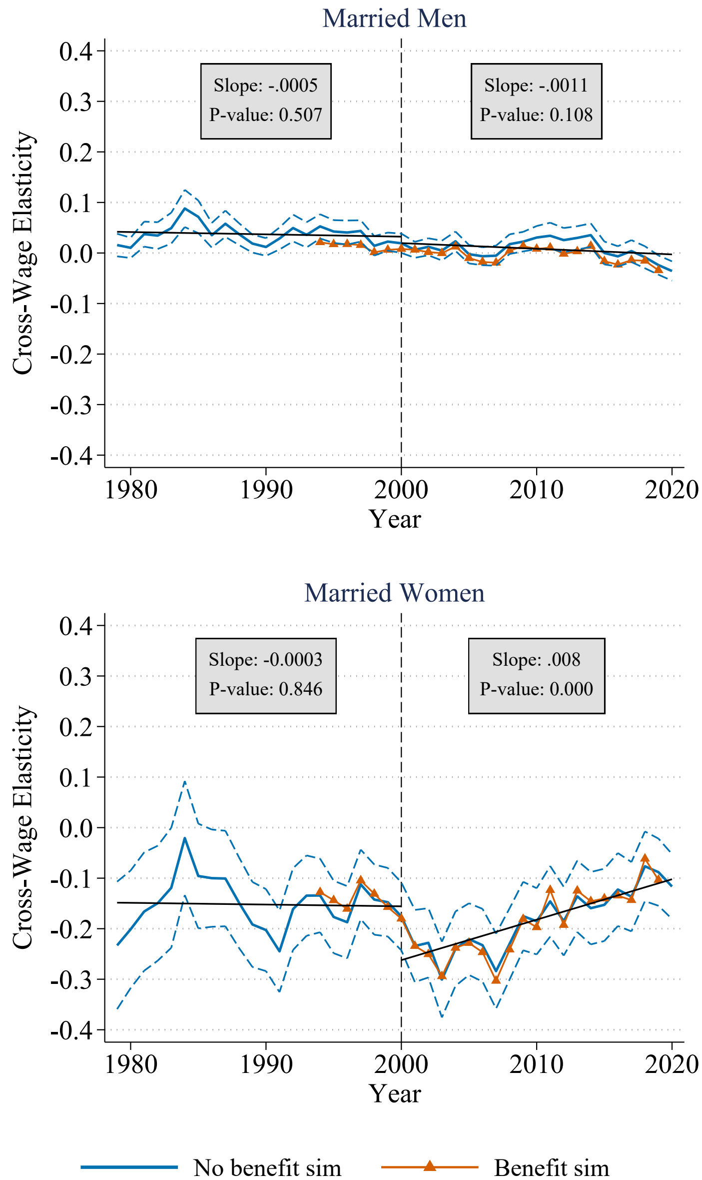
Continuous choice model To complement our baseline discrete choice model, we also estimate a continuous model using the same 1979-2020 March CPS data. Following Heim (2007), we use a multi-step procedure where we first predict participation as a function of non-labor income and controls such as age and educational attainment, then we predict log wages based on those same controls and the inverse Mills ratio calculated from the first stage. Next, we regress hours (and participation) on predicted log wages from the second step, the inverse Mills ratio from the first step, and the controls, generating estimates of intensive and extensive margin elasticities. We present the estimates for married women in Appendix Figure A12.

Figure A4: Goodness of Fit over Time



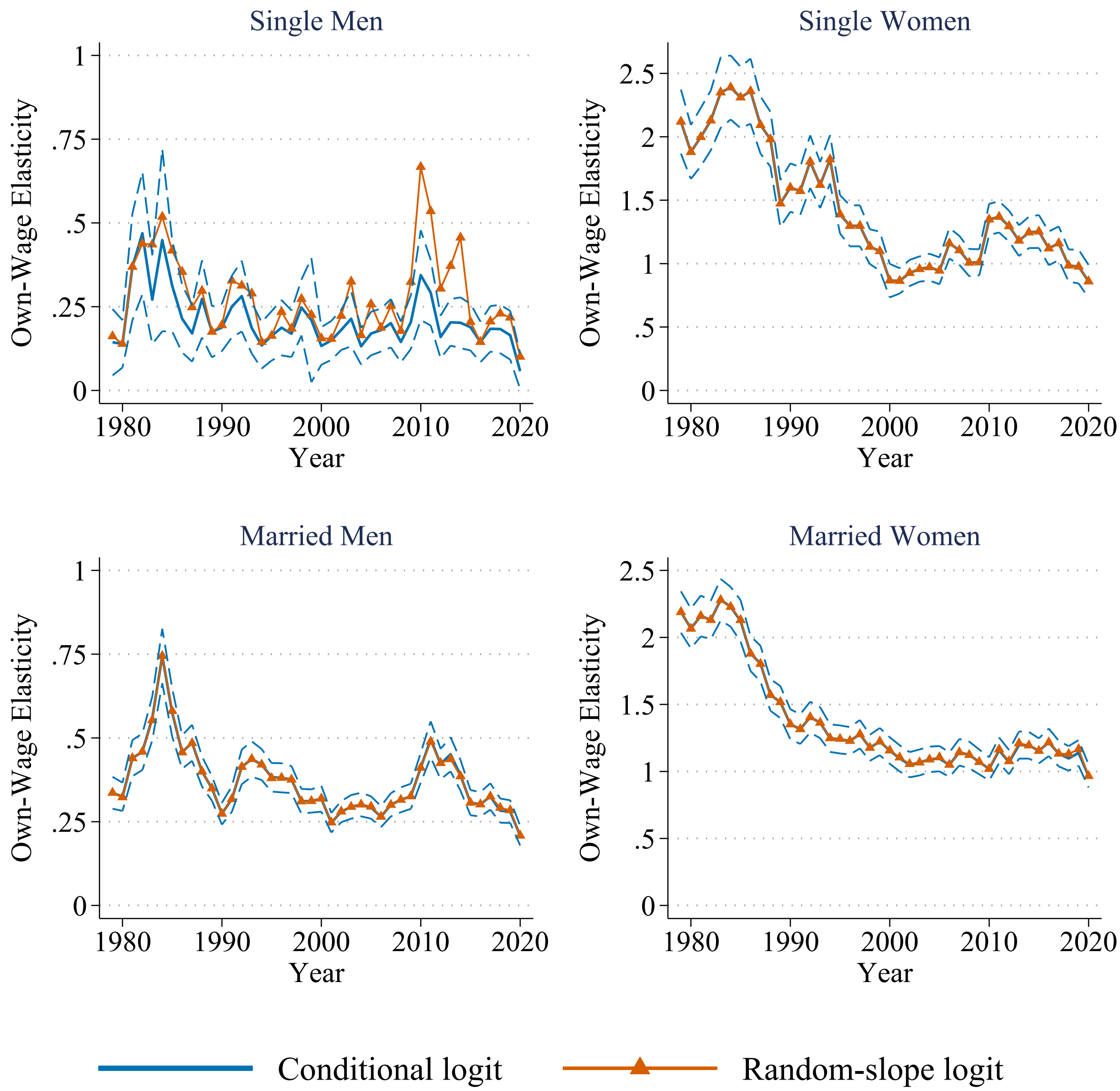
Notes: This figure presents the chi-squared statistics (squared errors divided by true probability summed across alternatives) for the fit between actual hours worked and predicted hours worked according to the parameter estimates of our baseline model without the benefit simulator.

Figure A5: Mean Cross-Wage Elasticities for Short- and Long-Panel Model



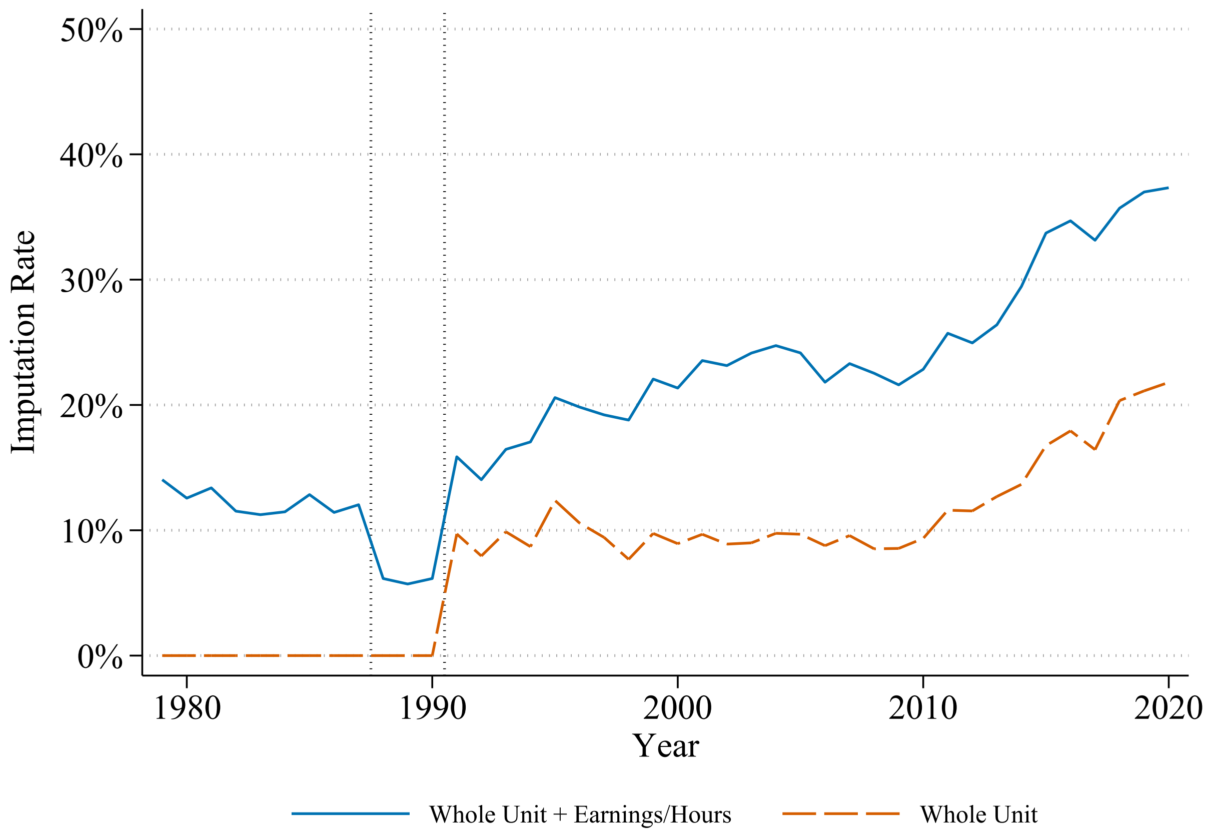
Notes: This figure presents estimated cross-wage elasticities separately by sex without the benefit simulator. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the join distribution of parameters, are denoted by dashed lines. Linear trend lines from 1970 to 2000 and 2000 to 2020 are also presented. Elasticity estimates from the model with a benefit simulator are presented for reference and denoted with a orange triangles.

Figure A6: Mean Own-Wage Elasticities, Random Slopes



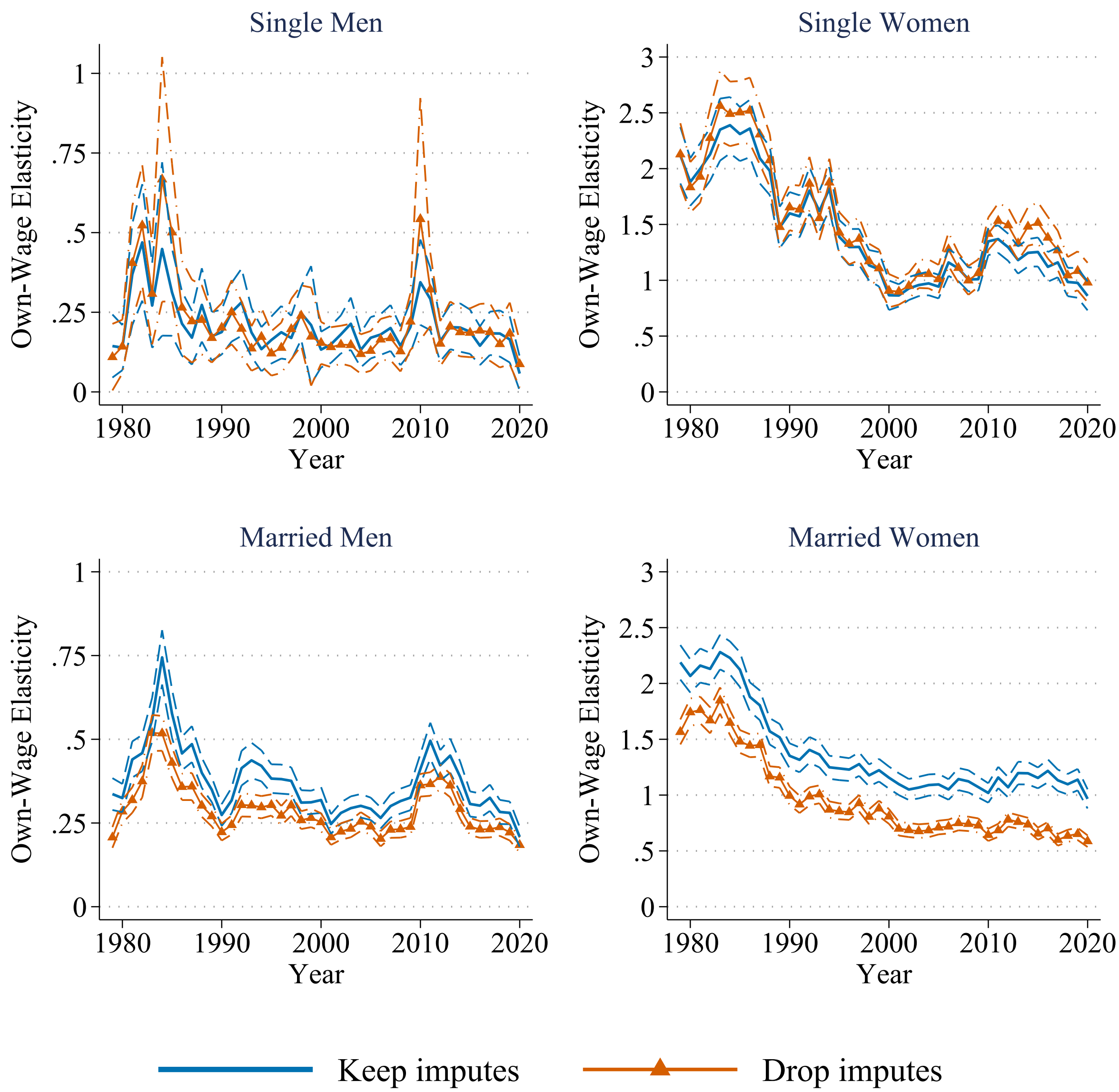
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model with random slopes (orange with triangle markers) is identical to the baseline model (solid blue line) except for the presence of a random coefficient on consumption. 95% confidence intervals, 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)



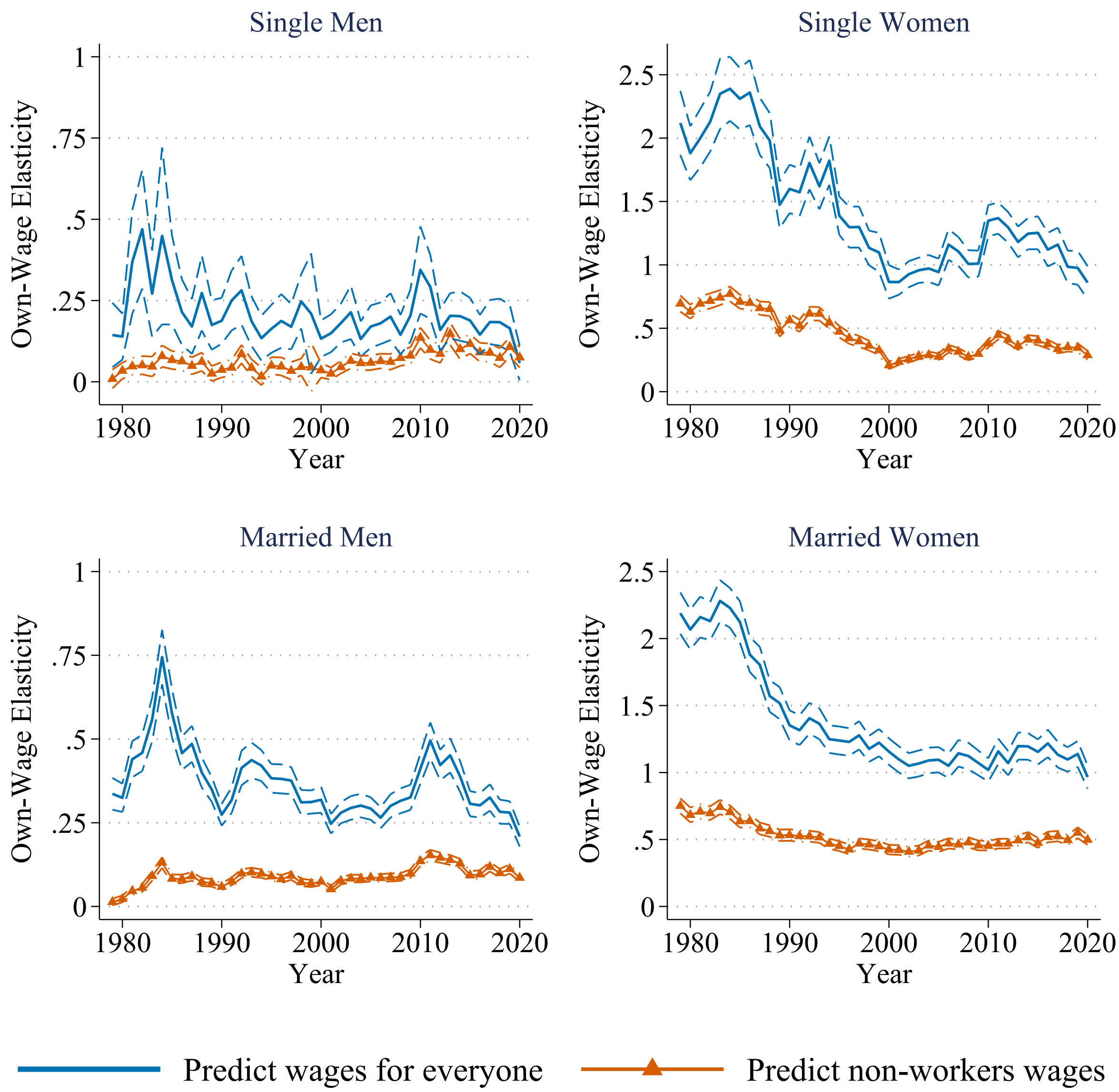
Notes: Whole unit imputation is based on UH_SUPREC_A1 (1991-2006) and UH_SUPREC_A2 (2007-2020). Earnings and hours imputation is based on the flags QINCWAGE (1979-1987), QINCLONG (1988-2020), QOINCWAGE (1988-2020), QWKSWORK (1988-2020), and QUHRSWORKLY (1988-2020). Source: 1979-2020 CPS-ASEC.

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



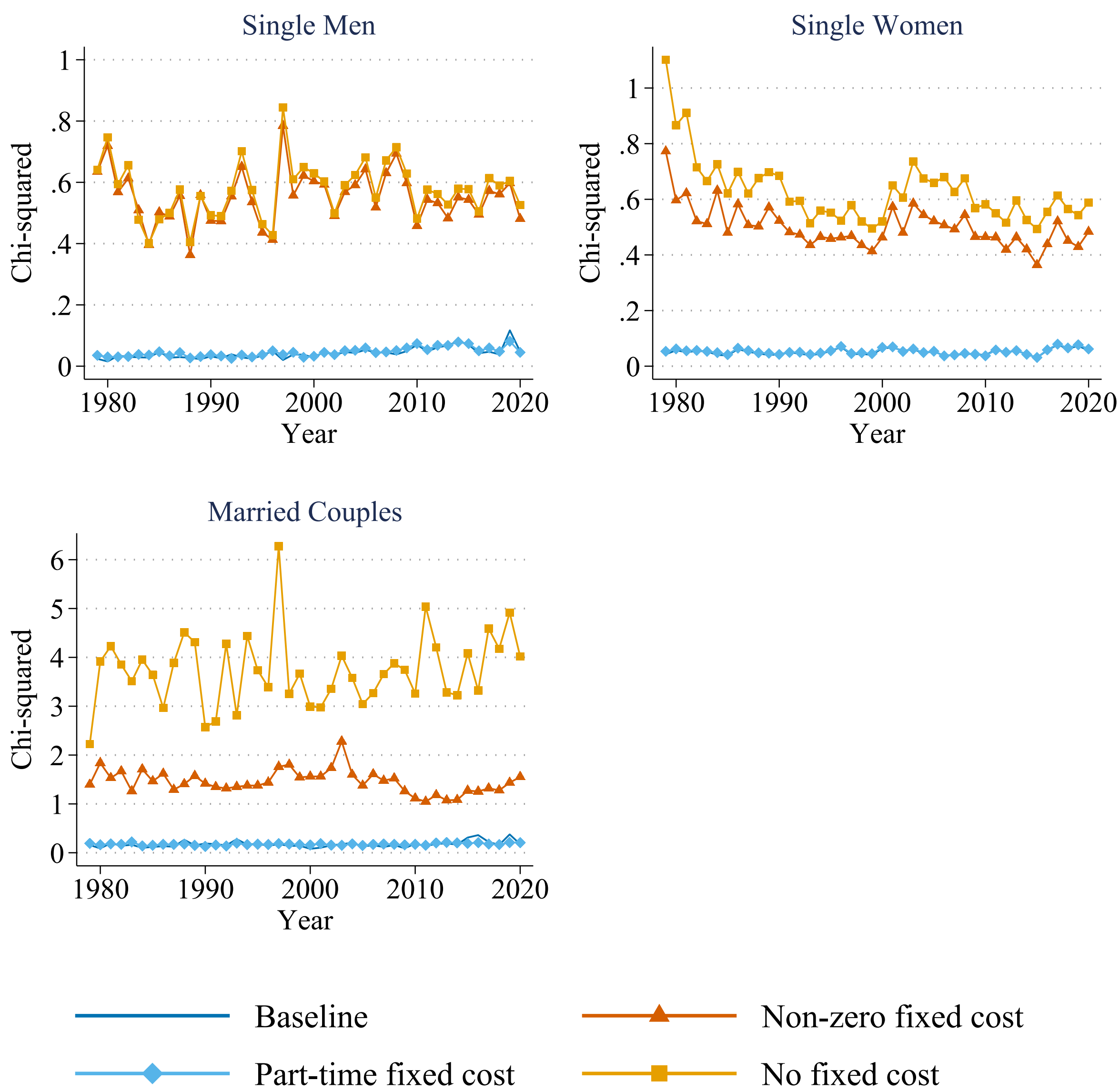
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model without imputed observations (orange with triangle markers) is identical to the baseline model (solid blue line) except for the change in sample. 95% confidence intervals, computed with a 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



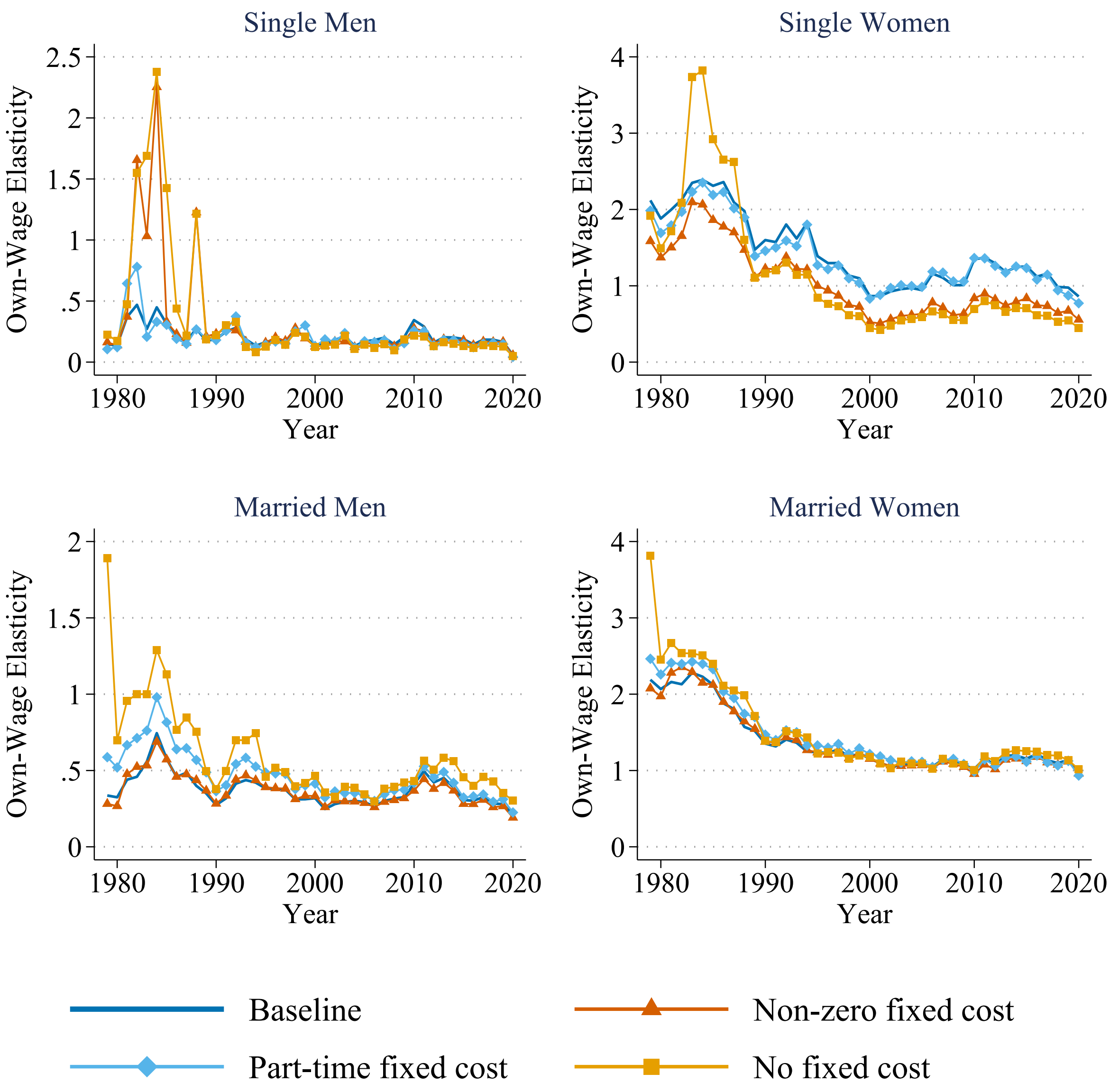
Notes: This figure presents estimated mean own-wage elasticities separately by sex and marital status. Our model predicting wages for non-workers only (orange with triangle markers) is identical to the baseline model (solid blue line) except for the use of observed wages for workers. 95% confidence intervals, 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



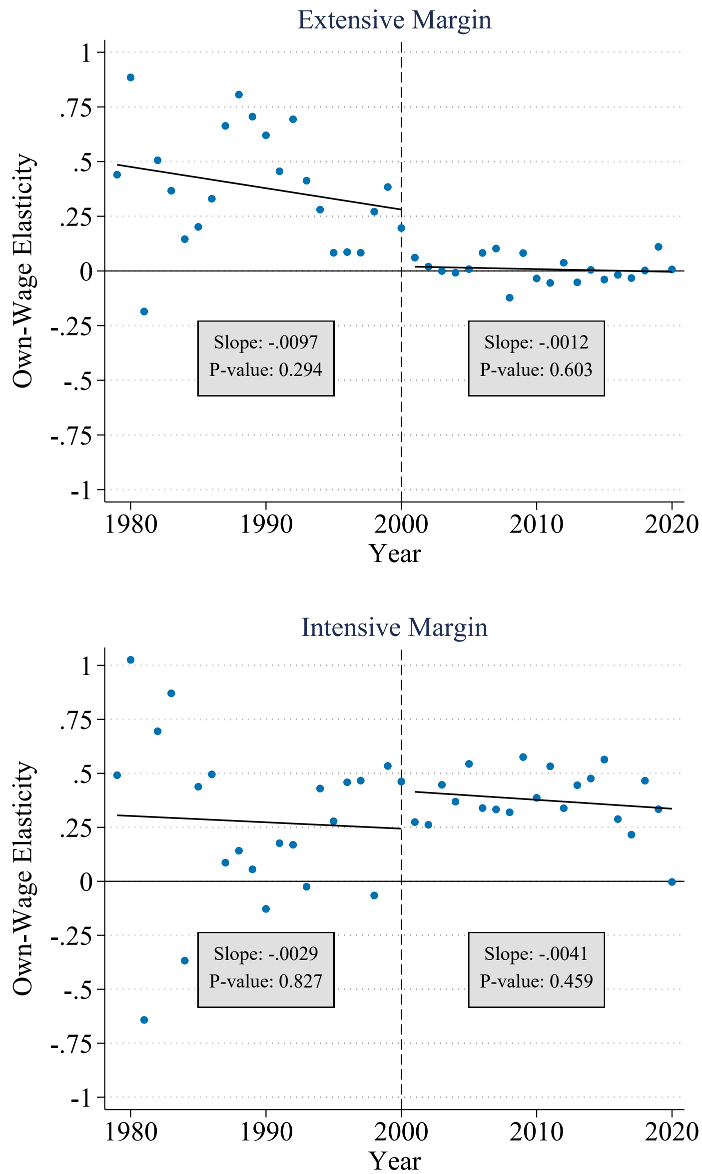
Notes: This figure presents the chi-squared statistics (squared errors divided by true probability summed across alternatives) for the fit between actual hours worked and predicted hours worked according to varying models. The baseline model includes a fixed cost of working non-zero hours and a separate 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: Mean Elasticities Over Time Using Heim's (2007) Method

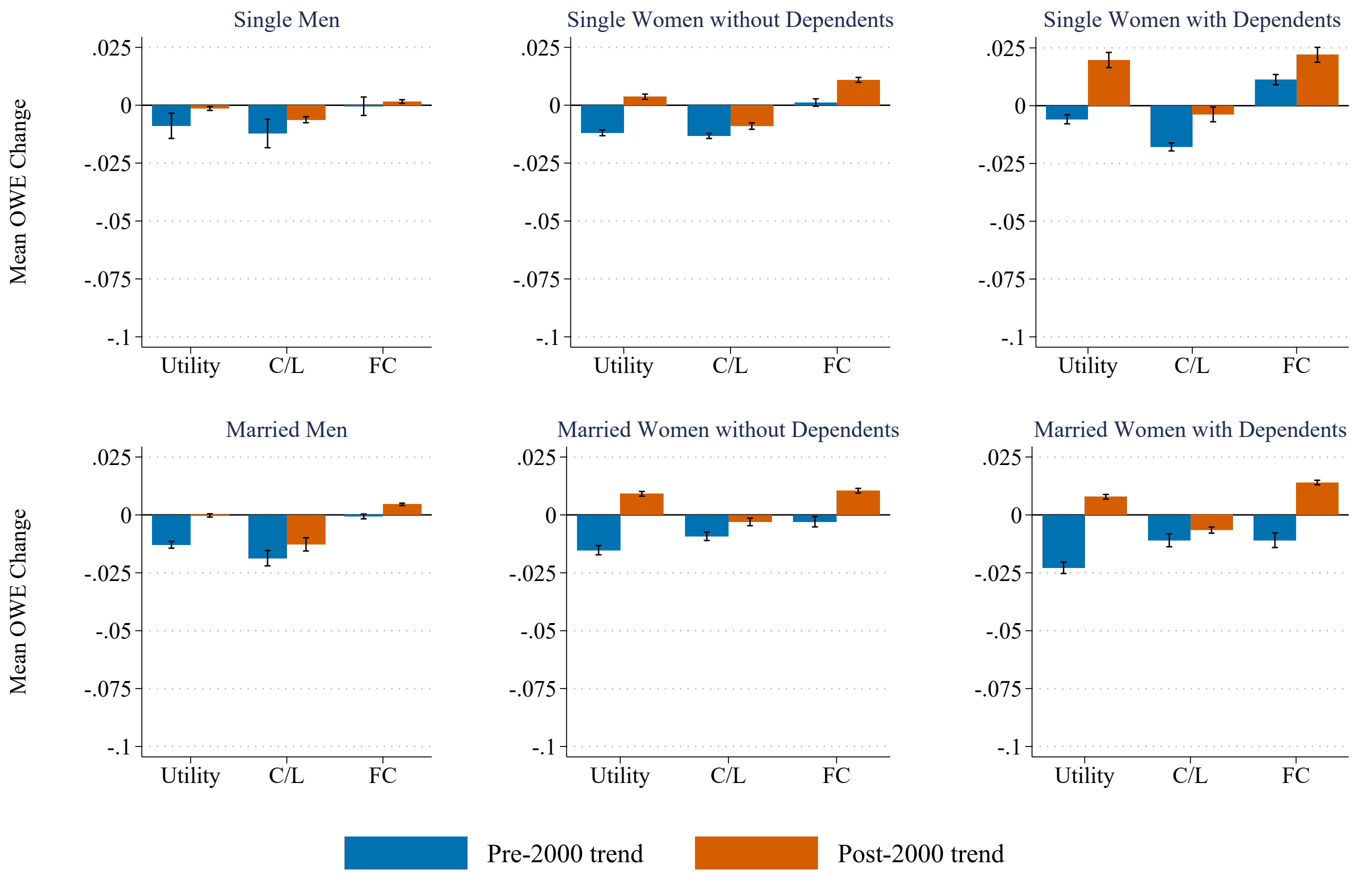


Notes: This figure presents estimated mean own-wage elasticities by year for married women based on Heim's (2007) estimation procedure, with extensive margin elasticities in the top panel and intensive margin elasticities in the bottom panel. Linear trend lines from 1979 to 2000 and 2000 to 2020 are also presented. All estimates are based on annual March CPS data.

Figure A13: Alternative Counterfactuals

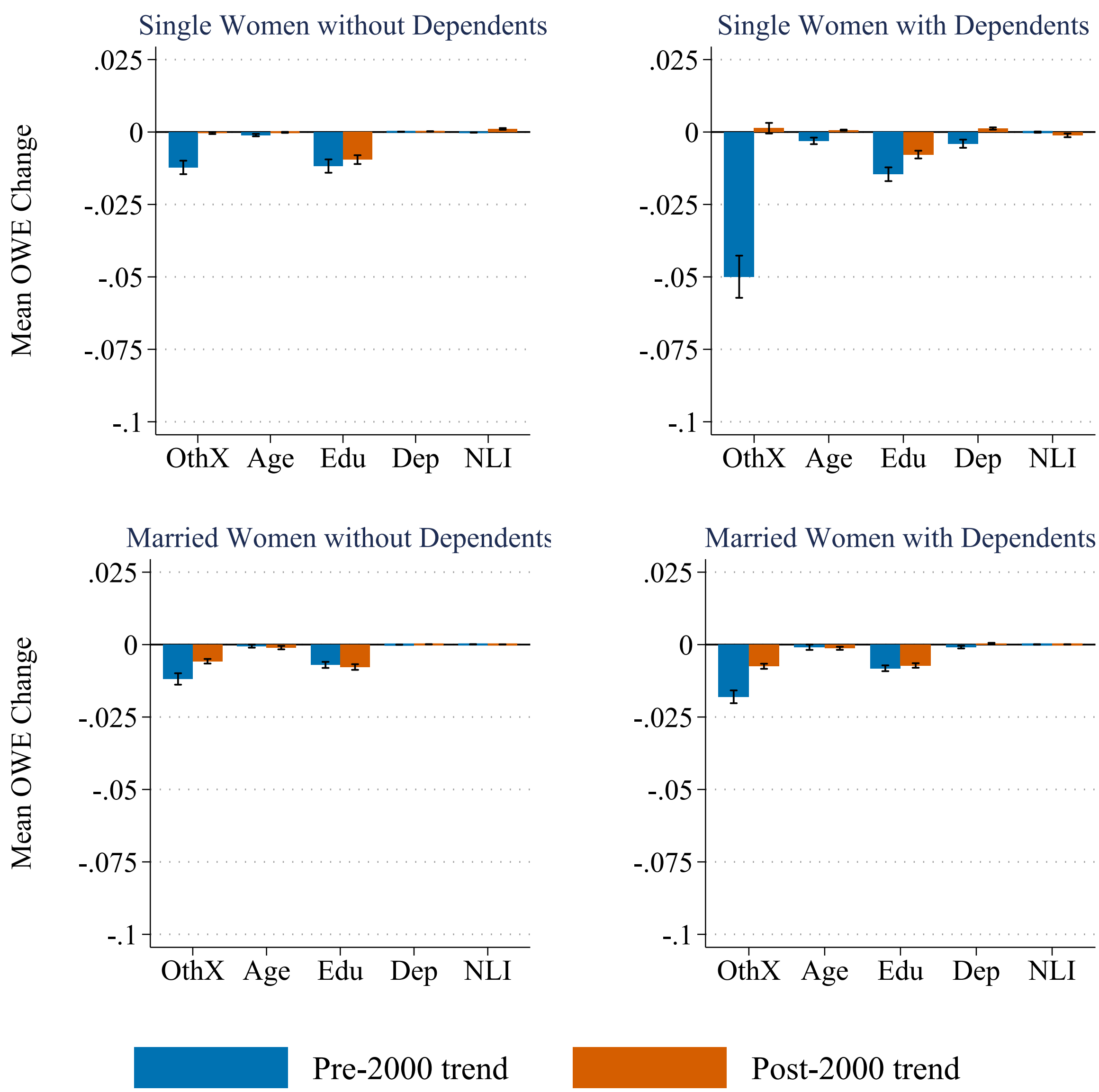
Notes: This figure presents the linear time trend in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. "Total" is based on the elasticities from the long-panel baseline model, allowing all of the model inputs and parameters to change each year. The other bars are based on allowing only one set of factors to change and fixing the others at their 1980 values: "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. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by black lines.

Figure A14: Utility Counterfactuals



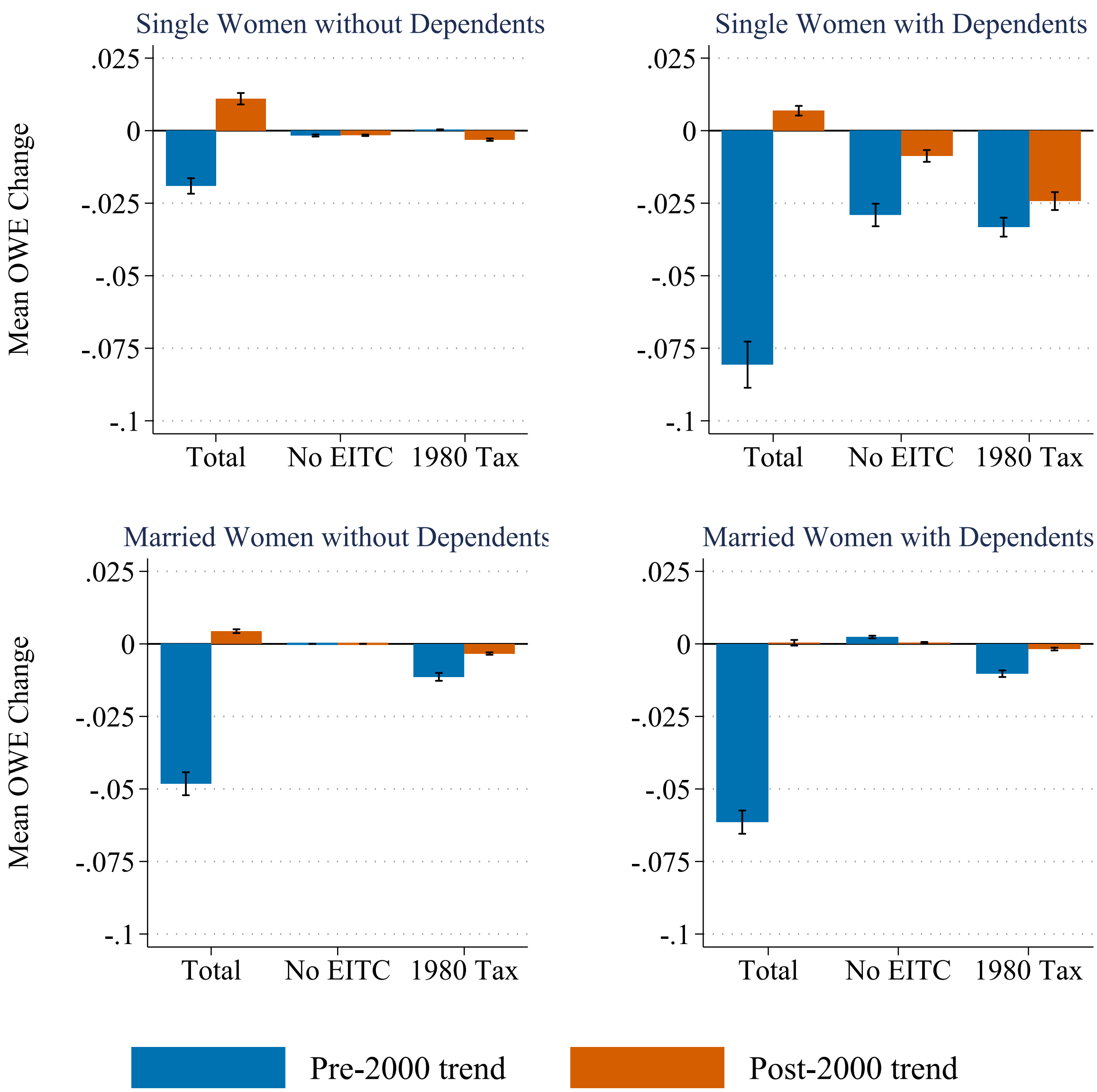
Notes: This figure presents the linear time trend in the OWE from 1979 to 2000 and from 2000 to 2020 by calculating the slope from various counterfactuals. "Utility" corresponds to the counterfactual holding all utility parameters constant at their 1980 values. "C/L" corresponds to the counterfactual 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. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by black lines.

Figure A15: Other Input Variables Counterfactuals



Notes: This figure presents the linear time trend 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. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by black lines.

Figure A16: EITC Counterfactuals



Notes: This figure presents the linear time trend 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. 95% confidence intervals, computed with a parametric bootstrap of 100 draws from the joint distribution of parameters, are denoted by black lines.

Table A13: Counterfactual Slopes

	Total	Wage	Tax	No EITC	OthX	Age	Edu	Dep	NLI	Util	C/L	FC
						Single Men						
Pre-2000	-0.006	-0.007	-0.006	-0.006	-0.005	-0.006	-0.006	-0.005	-0.006	0.003	0.006	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
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
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
						Single Women without Dependents						
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
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
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
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
						Single Women with Dependents						
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
	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
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
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

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Counterfactual Slopes (cont.)

	Total	**Wage**	**Tax**	**No EITC**	**OthX**	**Age**	**Edu**	**Dep**	**NLI**	**Util**	**C/L**	**FC**
Married Men												
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
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)
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
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Married Women without Dependents												
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
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
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
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Married Women with Dependents												
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
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
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
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)

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 9, A14, A15, and A16.