UPPSALA
UNIVERSITET

Department of Economics

Working Paper 2018:2

Taxes and Household Labor Supply: Estimating Distributional Effects of Nonlinear Prices on Multidimensional Choice

Che-Yuan Liang

Department of Economics
Uppsala University
Box 513
751 20 Uppsala
Sweden

Working Paper 2018:2
February 2018
ISSN 1653-6975

TAXES AND HOUSEHOLD LABOR SUPPLY: ESTIMATING DISTRIBUTIONAL EFFECTS OF NONLINEAR PRICES ON MULTIDIMENSIONAL CHOICE

CHE-YUAN LIANG

Taxes and Household Labor Supply: Estimating Distributional Effects of Nonlinear Prices on Multidimensional Choice*

Che-Yuan Liang[#]
February 5, 2018

Abstract: We develop a method for distributional regression of joint multidimensional choice on nonlinear prices departing from a household model of labor supply that focuses on tax policy effects. Our distribution functions are derived under minimal theoretical assumptions and have a simple structure. We allow distribution-free estimation, collective decision-making, and identification based on tax reforms. In our empirical application on U.S. panel data from 1980 to 2006, we provide a deepened understanding of how the configuration of the tax system affects the distribution of transitions between combinations of spouse labor supply. We also quantify biases from commonly imposed restrictions.

Keywords: household labor supply, nonlinear budget sets, distributional regression, collective choice, distribution-free estimation, tax reforms

JEL classification: D11, H24, J22

---

* I thank Thomas Aronsson, Mikael Elinder, Lennart Flood, Anil Kumar, Gauthier Lanot, Isabel Martinez, Whitney Newey, Håkan Selin, and seminar participants at the Uppsala Center for Fiscal Studies (UCFS) and Department of Economics at Uppsala University, Umeå School of Business at Umeå University, the Workshop on Public Economics and Public Policy in Copenhagen, the 28th Annual Conference of the European Economic Association in Gothenburg, the 2014 American Economic Association Meeting in Philadelphia, and the 73rd Annual Congress of the International Institute of Public Finance in Tokyo for valuable comments and suggestions. The Jan Wallander and Tom Hedelius Foundation, the Swedish Research Council for Health, Working Life and Welfare (FORTE), and the Uppsala Center for Fiscal Studies are acknowledged for their financial support.
# Institute for Housing and Urban Research, Uppsala Center for Fiscal Studies, and Department of Economics at Uppsala University. P.O. Box 514, SE-75120, Uppsala, Sweden; e-mail: che-yuan.liang@nek.uu.se.

1. Introduction

Microeconomic analysis frequently involves several choice variables that are jointly decided under multivariate budget constraints that sometimes contain nonlinear prices. Family labor supply is a canonical example where two spouses collectively decide on a vector of hours of work constrained by a nonlinear budget set. Many other decisions interact with labor supply or are made in a household context. Additional applications include, e.g., participation in social programs, pension savings, and consumption patterns. From a policy perspective, complicated tax structures can be set to affect behavior. Optimal policy design with respect to efficiency and welfare typically depends on policy effects on the entire joint distribution of choice variables. In this paper, we develop a method for estimating distributional effects of nonlinear prices on multidimensional choice. We center our exposition around tax price effects on household labor supply and include an application on U.S. data from the Panel Study of Income Dynamics (PSID) over the period 1980 to 2006.

As reviewed by Keane (2011), the literature on taxes and labor supply has developed different approaches to address nonlinear taxes. However, distributional inference was relatively rare and almost always relied on aligning data to distributions of unobserved heterogeneity with limited dimensions characterized by a few moments. Furthermore, although couples make up a major share of the labor force, most methods abstracted from features of family decision-making such as spouses having separate preferences, bargaining with each other, or sharing joint resources. There is also a lack of structural methods that can easily be combined with quasi-experimental variation in tax prices. Our method, which fully accounts for progressive taxes, enables distributional inference without distributional assumptions. It also allows collective decision-making and the use of variation in tax structure changes due to tax reforms for identification. We demonstrate that our methodological improvements have an impact on estimated labor supply responses to tax reforms as many restrictions that are often imposed lead to significant bias.

A multidimensional choice can be characterized by a response vector, in our case, $\boldsymbol{h} = (h^m, h^f) \in \boldsymbol{H}$, containing hours of work h of two spouses $s = m, f$. The budget constraint restricts household consumption according to $c = c(h^m, h^f|\boldsymbol{\tau})$, which could be nonlinear in either argument. The government can affect the constraint by setting a tax price vector $\boldsymbol{\tau}$. We are interested in the policy effect of $\boldsymbol{\tau}$ on $\boldsymbol{h}$. In our empirical application with joint taxation of total household earnings $y = y^m + y^f$ where $y^s = w^s h^s$ and w is the gross wage rate, the tax price function is $\tau = \tau(y|\boldsymbol{\tau})$. We characterize the tax structure using the vector $\boldsymbol{\tau} \sim (\tau_0, \tau_1, \dots, \tau_{200})$ with $\tau_j = \tau(y_j) = \left[c(y_{j+1}) - c(y_j)\right] / \left(y_{j+1} - y_j\right)$ being the marginal tax price at $y_j = j * \text{USD } 1000$.

We allow general heterogeneity of arbitrary dimensionality capturing, e.g., differences in taste for work and household decision-making process, as well as optimization and measurement errors. We use distributional regression and estimate conditional distribution functions of choice using the additively separable structure $Pr(\boldsymbol{h} \in \overline{\boldsymbol{H}}|\boldsymbol{\tau}) \approx \sum_j \pi_{\overline{\boldsymbol{H}}}(y_j)\tau_j$ for mutually exclusive and jointly exhaustive $\overline{\boldsymbol{H}} \subset \boldsymbol{H}$. To additionally address the high dimensionality of $\boldsymbol{\tau}$, we impose a flexible smooth functional form on the tax price effect $dPr/d\tau_j = \pi_{\overline{\boldsymbol{H}}}(y_j)$ approximated by a cubic polynomial in y_j weighted by the unconditional probability density function of earnings $p_j = p(y_j)$. We estimate two-year first-differences. Our main specification is of the type: $\Delta 1(\boldsymbol{h} \in \overline{\boldsymbol{H}}) = \boldsymbol{\beta}_{\overline{\boldsymbol{H}}} \Delta \boldsymbol{x} + \varepsilon,\ \boldsymbol{x} = \left[\sum_j \tau_j y_j^n p_j\right]_{n=0,1,2,3}$, where $1(.)$ is a binary indicator variable and ε is a disturbance term. The entire tax structure is represented by four predictor variables in $\boldsymbol{x}$. Estimates of $\boldsymbol{\beta}_{\overline{\boldsymbol{H}}}$ recover policy effects on the joint distribution in *levels* and allow each distinct earnings-specific tax price to have a separate effect on each probability of a family labor supply combination. By replacing $\Delta 1(\boldsymbol{h} \in \overline{\boldsymbol{H}})$ with the more general function $G(\boldsymbol{h}_{t+2} \in \overline{\boldsymbol{H}}_{t+2}, \boldsymbol{h}_t \in \overline{\boldsymbol{H}}_t)$, where t is the base year in the difference, we can additionally estimate policy effects on *transitions* between different combinations, allowing an exploration of mechanisms of behavioral response. We also elaborate with an approximation of the tax structure by a single predictor variable consisting of the density-weighted average tax price $\sum_j \tau_j p_j$.

Our estimates can be interpreted as average tax price effects for the households and tax structure changes in our data assuming only statistical independence of tax structure changes. Our method is also theoretically attractive because it allows predictions of different margins of behavioral response to policy counterfactuals[1] under a few of the commonly made assumptions in the previous literature. The key assumption is similar to but weaker than utility maximization with convex budget sets.[2]

We find total hours-of-work elasticities of approximately 0.5 for households as well as for husbands and wives separately. In terms of the per-percentage-point tax price effect, tax cuts at annual household earnings around USD 50,000, which is somewhat below the mean level, are the most efficient. From a distributional perspective, general across-the-board tax cuts primarily increase the share of households with husbands working at least full-time and wives working full-time. Our results also show that reductions in working hours, e.g., job exits, are the most important margin of response. While we find fairly large tax price effects on labor supply, tax reforms cannot explain much of the aggregate variation over time, e.g., the strong rise in the labor supply of the wives during the sample period.

The previous literature identified three types of household models: sequential models with a secondary earner acting after a primary earner, unitary models with a joint family utility function, and collective models where spouses with separate utility functions act simultaneously and divide joint income (Chiappori, 1988; 1992). In line with sequential secondary earner models, empirical work typically estimated the labor supply of each spouse separately, treating the earnings of the other spouse as unearned income. Several papers instead departed from unitary models allowing estimation of cross effects between spouses, e.g., Hausman and Ruud (1984), Blundell and Walker (1986), Ransom (1987), Van Soest (1995), Aaberge et al. (1999), and Gelber (2014). Estimation of collective models evolved around testing income pooling, e.g., Lundberg (1988), Fortin and Lacroix (1997), Blundell et al. (2007), and Blundell et al. (2016). Our model nests all three models, but empirically we do not estimate consumption sharing patterns.

[1] However, methods that estimate labor supply functions cannot *directly* recover preference parameters. We only recover the functions of preference parameters necessary for predicting labor supply under tax regimes that are similar to those in our data.

[2] This common assumption enables dimensionality reduction by leveraging regularities of the choice problem across choice space and is made by, e.g., Hausman (1985) and Blomquist and Newey (2002).

The early literature focused on mean total hours of work, sometimes conditional on work participation. However, because distributional tax effects affect efficiency and welfare, tax reforms often target individuals in certain parts of the distribution, e.g., earned income tax credits primarily attempt to stimulate work participation.[3] More recent methods that were structural regarding nonlinear prices relied on maximum likelihood estimation and provided distributional estimates of error term parameters. While the pioneering studies by Burtless and Hausman (1978) and Hausman (1985) estimated choice functions, developments by Dagsvik (1994), Van Soest (1995), Hoynes (1996), Keane and Mofitt (1998), Van Soest et al. (2002), and Blundell and Shephard (2012) on discrete choice methods enabled estimation of preferences. In either case, estimation relied on distributional assumptions.[4] The evidence is scarce on whether the validity of these assumptions is important. Blomquist and Newey (2002), Van Soest et al. (2002), and Kumar and Liang (2017) provided indications of violations with respect to functional form and dimensionality that bias inference on the conditional *mean*.[5] Blomquist and Newey (2002) developed a method applicable to secondary earners, allowing non-parametric distribution-free estimation of choice functions and, as showed by Blomquist et al. (2014), also general heterogeneity .

For distributional inference on conditional *distributions*, error term parameters are no longer nuisance parameters. While the plausibility of distributional assumptions becomes crucial, relaxing assumptions often hampers feasible estimation. In practice, alternatives to discrete choice methods were few, although reduced-form methods were frequently used to estimate tax effects on work participation (e.g., Eissa and Liebman 1996; Eissa et al., 2008). Distributional or quantile regression of conditional distribution or quantile functions that inversely map into each other offer two distribution-free strategies (Rothe, 2012; Chernozhukov et al., 2013). We focus on distribution functions which under fairly weak assumptions have the same simple structure. We apply the approach used by Blomquist and Newey (2002), adapting it for distributional inference, multidimensional collective choice, and quasi-experimental identification.[6]

Structural methods based identification on level variation in tax structures and gross wage rates. On the other hand, methods that relied on linearizing the budget constraint around observed choice have evolved toward exclusively exploiting differential changes in tax rates across taxpayers due to tax reforms for a more credible identification of causal effects. Such examples of quasi-experimental methods include, e.g. Feldstein (1995), Eissa and Liebman (1996), Blundell et al. (1998), Gruber and Saez (2002), Gelber (2014). We combine nonlinear tax structures and tax reforms.[7] We avoid variation in gross wage rates or their trends that are associated with a number of issues including being unobserved for some individuals,

[3] There is an extensive literature, separate from policy evaluations, on income inequality (see Atkinson et al., 2011; Roine and Waldenström, 2015) and its relation to social choice (e.g., Harsanyi, 1953; Rawls, 1971).

[4] Normal and extreme-value distributed errors with limited dimensions were often used.

[5] Blomquist and Newey (2002) evaluated normally distributed preference heterogeneity, Van Soest et al. (2002) evaluated optimization/measurement errors, and Kumar and Liang (2017) evaluated allowing only one-dimensional heterogeneity. Each study found bias of practical significance.

[6] Previous application on distributional inference without nonlinear prices include, e.g., distributional regression of excess stock market return (Foresi and Peracchi, 1995) and quantile regression of return to schooling (Angrist et al. 2006).

[7] This rarity is possibly due to the wide use of discrete choice method estimating preference parameters. Taxpayer-fixed effects in choice that can be differenced away do not transform into fixed effects in ordinal preferences that are invariant to affine transformations.

observed or predicted with errors, and endogenous effort. Blomquist (1996), Keane (2011), and Loffler et al. (2014) reported considerable sensitivity to how gross wage rates are handled.

Some of our empirical results do not support commonly expressed beliefs; e.g., we do *not* find that relative to husbands, the labor supply of wives is more responsive or that it has declined over time. To explore sources of divergence, we derive and estimate labor supply functions imposing several common restrictions. Secondary earner functions suppress effects from the primary earner portion of the household tax structure. Limited heterogeneity (no optimization and gross wage prediction errors) lead to a linearized representation of the tax structure where only the local tax price at observed earnings matter. Gross wages are likely endogenously determined. Empirically, these restrictions lead to substantially downward-biased price effects. For total hours of work, the biases amount to 8-42 percent for secondary earner estimates, 53-78 percent for limited heterogeneity estimates, and 33-78 percent for gross wage estimates. On the other hand, relying on the variation in tax structures rather than their changes for identification yields an upward bias of almost 200 percent.

2. Theory

2.1 Theoretical framework for multidimensional choice

We consider collective choice as exemplified by a household with two spouses $s = m, f$ where m denotes the male husband and f denotes the female wife. The spouses jointly decide choice vectors of hours of work $\boldsymbol{h} = (h^m, h^f) \in \boldsymbol{H}$ and consumption $\boldsymbol{c} = (c^m, c^f)$. With $\boldsymbol{w} = (w^m, w^f)$ denoting gross wage rates, we have spouse earnings $y^s = w^s h^s$, and $\boldsymbol{y} = (y^m, y^f) \in \boldsymbol{Y}$. Total household earnings are $y = y^m + y^f \in Y$, total household consumption is $c = c^m + c^f$, and we let c_0 denote unearned income.

Government policy decides an earnings tax function $T(\boldsymbol{y})$ that is allowed to vary across households, which gives the budget constraint $c(\boldsymbol{y}) = y - T(\boldsymbol{y}) + c_0$. Without loss of generality, we work with constraints that are continuous in $\boldsymbol{y}$. Let a price parameter vector $\boldsymbol{\tau}$ characterize the tax structure. With joint taxation of (total) household earnings, the derivative of $c(y)$ (from above) gives the tax price $\tau(y) = \lim_{\epsilon \downarrow 0} [c(y + \epsilon) - c(y)]/\epsilon$. Now, $\boldsymbol{\tau} = [\tau(y)]_{y \in Y}$ and c_0 fully characterize $\tau(.)$, $T(.)$, $c(.)$, and the budget set in the (y, c)-space. While Y is one-dimensional, a vector $\boldsymbol{\tau}$ is needed to capture price nonlinearities. With two-dimensional $\boldsymbol{Y}$, $\tau^s(\boldsymbol{y}) = \lim_{\epsilon \downarrow 0} [c(\boldsymbol{y} + \boldsymbol{\epsilon}^s) - c(\boldsymbol{y})]/\epsilon$ where $\boldsymbol{\epsilon}^m = (\epsilon, 0)$ and $\boldsymbol{\epsilon}^f = (0, \epsilon)$. Now, $\boldsymbol{\tau} = [\tau^m(\boldsymbol{y}), \tau^f(\boldsymbol{y})]_{\boldsymbol{y} \in \boldsymbol{Y}}$ and c_0 fully characterize the budget set in the $(\boldsymbol{y}, c)$-space. This setting allows separate taxation of spouse earnings.

We assume that household preferences over $(\boldsymbol{h}, \boldsymbol{c})$ are decreasing in $\boldsymbol{h}$,[8] increasing in $\boldsymbol{c}$, complete, reflexive, transitive, and continuous, which ensures the existence of a continuous objective function. We allow general preference heterogeneity, possibly unobserved, with each household represented by $\boldsymbol{\rho} = (\boldsymbol{\rho}^m, \boldsymbol{\rho}^f)$ where $\boldsymbol{\rho}^s$ are random vectors of any dimensions. The heterogeneity may depend on characteristics of both spouses and may affect,

[8] While $\boldsymbol{h}$ is typically assumed to affect preferences only by reducing leisure, our setting allows search costs attached to different $\boldsymbol{h}$ due to demand-driven quantity constraints.

among other things, gross wage rates and unearned income. Our model is static and we assume local nonsatiation which implies a binding budget constraint. For some results, we also need the utility function to be twice differentiable. With $\boldsymbol{\theta}^u$ denoting preference parameters, the decision problem is:

$$\max_{\boldsymbol{c},\boldsymbol{h}} u(\boldsymbol{c}, \boldsymbol{h}|\boldsymbol{\rho}, \boldsymbol{\theta}^u) \text{ s.t. } c = c[\boldsymbol{y}(\boldsymbol{h}|\boldsymbol{\rho})|\boldsymbol{\tau}]. \tag{1}$$

Using $-s$ to denote the other spouse, the sequential model imposes the restriction $u = u^s[c, h^s|\boldsymbol{\rho}, argmax\, u^{-s}(h^{-s}|\boldsymbol{\rho}^{-s})] + u^{-s}(h^{-s}|\boldsymbol{\rho}^{-s})$. The unitary model assumes $u = u(c, \boldsymbol{h}|\boldsymbol{\rho})$. As demonstrated by Chiappori (1992), the collective model corresponds to using $u = u^s(c^s, h^s|\boldsymbol{\rho}^s) + \mu(\boldsymbol{c}, \boldsymbol{h}|\boldsymbol{\rho})u^{-s}(c^{-s}, h^{-s}|\boldsymbol{\rho}^{-s})$. The parameter μ can be interpreted as the weight given to each spouse and corresponds to a sharing rule deciding how consumption is divided between spouses. A distinguishing feature of collective models is that μ is state-dependent. The collective model nests the bargain model where hours of work are decided in the cooperative equilibrium. Eq. (1) nests all these models and therefore allows several possibly interacting decision makers although the decision problem is expressed using the construct of a single household objective function.

For a given individual, there is a one-to-one mapping between hours of work and earnings, and we can treat earnings as the choice variable. Plugging in the budget constraint into the objective function, we obtain the constrained optimization problem:

$$\max_{\boldsymbol{c},\boldsymbol{h}}\ u[c^m, c(\boldsymbol{y}|\boldsymbol{\tau}) - c^m, \boldsymbol{h}(\boldsymbol{y}|\boldsymbol{\rho})|\boldsymbol{\rho}] = \max_{c^m,\boldsymbol{y}} u(c^m, \boldsymbol{y}|\boldsymbol{\tau}, \boldsymbol{\rho}). \tag{2}$$

Once $(c^m, \boldsymbol{y})$ is known, c^f is implied. Assuming the typical case with only data on $\boldsymbol{h}$ (and $\boldsymbol{y}$) with the intra-household allocation $\boldsymbol{c}$ unobserved, we proceed by concentrating out c^m using the fact that the constraint on c^m depends on the other choice variables $\boldsymbol{y}$:

$$\max_{\boldsymbol{y}} u(\boldsymbol{y}|\boldsymbol{\tau}, \boldsymbol{\rho}) = \max_{\boldsymbol{y}} \left[\max_{c^m} u(c^m, \boldsymbol{y}|\boldsymbol{\tau}, \boldsymbol{\rho})\right] = \max_{\boldsymbol{y}} u(c, \boldsymbol{y}|\boldsymbol{\rho}) \text{ s.t. } c(\boldsymbol{y}|\boldsymbol{\tau}). \tag{3}$$

The function $u(\boldsymbol{y})$ is a budget-constrained utility and $u(c, \boldsymbol{y})$ is a reduced-form of $u(\boldsymbol{c}, \boldsymbol{h})$. When prices in $\boldsymbol{\tau}$ are common to c^m and c^f, we can typically only attempt to estimate parameters of $u(c, \boldsymbol{y})$. As known from the assignability literature (e.g., Deaton et al., 1989), parameters of $u(\boldsymbol{c}, \boldsymbol{h})$ are needed for separate predictions of c^s and for testing unitary models against collective models. Additional restrictions are required for estimating these parameters without data on $\boldsymbol{c}$. Because we focus on price effects on hours of work and only require compatibility with either model, the reduced-form utility function $u(\boldsymbol{y}|\boldsymbol{\tau}, \boldsymbol{\rho})$ of the unitary type captures all collective features needed for counterfactual policy predictions. However, allowing general preference heterogeneity with dimensions representing differences in decision process across collectives, in addition to the typical heterogeneity in taste for work, is critical for achieving this result.

The optimum yields the *desired* choice function:

$$\boldsymbol{h}_d(\boldsymbol{\tau}, \boldsymbol{\rho}) = \left(h_d^m, h_d^f\right). \tag{4}$$

Observed choice may differ from desired choice if there are optimization or measurement errors $\boldsymbol{\sigma} = (\boldsymbol{\sigma}^m, \boldsymbol{\sigma}^f)$. While some methods interpret some terms in $\boldsymbol{\rho}$ as optimization errors, following Hausman (1985), it is common to (also) enter an error term on top of desired hours of work. The observed choice function with parameters $\boldsymbol{\theta}^h$ becomes:

$$\boldsymbol{h}(\boldsymbol{\tau}, \boldsymbol{e}|\boldsymbol{\theta}^h) = (h^m, h^f). \tag{5}$$

We let $\boldsymbol{e} = (\boldsymbol{\rho}, \boldsymbol{\sigma})$ collect all the error terms in the model. We assume that $\boldsymbol{e}$ belongs to a complete separable metric space and that it is continuously distributed with the joint probability density function $p(\boldsymbol{e}|\boldsymbol{\theta}^e)$ with distributional parameters $\boldsymbol{\theta}^e$. For some results, we also need $p(\boldsymbol{e})$ to be continuous. We normalize $E(e_a) = 0$ for each element e_a in $\boldsymbol{e}$. In general, there is no simple mapping between $\boldsymbol{\theta}^h$ and $\boldsymbol{\theta}^u$.

The nomenclature of Eq. (5) relating choice $\boldsymbol{h}$ to policy $\boldsymbol{\tau}$, both of which are multidimensional, can be understood from, but does not require, our choice-theoretical framework. Multidimensional choice may arise from multiple agents or choice variables per agent. We are agnostic about the mode of decision-making. Multidimensional policy can arise from agent-specific or nonlinear policies.[9]

2.2 Outline of empirical strategy

We focus on estimating expectation functions of choice over $\boldsymbol{e}$ conditional on policy $\boldsymbol{\tau}$, i.e., $E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = g(\boldsymbol{\tau}|\boldsymbol{\theta}_g^E)$ with expected choice parameters $\boldsymbol{\theta}_g^E$ consisting of mixtures of $\boldsymbol{\theta}^u$ and $\boldsymbol{\theta}^e$. We allow $g(\boldsymbol{h})$ to be any scalar function, e.g., expected total household hours of work is $E_{\boldsymbol{e}}(h|\boldsymbol{\tau})$, and the joint probability of both spouses working 40 hours per week is $Pr(h^m = 40, h^f = 40) = E_{\boldsymbol{e}}[1(h^f = 40)1(h^m = 40)]$. By estimating $\boldsymbol{\theta}_{\overline{\boldsymbol{H}}}^E$ for $Pr(\boldsymbol{h} \in \overline{\boldsymbol{H}})$ across mutually exclusive and jointly exhaustive $\overline{\boldsymbol{H}} \in \boldsymbol{H}$, we recover distributional policy effects.

To illustrate our method, consider a simplistic joint taxation case where the government can set only a high-earnings and a low-earnings tax price applicable to two different tax brackets separated by a fixed earnings cutoff kink. Now, assume that $\boldsymbol{\tau} = (\tau_{low}, \tau_{high})$ is statistically independent of $\boldsymbol{e}$. In this case, distribution-free estimation of $1(\boldsymbol{h} \in \overline{\boldsymbol{H}}) = \boldsymbol{\theta}_{\overline{\boldsymbol{H}}}^E \boldsymbol{\tau} + \varepsilon$, where ε is the disturbance term, using least squares yields estimates representing weighted average tax price effects over $(\boldsymbol{\tau}, \boldsymbol{e})$ in the sample. Even with nonlinear and interaction effects, this interpretation of linear regressions holds, but now, the averaging also goes over the distribution of such effects (Angrist and Pitchke, 2008),

While the additive separable structure helps in reducing the number of predictor variables and parameters, it is not feasible to estimate $\boldsymbol{\theta}_{\overline{\boldsymbol{H}}}^E \boldsymbol{\tau}$ in the general case with nonlinear policy with high-dimensional $\boldsymbol{\tau}$. Our strategy, as outlined in the introduction, uses the representation $Pr(\boldsymbol{h} \in \overline{\boldsymbol{H}}|\boldsymbol{\tau}) \approx \sum_j \pi_{\overline{\boldsymbol{H}}}(y_j)\tau_j$, and with $\pi_{\overline{\boldsymbol{H}}}(y_j)$ being a smooth function of y_j, additional dimensionality reduction can be achieved.

Although our method is intuitive, consistency with microeconomic theory is important as estimates that are structural are needed for predictions of different margins of behavioral response to policy counterfactuals (Blundell, 2016). After placing our method in the literature in the next subsection, we will theoretically derive expectation functions of choice under the assumptions needed for structural interpretation of our estimates.

[9] With data on c^m (and implicitly $\boldsymbol{c}$), we may also be interested in $c^m(\boldsymbol{\tau}, \boldsymbol{e})$, derived from Eq. (2).

2.3 Relation to previous approaches

The earliest literature (for a review, see Pencavel, 1986) estimated a reduced-form of the labor supply function in Eq. (4) in which the gross wage rate w empirically enters as the price variable. For linear constraints with a single tax rate τ^*, $w\tau^*$ is the price variable in the (c, h)-space, and independent variation in w or τ^* leads to the same price variation. With nonlinear constraints, Blomquist (1988) showed that variation in w alone cannot identify price effects because of complications at kink points, as we will further discuss in Subsection 2.5.

With linear constraints, the desired choice function can be written as $h^*(\tau^*, c_0, \boldsymbol{\rho}|\boldsymbol{\theta}^*)$ with parameters $\boldsymbol{\theta}^*$. There is a correspondence between $\boldsymbol{\theta}^*$ and $\boldsymbol{\theta}^u$. Hall (1973) noted that desired choice is the same with constraints that are nonlinear or that are linearized around desired choice, i.e., $h_d(\boldsymbol{\tau}, \boldsymbol{\rho}) = h^*(\tau^* = \tau(y_d), c_0^*, \boldsymbol{\rho})$ where c_0^* is the intercept of the linearized constraint. Thus, data with nonlinear constraints can be used for estimation of $\boldsymbol{\theta}^*$.

Hausman (e.g., 1985) developed a method that also estimates $\boldsymbol{\theta}^*$ but that fully accounts for the endogenous selection of the linearized tax price. Later, discrete choice methods based on multinomial logistic regressions were developed that directly estimate $\boldsymbol{\theta}^u$ (e.g., Dagsvik, 1994; Aaberge et al., 1999; Van Soest, 1995; Hoynes, 1996; Keane and Mofitt, 1998; and Van Soest et al., 2002).

As noted by, e.g., Blomquist (1983), with nonlinear constraints, we need to know $\boldsymbol{\theta}^e$ in addition to either $\boldsymbol{\theta}^u$ (or $\boldsymbol{\theta}^*$) to simulate aggregate policy effects. Most structural methods with respect to nonlinear prices estimated $\boldsymbol{\theta}^e$ jointly with $\boldsymbol{\theta}^u$ by also aligning a few sample moments other than the mean. Feasible estimation typically requires the assumption that $\boldsymbol{e}$ has limited dimensions and that certain of its elements have normal or extreme-value distributions.

Blomquist and Newey (2002), Van Soest et al. (2002), and Kumar and Liang (2017) reported evidence on violations of distributional assumptions that bias estimation of $\boldsymbol{\theta}^u$ and consequently simulations of effects on the conditional mean. For consistent estimation of $\boldsymbol{\theta}^e$ and distributional inference of policy effects, distributional assumptions regarding dimensionality and functional form are crucial. Methods allowing flexible estimation of distributional parameters importantly achieved a good fit to observed *unconditional* labor supply distributions (e.g., Van Soest et al., 1990; Aaberge et al., 1995; Van Soest et al., 1995). Distribution-free estimation with general heterogeneity and flexible alignment of *conditional* distributions would additionally improve the reliability of distributional inference.

Blomquist and Newey (2002) developed a distribution-free structural method for nonlinear prices and focused on $E_{\boldsymbol{e}}(h|\boldsymbol{\tau}) = h(\boldsymbol{\tau})$. Under fairly weak assumptions, they demonstrated that this choice function is three-dimensional. Predictions of policy effects are straightforward and do not require simulations or separating out $\boldsymbol{\theta}^e$ from $\boldsymbol{\theta}^u$. Because their method overcomes many issues discussed in the literature, we take their approach in developing a method for distributional inference.

2.4 Conditional expectation functions of choice

Let $\boldsymbol{y}_{kl} = (y_k^m, y_l^f)$, $\boldsymbol{\tau}_{kl} = [\tau_{kl}^m = \tau^m(\boldsymbol{y}_{kl}), \tau_{kl}^f = \tau^f(\boldsymbol{y}_{kl})]$ and $c_{kl} = c(\boldsymbol{y}_{kl})$. For a household with $\boldsymbol{e}$, which specifies $\boldsymbol{\rho}$ (and given parameters $\boldsymbol{\tau}$ and $\boldsymbol{\theta}^u$), let $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e})$ describe whether $\boldsymbol{y}_{kl}$ (and implicitly $\boldsymbol{h}_{kl}$) is optimal conditional on $\boldsymbol{e}$ (and $\boldsymbol{\tau}$). Because the optimality condition of a choice exhibits a regular pattern across possible choices, deriving expectation functions of choice over $\boldsymbol{e}$ given $\boldsymbol{y}_d = \boldsymbol{y}_{kl}$ and then over $\boldsymbol{y}_{kl}$ yields an additive separable function of terms with the same structure. By the law of total expectation:

$$\begin{aligned} g(\boldsymbol{\tau}) &= E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = E_{\boldsymbol{y}_{kl}}\left[E_{\boldsymbol{e}}\left[g\big(\boldsymbol{h}(\boldsymbol{y}_{kl}|\boldsymbol{e})\big)|\boldsymbol{y}_{kl}\right]\right] \\ &= \iint g(\boldsymbol{y}_{kl}, \boldsymbol{e}) p(\boldsymbol{y}_d = \boldsymbol{y}_{kl}, \boldsymbol{e}) \boldsymbol{dedy}_{kl} = \iint g(\boldsymbol{y}_{kl}, \boldsymbol{e}) 1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e}) p(\boldsymbol{e}) \boldsymbol{dedy}_{kl}. \end{aligned} \tag{6}$$

The dimension of $g(\boldsymbol{\tau})$ depends crucially on the dimension of $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e})$. From the optimization problem in Eq. (3), $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e}) = 1[u(c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}) > u(c_{ab}, \boldsymbol{y}_{ab}, \boldsymbol{e}), \forall \boldsymbol{y}_{ab} \neq \boldsymbol{y}_{kl}]$. In general, $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e}) = 1(\boldsymbol{\tau}, \boldsymbol{e})$ may depend on the entire policy vector for two reasons. First, the condition for a given comparison $1[u(c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}) > u(c_{ab}, \boldsymbol{y}_{ab}, \boldsymbol{e})]$ is a function of c_{ab}, which depends on multiple elements in $\boldsymbol{\tau}$. Second, optimality requires global comparisons across $\boldsymbol{y}_{ab} \in \boldsymbol{Y}$ with different c_{ab}, each depending on different elements in $\boldsymbol{\tau}$.

We can reduce the dimension of $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl}|\boldsymbol{e})$ by reducing the number of comparisons needed for $\boldsymbol{y}_{kl}$ to be optimal. We accomplish this with the key assumption that budget-constrained preferences are quasi-concave in $\boldsymbol{y}$. While such assumptions are common to guarantee uniqueness, we also take advantage of how it allows us to infer the optimality of $\boldsymbol{y}_{kl}$ from comparisons with only adjacent choices that only depend on one local tax price.

Assumption 1. Budget-constrained preferences $u(\boldsymbol{y}|\boldsymbol{\tau}, \boldsymbol{\rho})$ in Eq. (2) is strictly quasi-concave in $\boldsymbol{y}$. Corollary: This assumption allows utility maximization with convex preferences and budget sets where $u(\boldsymbol{c}, \boldsymbol{h}|\boldsymbol{\rho})$ is quasi-concave in $(\boldsymbol{c}, \boldsymbol{h})$ and $c(\boldsymbol{h}|\boldsymbol{\tau})$ is concave in $\boldsymbol{h}$.

Assumption 1 requires budget sets to be less nonconvex than preferences are convex.[10] It allows but does not limit behavior to utility maximization with convex preferences and budget sets which is a standard assumption in structural methods based on piecewise-linear budget sets (e.g., Hausman, 1985; Blomquist and Newey, 2002).

We also make a typical statistical independence assumption of $\boldsymbol{\tau}$ from $\boldsymbol{e}$ (later relaxed for panel data). Expectation functions of choice are derived below. All proofs are reported in Appendix A.

Assumption 2. Policy $\boldsymbol{\tau}$ is statistically independent.

Theorem 1. Assume the utility maximization setup in Subsection 2.1 holds, and suppose Assumptions 1 and 2 are satisfied. Then, expectation functions of choice have the structure:

$$E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = \int g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl}) p(\boldsymbol{y}_{kl}) \boldsymbol{dy}_{kl}. \tag{7}$$

The expectation integrates over $\boldsymbol{y}_{kl}$ with each term being a four-dimensional function $g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl})$. The integral itself is also four-dimensional because $g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl})$ has the same functional form across $\boldsymbol{y}_{kl} \in \boldsymbol{Y}$. As shown by Newey (1997) and Blomquist and Newey (2002), imposing additivity and equality restrictions in the estimation leads to convergence

[10] Assumption 1 is a *disjoint* assumption on the budget set and preferences. Given convex preferences, it reduces to an assumption on only the degree of possible non-convexity of the budget set.

properties that are unaffected by the number of terms in such an integral. This justifies an empirical approximation of $\boldsymbol{Y}$ by a finite number of points.

In our empirical application, household earnings are jointly taxed. In this special case, expectation functions are only three-dimensional, where we let $\tau_j = \tau(y_j)$, $c_j = c(y_j)$.

Theorem 2. Assume the utility maximization setup in Subsection 2.1 holds, and suppose Assumptions 1 and 2 are satisfied. If tax prices only depend on total household earnings, expectation functions of choice have the structure:

$$E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = \int g(\tau_j, c_j, y_j)p(y_j)dy_j. \tag{8}$$

While the choice functions in Eq. (8) are structural, (uncompensated) price and income effects are intertwined.[11] The tax price effect $dE_{\boldsymbol{e}}/d\tau_j$ depends on (τ_j, c_j) because $g(\tau_j, c_j, y_j)$ is not separable in these variables. Furthermore, c_j is a function of each τ_a at $y_a \leq y_j$ as $\partial c_j/\partial \tau_a = 1$. Therefore, $dE_{\boldsymbol{e}}/d\tau_j$ indirectly also depends tax prices other than τ_j. We demonstrate that separability of unearned income effects from tax prices is a sufficient condition for reducing the dimensionality of expectation functions to two.[12]

Assumption 3. The effect of unearned income c_0 on choice $\boldsymbol{h}$ is separable from tax prices $\boldsymbol{\tau}$.

Theorem 3. Suppose the assumptions made in Theorem 2 and Assumption 3 are satisfied. Then, expectation functions of choice have the structure:

$$E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = \int g(\tau_j, y_j)p(y_j)dy_j. \tag{9}$$

2.5 Imposing additional common restrictions

We now derive expectation functions of choice under additional restrictions that are commonly made in the literature and show that these functions incompletely characterize tax structure effects.[13] We begin with the secondary earner restriction where earnings of the primary earner are assumed to be exogenously given. While a primary earner model is used for the husband in studies that separately estimate labor supply functions for both spouses (e.g., Eissa and Hoynes, 2004), secondary earner models are commonly used for both spouses in studies that focus on either spouse (Keane, 2011).

Assumption 4. Earnings of the other spouse y^{-s} are given and statistically independent.

---

[11] With nonlinear constraints, price and income effects can be defined in multiple ways. Typically, policy parameters for linearized constraints ($\boldsymbol{\theta}^*$ in subsection 2.3) were estimated. We discuss how to define nonlinear policy price effects in the next section.

[12] Separability between price and income effects for linearized choice functions implies Assumption 3.

[13] We do not provide an exhaustive evaluation of any particular method. Existing methods typically impose different combinations of additional restrictions, estimate parameters that are not directly comparable to ours, and are often applicable to other response variables, which make the evaluation of methods challenging.

Theorem 4. Suppose the assumptions made in Theorem 3 and Assumption 4 are satisfied. For the secondary earner s, let $y_j^s = y_j - y^{-s}$. Then, expectation functions have the structure:

$$E_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}] = \int_{y_j \geq y^{-s}} g(\tau_j, y_j^s) p(y_j^s) dy_j + g[c(y^{-s})]. \tag{10}$$

The integral term in Eq. (10) is the unrestricted choice function in Eq. (9) over the domain with positive secondary earnings. It captures direct tax price effects from the secondary earner portion of the household tax structure on the own choice. The second term restricts indirect tax price effects that operate through spouse choice to affect own choice via net primary income. This suppresses direct tax price effects from the primary earner portion of the household tax structure on the own choice. Estimates of the unrestricted choice function can be used to quantify the specification bias of the restricted choice function. For expected mean hours of work, Blomquist and Newey (2002) derived a function similar to Eq. (10).[14]

In the literature, with the exception of the method by Blomquist and Newey (2002), methods for nonlinear prices limit the dimensionality of error terms; e.g., discrete choice methods abstracted from optimization and measurement errors attached to desired choice.[15] Previous methods also utilized gross wage rates and had to address the fact that these rates are observed with errors for at least some non-working individuals. We demonstrate that without optimization, measurement, and gross wage errors, cumulative distribution functions for secondary earners have a particular simple linear structure.

Assumption 5. The gross wage rate w^s is given (without error) and statistically independent.

Theorem 5. Suppose the assumptions made in Theorem 4 and Assumption 5 are satisfied. Furthermore, assume that there are no optimization errors, i.e., $\boldsymbol{\sigma} = \boldsymbol{0}$, implying $\boldsymbol{h} = \boldsymbol{h}_d$. Let $\bar{y}^s = y^{-s} + w^s \bar{h}^s$. Then, cumulative distribution functions have the structure:

$$Pr(h^s > \bar{h}^s | \boldsymbol{\tau}, y^{-s}, w^s) = g[\tau(\bar{y}^s)] + g[c(\bar{y}^s)]. \tag{11}$$

With limited error terms, the cumulative distribution function at each $\bar{h}^s$ depends directly only on the single local tax price of the linearized budget constraint $\tau(\bar{y}^s)$.[16] As an example, the probability of the husband working at least 40 hours a week $Pr(h^m \geq 40)$ only directly depends on the tax price at $y = y^f + w^m 40$. Non-local tax price effects are restricted to enter in the form of income effects through $c(\bar{y}^s)$.

Many labor supply studies primarily utilized variation in gross wage rates or their changes to identify price effects. While often providing more variation than tax structures, gross wage rates or their trends are more likely endogenous to preferences. Furthermore, although variation in gross wage rates and tax prices are comparable with linear budget

[14] Because they work with tax prices specified for entire tax brackets (segments) rather than each possible choice, their representation of nonlinear constraints requires fewer tax prices. On the other hand, they also need to specify kink points between segments. With a continuum of fixed discretized kink points, their choice function with two terms collapses to our function. Our method exhausts all equality conditions implied by theory which yields more parsimonious choice functions.

[15] Flexible preference errors in $\boldsymbol{\rho}$ have been argued to do the same job, e.g., by van Soest et al. (1995).

[16] Without these error term restrictions, the linearized local tax price at $\bar{h}^s$ is unobserved.

constraints, variation in gross wage rates also affect kink hours at which earnings tax brackets begins. Blomquist (1988) showed that labor supply functions can be upward sloping in tax price but downward sloping in gross wage rate because of counteracting kink effects. We show how to separate out price and kink effects.

Theorem 6. Suppose the assumptions made in Theorem 4 and Assumption 5 are satisfied. Make the normalization $\widehat{w}^s = w^s/E(w^s)$ and let $h_j^s = \left(y_j - y^{-s}\right)/\widehat{w}^s$. Then, expectation functions conditional on $\boldsymbol{\tau}$ and $\widehat{w}^s$ can be separated into a tax price function and a gross wage function that in turn consists of a price and a kink component according to:

$$\begin{aligned} &E_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}, \widehat{w}^s] = E_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}] \\ &+ \int_{y_j \geq y^{-s}} \left[g\left(\widehat{w}^s \tau_j, y_j^s\right) - g\left(\tau_j, y_j^s\right)\right] p\left(h_j^s\right) dy_j + \int_{y_j \geq y^{-s}} g\left(\tau_j, y_j^s\right)\left[p\left(h_j^s\right) - p\left(y_j^s\right)\right] dy_j. \end{aligned} \tag{12}$$

Tax price effects rotate nonlinear constraints keeping kink points fixed in the (c, h^s)-space. The first integral in Eq. (12) captures a comparable gross wage price effect. The second integral captures that kink hours are shifted downwards as gross wage rate increases. With progressive tax rates, higher tax rates therefore kicks in at lower hours of work, counteracting the rotational price effect. We can predict the kink effects from tax price estimates of $g\left(\tau_j, y_j^s\right)$ and correct the left-hand side prior to estimating price effects due to the variation in gross wage rates.

3. Estimation

3.1 Empirical representation of nonlinear prices

Empirically, we start from the choice functions in Eq. (9) in Theorem 3 and make the approximation $g\left(\tau_j, y_j\right) \approx \beta_{gj}\tau_j$ where $\beta_{gj} = \beta_g\left(y_j\right)$ leading to $E_{\boldsymbol{e}}[g(h)|\boldsymbol{\tau}] \approx \int \beta_{gj}\tau_j p_j dy_j$ where $p_j = p\left(y_j\right)$. We let $\beta_{gj} \approx \boldsymbol{\beta}_g \boldsymbol{y}_j^{cubic}$ with $\boldsymbol{\beta}_g = \left(\beta_{g0}, \beta_{g1}, \beta_{g2}, \beta_{g3}\right)$ and $\boldsymbol{y}_j^{cubic} = \left(1, y_j, y_j^2, y_j^3\right)$. Because $dE_{\boldsymbol{e}}/d\tau_j = \beta_{gj}p_j$, β_{gj} can be interpreted as a per-household marginal effect of the distinct earnings-specific tax price τ_j at y_j, and our specification allows heterogeneous effects across tax prices in the tax structure. We construct $\boldsymbol{\tau}$ by approximating Y by a discretized continuum with 201 points with $y_j = j *$ USD 1000. (2006 price level). We set p_j to the sample share of households observed at y_j. Therefore:

$$E_{\boldsymbol{e}}[g(h)|\boldsymbol{\tau}] \approx \boldsymbol{\beta}_g \boldsymbol{x}, \qquad \boldsymbol{x} = \left[\sum_{j=0}^{200} \tau_j y_j^n p_j\right]_{n=0,1,2,3}. \tag{13}$$

Because of these approximations, predictions of counterfactual policy effects require that marginal price effects are constant in τ_j at each y_j. While such restrictions are not uncommon, we prefer to interpret β_{gj} as a weighted average effect (of τ_j) over nonlinearities in τ_j (see Eq. (A16) for the exact expression). If there are non-separable price and income effects, our weighted average effect also goes over the distribution of interacting tax prices in $\boldsymbol{\tau}$ (Angrist and Pitchke, 2008).

In a sensitivity test, we estimate the more flexible choice functions in Eq. (8) in Theorem 2 by adding additional predictor variables to approximate $g(\tau_j, c_j, y_j)$ with a second-order polynomial. For predictions of policy effects, our preferred and more transparent cubic representation of the tax structure turns out to deliver estimates that are robust to specification errors due to functional forms.

An ultimately convenient representation of the tax structure would have only one predictor variable with estimated parameter representing a summarizing weighted average of the effects of the multiple tax prices in the tax structure. We show that among best linear approximations of expected choice functions in the mean-square-error sense, only one predictor variable consisting of a certain linear combination of tax prices can accomplish this task. This single predictor variable $\tilde{\tau}$ is the density-weighted average tax price across the tax structure.[17]

Theorem 7. Suppose the assumptions made in Theorem 3 are satisfied. For predictors with one parameter and one predictor variable that is linear in each element of $\boldsymbol{\tau}$, among best linear approximations of expected choice functions in the mean-square-error sense:

$$E_{\boldsymbol{e}}[g(h)|\boldsymbol{\tau}] \approx \tilde{\beta}_g \tilde{\tau}, \qquad \tilde{\tau} \approx \sum_{j=0}^{200} \tau_j p_j, \tag{14}$$

yields the only predictor where the parameter $\tilde{\beta}_g$ has the interpretation of a weighted average of each distinct tax price effect β_{gj} across tax prices τ_j in $\boldsymbol{\tau}$.

3.2 Policy effects

Tax policy can affect a combination of tax prices in the tax structure and Hendren (2016) defined comparable behavioral elasticities with respect to different nonlinear policies. For a tax reform, let $\dot{\boldsymbol{\tau}}$ be a vector with elements $\dot{\tau}_j$ characterizing tax price change at y_j. We construct policy effects for $\dot{\boldsymbol{\tau}}$ normalized with respect to across-the-board average tax price change. Such policy (price) effects correspond to weighted averages of tax price effects β_{gj} across the tax structure according to:

$$\beta_g(\dot{\boldsymbol{\tau}}) = \frac{\int \beta_{gj} \dot{\tau}_j p_j \, dy_j}{\int \dot{\tau}_j p_j \, dy_j}. \tag{15}$$

In the literature, Blomquist et al. (2014) and Blundell and Shephard (2012) converted their estimates into the effect of varying a uniform (e.g., linear local government) tax rate, which corresponds to setting $\dot{\boldsymbol{\tau}} = \mathbf{1}$. On the other hand, Kumar and Liang (2017) interpreted their estimates in terms of varying a proportional (e.g., consumption) tax rate, which corresponds to setting $\dot{\boldsymbol{\tau}} = \boldsymbol{\tau}$. The price effect of varying gross wage rates, i.e., the effects due to the first integral in Eq. (12) is also a proportional policy effect. We use estimates of β_{gj} to

[17] This should not be confused with the commonly used participation tax price from zero to observed earnings, which is an endogenous variable because observed earnings are endogenously determined.

construct uniform and proportional policy effects. These effects can be normalized by the sample means of labor supply and average tax price (mean $\tilde{\tau}$) to yield sample elasticities.

3.3 Identification based on tax reforms

Tax structures for earnings typically vary between groups of taxpayers depending on state of residence, demographics, income composition across different sources, and deduction choices.[18] Structural labor supply methods typically assume statistical independence of tax structures (Assumption 2). With access to larger data sets over time, there is a trend toward using more of the time series variation (e.g., Eissa and Liebman, 1996; Blundell et al., 1998; Blundell and Shephard, 2012). In the related taxable income literature (e.g., Feldstein, 1995; Gruber and Saez, 2002; Gelber, 2014; Saez et al., 2012), tax reforms and differential *changes* in tax rates across taxpayers have been utilized as quasi-experimental variation for more credible identification of causal effects.

For clarity, all theorems have been derived in a level setting. It is straightforward to modify them to derive expectation functions of choice *change* conditional on tax structure *change* to exploit the weaker identifying assumption required when panel data are available. Letting t index time, assuming statistical independence of policy change $\boldsymbol{\tau}_T - \boldsymbol{\tau}_t$ where $T = t + \dot{t}$, and approximating marginal effects by linear functions, we show for Theorem 3 that expectation functions of choice change have the same structure as before.

Assumption 6. Policy change $\boldsymbol{\tau}_T - \boldsymbol{\tau}_t$ is statistically independent.

Theorem 8. Suppose the assumptions made in Theorem 3 are satisfied but relax Assumption 2 into Assumption 6. Under the approximation $g(\tau_j, y_j) \approx \beta_{gj}\tau_j$, expectation functions of choice change have the structure:

$$E_{\boldsymbol{e}}[G(\boldsymbol{h}_T, \boldsymbol{h}_t)|\boldsymbol{\tau}_T, \boldsymbol{\tau}_t] = \int \beta_{Gj}(\tau_{jT} - \tau_{jt})p_j dy_j. \quad (16)$$

When $G(\boldsymbol{h}_T, \boldsymbol{h}_t) = g(\boldsymbol{h}_T) - g(\boldsymbol{h}_t)$, $\beta_{Gj} = \beta_{gj}$ identifies parameters of expectation functions of choice in *levels*.

Theorem 8 not only allows distributional inference of policy effects on choice *levels* using differencing techniques but also on choice *changes*. For instance, letting $G(\boldsymbol{h}_T, \boldsymbol{h}_t) = 1(h_T^f = 0, h_t^f = 40)$ yields the probability of the wife quitting a job with 40 hours of work per week within $\dot{t}$ years.

In our empirical application, we focus on two-year changes in labor supply and tax structure. Representing the tax structure by $\boldsymbol{x}$ in Eq. (13), letting i index households in our panel with multiple base years, we estimate the following specification with least squares:

$$G(\boldsymbol{h}_{i,t+2}, \boldsymbol{h}_{it}) = \boldsymbol{\beta}_G \Delta_{it}\boldsymbol{x} + \boldsymbol{\gamma}\boldsymbol{z}_{it} + \mu_t + \varepsilon_{it}, \quad (17)$$

where $\boldsymbol{z}_{it}$ is a vector of demographic covariates, μ_t is time-fixed trends, and ε_{it} is a trend disturbance term.

[18] Even universal components of a tax system typically interact with group-specific programs.

In the taxable income literature, the removal of unit-fixed effects with first-differencing is combined with linearized budget constraints at observed levels of earnings, which are endogenously determined.[19] In contrast, we fully account for nonlinear constraints by entering all tax prices determining the tax structure in our regressors.

If tax structure changes are correlated with heterogeneous labor supply *trends* that are endogenous to preferences or their changes, identification would still be threatened. We include covariates to address remaining endogeneity. We use dummy variables to control for number of children, state of residence, and the age and education levels of each spouse. To account for trends correlated with base-year hours of work, possibly due to mean reversion which has received considerable attention in the taxable income literature, we also include base-year hours of work of each spouse as control variables.

4. Data

4.1 Data

We use data from the Panel Study of Income Dynamics (PSID) from 1980 to 2006, which are available for each year from 1980 to 1996 and for each second year from 1996 to 2006. We create two-year changes with base years from 20 years between 1980 and 2004. The PSID contains some demographic background variables and using group-level dummy variables, we control for number of children (3 groups), state of residence (50 groups), and the age (8 groups) and education levels (4 groups) of each spouse. We limit the sample to married joint filing households where both spouses were between 21 and 60 years old – in total, 46,167 observations without missing values.

We use NBER-TAXSIM to construct the tax structure of each household conditional on observed variables. Income from sources other than household earnings such as capital income is considered to be exogenously given and is held at the observed levels. Capital gains, however, are not observed and are set to zero. All components of the tax and transfer system that are included in NBER-TAXSIM and for which we have the relevant input variables are accounted for in the constructed tax structures. This includes, among other items, payroll taxes and tax credits. However, consumption taxes are not adjusted for.

4.2 Sample statistics

In Table 1 we report means and standard deviations for a number of variables of weekly hours, tax prices, and demographic characteristics. To get a better sense of magnitudes, we report sample statistics for the variables in both two-year changes and levels, when applicable and relevant. On average, households had 1.419 children, husbands were 38.56 years old and had 13.01 years of education, and wives were 36.36 years old and had 12.93 years of education. Mean weekly hours were 41.20 for husbands and 24.70 for wives. For convenience, we will sometimes sloppily refer to the four intervals of weekly hours: 0-15, 15-30, 30-45, and >45, as non-work, part-time, full-time, and overtime work, respectively. For each of the spouses, full-time work was the most common. Compared to husbands, wives

[19] Kumar and Liang (2017) discussed the issue of only entering tax prices at observed levels of earnings in depth.

more frequently worked part-time or less. Mean annual earnings were USD 67,788 for households, with USD 47,929 for husbands and USD 19,858 for wives. Mean average tax price as defined in Eq. (14) was 0.726 with mean tax prices of 1.053 at zero earnings to 0.605 at USD 200,000.

Table 1. Sample statistics

	Two-year change		Level	
	Mean	Std. dev.	Mean	Std. dev.
Weekly hours household	0.223	19.60	65.91	22.70
Weekly hours husband	-0.241	13.43	41.20	14.40
Weekly hours wife	0.464	13.96	24.70	17.09
Weekly hours husband 0-15	0.011	0.239	0.058	0.234
Weekly hours husband 15-30	-0.003	0.311	0.065	0.246
Weekly hours husband 30-45	-0.014	0.545	0.537	0.499
Weekly hours husband >45	0.006	0.487	0.340	0.474
Weekly hours wife 0-15	-0.010	0.418	0.320	0.467
Weekly hours wife 15-30	0.000	0.467	0.184	0.388
Weekly hours wife 30-45	0.005	0.496	0.428	0.495
Weekly hours wife >45	0.006	0.292	0.067	0.251
Annual earnings household	2,473	27,629	67,788	40,642
Annual earnings husband	1,382	24,502	47,929	33,425
Annual earnings wife	1,091	12,473	19,858	19,858
Average tax price	0.000	0.044	0.726	0.043
Tax price at earnings = 0	0.016	0.098	1.053	0.128
Tax price at earnings = 20,000	-0.016	0.096	0.805	0.087
Tax price at earnings = 40,000	0.002	0.072	0.752	0.067
Tax price at earnings = 60,000	0.001	0.048	0.730	0.044
Tax price at earnings = 80,000	-0.001	0.064	0.694	0.059
Tax price at earnings = 100,000	0.004	0.068	0.664	0.061
Tax price at earnings = 120,000	0.007	0.054	0.662	0.055
Tax price at earnings = 140,000	0.004	0.052	0.652	0.049
Tax price at earnings = 160,000	0.008	0.056	0.635	0.056
Tax price at earnings = 180,000	0.010	0.058	0.620	0.060
Tax price at earnings = 200,000	0.012	0.058	0.605	0.063
Number of children			1.419	1.221
Age husband			38.56	9.119
Age wife			36.36	8.785
Education husband			13.01	2.392
Education wife			12.93	2.133

Notes: We report annual earnings in USD (2006 price level).

In terms of two-year changes, on average, weekly hours decreased by 0.241 for husbands and increased by 0.464 for wives. Over the 26 years in the sample period, this corresponds to a decrease of 3.133 hours per week for husbands and an increase of 6.032 hours per week for wives. Mostly, this pattern is due to fewer full-time working husbands (-0.014 each second year) and non-working wives (-0.010 each second year). During the same period, the average tax price did not change much. Across the earnings distribution, the zero earnings tax price increased the most – by 0.016. The standard deviation is 0.044 for change in average tax price and from 0.048 to 0.098 for changes in earnings-specific tax prices. This is the variation we exploit for identifying policy effects.

To explore the entire distribution of weekly hours, in Figure B1 in Appendix B, we plot kernel fits to histograms on the distributions of weekly hours. For two-year changes, in Figure B2 in Appendix B, we plot kernel fits to histograms on the distribution of *changes* in weekly hours. The graphs in Figure B2 are bell-shaped and centered around zero. Smaller changes were therefore more common than larger ones for both spouses. The figure also shows that on average, two-year changes in weekly hours were somewhat larger in magnitude for husbands than for wives.

In Table B1 in Appendix B, we instead explore the joint household distribution by subsets of joint weekly hours. The table shows that every fourth household (0.248) had two full-time working spouses. Other common combinations were households with husbands that worked at least full-time and wives that worked full-time or less.

The sample period spans a number larger reforms to the tax and transfer system including Economic Recovery Tax Act of 1981, Tax Reform Act of 1986, Omnibus Budget Reconciliation Act of 1990, Omnibus Budget Reconciliation Act of 1993, Economic Growth and Tax Relief Reconciliation Act of 2001, and Jobs and Growth Tax Relief Reconciliation Act of 2003. See Kumar and Liang (2016) for a description of these reforms. In Figure 1, we plot two-year changes in mean weekly hours and average tax price across base years. Except for changes 1982 to 1984 (base year in 1982), the correlation between the graphs over time seems low. In Figure B3 in Appendix B, we plot changes in tax prices at different levels of household earnings across base years.

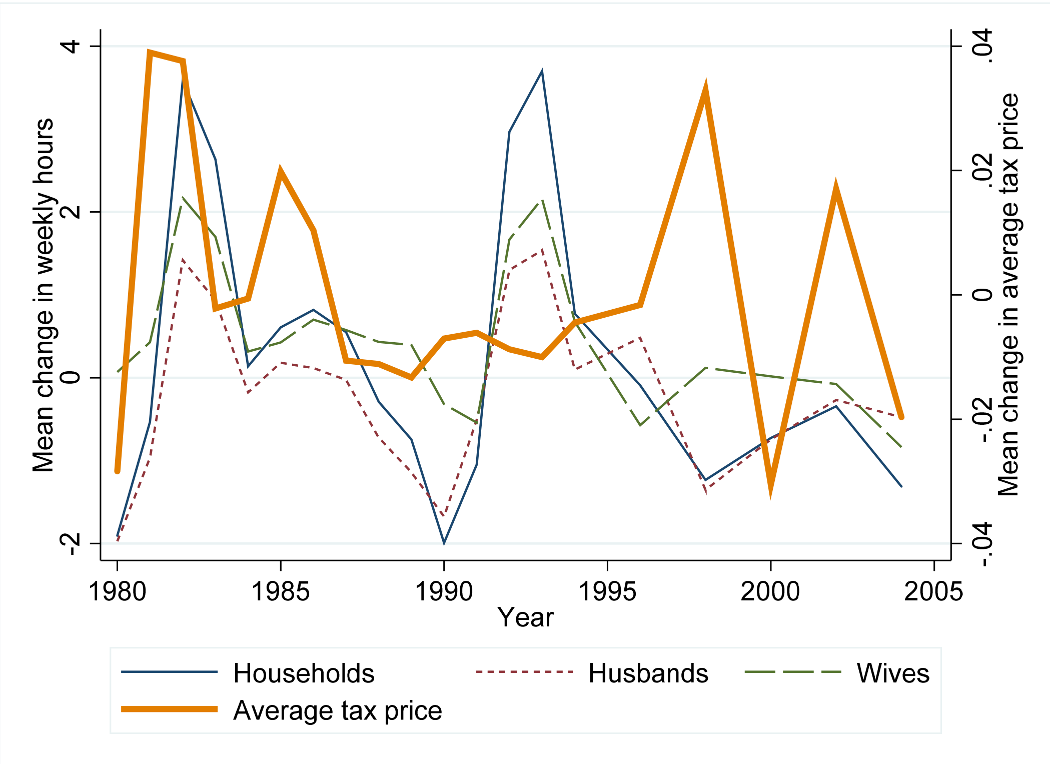


Figure 1. Changes in weekly hours and average tax price across base years

4. Empirical results

4.1 Policy effects

In Table 2, we report estimates of weekly hours using the (density-weighted) average tax price variable $\sum_j \tau_j p_j$ in Eq. (14) to represent the tax structure. We use level specifications in the first section and the two-year first-difference specifications in Eq. (17) in the second section. Across the columns, we subsequently include year dummies, and then dummies for number of children and the age and education levels of each spouse. In the difference specifications, we also add base-year weekly hours of each spouse as covariates.

Table 2. Average tax price effects on weekly hours

	(1)	(2)	(3)	(4)
		Level		
Households	61.47	95.75	110.0	
	(4.53)	(4.93)	(5.0)	
Husbands	47.40	59.61	59.44	
	(2.92)	(3.34)	(3.44)	
Wives	14.07	36.14	50.51	
	(3.38)	(3.66)	(3.51)	
		Two-year difference		
Households	34.51	37.57	37.57	36.58
	(2.61)	(2.98)	(2.98)	(2.58)
Husbands	19.39	21.48	20.73	21.73
	(1.80)	(2.10)	(2.10)	(1.80)
Wives	15.12	16.09	16.84	14.86
	(1.69)	(1.92)	(1.93)	(1.70)
Years	No	Yes	Yes	Yes
Demographics	No	No	Yes	Yes
Base-year weekly hours	No	No	No	Yes

Notes: (Change in) weekly hours are dependent variables. (Change in) average tax price are regressors. Each cell reports an estimate from one regression. Demographic covariates in levels include fixed effects for number of children (3 groups), state of residence (50 groups), and the age (8 groups) and education levels (4 groups) of each spouse. Each regression contains 46,167 observations. Individual-level clustered standard errors are reported within parentheses.

The level estimates vary considerably as covariates are added. After controlling for time and demographics in column (3), we find average tax price effects of 110.0 hours per week for the household as a whole, with equal contribution from each spouse. This effect corresponds to 1.1 weekly hours per percentage-point of across-the-board tax price change. The difference estimates are, on the other hand, fairly stable across columns. After controlling for all covariate trends, we obtain estimates of 36.58 for households, 21.73 for husbands, and 14.86 for wives, which are approximately one-third of the level estimates.

In Table 3, we report estimates of weekly hours transformed to uniform and proportional policy (tax price) elasticities according to Eq. (15). In column (1), we convert the average tax price estimates from the differenced specification with all covariates (in column (4) of Table 2). In column (2), we instead use our main cubic vector representation of the tax structure with four tax price predictor variables in Eq. (13), which allows heterogeneous effects for each distinct earnings-specific tax price. In column (3), as a sensitivity test, we estimate the flexible choice functions in Eq. (8) that allow non-separable price and income effects. The non-transformed cubic and flexible estimates are reported in Tables B2 and B3 in Appendix B.

Table 3. Policy elasticities of weekly hours

		(1) Average tax price	(2) Cubic	(3) Flexible
Uniform elasticity	Households	0.403	0.540	0.504
		(0.028)	(0.030)	(0.050)
	Husbands	0.383	0.517	0.517
		(0.032)	(0.034)	(0.058)
	Wives	0.437	0.577	0.482
		(0.050)	(0.053)	(0.084)
Proportional elasticity	Households	0.403	0.600	0.580
		(0.028)	(0.033)	(0.045)
	Husbands	0.383	0.582	0.607
		(0.032)	(0.038)	(0.052)
	Wives	0.437	0.629	0.535
		(0.050)	(0.059)	(0.076)

Notes: Change in weekly hours is the dependent variable. Different regressors are used across columns to represent the tax structure change. The tax structure is approximated by $\sum_j \tau_j p_j$ in column (1); additionally $\sum_j \tau_j y_j p_j$, $\sum_j \tau_j y_j^2 p_j$, and $\sum_j \tau_j y_j^3 p_j$ in column (2); and additionally $\sum_j c_j p_j$, $\sum_j \tau_j c_j p_j$, $\sum_j c_j y_j p_j$, $\sum_j \tau_j^2 p_j$ and $\sum_j c_j^2 p_j$ in column (3). Each cell reports an estimate from one regression including fixed effects for number of children, state of residence, and the age and education levels, and base-year weekly hours of each spouse. Elasticities are constructed by normalizing policy effects by sample means of weekly hours and average tax price. Individual-level clustered standard errors are reported within parentheses.

In terms of policy elasticities, average tax price estimates imply (identical) uniform and proportional elasticities of 0.403 for households, 0.383 for husbands, and 0.437 for wives. Our main cubic estimates yield higher elasticities: at the household level, 0.540 for uniform and 0.600 for proportional across-the-board tax price changes and similar values for each spouse. These estimates are robust to relaxing functional form assumptions as estimated elasticities based on the flexible representation of the tax structure are similar.

Previously, the estimated uncompensated elasticities of husbands were often low (Keane, 2011).[20] For instance, Ziliak and Kniesner (1999) and Kumar (2007) also used PSID and found net wage elasticities in the region of 0.10 to 0.15. For wives, Keane reported a wider spread of estimates. Using PSID, Kumar (2012) and Kumar and Liang (2016) estimated net wage elasticities between 0.4 and 0.8. The overall pattern of our estimates challenges the conventional belief that wives are more responsive to tax changes than husbands.

In Figure 2, we proceed to report the estimates from distributional regressions using the single average tax price to represent the tax structure. We use thirteen mutually exclusive and jointly exhaustive intervals across the distribution of weekly hours for each spouse. The figure shows that tax cuts increase the probability of working at least 40 hours per week for

[20] In comparing elasticity estimates across studies, it is important but difficult to account for the fact that different methods estimate parameters that are not directly comparable with each other. Preference estimates were typically converted to policy elasticities comparable to our estimates. On the other hand, labor supply estimates were typically expressed with respect to linearized budget constraints (see Subsection 2.3). Such linearized elasticities imply considerably lower policy elasticities because taxpayers that switch tax brackets due to tax changes face counteracting tax effects (Blomquist and Simula, 2016; Kumar and Liang, 2017).

husbands and at least 30 hours per week for wives. Tax effects on positive weekly hours (5 or more) are equally strong for the two spouses, but tax effects on overtime work (45 hours or more) are stronger for husbands. Our estimates cast doubt on the often-expressed belief that work participation responses are stronger for wives (e.g., Eissa, 1995; 1996).[21]

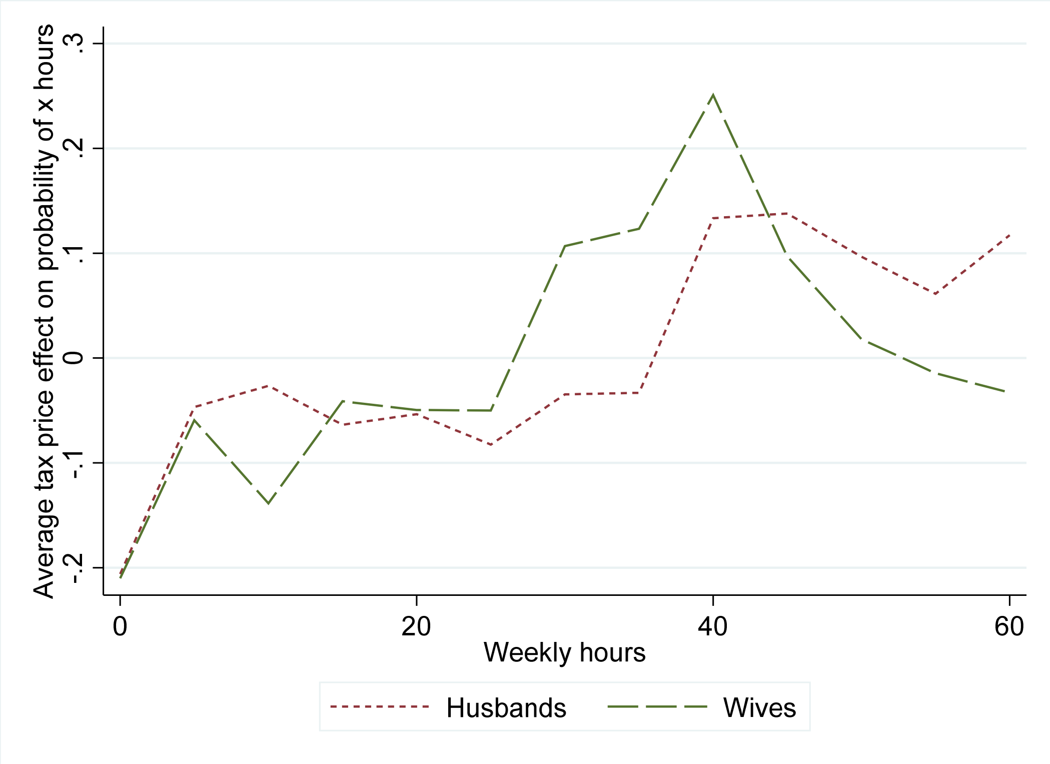


Figure 2. Average tax price effects on the distribution of weekly hours

Notes: Changes in interval indicators of weekly hours are dependent variables. Change in average tax price is the regressor. Each point represents an estimate from one regression including control variables. The first interval spans 0-2.5 hours, the subsequent 11 intervals each span 5 hours, and the last residual interval represents >57.5 hours.

4.2 Earnings-specific tax price effects

We now explore the heterogeneity of distinct earnings-specific tax price effects on weekly hours using the cubic representation of the tax structure in Eq. (13). In Figure 3, we plot the effects of tax prices across the distribution of household earnings. Tax cuts at low levels of earnings (< USD 15,000 per year) have positive effects on husbands. Tax cuts at mid-levels of earnings (USD 15,000-100,000 per year) have positive effects on both spouses. The per-percentage-point tax price effect on weekly hours of each spouse is largest for tax changes at annual household earnings of USD 50,000, which is slightly below the mean of USD 68,000. Tax cuts at high levels of earnings (> USD 100,000) have negative effects on both spouses.

[21] There are limited comparable previous distributional results as distributional inference rarely went beyond sorting out extensive and intensive margin effects.

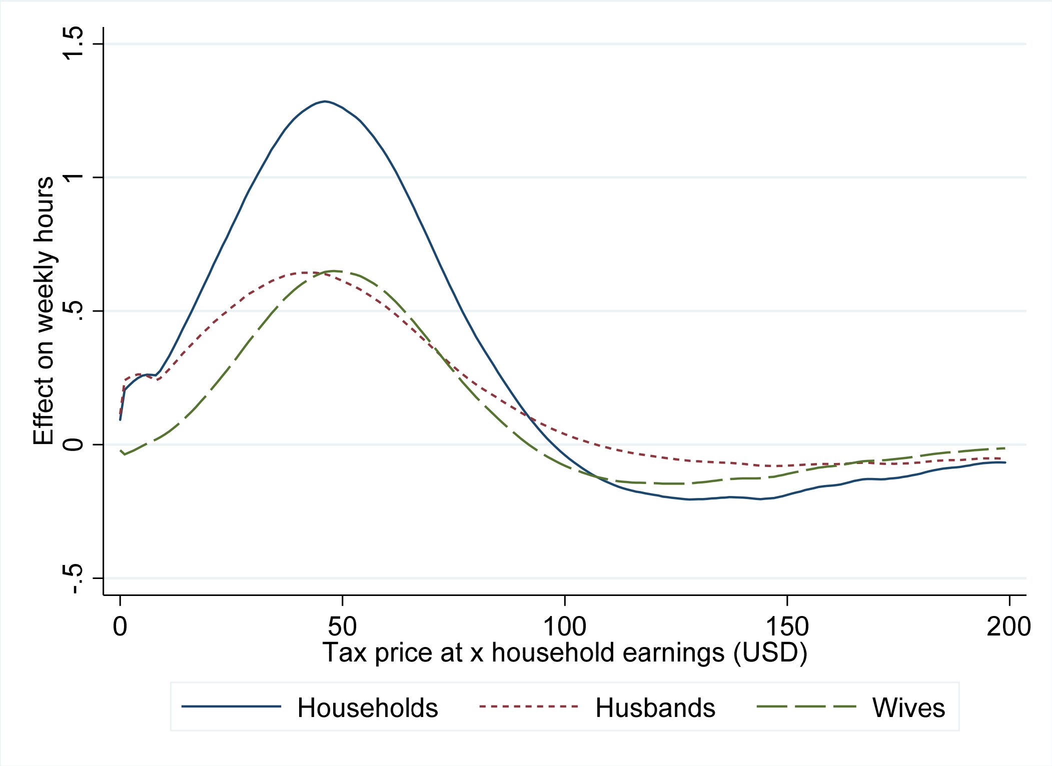


Figure 3. Earnings-specific tax price effects on weekly hours

Notes: Change in weekly hours is the dependent variable. Changes in (up to) cubic tax price terms are regressors. Each curve is predicted using estimates from one regression including control variables.

In Figure 4, we plot effects of earnings-specific tax prices on probabilities of non-work, part-time, full-time, and overtime work. Providing similar information in Figure B4 in Appendix B, we plot the effects of tax prices at only 5 different levels of earnings (USD 0, 40,000, 80,000, 120,000, and 160,000) but on probabilities of 13 intervals of weekly hours. Tax cuts at low levels of earnings increase the probability of husbands working full-time at the expense of non-work. At the same time, the probability of wives not working increases at the expense of part-time work. This pattern reflects the negative income effect inflicted on the wives as the husbands work more. Tax cuts at mid-levels of earnings increase the probability of husbands working overtime. For wives, the probability of full-time work increases at the expense of non-work. Tax cuts at high levels of earnings (> USD 100,000) increase the probability of husbands working full-time at the expense of overtime work and increase the probability of wives not working. These effects can be rationalized only by negative income effects on both spouses.

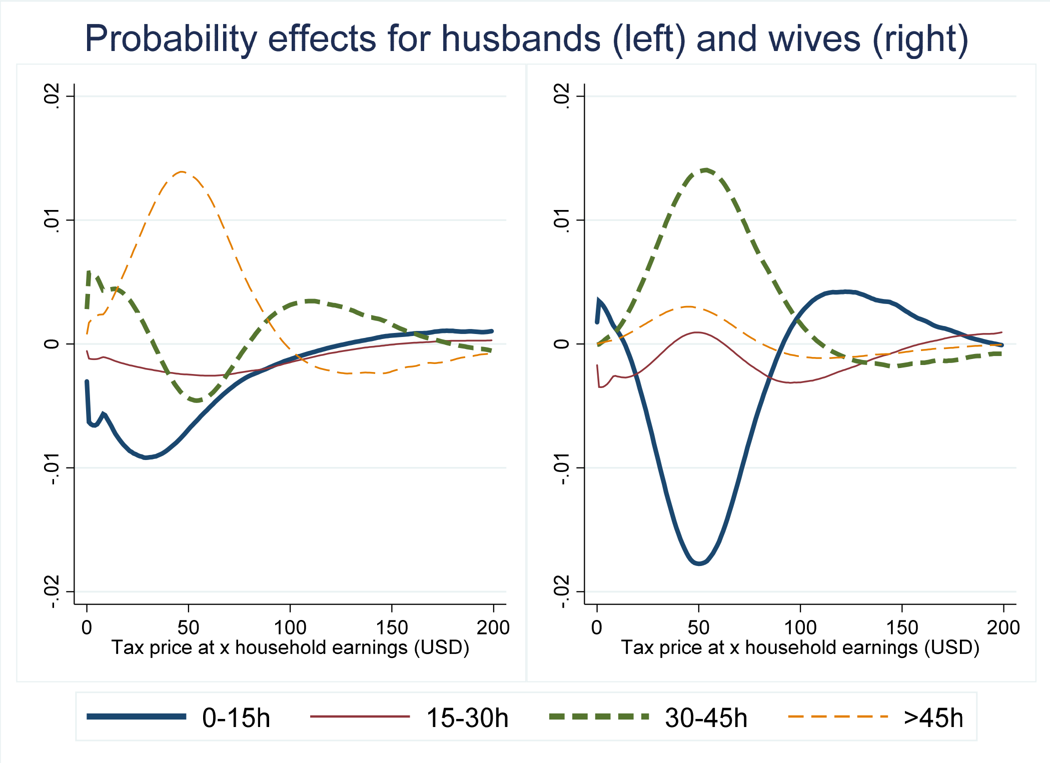


Figure 4. Earnings-specific tax price effects on the distribution of weekly hours

Notes: Changes in interval indicators of weekly hours are dependent variables. Changes in (up to) cubic tax price terms are regressors. Each curve is predicted using estimates from one regression including control variables.

4.3 Effects on the joint distribution and on transitions

In Table 4, we report average tax price effects on the joint household distribution of weekly hours. Tax cuts primarily increase the share of households with husbands working at least full-time and wives working full-time. An average tax price reduction increases the probability of these two subsets by 0.263 and 0.376. The two subsets with the highest reduced probabilities are households with non-working wives where husbands are either non-working or full-time working, with decreases of 0.140 and 0.220, respectively.

Table 4. Average tax price effects on the joint distribution of weekly hours

		Weekly hours of wives				
		0-15	15-30	30-45	>45	Total
Weekly hours of husbands	0-15	-0.140	-0.070	-0.082	-0.015	-0.307
	15-30	-0.058	-0.025	-0.067	-0.028	-0.177
	30-45	-0.220	0.060	0.263	0.016	0.120
	>45	-0.003	-0.056	0.376	0.047	0.364
	Total	-0.420	-0.090	0.491	0.020	

Notes: Changes in subset indicators of joint weekly hours are dependent variables. Change in average tax price is the regressor. Each cell reports an estimate from one regression including control variables.

In Figure 5, we report average tax price effects on the distribution of *changes* in weekly hours. Tax cuts increase labor supply by diminishing reductions of working hours and by enhancing extensions of working hours. Because tax cuts increase the probability of non-transition, the reduction margin is more important than the extension margin. In particular, for two-year changes of 40 hours per week corresponding to a full-time job, the effect on preventing reductions is twice the effect on encouraging extensions.

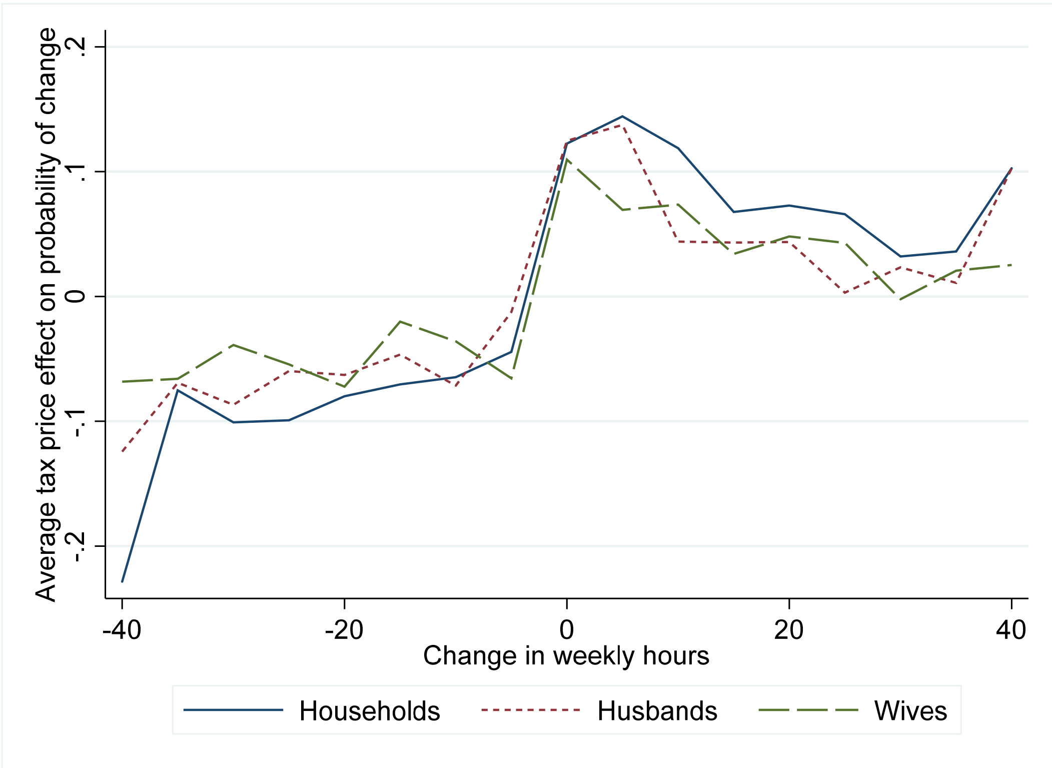


Figure 5. Average tax price effects on the distribution of changes in weekly hours

Notes: Interval indicators of change in weekly hours are dependent variables. Change in average tax price is the regressor. Each point represents an estimate from one regression including control variables.

Our method allows a deeper investigation of transition effects to further explore the mechanisms of behavioral response. We divide the joint distribution into 16 subsets and estimate average tax price effects on probabilities of two-year transitions between each of the subsets. These estimates are reported in Table B4 in Appendix B. In Table 5, we summarize the main features by schematically plotting all average tax price effects larger than 3.

Table 5. Summary of tax effects on transitions between subsets of joint weekly hours

		Weekly hours of wives			
		0-15	15-30	30-45	>45
Weekly hours of husbands	0-15				
	15-30				
	30-45	Less		More	
	>45	More		More	

Notes: This figure summarizes the main features of the estimates in Table B4 in Appendix B. Each regression uses an indicator of transition between subsets of joint weekly hours as the dependent variable, change in average tax price as the regressor, and includes control variables. Thick solid arrows and "More" are used to indicate enhanced transitions (and non-transitions). Dashed thin arrows and "Less" are used to indicate diminished transitions.

Table 5 shows that tax policy primarily affects transitions involving adjustments of weekly hours for just one spouse. Tax cuts enhance positive transitions primarily by extending working hours from full-time to overtime for husbands (with non-working or full-time working wives), and from part-time to full-time for wives (with full-time or overtime working husbands). Tax cuts diminish negative transition primarily by limiting job exits to non-work for either spouse. The job exit margin, often involving exits from full-time work, is therefore more important than the job entry margin. Tax cuts also enhance non-transitions for households with full-time working wives and at least full-time working husbands, and households with non-working wives and overtime working husbands.

4.4 Imposing additional common restrictions

We now explore estimates based on the imposition of additional restrictions that are frequently made in the literature. In Table 6, we begin with the secondary earner restriction leading to the choice functions in Eq. (10). The average tax price on the secondary earner portion of the household tax structure is used to capture direct tax price effects. Net primary income is included as in much of the literature. We also use the estimates to construct policy elasticities comparable to the unrestricted elasticities in Table 2.

Table 6. Secondary earner average tax price effects on weekly hours

	(1)	(2)	(3)	(4)
	Husbands		Wives	
	Level	Difference	Level	Difference
Secondary average tax price	55.60	19.89	35.67	9.540
	(3.33)	(1.75)	(3.10)	(1.516)
Net primary income	0.0365	0.00715	-0.0435	-0.0197
	(0.0090)	(0.00658)	(0.0073)	(0.0047)
Uniform elasticity	0.992	0.353	0.987	0.253
	(0.060)	(0.032)	(0.095)	(0.047)
Proportional elasticity	0.987	0.351	0.957	0.243
	(0.060)	(0.031)	(0.094)	(0.047)

Notes: (Change in) weekly hours are dependent variables, and (change in) the tax structure are regressors. The secondary earner average tax price is $\sum_j \tau_j p_j^s 1(y_j \geq y^{-s})$. All regressions include control variables. Individual-level clustered standard errors are reported within parentheses. Net primary income is measured in USD 10,000 (2006 price level).

Estimates of secondary average tax price effects on weekly hours in the difference specifications are around a third of the estimates in the level specifications, which is a pattern similar to the unrestricted estimates. We also find small effects of net primary income. The implied uniform and proportional elasticities are similar to each other. The uniform elasticity of 0.353 for husbands is 92 percent of the corresponding unrestricted elasticity (0.383 in Table 3). On the other hand, for wives, the uniform elasticity of 0.253 is only 58 percent of the corresponding unrestricted elasticity (0.437 in Table 3). Although wives are more often conceptually believed to be secondary earners, it is estimation-wise less suitable to treat them as such. The reason is that husbands earn on average more than wives; a larger primary earner portion of the tax structure is therefore incompletely characterized for secondary earner wives compared to husbands.

Imposing limited unobserved heterogeneity without optimization and measurement errors in weekly hours and prediction errors in gross wage rates, we derived (cumulative) distribution functions for secondary earners in Eq. (11) that only directly depend on local tax prices. In Figure 6, we plot the implied uniform policy effect on the distribution of weekly hours for comparability with Figure 2. The pattern of effects across the distribution of weekly hours is similar in the two figures. However, the overall magnitude of the tax effects is much smaller in Figure 6 and implies uniform policy elasticities of total weekly hours of 0.077 for husbands and 0.119 for wives. These elasticities are only 22 and 47 percent, respectively, of the elasticities with unlimited heterogeneity (0.353 for husbands and 0.253 for wives in Table 6). Thus, policy effects are grossly understated when the tax structure is represented by only the local tax price of the linearized tax structure. This illustrates the potential pitfalls of low-dimensional heterogeneity, distributional assumptions, predicted gross wage rates, and linearized budget constraints.

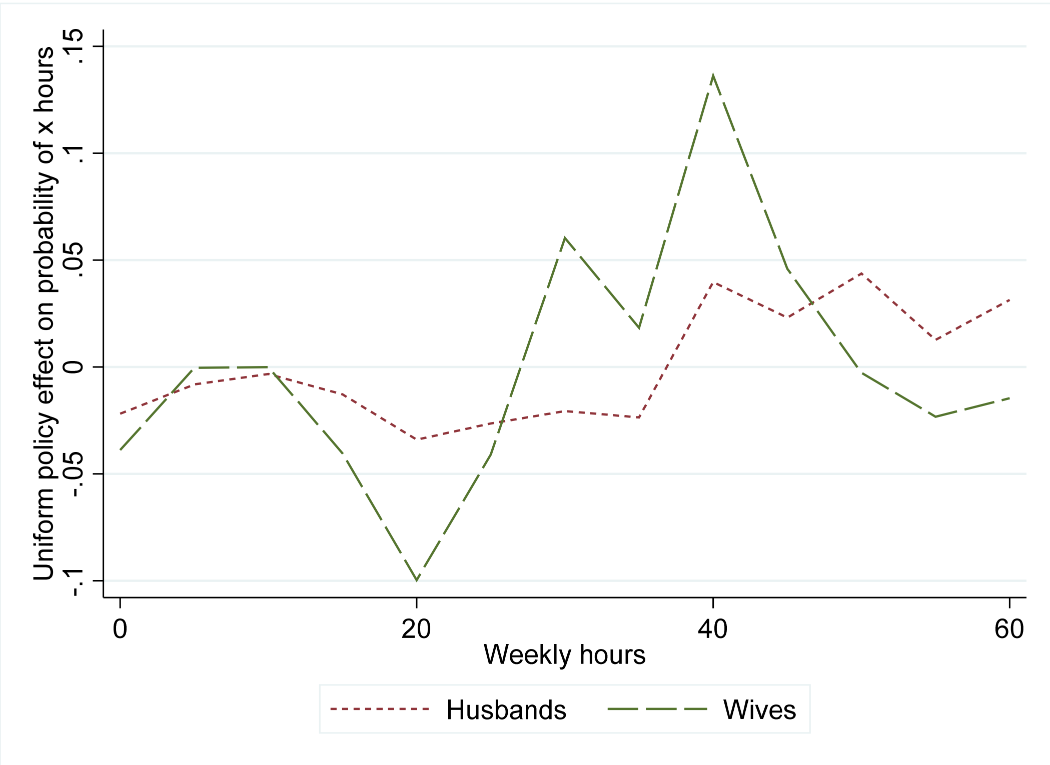


Figure 6. Limited heterogeneity uniform policy effects on the distribution of weekly hours

Notes: Changes in interval indicators of weekly hours are dependent variables. Changes in local tax prices $\tau(\bar{y}^s)$ and net income $c(\bar{y}^s)$ across different $\bar{y}^s = y^{-s} + w^s\bar{h}^s$ are regressors. Log gross wage rate $\ln w^s$ is predicted using a traditional Heckman-type selection-corrected specification (see Notes for Table 7). Each point represents an estimate from one regression.

In Table 7, we report the effects of predicted log gross wage rates on weekly hours. Using predicted wage rates is a standard approach to handle missing wage rates for non-workers (Van Soest, 1995). We use a two-step Heckman-type selection-corrected prediction similar to Heim (2007). We have tried alternative prediction procedures with similar results. In Eq. (12), we showed that to identify price effects with variation in predicted gross wage rates we need to correct for gross wage effects on kink points of weekly hours at which different tax brackets begin, which we do in the second section of rows in Table 7. Log gross wage effects are comparable to proportional policy tax price effects, and we also construct implied proportional elasticities.

Table 7. Effects of predicted log gross wage rate on weekly hours

		(1)	(2)	(3)	(4)
		Husbands		Wives	
		Level	Difference	Level	Difference
Basic	Log gross wage effect	7.890	2.019	8.723	3.838
		(0.813)	(1.096)	(1.228)	(1.555)
	Proportional elasticity	0.192	0.049	0.353	0.155
		(0.020)	(0.027)	(0.050)	(0.063)
Kink-corrected	Log gross wage effect	10.52	3.113	9.577	4.109
		(0.820)	(1.099)	(1.227)	(1.558)
	Proportional elasticity	0.256	0.076	0.388	0.166
		(0.020)	(0.027)	(0.050)	(0.063)

Notes: The dependent variable is (change in) weekly hours in the Basic section and (change in) weekly hours minus $\widehat{\boldsymbol{\beta}} \sum \tau_j \left[p\left(h_j^s\right) - p\left(y_j^s\right)\right] 1\left(y_j \geq y^{-s}\right)$ with $\widehat{\boldsymbol{\beta}}$ from Table 6 in the Kink-corrected section (see Eq. (12) for additional details). (Change in) log gross wage rate, predicted using a traditional Heckman-type selection-corrected specification, is the regressor. The wage equation includes dummy covariates for year, state of residence, and own age and education levels. The selection equation additionally includes dummy covariates for number of children, and spouse age and education levels. All regressions include control variables with own education level excluded in the level specifications to identify wage effects. Individual-level clustered standard errors are reported within parentheses.

The corrected effects are somewhat higher than the uncorrected ones, which is consistent with the theoretical prediction that kink effects are negative when price effects are positive. The corrected proportional policy elasticities are 0.076 for husbands and 0.166 for wives. These estimates are 22 and 67 percent respectively of the comparable elasticities identified by variation in tax price changes (0.351 for husbands and 0.246 for wives in Table 6). Trade and technological changes leading to heterogeneous trends in both gross wage rates and working hours are possible sources of endogeneity behind these underestimated price effects.

4.5 Effects over time

In Figure 7, we plot observed and predicted sample mean two-year changes in weekly hours across base years. The predictions are based on the cubic estimates in Table B2 in Appendix B. With the exception of the extensive tax reductions between 1982 and 1984 that lead to increased observed and predicted weekly hours, the two graphs in each figure do not follow each other. Specifically, tax reform effects cannot explain the clearest trend during the sample period which is the strong rise in female working hours. In Figures B5 and B6 in Appendix B, we plot the observed and predicted distributional effects across base years. The overall picture is that tax policy can explain very little of the aggregate pattern over time despite sizable policy elasticities.

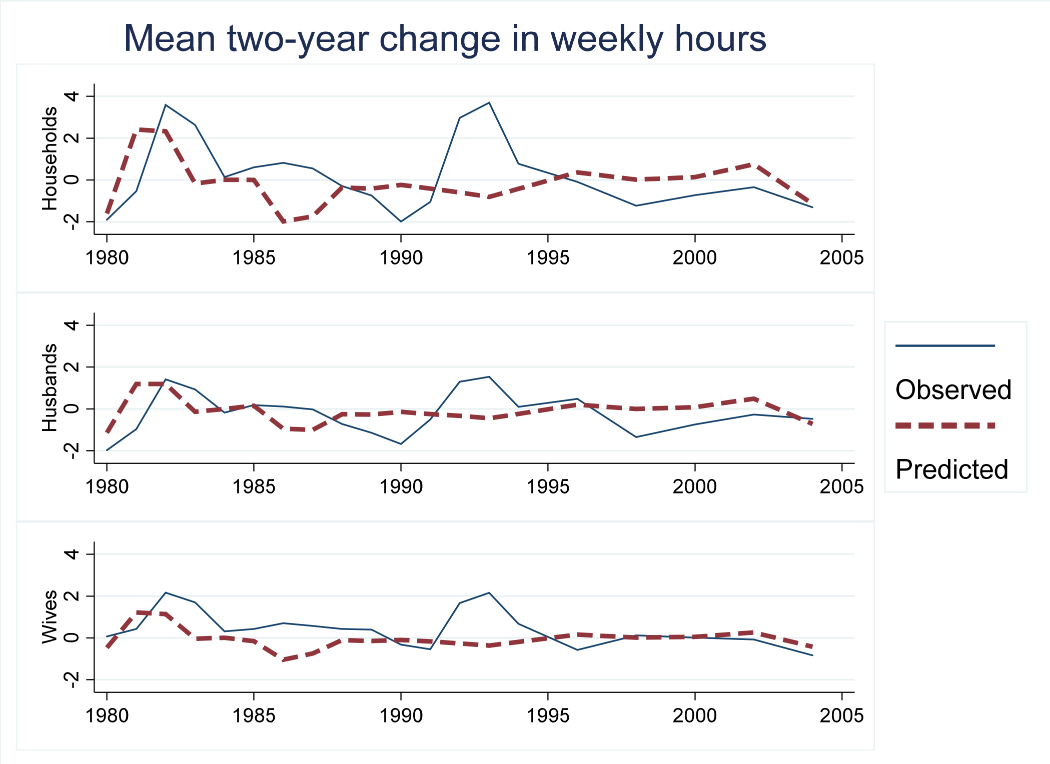


Figure 7. Observed and predicted two-year changes in weekly hours
Notes: The predictions are based on the cubic estimates in Table B2 in Appendix B.

For our sample period, several papers in the literature documented a decline in price effects on weekly hours for wives identified primarily by variation in (predicted) gross wage rates or their trends (e.g., Goldin, 1990; Juhn and Murphy, 1997; Blau and Kahn 2007; Heim 2007). In Figure 8, we plot predicted tax price and gross wage effects across base years estimated using changes in either tax structures or gross wage rates as regressors. We use the cubic representation of the tax structure or predicted log gross wage rate and crudely interact the regressors with a quadratic in base year. For wives, the uniform policy tax price effect falls only from the mid-1990s. However, gross wage effects reveal a clear and substantial decline during the entire sample period but, as discussed in connection to Table 6, we find such estimates unreliable estimates of price effects. If anything, the declining trend is clearer for husbands with monotonously declining tax price and gross wage effects.

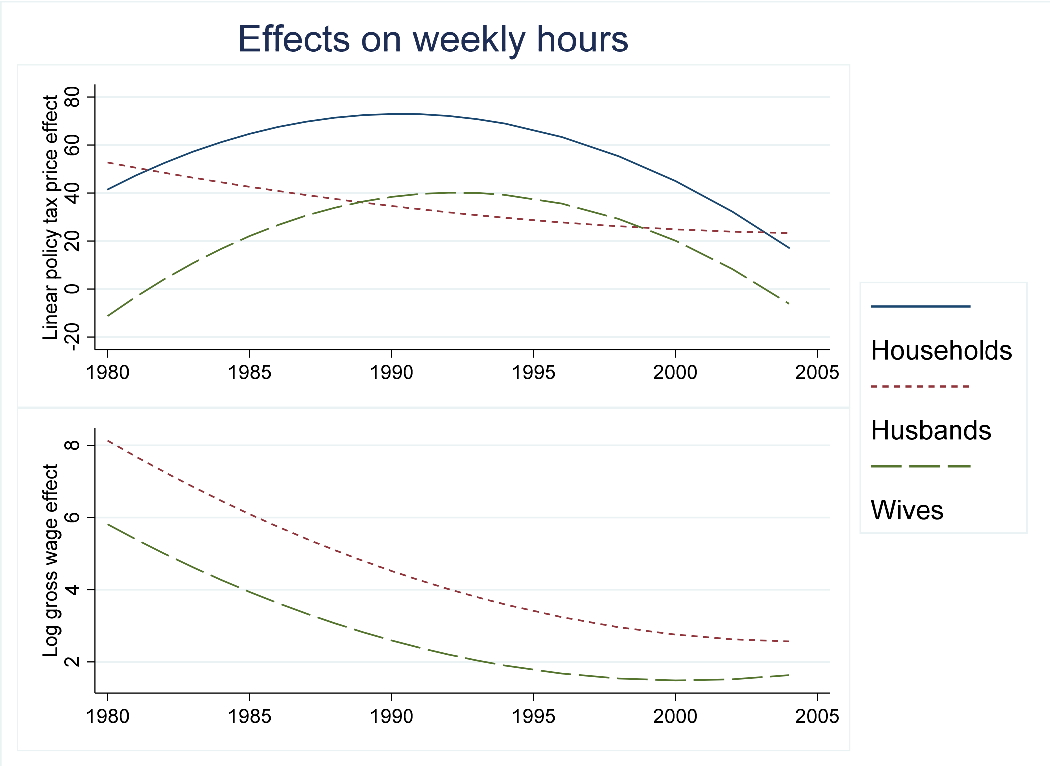


Figure 8. Tax price and gross wage effects on weekly hours

Notes: The predictions are based on regressions of change in weekly hours on the cubic regressors in Table B2 in Appendix B or gross wage rate predicted as in Table 7, and all regressors are interacted with a quadratic in base year and include control variables.

5. Conclusion

We developed a method for estimating the distributional effects of nonlinear prices on multidimensional choice. We departed from a general household model of labor supply that nests secondary earner, unitary, and collective models. We then derived conditional expectation functions of choice that may depend on each of the distinct tax prices at different combinations of spouse labor supply. Under a key assumption that is weaker than utility maximization with convex budget sets, we reduced the dimensionality of the distributional functions to four and in the special case with joint taxation of household earnings to three.

In our preferred method, we estimated two-dimensional distribution functions and our estimates can either be interpreted as weighted average tax price effects or given structural interpretation under the assumption of separable income effects. Our estimates were, however, insensitive to this functional form assumption. In fact, even a simple representation of the nonlinear tax structure using a single predictor variable consisting of the density-weighted average tax price yielded similar policy elasticities for uniform and proportional tax reforms. In addition to distribution-free estimation, our choice functions can easily be first-differenced to base identification on variation in tax structure changes, and we can estimate the distribution of transitions.

In our empirical application on U.S. panel data from 1980 to 2006, we found total hours-of-work elasticities of approximately 0.5 for households as well as for husbands and wives separately. General across-the-board tax cuts increase the probability of working at least 40 hours per week for husbands and at least 30 hours per week for wives. For the finer details of the configuration of the tax structure, we found intricate distributional effects of distinct tax prices. Most notably, the per-percentage-point tax-price effect on weekly hours of each spouse is largest for tax changes at household earnings around USD 50,000, which is somewhat below the mean level.

In terms of the joint distribution of weekly hours, we found that tax cuts primarily increase the share of households with husbands working at least full-time and wives working full-time. Our results also showed that tax cuts diminish reductions of working hours and enhance non-transitions more than they enhance extensions of working hours. The job exit margin is more important than the job entry margin. Although labor supply is fairly responsive to tax changes, tax reforms can explain only a small part of the aggregate variation over time, e.g., the strong rise in the labor supply of the wives during the sample period can not be accounted for.

While we uncovered transition patterns, many without counterparts in the literature, among results that can be compared, some do not support commonly expressed beliefs such as that price effects are lower for wives than for husbands and that they have declined over time. In order to explore sources of divergence, we derived and estimated labor supply functions imposing several common restrictions. These restrictions lead to incomplete representations of the tax structure and downward-biased price effects. We found substantial biases for total hours of work amounting to 8-42 percent for secondary earner estimates, 53-78 percent for limited heterogeneity estimates, and 33-78 percent for gross wage estimates. In contrast, relying on variation in tax structures rather than their changes for identification yielded an upward bias of almost 200 percent.

Our method for inferring mean or distributional policy effects with multidimensional choice possibly involving nonlinear prices is useful for many other applications. We have incorporated components of the transfer system into the tax structure and treated unearned income as exogenous to earnings. In reality, eligible but incomplete participation in social programs and income-shifting between different sources may interact with labor supply. We have also abstracted from dynamic and life-cycle concerns. Many people may jointly decide on labor supply and pension savings. Insights can be gained from simultaneous treatments of these choices. Many consumption patterns also exhibit mutual dependence. Furthermore, multidimensional choice also frequently arises due to collective choice by multiple agents, e.g., many of the decisions discussed are made in a household context. Behavioral and functional form assumptions as well as regularities in the price structure may provide essential dimensionality reduction. Despite this, price and distributional variation in data may limit the number of choice variables that can be treated jointly.

Appendices

Appendix A. Proofs of theorems

Proof of Theorem 1. Denote the set with earnings of the husband lower than at $\boldsymbol{y}_{kl}$:

$$\boldsymbol{Y}_{kl}^{lower} = \{\boldsymbol{y}: y^m \leq y_k^m, y^f = y_l^f\}. \tag{A1}$$

Let $\overline{\boldsymbol{Y}}_{kl}^{lower} = \boldsymbol{Y} \backslash \boldsymbol{Y}_{kl}^{lower}$ be the complement of $\boldsymbol{Y}_{kl}^{lower}$. By quasi-concavity of $u(\boldsymbol{y})$:

$$1\left(\boldsymbol{y}_d \in \overline{\boldsymbol{Y}}_{kl}^{lower} | \boldsymbol{e}\right) = 1\left[u\left(c_{k+\epsilon,l}, \boldsymbol{y}_{k+\epsilon,l}, \boldsymbol{e}\right) > u(c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e})\right] = 1(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}), \tag{A2}$$

as $c_{k+\epsilon,l} = c_{kl} + \tau_{kl}^m$ and $\boldsymbol{y}_{k+\epsilon,l} = \boldsymbol{y}_{kl} + (\epsilon, 0)$. Whether desired choice is in this complement set only depends on four arguments. Crucially, we can decompose $1(\boldsymbol{y}_d = \boldsymbol{y}_{kl} | \boldsymbol{e})$ into terms that only depend on such low-dimensional functions because:

$$\boldsymbol{y}_{kl} = \left(\overline{\boldsymbol{Y}}_{k-\epsilon,l}^{lower} \backslash \overline{\boldsymbol{Y}}_{kl}^{lower}\right), \tag{A3}$$

as $\overline{\boldsymbol{Y}}_{kl}^{lower} \subset \overline{\boldsymbol{Y}}_{k-\epsilon,l}^{lower}$. Combining Eqs. (A2) and (A3) yields the decomposition:

$$\begin{aligned} 1(\boldsymbol{y}_d = \boldsymbol{y}_{kl} | \boldsymbol{e}) &= 1\left(\boldsymbol{y}_d \in \overline{\boldsymbol{Y}}_{k-\epsilon,l}^{lower} | \boldsymbol{e}\right) - 1\left(\boldsymbol{y}_d \in \overline{\boldsymbol{Y}}_{kl}^{lower} | \boldsymbol{e}\right) \\ &= 1\left(\tau_{k-\epsilon,l}^m, c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}\right) - 1(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}). \end{aligned} \tag{A4}$$

Plugging Eq. (A4) into the expectation function in Eq. (6) and collecting terms yields Eq. (7) with:

$$g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl}) = \int \left[g\left(\boldsymbol{y}_{k-\epsilon,l}, \boldsymbol{e}\right) - g(\boldsymbol{y}_{kl}, \boldsymbol{e})\right] 1(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl}, \boldsymbol{e}) \frac{p(\boldsymbol{e})}{p(\boldsymbol{y}_{kl})} \boldsymbol{de}. \ \blacksquare \tag{A5}$$

Remark 1: Because c_{kl} is a function of tax prices of both the husband and the wife, the tax prices of the wife enters the expectation functions implicitly. Remark 2: We could have worked with the set with earnings of the wife lower than at $\boldsymbol{y}_{kl}$ instead of Eq. (A1), which would have yielded $E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = \int g\left(\tau_{kl}^f, c_{kl}, \boldsymbol{y}_{kl}\right) p(\boldsymbol{y}_{kl}) \boldsymbol{dy}_{kl}$. Remark 3: We can cancel out $p(\boldsymbol{y}_{kl})$ in $E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}]$ and $g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl})$. However, the current representation allows a more precise approximation of $g(\tau_{kl}^m, c_{kl}, \boldsymbol{y}_{kl})$ as $p(\boldsymbol{y}_{kl})$ picks up most of the variation in the integrand across $\boldsymbol{y}_{kl}$ owing to the distribution of $\boldsymbol{e}$. Conveniently, this also restricts prices to have no effects at points with zero density and allows integration over a bounded domain.

Proof of Theorem 2. Instead of integrating over $\boldsymbol{y}_{kl}$ in Theorem 1, we can integrate over y_j. Now, we want to reduce the dimensionality of $1\left(y_d = y_j | \boldsymbol{e}\right)$. Quasi-concavity of $u(\boldsymbol{y})$ implies quasi-concavity of $u(y)$ and:

$$1\left(y_d > y_j | \boldsymbol{e}\right) = 1\left[u\left(c_{j+\epsilon}, y_{j+\epsilon}, \boldsymbol{e}\right) > u\left(c_j, y_j, \boldsymbol{e}\right)\right] = 1\left(\tau_j, c_j, y_j, \boldsymbol{e}\right). \tag{A6}$$

The equivalent of Eq. (A4) becomes:

$$1\left(y_d = y_j | \boldsymbol{e}\right) = 1\left(y_d > y_{j-\epsilon} | \boldsymbol{e}\right) - 1\left(y_d > y_j | \boldsymbol{e}\right) = 1\left(\tau_{j-\epsilon}, c_j, y_j, \boldsymbol{e}\right) - 1\left(\tau_j, c_j, y_j, \boldsymbol{e}\right) \tag{A7}$$

Plugging Eq. (A7) into the equivalent of Eq. (6) yields Eq. (8) with:

$$g\left(\tau_j, c_j, y_j\right) = \int \left[g\left(y_{j-\epsilon}, \boldsymbol{e}\right) - g\left(y_j, \boldsymbol{e}\right)\right] 1\left(\tau_j, c_j, y_j, \boldsymbol{e}\right) \frac{p(\boldsymbol{e})}{p\left(y_j\right)} \boldsymbol{de}. \ \blacksquare \tag{A8}$$

Proof of Theorem 3. By Assumption 3, $dE_{\boldsymbol{e}}/dc_0 = \int [d[g(\tau_j, c_j, y_j)p(y_j)]/c_j]dy_j$ cannot be a function $\boldsymbol{\tau}$. Therefore, local income effects $d[g(\tau_j, c_j, y_j)p(y_j)]/c_j$ cannot depend on τ_j. Since $c_j = c_0 + \int \tau_a 1(y_a < y_j)dy_a$, local income effects can neither depend on c_j. Thus, $d[g(\tau_j, c_j, y_j)p(y_j)]/c_j = \gamma(y_j)$. Generally, the local choice function needs to be separable in price and income effects according to:

$$g(\tau_j, c_j, y_j)p(y_j) = \gamma(\tau_j, y_j) + \gamma(y_j)c_j. \tag{A9}$$

Plugging Eq. (A9) into Eq. (8) and collecting similar-structured terms yield Eq. (9) with:

$$g(\tau_j, y_j)p(y_j) = \gamma(\tau_j, y_j) + \gamma(y_j)c_0 + \tau_j \int_{y_a > y_j} \gamma(y_{j+\epsilon})dy_a\,. \ \blacksquare \tag{A10}$$

Proof of Theorem 4. Conditional on y^{-s}, we can discard all terms in Eq. (A9) with $y_j < y^{-s}$. Eq. (10) follows by collecting the rest of the terms according to:

$$\begin{aligned} g(\tau_j, y_j^s)p(y_j^s) &= \gamma(\tau_j, y_j^s) + \tau_j \int_{y_a^s > y_j^s} \gamma(y_{j+\epsilon}^s)dy_a^s, \\ g[c(y^{-s})] &= \int_{y_j \geq y^{-s}} \gamma(y_j)c(y^{-s})dy_j\,. \ \blacksquare \end{aligned} \tag{A11}$$

Proof of Theorem 5. Conditional on (y^{-s}, w^s) that are statistically independent, for each h_j^s:

$$1(h^s > h_j^s | \boldsymbol{e}, y^{-s}, w^s) = 1(y^s > y_j^s | \boldsymbol{e}, y^{-s}, w^s) = 1[\tau(y_j^s), c(y_j^s), y_j^s, \boldsymbol{e}]. \tag{A12}$$

In particular, this holds for $h_j^s = \bar{h}^s$. Eq. (11) follows from the steps in Theorems 2 to 4 with:

$$g[\tau(\bar{y}^s)] = \gamma[\tau(\bar{y}^s), \bar{y}^s], \qquad g[c(\bar{y}^s)] = \gamma(\bar{y}^s)c(\bar{y}^s). \ \blacksquare \tag{A13}$$

Proof of Theorem 6. Conditional on $(y^{-s}, \widehat{w}^s)$, in (c, h^s)-space, for each $y_j > y^{-s}$, tax prices are $\widehat{w}^s\tau_j$. Deriving the equivalent of Eq. (10) and reorganizing terms yields:

$$\begin{aligned} E_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}, \widehat{w}^s] &= \int_{y_j \geq y^{-s}} g(\widehat{w}^s\tau_j, h_j^s)p(h_j^s)dy_j + g[c(y^{-s})] \\ &= E_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}] + \int_{y_j \geq y^{-s}} [g(\widehat{w}^s\tau_j, h_j^s) - g(\tau_j, y_j^s)]p(h_j^s)dy_j \\ &\quad + \int_{y_j \geq y^{-s}} g(\tau_j, y_j^s)[p(h_j^s) - p(y_j^s)]dy_j. \end{aligned} \tag{A14}$$

By statistical independence of $\widehat{w}^s$ and $E(\widehat{w}^s) = 1$:

$$\begin{aligned} \frac{dg(\tau_j, y_j^s)}{d\tau_j} &= \frac{dE_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}]}{d\tau_j} = E\left[\frac{dE_{\boldsymbol{e}}[g(h^s)|\boldsymbol{\tau}, y^{-s}, \widehat{w}^s]}{d\tau_j}\right] \\ &= E\left[\frac{dg(\widehat{w}^s\tau_j, h_j^s)}{d\widehat{w}^s\tau_j}\frac{d\widehat{w}^s\tau_j}{d\tau_j}\right] = \frac{dg(\widehat{w}^s\tau_j, h_j^s)}{d\widehat{w}^s\tau_j}E[\widehat{w}^s] = \frac{dg(\widehat{w}^s\tau_j, h_j^s)}{d\widehat{w}^s y_j}. \end{aligned} \tag{A15}$$

Therefore, a change in price $\widehat{w}^s\tau_j$ due to a change in $\widehat{w}^s$ has the same interpretation as a change in tax price τ_j. By Eq. (A12), it follows that $g\left(\widehat{w}^s\tau_j, h_j^s\right) = g\left(\widehat{w}^s\tau_j, y_j^s\right)$, and making use of this equality in Eq. (A14) yields Eq. (12). ■

Proof of Theorem 7. Let $x(\boldsymbol{\tau}) = \int \tau_j\eta_j dy_j$ be predictor variable candidates with the normalization $\int \eta_j dy_j = 1$. By the second fundamental theorem of calculus, we can rewrite the choice function in Theorem 3 as $E_{\boldsymbol{e}}[g(\boldsymbol{h})|\boldsymbol{\tau}] = \int \beta_{gj}\tau_j p_j dy_j$ where:

$$\beta_{gj}p_j = \int_{\tau_a \le \tau_j} \frac{dE_e[g(\boldsymbol{h})|\boldsymbol{\tau}]}{d\tau_a} d\tau_a \Bigg/ \int_{\tau_a \le \tau_j} d\tau_a. \tag{A16}$$

The parameter β_{gj} is a per-household weighted average tax price effect over the nonlinearities in τ_j. Let $\hat{\tau}_j = \tau_j - E(\tau_j)$ denote the sample-demeaned τ_j. For βx to minimize the mean square error, we need, by the definition of the least square estimator:

$$\beta = \frac{E\left[\int \beta_{gj}\hat{\tau}_j p_j dy_j \int \hat{\tau}_a\eta_a dy_a\right]}{E\left[\int \hat{\tau}_j\eta_j dy_j \int \hat{\tau}_a\eta_a dy_a\right]} = \frac{\int \beta_{gj}p_j E\left[\hat{\tau}_j \int \hat{\tau}_a\eta_a dy_a\right]dy_j}{\int \eta_j E\left[\hat{\tau}_j \int \hat{\tau}_a\eta_a dy_a\right]dy_j}. \tag{A17}$$

Now, for β to be a weighted average of β_{gj} across y_j:

$$\omega_j = \int \eta_j E\left[\hat{\tau}_j \int \hat{\tau}_a\eta_a dy_a\right] dy_j = \int p_j E_i\left[\hat{\tau}_j \int \hat{\tau}_a\eta_a dy_a\right] dy_j, \tag{A18}$$

which only holds generally when $\eta_j = p_j$, in which case $x(\boldsymbol{\tau}) = \tilde{\tau}$ and:

$$\beta = \tilde{\beta}_g = \int \beta_{gj}\omega_j dy_j, \tag{A19}$$

where ω_j is the weight given to each β_{gj} and $\int \omega_j dy_j = 1$. ■

Proof of Theorem 8. We can derive a difference version of Eq. (9) according to:

$$\begin{aligned} E_{\boldsymbol{e}}[G(\boldsymbol{h}_T, \boldsymbol{h}_t)|\boldsymbol{\tau}_T, \boldsymbol{\tau}_t] &= E_{y_j}\left[E_{\boldsymbol{e}}\left[G\left(\boldsymbol{h}_T(y_j, \boldsymbol{e}), \boldsymbol{h}_t(y_j, \boldsymbol{e})\right)|y_j\right]\right] \\ &= \iint G(y_j, \boldsymbol{e})\left[1(y_T = y_j|\boldsymbol{e}) - 1(y_t = y_j|\boldsymbol{e})\right]p(\boldsymbol{e})\boldsymbol{de}dy_j. \end{aligned} \tag{A20}$$

Reproducing the steps in Theorem 3 and making use of the approximation yield:

$$\begin{aligned} E_{\boldsymbol{e}}[G(\boldsymbol{h}_T, \boldsymbol{h}_t)|\boldsymbol{\tau}_T, \boldsymbol{\tau}_t] &= \iint G(y_j, \boldsymbol{e})\left[1(\tau_{jT}, c_{jT}, y_j, \boldsymbol{e}) - 1(\tau_{jt}, c_{jt}, y_j, \boldsymbol{e})\right]p(\boldsymbol{e})\boldsymbol{de}dy_j \\ &= \int \left[G(\tau_{jT}, c_{jT}, y_j) - G(\tau_{jt}, c_{jt}, y_j)\right]dy_j = \int \left[\beta_{Gj}(\tau_{jT} - \tau_{jt})p_j\right]dy_j. \end{aligned} \tag{A21}$$

It is straightforward to plug in $G(\boldsymbol{h}_T, \boldsymbol{h}_t) = g(\boldsymbol{h}_T) - g(\boldsymbol{h}_t)$ in Eq. (A20) and show that in this case $\beta_{Gj} = \beta_{gj}$ in Eq. (A21). ■

Appendix B. Additional empirical results

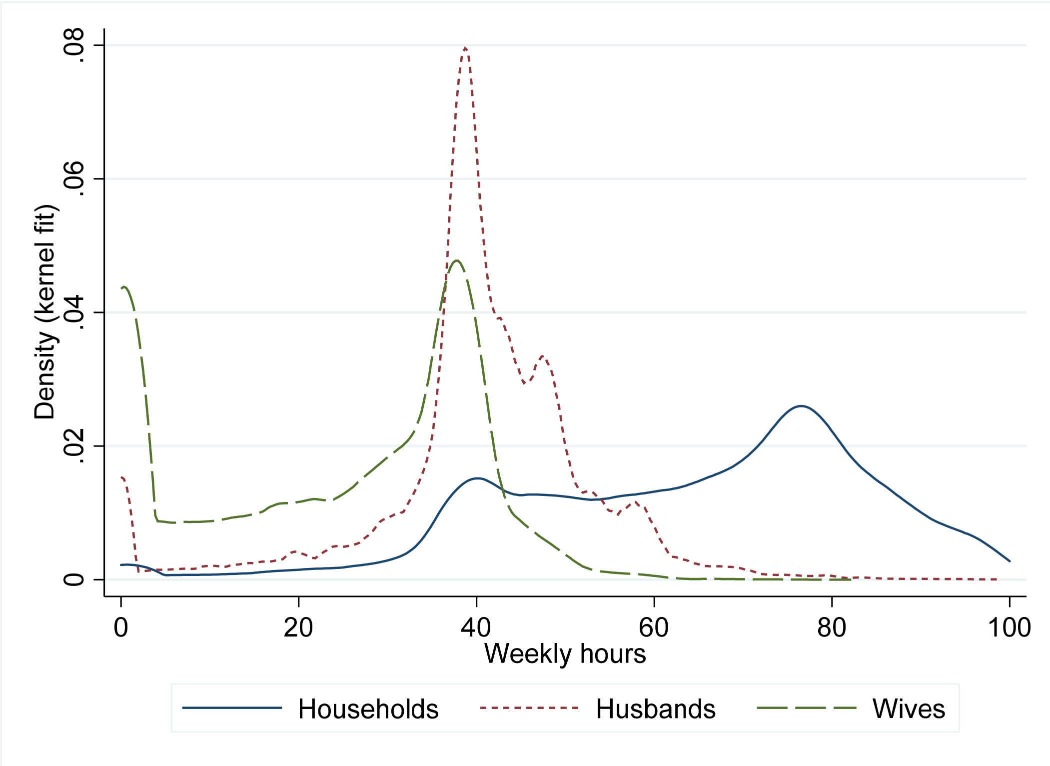
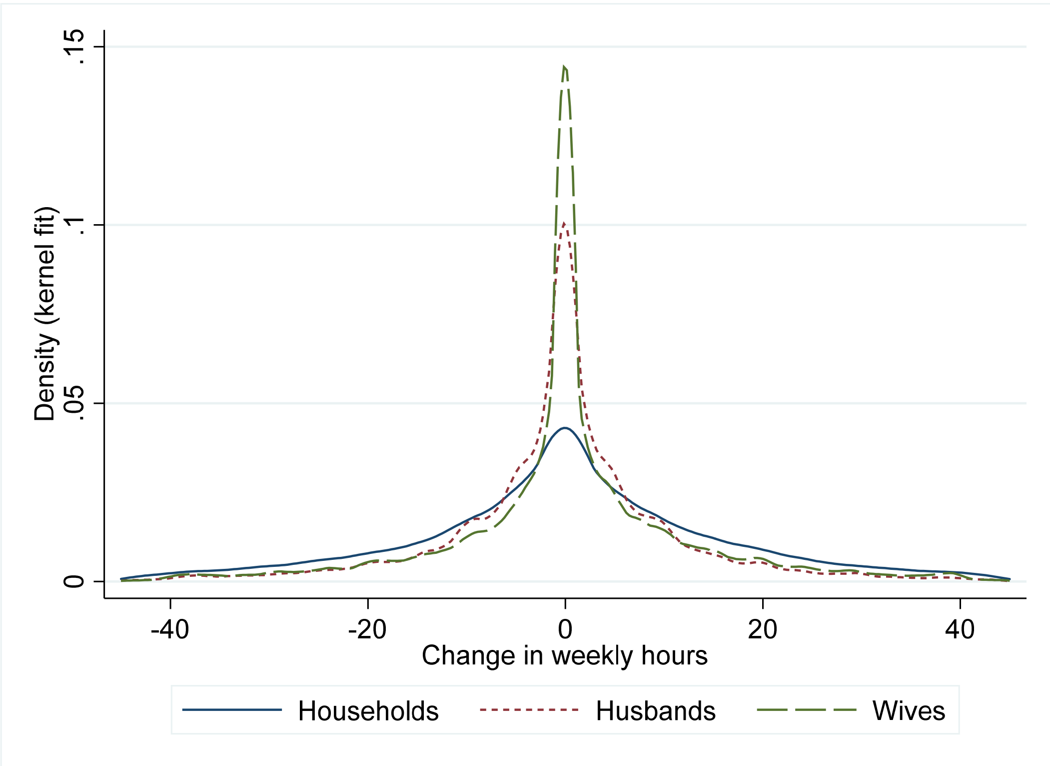


Figure B1. The distribution of weekly hours



3

Figure B2. The distribution of changes in weekly hours

Table B1. The joint distribution of weekly hours

		Weekly hours wife				
		0-15	15-30	30-45	>45	Total
Weekly hours husband	0-15	0.024	0.009	0.021	0.004	0.058
	15-30	0.021	0.014	0.027	0.004	0.065
	30-45	0.162	0.099	0.248	0.029	0.537
	>45	0.114	0.064	0.132	0.030	0.340
	Total	0.321	0.184	0.428	0.067	1.00

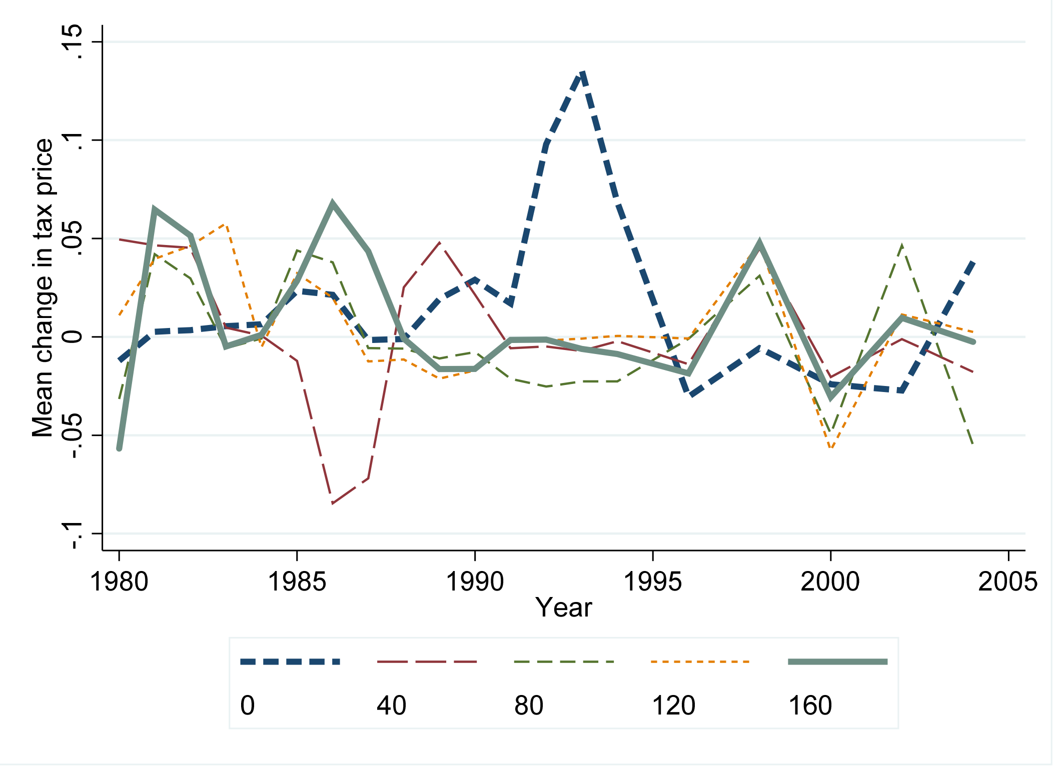


Figure B3. Changes in earnings-specific tax prices across base years

Notes: For each base year, we plot mean change in tax prices at USD 0, 40,000, 80,000, 120,000, and 160,000 (2006 price level).

Table B2. Estimates based on the cubic representation of the tax structure

Regressors	(1) Households	(2) Husbands	(3) Wives
$\sum_j \Delta\tau_j p_j$	85.84	105.0	-19.16
	(38.92)	(26.7)	(28.07)
$\sum_j \Delta\tau_j y_j p_j$	2.259	-1.488	3.747
	(1.760)	(1.206)	(1.270)
$\sum_j \Delta\tau_j y_j^2 p_j$	-0.0437	0.0109	-0.0546
	(0.0232)	(0.0159)	(0.0168)
$\sum_j \Delta\tau_j y_j^3 p_j$	0.000118	-0.0000578	0.000175
	(0.000087)	(0.0000597)	(0.000063)

Notes: Change in weekly hours is the dependent variable. Each column reports estimates from one regression including fixed effects for number of children, state of residence, and the age and education levels, and base-year weekly hours of each spouse. Individual-level clustered standard errors are reported within parentheses.

Table B3. Estimates based on the flexible representation of the tax structure

Regressors	(1) Households	(2) Husbands	(3) Wives
$\sum_j \Delta\tau_j p_j$	517.1	302.7	214.4
	(99.5)	(69.6)	(71.5)
$\sum_j \Delta\tau_j y_j p_j$	-12.18	-9.415	-2.767
	(4.09)	(2.772)	(2.757)
$\sum_j \Delta\tau_j y_j^2 p_j$	0.0197	0.0438	-0.0241
	(0.0403)	(0.0282)	(0.0281)
$\sum_j \Delta\tau_j y_j^3 p_j$	-0.000096	-0.000163	0.0000671
	(0.000143)	(0.000100)	(0.0000992)
$\sum_j \Delta c_j p_j$	-7.823	-4.203	-3.620
	(1.786)	(1.192)	(1.165)
$\sum_j \Delta\tau_j c_j p_j$	12.56	7.654	4.902
	(2.77)	(1.867)	(1.810)
$\sum_j \Delta c_j y_j p_j$	0.151	0.103	0.0477
	(0.040)	(0.026)	(0.0250)
$\sum_j \Delta\tau_j^2 p_j$	-241.1	-120.2	-120.9
	(53.7)	(37.6)	(36.8)
$\sum_j c_j^2 p_j$	-0.106	-0.0775	-0.0289
	(0.027)	(0.0176)	(0.0167)

Notes: Change in weekly hours is the dependent variable. Each column reports estimates from one regression including fixed effects for number of children, state of residence, and the age and education levels, and base-year weekly hours of each spouse. Individual-level clustered standard errors are reported within parentheses.

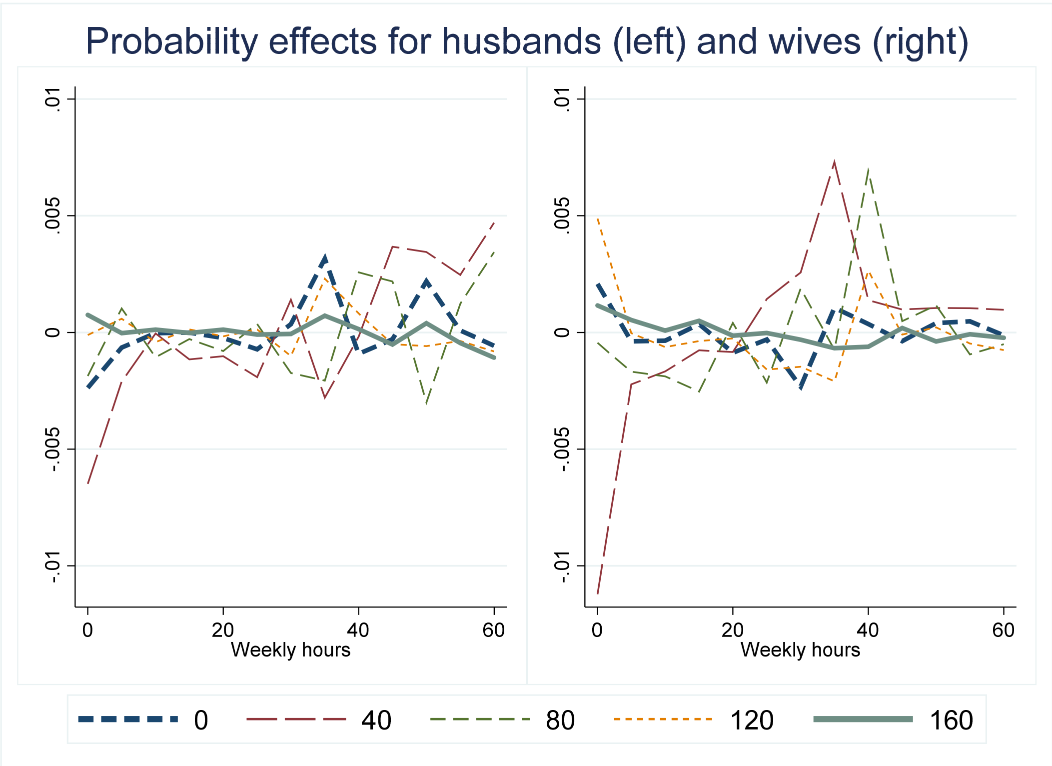


Figure B4. Earnings-specific tax price effects on the distribution of weekly hours

Notes: Changes in interval indicators of weekly hours are dependent variables. Changes in (up to) cubic tax price terms are regressors. For each interval of weekly hours, estimates from one regression including control variables are used to predict the effects of tax price at USD 0, 40,000, 80,000, 120,000, and 160,000.

Table B4. Average tax price effects on transitions between subsets of joint weekly hours

			End year							
		M	0-15	0-15	0-15	0-15	15-30	15-30	15-30	15-30
	M	F/F	0-15	15-30	30-45	>45	0-15	15-30	30-45	>45
Base year	0-15	0-15	-2.9	0.3	0.1	-0.2	-0.6	0.2	-0.1	0.0
	0-15	15-30	-0.4	-0.2	0.1	0.0	0.0	0.1	-0.3	0.0
	0-15	30-45	-1.1	-0.4	-0.6	1.1	-0.1	-0.1	-0.7	0.0
	0-15	>45	-0.3	0.1	0.2	0.2	0.0	0.2	0.1	-0.2
	15-30	0-15	-0.6	-0.2	-0.6	0.1	-1.1	-0.2	-0.1	0.1
	15-30	15-30	0.0	-0.5	-0.3	0.1	-0.3	0.0	0.0	0.0
	15-30	30-45	-0.1	-0.4	-1.8	-0.3	-0.1	-0.5	-0.9	0.0
	15-30	>45	0.0	0.1	0.0	0.4	0.0	0.0	0.3	-0.1
	30-45	0-15	-6.2	-0.8	-0.4	-0.1	-1.8	-0.1	-0.2	-0.1
	30-45	15-30	0.0	-1.7	-0.8	-0.5	-0.8	-0.8	-0.3	-0.1
	30-45	30-45	-1.3	-1.8	-3.6	-1.2	-0.6	-1.5	-1.7	0.0
	30-45	>45	-0.3	-0.1	0.0	-0.1	0.0	0.0	-0.4	-0.5
	>45	0-15	-1.8	-0.3	-0.2	-0.1	-0.8	0.0	-0.1	-0.1
	>45	15-30	-0.3	-0.4	-0.1	-0.4	-0.3	-0.3	-0.3	0.0
	>45	30-45	-0.8	-0.3	-1.3	0.1	-0.5	-0.2	-2.2	-0.1
	>45	>45	-0.1	0.0	0.5	0.1	-0.1	0.0	-0.4	0.1
			End year							
		M	30-45	30-45	30-45	30-45	>45	>45	>45	>45
	M	F/F	0-15	15-30	30-45	>45	0-15	15-30	30-45	>45
Base year	0-15	0-15	0.3	0.2	0.1	0.0	0.2	0.0	0.2	0.1
	0-15	15-30	-0.3	0.2	0.3	0.0	0.2	0.3	0.2	0.0
	0-15	30-45	-0.2	0.2	0.5	0.1	0.0	0.3	0.4	0.0
	0-15	>45	0.0	0.0	0.1	0.1	0.0	-0.1	-0.1	0.4
	15-30	0-15	-0.5	-0.1	0.5	-0.1	0.7	0.5	0.1	0.1
	15-30	15-30	1.0	-0.4	-0.5	0.1	-0.2	0.2	0.0	0.1
	15-30	30-45	0.0	0.1	1.8	0.2	0.1	0.0	1.2	0.2
	15-30	>45	-0.1	0.3	0.5	-0.2	0.0	0.1	0.1	0.6
	30-45	0-15	-3.1	3.9	2.9	0.6	5.3	1.7	1.9	-0.1
	30-45	15-30	-3.1	2.3	4.2	0.0	-0.6	-1.0	1.8	0.0
	30-45	30-45	-6.2	-2.5	14.3	1.8	-1.8	-2.7	8.8	0.7
	30-45	>45	-1.0	0.4	1.7	0.7	0.0	-0.4	-0.3	2.1
	>45	0-15	-3.2	1.5	1.4	-0.3	5.2	0.2	2.5	0.2
	>45	15-30	0.0	1.1	0.3	0.0	-0.7	-0.3	4.9	0.4
	>45	30-45	-1.9	-2.0	-0.5	0.2	-3.2	-1.4	5.2	-0.2
	>45	>45	-0.3	-0.5	-0.8	0.5	-1.3	0.6	1.6	-0.8

Notes: Changes in subset indicators of joint weekly hours are dependent variables. Change in average tax price is the regressor. Each cell reports an estimate from one regression including control variables.

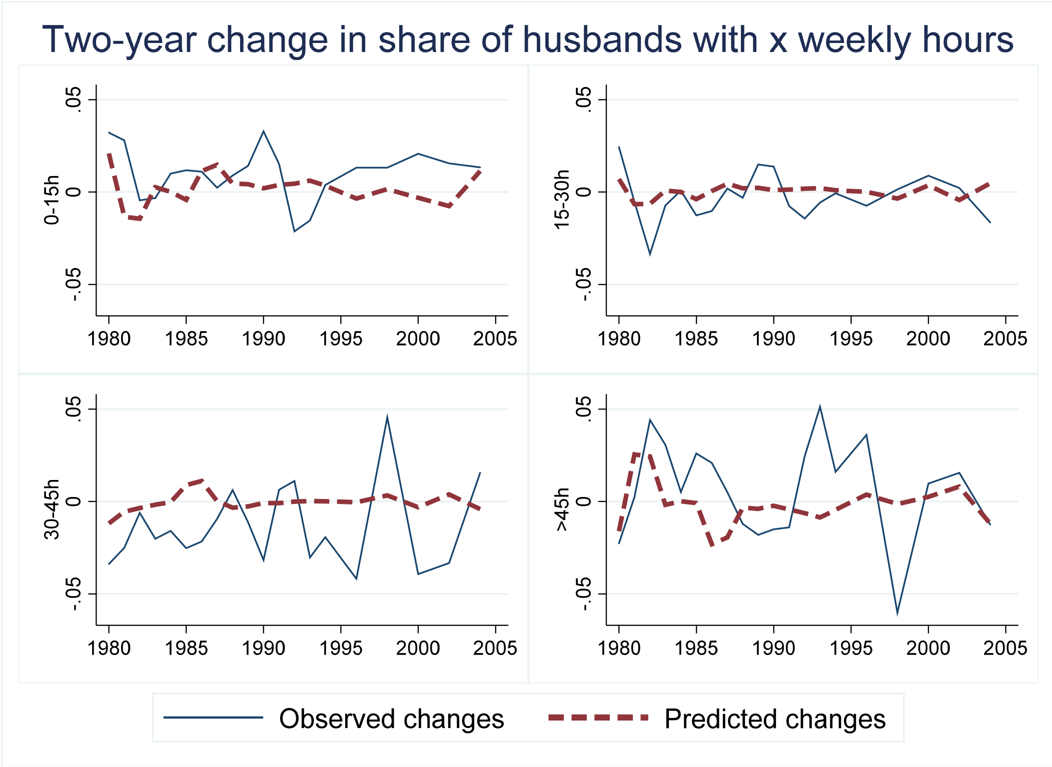


Figure B5. Observed and predicted changes in the distribution of weekly hours for husbands

Notes: The predictions are based on the cubic estimates in Table B2.

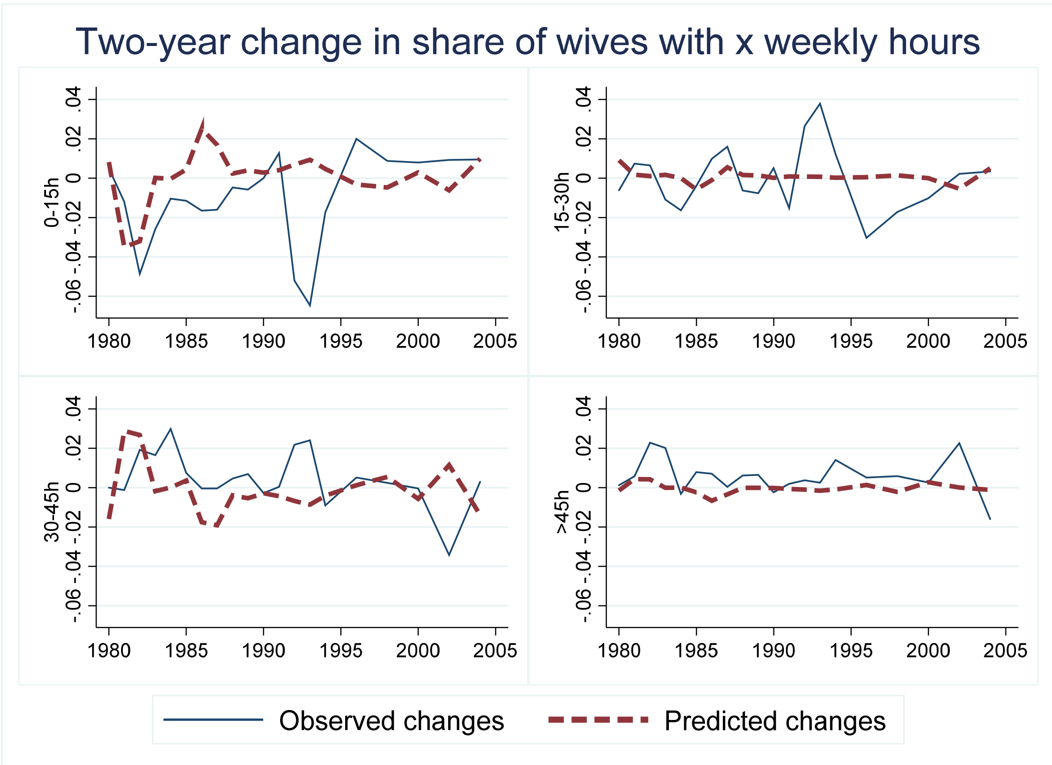


Figure B6. Observed and predicted changes in the distribution of weekly hours for wives

Notes: The predictions are based on the cubic estimates in Table B2.

References

Aaberge R., Dagsvik J., Strom S., 1995. Labor supply responses and welfare effects of tax reforms, Scandinavian Journal of Economics 97, 635-659.

Aaberge R., Colombino U., Strom S., 1999. Labor supply in Italy: an empirical analysis of joint household decisions, with taxes and quantity constraints, Journal of Applied Econometrics 14, 403-422.

Angrist J., Chernozhukov V., Fernández-Val I., 2006. Quantile regression under misspecification, with an application to the U.S. wage structure. Econometrica 74, 539-563.

Angrist J., Pischke J., 2008. Mostly Harmless Econometrics: An Empiricist's Companion, Princeton University Press, Princeton, New Jersey.

Atkinson A., Saez E., Piketty T., 2011. Top incomes in the long run of history. Journal of Economic Literature 49, 3-71.

Blau F., Kahn. L., 2007. Changes in the labor supply behavior of married women: 1980-2000. Journal of Labor Economics 25, 393-438.

Blomquist S., 1983. The effect of income taxation on the labor supply of married men in Sweden. Journal of Public Economics 22, 169-197.

Blomquist S., 1996. Estimation methods for male labor supply functions: how to take account of nonlinear taxes. Journal of Econometrics 70, 383-405.

Blomquist S., 1988. Nonlinear taxes and labor supply. European Economic Review 32, 1213-1226.

Blomquist S., Kumar A., Liang C., Newey W., 2014. Individual heterogeneity, nonlinear budget sets, and taxable income. Uppsala Center for Fiscal Studies Working Paper 2014:1.

Blomquist S., Newey W., 2002. Nonparametric estimation with nonlinear budget sets. Econometrica 70, 2455-2480.

Blomquist S., Simula L., 2016. Marginal deadweight loss when income tax is nonlinear. Working Paper, Université de Grenoble Alpes INRA-GAEL.

Blundell R., Chiappori P.-A., Magnac T., Meghir C., 2007. Collective labour supply: heterogeneity and non-participation. Review of Economic Studies 74, 417-445.

Blundell R., Duncan A., Meghir C., 1998. Estimating labor supply responses using tax reforms. Econometrica 66, 827-861.

Blundell R., Shephard A., 2012. Employment, hours of work and the optimal design of earned income tax credits. Review of Economic Studies 72, 481-510.

Blundell R., Walker I., 1986. A life-cycle consistent empirical model of family labour supply using cross-section data. Review of Economic Studies 53, 539-558.

Blundell R., 2016. What have we learned from structural methods. American Economic Review Papers and Proceedings 107, 287-292.

Blundell R., Pistaferri L., Saporta-Eksten I., 2016. Consumption inequality and family labor supply. American Economic Review 106, 387-435.

Burtless G., Hausman J., 1978. The effect of taxation on labor supply: evaluating the Gary negative income tax experiment. Journal of Political Economy 86, 1103-1130.

Chernozhukov V., Fernández-Val I., Melly B., 2013. Inference on counterfactual distributions. Econometrica 81, 2205-2268.

Chiappori P.-A., 1988. Rational Household Labor supply. Econometrica 5, 63-89.
Chiappori P.-A., 1992. Collective labor supply and welfare. Journal of Political Economy 100, 437-467.
Dagsvik J., 1994. Discrete and continuous choice, max-stable processes and independence from irrelevant attributes. Econometrica 62, 1179-1205.
Deaton A., Ruiz-Castillo J., Duncan T., 1989. The influence of household composition on household expenditure patterns: theory and Spanish evidence. Journal of Political Economy 97, 179-200.
Eissa N., 1995. Taxation and labor supply of married women: the tax reform act of 1986 as a natural experiment. National Bureau of Economic Research Working Paper 5023.
Eissa N., 1996. Labor supply and the economic recovery tax act of 1981. In Feldstein M., Poterba J. (eds.), Empirical Foundations of Household Taxation, 5-38, University of Chicago Press, Chicago, Illinois.
Eissa. N., Hoynes H., 2004. Taxes and the labor market participation of married couples: the earned income tax credit. Journal of Public Economics 88, 1931-1958.
Eissa N., Kleven H., Kreiner C., 2008. Evaluation of four tax reforms in the United States: labor supply and welfare effects for single mothers. Journal of Public Economics 92, 795-816.
Eissa N., Liebman J., 1996. Labor supply response to the earned income tax credit. Quarterly Journal of Economics 61, 605-637.
Feldstein M., 1995. The effect of marginal tax rates on taxable income: a panel study of the 1986 tax reform act. Journal of Political Economy 103, 551-572.
Foresi S., Peracchi, F., 1995. The conditional distribution of excess returns: an empirical analysis. Journal of the American Statistical Association 90, 451-466.
Fortin B., Lacroix G., 1997. A test of neoclassical and collective models of household labor supply. Economic Journal 107, 933-955.
Gelber A., 2014. Taxation and the earnings of husbands and wives: evidence from Sweden. Review of Economics and Statistics 96, 287-305.
Goldin C., 1990. Understanding the Gender Gap: An Economic History of American Women, Oxford University Press, Oxford, United Kingdom.
Gruber J., Saez E., 2002. The elasticity of taxable income: evidence and implications. Journal of Public Economics 84, 1-32.
Harsanyi J., 1953. Cardinal utility in welfare economics and in the theory of risk-taking. Journal of Political Economy 61, 434-435.
Hausman J., 1985. The econometrics of nonlinear budget sets. Econometrica 53, 1255-1282.
Hausman J., Ruud P., 1984. Family labor supply with taxes. American Economic Review 74, 242-248.
Heim B., 2007. The incredible shrinking elasticities: married female labor supply, 1978-2002. Journal of Human Resources 42, 881-918.
Hendren N., 2016. The policy elasticity. Tax Policy and the Economy 30, 51-89.
Hoynes H., 1996. Welfare transfers in two-parent families: labor supply and welfare participation under AFDC-UP. Econometrica 64, 295-332.
Juhn C., Murphy K., 1997. Wage inequality and family labor supply. Journal of Labor Economics 15, 72-97.

Keane M., 2011. Labor supply and taxes: a survey. Journal of Economic Literature, 49, 961-1075.

Keane M., Mofitt R., 1998. A structural model of multiple welfare program participation and labor supply. International Economic Review 39, 553-589.

Kumar A., 2007. Labor supply, deadweight loss and tax reform act of 1986: a nonparametric evaluation using panel data. Journal of Public Economics 92, 236-253.

Kumar A., 2012. Nonparametric estimation of the impact of taxes on female labor supply Journal of Applied Econometrics 27, 415-439.

Kumar A., and Liang C.-Y., 2017. Estimating taxable income responses with elasticity heterogeneity. Working paper 2017:5, Department of Economics, Uppsala University 2017:5.

Kumar A., and Liang C.-Y., 2016. Declining female labor supply elasticities in the United States and implications for tax policy: evidence from panel data, National Tax Journal 69, 481-516.

Loffler M., Peichel A., Siegloch S., 2014. Structural labor supply models and wage exogeneity. Discussion paper 8281, Institute for the Study of Labor.

Lundberg S., 1988. Labor supply of husbands and wives, Review of Economics and Statistics 70, 635-666.

Newey W., 1997. Convergence rates and asymptotic normality for series estimators. Journal of Econometrics 79, 147-168.

Pencavel J., 1986. Labor supply of men: a survey. In Ashenfelter O., Layard R. (eds.) Handbook of Labor Economics 1, 2-102.

Ransom M., 1987. An empirical model of discrete and continuous choice in family labor supply. Review of Economics and Statistics 69, 465-472.

Rawls J., 1971. A Theory of Justice. Harvard University Press, Cambridge, Massachusetts.

Roine J., Waldenström D., 2015. Long run trends in the distribution of income and wealth. In Atkinson A., Bourguignon F. (eds.), Handbook of Income Distribution 2, 469-592, Elsevier, North-Holland.

Rothe C., 2012. Partial distributional policy effects. Econometrica, 80, 2269-2301.

Saez E., Slemrod J., Giertz, S., 2012. The elasticity of taxable income with respect to marginal tax rates: a critical review. Journal of Economic Literature 50, 3-50.

Van Soest A., Woittiez I., Kapteyn A., 1990. Labor supply, income taxes, and hours restrictions in the Netherlands. Journal of Human Resources 25, 517-58.

Van Soest A., 1995. Structural models of family labor supply: a discrete choice approach. Journal of Human Resources 30, 63-88.

Van Soest A., Das M., Gong X., 2002. A structural labour supply model with flexible preferences. Journal of Econometrics 107, 345-374.

Ziliak J., Kniesner P., 1999. Estimating life cycle labor supply tax effects. Journal of Political Economy 107, 326-359.